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The Impact of Digital Learning Environments on Science Learning: Two Possible Ways to Foster Cognitive Learning Processes

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- Ruf, A., Zahn, C., Agotai, D., Iten, G., & Opwis, K. (2022). Aesthetic design of app interfaces and their impact on secondary students' interest and learning. *Computers and Education Open, 3*. https://doi.org/https://doi.org/10.1016/j.caeo.2022.100075
- Ruf, A., Leisner, D., Zahn C., & Opwis, K. (2021). Impact of learners' video interactions on learning success and cognitive load. In C. Hmelo-Silver, B. de Wever, & J. Oshima (Eds.), 14th International Conference on Computer-Supported Collaborative Learning – CSCL 2021 (pp. 3-10). International Society of the Learning Sciences, 2021.
- Ruf, A., Zahn, C., Roos, A., & Opwis, K. (submitted). How do digital video tools support conceptual understanding and creative learning in individuals and groups?

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Alessia Ruf

Contents

Abstract

Fostering understanding and interest in (natural) science-related topics is of the utmost scientific and practical relevance. Digital learning environments offer interesting opportunities in this regard. However, in order for them to support learning, attention must be paid to both their instructional design and the ongoing learning processes that influence the way in which learners can use them effectively for learning. Thus, following situative and cognitive perspectives taken from learning science and cognitive psychology, this thesis aims to obtain a holistic understanding of learning using digital environments by simultaneously examining different antecedents, processes, and consequences of learning. Over the course of three manuscripts, we pursued two possible ways to foster science learning with digital learning environments. We investigated the effects of aesthetic interfaces in a learning application (Manuscript 1) and the effects of enhanced video tools designed to foster generative learning on scientific interest and learning (Manuscripts 2 and 3). Our results revealed that cognitive processes can be successfully fostered using both ways, leading to increased interest and learning in science.

This cumulative dissertation is based on the following three manuscripts:

1. Ruf, A., Zahn, C., Agotai, D., Iten, G., & Opwis, K. (2022). Aesthetic design of app interfaces and their impact on secondary students' interest and learning. *Computers and Education Open, 3.* https://doi.org/https://doi.org/10.1016/j.caeo.2022.100075
2. Ruf, A., Leisner, D., Zahn C., & Opwis, K. (2021). Impact of learners' video interactions on learning success and cognitive load. In C. Hmelo-Silver, B. de Wever, & J. Oshima (Eds.), *14th International Conference on Computer-Supported Collaborative Learning – CSCL 2021* (pp. 3–10). International Society of the Learning Sciences, 2021.
3. Ruf, A., Zahn, C., Roos, A., & Opwis, K. (submitted). How do digital video tools support conceptual understanding and creative learning in individuals and groups?

Introduction

Finding ways to support learning effectively is essential for successful educational and work performance and, thus, of great scientific and practical relevance. Fostering interest in and understanding of (natural) science, in particular, is central to daily life, since this can contribute to a greater awareness of and willingness to engage with global issues and to take responsibility (Bencze & Carter, 2011; Oliver & Adkins, 2020). It also promotes good decision-making based on sound reasoning (He et al., 2021). However, science topics are often perceived as difficult, challenging to learn, or boring, which provokes a lack of interest in learners (Bernacki et al., 2015; Uitto, 2014). Hence, it is not surprising that students' interest in science-related topics steadily declines (OECD, 2018). *Digital learning environments* (cf. Wang & Hannafin, 2005) offer promising opportunities to support scientific interest and learning (Chen et al., 2018; Jung et al., 2019; Leisner et al., 2020). Recently, boosted by the COVID-19 pandemic (Schilirò, 2020), educational institutions have increasingly relied on new digital classroom settings (Marinoni et al., 2020; Yan et al., 2021), including mobile apps (Qureshi et al., 2020; Zydney & Warner, 2016) and enhanced video-based environments (Evi-Colombo et al., 2020; Noetel et al., 2021). However, in line with earlier debates (Clark, 1994; Kozma, 1994), it cannot be assumed that interest and learning can be promoted by providing digital learning environments alone. In fact, whether such environments can exploit their potential to foster learning depends on two important factors: on their *instructional design* and on how learners (can) *use* them to learn effectively (cf. Fiorella & Mayer, 2016). Hence, to understand how learning can be fostered with digital learning environments, it is crucial to consider both situative perspectives on learning, proposing to understand learning as a holistic construct that is shaped by several components (Greeno & Engeström, 2015; Janssen & Kirschner, 2020) and cognitive perspectives, focusing on the cognitive learning processes responsible for individual knowledge acquisition (Mayer, 2005; Sweller, 2005).

Given these approaches, the goal of this doctoral thesis is to expand the understanding of how digital learning environments can support science learning by simultaneously investigating different *antecedents*, *processes*, and *consequences* of learning. In three manuscripts, my co-authors and I empirically examined the impact of two different digital learning environments (i.e., a mobile learning app and an enhanced video-based environment) on different learning processes (i.e., aesthetic experience, learning activity, cognitive load) and learning outcomes (i.e., interest, knowledge acquisition, self-created information structures). We pursued two different ways to foster the cognitive processes that are relevant for effective learning (Mayer, 2005): supporting learning, firstly, through a learning application designed to be *aesthetically appealing* and, secondly, through an enhanced-video based environment designed to *foster generative learning*. We draw on theories from the field of cognitive multimedia learning (Mayer, 2005; Sweller, 2005) and research on aesthetic and emotional design (Moreno & Mayer, 2007; Thielsch et al., 2019; Um et al., 2012), and refer to approaches on generative learning (Fiorella & Mayer, 2016; Wittrock, 1992). In the following sections, we first introduce situative and cognitive perspectives on learning. We then discuss these perspectives in the context of the two possible ways to foster learning with digital learning environments and derive two overarching research questions. Next, the three manuscripts are each summarized before they are discussed within the larger research context. We conclude with practical implications, limitations, and recommendations for future research.

Theoretical Background

Situative Perspectives on Learning

Earlier approaches from psychology traditionally examined learning at the individual level, while the larger context in which learning occurs was viewed as an external influencing factor. A *situative*

perspective on learning in *higher-level* learning contexts was presented by Greeno and Engeström (2015). In their framework, Greeno and Engeström (2015) referred to these contexts as *activity systems* in which learners actively engage with group members, learning environments, and tools. They describe three major components of activity systems: the *subject*, which can be an individual learner or a group, the *object*, which is a topic or task learners work on, and the *resources* learners use to transform the object according to a desired outcome.

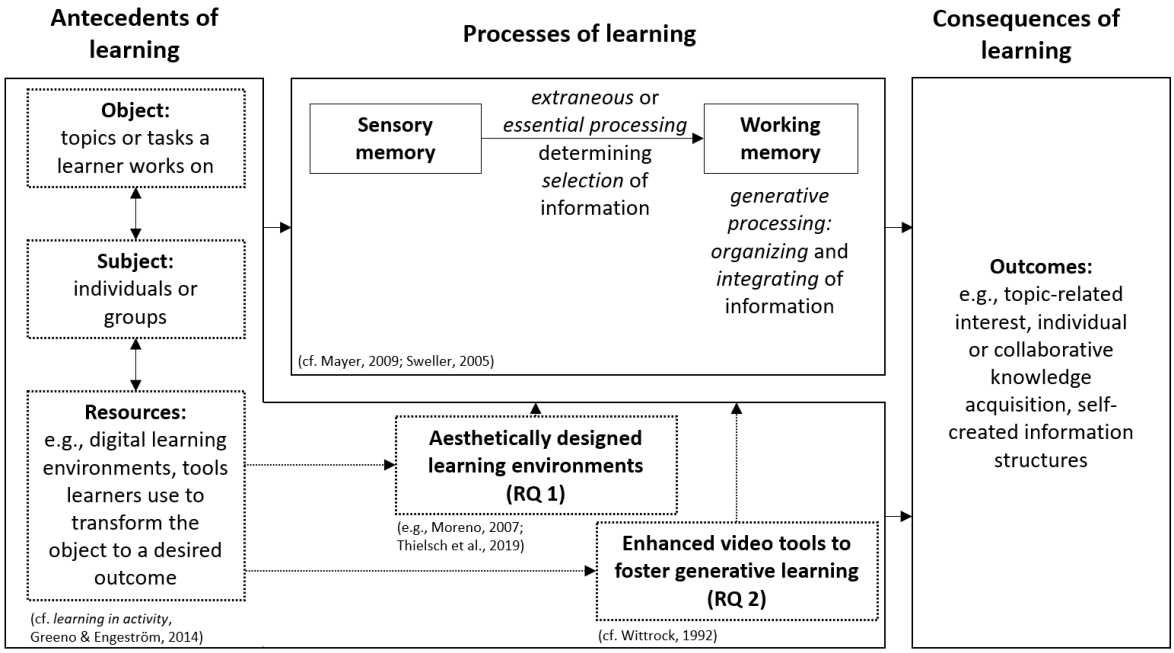
A similar approach is provided by Janssen and Kirschner (2020), who draw on theories of computer-supported collaborative learning (CSCL, cf. Jeong et al., 2019) and collaborative cognitive load (cf. Kirschner et al., 2018). In their model, they considered both effect-oriented approaches to examine the effects of CSCL environments on learning outcomes (cf. Chen et al., 2018) and process-oriented approaches (cf. Stahl, 2015) to respect the learning processes responsible for these effects. To gain a fundamental understanding of CSCL, they emphasize that research should increasingly address simultaneous investigations of different *antecedents* of collaborative learning, collaborative *learning processes*, and *consequences* of collaborative learning (see also Dillenbourg et al., 2009; Janssen et al., 2010). Similar to Greeno and Engeström's (2015) framework, Janssen and Kirschner (2020) refer to *antecedents* as student and group characteristics (e.g., prior knowledge, group experience), task characteristics (e.g., task complexity), and technology characteristics (e.g., scaffolds) that affect how individuals learn in CSCL environments (see also Le et al., 2018). In addition, they define collaborative *learning processes* as the processes occurring during collaborative tasks, such as individual invested mental effort (cf. Retnowati et al., 2018), and the *consequences* of collaborative learning as learning outcomes, such as individual achievement, motivation, or group performance.

Both approaches serve as an overarching framework in this thesis. Figure 1 represents an attempt to unify these theories into one model. Since learning in higher-level learning contexts in turn influences learning at the individual level, involving mental cognitive processes in individuals' minds, it is

crucial to consider both the situative and cognitive perspectives on learning as being complementary (cf. Greeno & Engeström, 2015). The next section discusses theories from the field of cognitive psychology that describe the cognitive processes responsible for the emergence of learning with multimedia learning materials.

Figure 1

The Relationship Between the Antecedents, Processes, and Consequences of Learning Based on Situative Approaches to Learning (Greeno & Engeström, 2015; Janssen & Kirschner, 2020)



Cognitive Perspectives on Learning

Based on fundamental cognitive theories on multimedia processing (i.e., processing of the simultaneous presentation of image and text or audio material, cf. Baddeley, 1992; Paivio, 1986), both the cognitive theory of multimedia learning (Mayer, 2005, 2011) and the cognitive load theory (Sweller, 2005) were established to explain which cognitive processes are central for learning with multimedia learning materials and how these processes can be fostered through appropriate instructional designs of

these materials. Both approaches assume that the working memory has limited capacity, which is strained by different forms of cognitive load. According to Mayer (2011), these loads result from *extraneous*, *essential*, and *generative* processing (see Figure 1). This is illustrated with the following example: multimedia information is recorded through learners' ears or eyes and stored in the sensory memory. Next, pieces of information are *selected* from sensory memory to be transferred to working memory. The information pieces that are selected depend on extraneous and essential processing. Extraneous processing means the processing of extraneous material that is not relevant to learning (e.g., appealing but irrelevant graphics, see also seductive details effect, Mayer, 2019). This unnecessarily strains the capacity of working memory and should, therefore, be avoided. In contrast, essential processing means the processing of learning-relevant information. To avoid extraneous processing and facilitate the processing of essential material, learning material should be designed according to concrete design guidelines (for an overview, see Mayer, 2008). Finally, in the working memory, generative processing aims to make sense of the selected information pieces by *organizing* and *integrating* them with each other and with learners' prior knowledge. Mayer (2005) concludes that meaningful and effective learning can be promoted by fostering the cognitive processes of *selecting*, *organizing*, and *integrating* of essential learning material (see *select-organize-integrate (SOI) model*, Mayer, 2005). In the next section, we present two ways in which these processes can be fostered through different design approaches in digital learning environments: *aesthetic designs* and enhanced video-based environments *designed to foster generative learning*.

Two Ways to Foster Cognitive Processes using Digital Learning Environments

Aesthetically Designed Learning Environments

In this thesis, the first way we present addresses the *aesthetic design* of digital learning environments. Approaches in this direction arise, on the one hand, from the multimedia theories

described above and, on the other hand, from the research field of human–computer interaction (HCI). Based on the cognitive affective theory of learning with media (Mayer & Estrella, 2014; Moreno, 2007; Moreno & Mayer, 2007), Um et al. (2012) introduced the *emotional design hypothesis*. This assumes that cognitive processes can be fostered when essential elements of the learning material are presented in a visually appealing manner that captures learners' attention. As a result, this information should preferably be selected for the transfer into working memory (see *essential processing*, Mayer, 2005). It is further assumed that appealing design elements enhance learners' motivation to engage with the material, which, in turn, should also promote the organization and integration of the information in working memory. Research on emotional design has mainly investigated the effects of *facial anthropomorphisms in non-human graphical elements* and the effects of *color* of the design features (for an overview, see Brom et al., 2018; Wong & Adesope, 2021). The assumption that specific design features might influence learning is also discussed in research on aesthetic design, which stems from HCI research (Thielsch et al., 2019). Thielsch et al. (2019) argue that aesthetic design features such as color (e.g., Palmer et al., 2013; Seckler et al., 2015) or familiarity (e.g., Lindgaard et al., 2006) might provoke pleasurable subjective experiences in viewers (Moshagen & Thielsch, 2010), leading to positive emotions (see also *affect mediation theory*, Norman, 2004) that, in turn, result in improved performance. The positive effects of emotional and aesthetic designs on interest-related factors and their facilitating effects on learning have been demonstrated in three recently published meta-analyses, where the included studies each compared emotional with neutral or aesthetic with unaesthetic design variants (Brom et al., 2018; Thielsch et al., 2019; Wong & Adesope, 2021).

However, it often remains unclear in these studies whether the superior effects of emotional and aesthetic designs occurred as a result of the different manipulation of the *aesthetics* of the design variants, or rather as a result of different implementations of multimedia design principles (i.e., instructional design, Mayer, 2005, 2008; Sweller, 2005). For example, a colorful design, as opposed to a

black-and-white design, could have a superior effect on learning because it triggers more positive emotions in learners, as well as because color might highlight learning-relevant elements in the material (see also signaling effect, Mautone & Mayer, 2001). Moreover, although the *experience of aesthetics*, previously defined as processes occurring through the processing and evaluation of artwork (cf. Leder et al., 2004; Marković, 2012), might provide a deeper understanding on why aesthetic designs influence learning, in-depth investigations of this construct are still missing (e.g., Thielsch et al., 2019). To address these gaps, we conducted a controlled field study in which we investigated the effects of two appealing aesthetic interface variants of a mobile app, both designed according to multimedia design principles (see antecedents of learning in Figure 1), on interest and learning outcomes in science. Moreover, we considered *aesthetic experience* to be an important process occurring during learning using aesthetic digital learning environments. We focused on teenage students since previous research indicates that early interventions to spark students' interest in science are important to foster science literacy (Vieira & Tenreiro-Vieira, 2016). We addressed the research question of *how the aesthetic design of a learning app impact teenage students' aesthetic experience, interest, and learning in science* (RQ 1).

Enhanced Video-Based Environments to Foster Generative Learning

The second way we present in this thesis to foster cognitive processes addresses enhanced video-based environments *designed to foster generative learning*. The use of videos in educational institutions already has a long tradition (for an overview, see Poquet et al., 2018), not least because videos are a good option for imparting complex and abstract information (Overbaugh, 1995) such as scientific processes (e.g., Mayer & Chandler, 2001). Owing to the dynamic representations in videos, related audiovisual information is already linked, allowing learners to organize and integrate the information more effectively and efficiently in working memory (Hegarty et al., 2003; Schnotz & Rasch, 2005). However, *passive* video viewing may lead to learners reflecting little on the content, which could impede a deeper understanding of the learning material (Shin et al., 2018). For this reason, research

emphasizes the importance of allowing learners to actively *interact* with the learning material (Hasler et al., 2007). Even providing basic video control tools, such as play, pause, and rewind, helps learners to adapt the information to their own cognitive needs (Schwan & Riempp, 2004). However, when the learning material contains highly complex concepts or processes that need to be linked to understand them within the whole context, learning should additionally be enhanced with options to engage in *generative activities* (Fiorella & Mayer, 2016). Fiorella and Mayer (2016) state that research needs to expand from instructional approaches – i.e., how learning environments need to be designed to present information in a way that is supportive of learning – to approaches that focus on how to help learners to *actively* make sense of this information. This statement is based on the assumption that learning is not the passive consumption of information, but rather the active construction of own interpretations by generating relations among concepts and prior knowledge (Wittrock, 1992). In line with Mayer's (2005) SOI model, such *generative learning* should foster generative processing as it supports learners in actively (re)organizing and integrating information with their prior knowledge. This, in turn, promotes a deeper understanding of the learning material (Fiorella & Mayer, 2016).

In recent years, *enhanced video-based environments* have gained increasing interest in higher education (Noetel et al., 2021). These environments can support learners to engage in generative activities by using *enhanced video tools* such as annotations, hyperlinks, in-video quizzes, or tables of contents (for an overview, see Evi-Colombo et al., 2020). *Annotations*, for example, can be defined as self-written notes or summaries that can be added to a video (Chiu et al., 2018; Delen et al., 2014; Zahn et al., 2012). By enabling learners to write their own in-depth texts to link to related video information, annotations foster the cognitive processes of reflecting, organizing, and integrating of information (Lawson & Mayer, 2021) and help learners to gain a deeper understanding of the concepts contained in the learning material (Zahn et al., 2012). *Hyperlinks*, as another example, can be defined as supplementary information segments in the form of texts or pictures (e.g., Meixner, 2017). Adding hyperlinks to related

parts of a video fosters cognitive processes by requiring learners to select matching information from the video and hyperlinks, organize it, and finally integrate it, which promotes their understanding of the interrelations between concepts (Rickley & Kemp, 2020; Stahl et al., 2006; Zahn, 2017). Research further suggests that enhanced video tools can foster collaboration, such as group discussions (Sauli et al., 2018; Sinha et al., 2015; Zahn et al., 2012), and, thus, also promote socio-cognitive processes in learners that go beyond knowledge acquisition (Schwartz & Hartmann, 2007). Although comparisons between individual and collaborative learners are still lacking in research on enhanced video-based learning (a gap we address in Manuscript 3), research from related domains on animation and games suggests that collaborative learning is superior in problem-solving, retention, and transfer tasks (Bol et al., 2012; Kirschner et al., 2011; Liao et al., 2019; Retnowati et al., 2016).

Despite the theoretical basis pointing to the learning-supportive effects of enhanced tools, there is as yet no consensus in experimental research on whether and how these tools really support individual and collaborative learning (Evi-Colombo et al., 2020; Sauli et al., 2018). Two possible reasons should be mentioned: first, it needs to be considered that different enhanced video tools support learning differently. While some promote understanding of individual concepts (e.g., annotations, Zahn et al., 2012) or concept interrelations (e.g., hyperlinks, e.g., Zahn, 2017), others are intended to generate an overview of the learning content (e.g., table of contents, Merkt et al., 2011) or to identify own knowledge gaps (e.g., in-video quizzes, Panadero et al., 2017). The inclusion and simultaneous study of different enhanced tools, considering their different effects on learning, could provide deeper insights into the effectiveness of these tools in concrete learning situations. However, few research studies have considered such comparisons so far (e.g., Kim et al., 2021; Mirriahi et al., 2021; Van Sebille et al., 2018). Second, learners need to understand why enhanced tools might help them learn and how to use them meaningfully, otherwise such tools could increase extraneous load, leading to cognitively overwhelmed learners (e.g., Kirschner et al., 2018; Krauskopf et al., 2014). This is consistent with Mayer (2014), who

points to certain motivational and metacognitive processes to consider when supporting generative activities. Accordingly, enhanced tools need to be instructed very clearly and included as a necessary part of the learning task (Rice et al., 2019; Zahn et al., 2012) so that learners are able to develop appropriate strategies to use them effectively (Merkt et al., 2011) and are motivated to invest cognitive effort to engage in generative activities with these tools.

Hence, considering the situative approaches provided by Greeno and Engeström (2015) and Janssen and Kirschner (2020), with the second research question we aimed to investigate the effects of different enhanced video tools (i.e., annotation and hyperlinks) and social learning settings (individual vs. collaborative learning) on learning a complex science-related topic (see Figure 1). In addition, we considered learners' active use of enhanced tools (i.e., learning activity) and cognitive load as important processes that occur during learning. Specifically, we addressed the question of *how enhanced video tools for generative activities impact learning processes and outcomes in science-related topics in individuals and groups* (RQ 2).

Aims of this Thesis

The goal of this thesis is to add to the understanding of how science learning can be supported with two different design approaches in digital learning environments: *aesthetic designs* and designs that foster *generative learning using enhanced video tools* (see Figure 1). To achieve this goal, two experiments, a field study and a laboratory experiment, were conducted. The results are presented in the form of three manuscripts. While Manuscript 1 focused on the impact of different aesthetic design variants of a learning app on teenagers' aesthetic experience and scientific interest and learning (RQ 1), Manuscripts 2 and 3 focused on the impact of enhanced video tools on learning processes and outcomes in science-related topics (RQ 2). All three manuscripts are summarized in the following sections.

Summary of Manuscript 1: Aesthetic Design of App Interfaces and their Impact on Secondary Students' Interest and Learning

Aims of the Study and Contribution

Aesthetic designs for mobile learning apps are a promising approach to foster teenagers' scientific interest and learning. Given the knowledge gaps in the scientific literature (as described above), this study pursued three main objectives. First, we intended to provide new insights into the effects of aesthetic designs on interest and learning in science that are not confounded by beneficial or detrimental effects resulting from multimedia design principles (Mayer, 2005, 2008; Sweller, 2005). Second, while previous studies on aesthetic design considered measurements of viewers' aesthetic experiences, they focused mostly on perceptions of *surface structures*, such as the color or complexity of interfaces (Thielsch et al., 2019). However, in consideration of literature on the experience of artwork (Leder et al., 2004; Marković, 2012), we assumed that aesthetic experience also derives from *deeper perceptual processes*, including emotions and cognitive stimulations triggered by aesthetic designs. Hence, we intended to provide new work on the effects of aesthetic experience, including both *surface structures* and *deeper perceptual processes,* on learners' interest and learning in science. Third, we intended to contribute new results concerning the impact of aesthetic app interfaces on aesthetic experience, interest, and learning among *middle school teenage students*.

Method

This field study comprised 108 teenage student participants who were randomly assigned to one of two conditions using different interface designs of a learning app. We contrasted a *game-style* design variant with an *industrial-style* variant (see Figure 2). The two design variants were created in consideration of multimedia design principles, so that they were equally supportive of learning and

differed only in aesthetic features that did not directly affect learning (referred to as *Interface Aesthetics*). The app covered the topic of energy (physics) with the three subtopics of energy forms, energy sources, and power plants. The experiment followed a mixed two-factorial design with *Interface Aesthetics* (*game-style* vs. *industrial-style*) as the between factor and *Time of Measurement* (pre-post-test) as the within factor. Interest and learning performance served as primary dependent variables. To measure interest, we considered both *situational interest*, defined as a momentary experience triggered by an object and characterized by increased affect, effort, and attention, and *individual interest*, defined as a more prolonged experience, characterized by a persistent willingness to return to a certain object or topic over time. Situational interest was measured with two scales: interest in engaging with the topic and interest in engaging with the app. Individual interest was measured with three scales: general interest in physics, interest in physics compared to other school subjects (such as mathematics), and self-assessed gain in interest in physics after learning. Learning performance was measured using an objective knowledge test (i.e., matching tasks, transfer, and retention tasks) and subjective self-

Figure 2

Aesthetic Interface Design Variants: Game-style on the Left-hand Side and Industrial-style on the Right-hand Side

assessments. Finally, aesthetic experience was measured by means of a validated questionnaire which assessed the impact of perceived *surface structures* (perceived "expressive aesthetics" of the interface) and *deeper perceptual processes* (perceived "emotion" and "cognitive stimulation" provoked by the interface) on the dependent variables using multiple regression analyses.

Results

Our results suggested that participants who learned with the *game-style* variant rated the app significantly higher in *surface structures* (i.e., "expressive aesthetics") than students who learned with the *industrial-style* variant ($p = .048$). No differences were found for "emotion" or "cognitive stimulation" ($p > .10$). See Table 1 for the descriptive results.

Table 1

Means and Standard Deviations for Interface Designs (Game-style vs. Industrial-style) for Aesthetic Experience

Aesthetic Experience (Scale: 1-5)	*Game-style* Design		*Industrial-style* Design	
	M	*SD*	*M*	*SD*
Expressive Aesthetics	3.64	0.82	3.31	0.90
Emotion	3.93	0.68	3.95	0.68
Cognitive Stimulation	3.18	0.81	3.12	0.75

Our results on interest revealed a significant increase in situational interest after learning for both designs (both $p < .01$, see Table 2 for descriptive results). However, students who learned with the *game-style* design rated their interest to engage with the topic higher compared to students who learned with the *industrial-style* design ($p = .043$). Moreover, regression analyses revealed that students

who experience more positive "emotions" triggered by the design had a greater positive change in interest to engage with the app (*B* = .289, *p* = .007) and the topic (*B* = 2.091 *p* = .018). Regarding individual interest (see Table 2), we found that students who learned with the *game-style* design rated a marginally higher positive change in interest in physics after using the app than students who learned with the *industrial-style* variant (*p* = .063). Findings from regression analyses further suggested that students who experienced higher "cognitive stimulation" triggered by the design also stated higher self-assessed change in interest in physics (*B* = .570, *p* < .001).

Table 2

Means and Standard Deviations for Interface Designs (Game-style vs. Industrial-style) for Interest

	Game-style Design		*Industrial-style* Design	
Situational Interest	*Pre* *M (SD)*	*Post* *M (SD)*	*Pre* *M (SD)*	*Post* *M (SD)*
Interest to Engage with the Topic (Scale: 1-6)	3.29 (1.16)	3.76 (1.30)	3.47 (1.29)	3.59 (1.33)
Interest to Engage with the App (Scale: 1-5)	3.44 (0.69)	3.63 (0.86)	3.55 (0.60)	3.80 (0.69)
Individual Interest				
General Interest in Physics (Scale: 1-6)	3.91 (1.23)	3.98 (1.29)	3.71 (1.25)	3.83 (1.24)
Interest in Physics Compared to Other Subjects (Scale: 1-6)	2.97 (0.78)	3.00 (0.79)	3.19 (0.87)	3.21 (0.89)
Self-Assessed Change in Interest (Scale: -3 - +3)		1.02 (1.04)		0.66 (0.92)

Finally, the results on learning performance revealed an increase in objective ($p < .001$) and self-assessed knowledge ($p < .001$) after learning with both designs. However, no significant differences were found between the design variants (both $p > .10$). Regression analyses further revealed that "cognitive stimulation" predicted outcomes in matching tasks ($B = -.897$, $p = .011$), which indicated that the *less* "cognitive stimulation" that was perceived by students, the higher was their knowledge gain in matching tasks. Last, higher "cognitive stimulation" ($B = 0.349$, $p < .001$) induced by the aesthetic designs predicted higher ratings in self-assessed knowledge.

Discussion and Conclusion

In this study, we aimed to shed light on the effects of aesthetic design in a learning app (*game style* vs. *industrial style*) on teenagers' interest and learning in science, as well as the role played by aesthetic experience (*surface structures* and *deeper perceptual processes*). Our results revealed that students who learned with the *game-style* variant rated the design higher in its *surface structures* than students who learned with the *industrial-style* variant. This is in line with previous research, indicating that aesthetic features such as color (e.g., Palmer et al., 2013) and expressivity (Lavie & Tractinsky, 2004) have an impact on the perceived attractiveness of an object. However, no differences between the designs were found for *deeper perceptual processes*. One explanation for this result might be that the original definition of *aesthetic experience* focused on the experience of artwork (Leder et al., 2004; Marković, 2012). Thus, when it comes to learning applications, deeper processes of aesthetic experience might only play a minor role. Our results further revealed that the *game-style* variant led to a greater increase in students' situational interest. Situational interest was further found to be positively related to the *deep perceptual process* "emotion." This is not surprising as earlier research indicates that both situational interest and emotion are characterized by a short duration (Ekman, 1992; Harackiewicz & Hulleman, 2010). In contrast, no direct effect of *Interface Aesthetics* was found for individual interest.

Nevertheless, a positive relationship between the *deep perceptual process* “cognitive stimulation” and individual interest was found. Thus, it may be concluded that the more long-lasting construct of individual interest depends on how stimulating, involving, and exciting the interaction with a design is (Harackiewicz & Hulleman, 2010), whereas short-lasting situational interest depends more on short-term emotional responses elicited by aesthetic designs (Ekman, 1992; Harackiewicz & Hulleman, 2010). Moreover, in contrast to previous research on emotional design (Brom et al., 2018; Wong & Adesope, 2021), we could not confirm that *Interface Aesthetics* has a direct impact on objective or self-assessed learning performance. One explanation for this result is that both design variants were constructed according to multimedia design principles (cf. Mayer, 2005, 2008; Sweller, 2005). Hence, we argue that differently designed aesthetic interfaces that are equally learning-supportive are experienced differently in *surface structures* (“expressive aesthetics”), leading to different effects on appeal and attractiveness (Moshagen & Thielsch, 2010) and, in turn, on interest, but not in *deeper perceptual processes*, such as “emotion” and “cognitive stimulation” that are possibly related to learning performance. Another explanation might be that the *industrial-style*, in contrast to the *game-style* variant, had a closer resemblance to a classical schoolbook, which might have triggered a learning context association in learners. Hence, positive motivational factors induced by the *game-style* variant could be diminished. This is in line with our results indicating that *less* perceived “cognitive stimulation” led to higher results in learning performance: students learning with the *game-style* variant might be occupied with processing the *surface* of the interface rather than the material (see seductive-details effect, Mayer, 2019). We conclude that this study provides important implications for the future design of learning apps and highlights the importance of considering aesthetic experiences in future research.

Summary of Manuscript 2: Impact of Learners' Video Interactions on Learning Success and Cognitive Load

Aims of the Study and Contribution

Although previous approaches suggest that enhanced video tools can support generative activities and, in turn, knowledge acquisition (Wittrock, 1992), existing research is still conflicting (Evi-Colombo et al., 2020; Sauli et al., 2018). This study focused on two possible explanations for these results. First, enhanced tools are accompanied by high complexity which might manifest in an increased extraneous cognitive load in learners (e.g., Kirschner et al., 2018; Krauskopf et al., 2014). Second, previously investigated enhanced tools were often intended to be *optional* supporters to facilitate learning rather than necessary parts of the learning task (e.g., Merkt et al., 2011). It becomes apparent from previous work that an investigation of learners' interactions with videos might help to understand how enhanced video tools can successfully be used for learning. Merkt et al. (2011) suggested distinguishing between micro-level interactivity ("micro-actions"), resulting from using basic video control tools, and macro-level interactivity ("macro-actions"), resulting from using enhanced tools. Hence, considering previous research, the aim of this study was to investigate the relationships between learners' video interactions, learning success, and cognitive load using multiple and multivariate regression analyses.

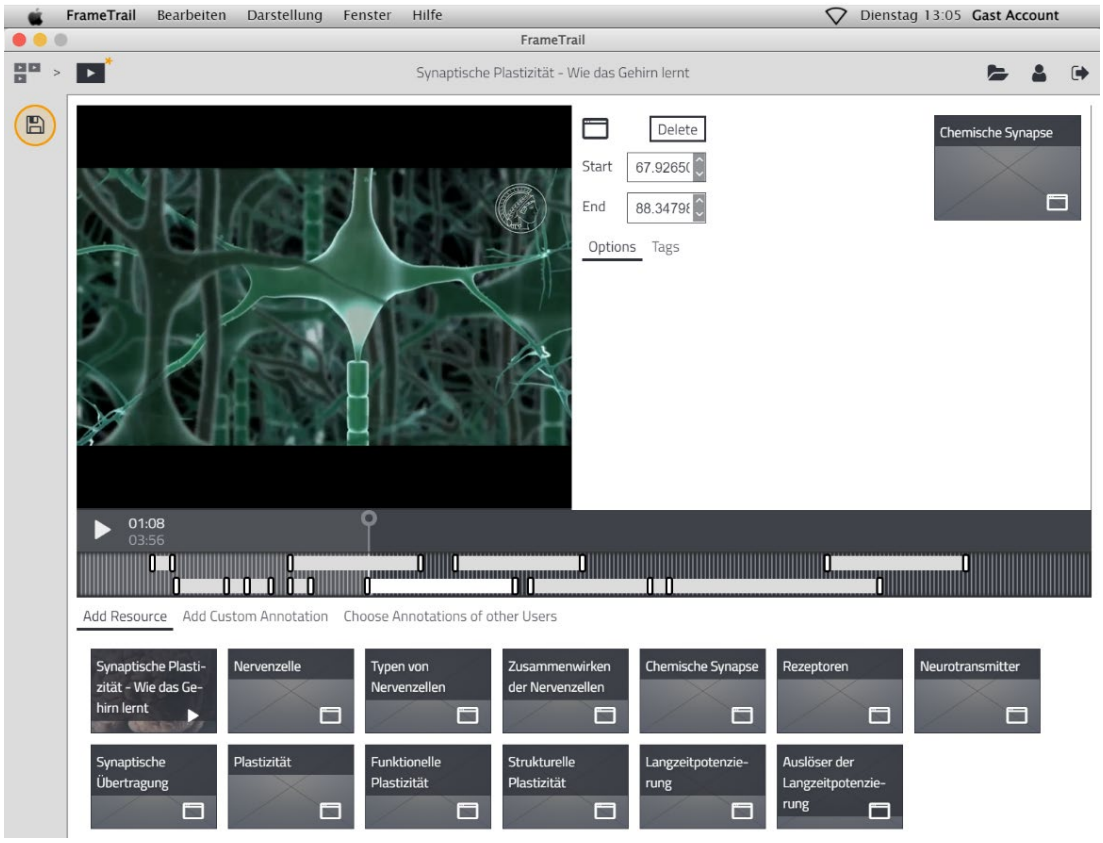
Method

To achieve our study goal, we used a subsample (N = 141) of a larger dataset consisting of 209 Swiss university students (see Manuscript 3). A 3 x 2 study design was used where the first factor concerned whether participants were allowed to use enhanced tools and/or which tools they were allowed to use (annotations vs. hyperlinks vs. control group). The second factor related to the social

learning setting (individual vs. dyadic collaborative learning). After a preparation phase, during which participants were instructed on their task and had time to familiarize themselves with the enhanced video-based environment *FrameTrail* (see Figure 3), they were asked to learn about the neuroscience topic *synaptic plasticity of the human brain*. They were provided with a video and additional topic-related in-depth information in the form of prepared text snippets. While participants in the control group were asked to watch the video and read these texts attentively to prepare for a post-experimental test, participants in the hyperlink condition were asked to grab these texts and add them directly into the video in the appropriate places. Participants in the annotation condition were asked to read the text snippets but write their own summaries to add into the video. Note, in contrast to

Figure 3

Illustration of the Enhanced Video-based Environment FrameTrail



Manuscript 3 (see below), we did not include the control group in further analyses because we were solely interested in the effects of enhanced tools. During learning, *FrameTrail* collected participants' *learning activities* by using log-file protocols. These files included (1) micro-actions, resulting from the use of basic video control tools, and (2) macro-actions, resulting from the use of enhanced tools. Note, to clarify that we were concerned with interactions resulting from necessary and *task-relevant* enhanced tools, in this manuscript we referred to macro-actions as *task-actions* (see Table 3 for an overview). Participants learned at their own pace to ensure that they had enough time to fully understand the learning topic, to complete the task, and to compensate for possible effects of extraneous cognitive load triggered by the environment and the tools. We considered relative frequencies of learning activity to address individual learning time.

Table 3

Logged Micro- and Macro-actions (Referred to as Task-actions in Manuscript 2)

	Micro-actions	*Macro-actions*
1	Play	Adding hyperlink or annotation to a video
2	Pause	Changing annotation text
3	Jump backwards	Changing display time of hyperlink or annotation on video timeline
4	Jump forward	Deleting hyperlink or annotation from timeline

Learning success was measured by means of a 20-item questionnaire on conceptual understanding, including questions on "understanding of concepts," "understanding of concept interrelations," and "transfer knowledge" (cf. Rebetez et al., 2010; Zahn, 2017). Additionally, we included a one-item scale to measure self-assessed knowledge gain. Cognitive load was measured by considering mental load (imposed by instructional parameters such as task structure) and mental effort (capacity assigned to instructional demands) separately (cf. Jong, 2010; Paas, 1992). Since collaborative

learners worked together on a shared desktop computer, only one file containing dyadic interactions was available. By referring to literature on joint attention (cf. Barron, 2003; Schneider & Pea, 2013), we thus used dyadic interaction data as *individual* data for the purpose of comparisons between conditions.

Results

The results on learning outcomes (see Table 4 for descriptive results) revealed that the more task-actions were performed by learners, the higher were their results in "understanding of concepts" (p = .023). The results on "understanding of concept interrelations" or "transfer knowledge" reached no significant level (both p > .10), nor could we confirm a positive relationship between micro-actions and learning success. The results on self-assessed knowledge gain indicated that the more micro-actions were performed, the lower was the self-assessed knowledge gain (p = .004) and that more frequently performed task-actions were (marginally) positively related to self-assessed knowledge gain (p = .056).

Table 4

Results on the Impact of Micro- and Task-actions on Learning Outcomes

Predictors	*Understanding of Concepts*				*Self-assessed Knowledge Gain*			
	B	*SE B*	R^2	ΔR^2	*B*	*SE B*	R^2	ΔR^2
Micro-actions	.023	.107	.039	.024	-.148*	.050	.088	.074
Task-actions	.493*	.214	.039	.024	.193	.100	.088	.074

The results on cognitive load (see Table 5 for descriptive results) suggested that frequently performed task-actions were related to lower perceptions of mental load (p = .021). No effects were

found for micro-actions, nor any effects for mental effort.

Table 5

Results on the Impact of Micro- and Task-actions on Cognitive Load

Predictors	*Mental Load*				*Mental Effort*			
	β	*SE* β	R^2	ΔR^2	β	*SE* β	R^2	ΔR^2
Micro-actions	.134	.092	.057	.042	-.092	.068	.018	.003
Task-actions	-.435*	.186	.057	.042	-.113	.137	.018	.003

Discussion and Conclusion

This study focused on the relationship between learning activity resulting from the use of basic video control tools (micro-actions) and task-relevant enhanced tools (task-actions), learning success, and cognitive load. We found that frequently performed macro-actions were positively related to objective learning success. Hence, in line with earlier research (e.g., Delen et al., 2014; Zahn, 2017), we argued that task-relevant enhanced tools can substantially foster learning, as they help learners to actively generate meaning by designing own information structures (Clark, 1994; Kafai & Resnick, 1996; Wittrock, 1992). However, as we did not distinguish between annotations and hyperlinks, it is questionable whether one of the enhanced tools could have contributed more to this result. Furthermore, in contrast to previous research (Zahn et al., 2004), no positive relation between frequently performed micro-actions and objective learning success was found – indeed, a negative relation with subjective knowledge gain was found. We assumed that the target-oriented use, rather than the frequent use, of basic control tools might be crucial for a deep engagement with the material. For example, learners who first watch the video in its entirety before starting to add enhanced tools

might need fewer micro-actions to complete the task than learners who start directly with the task and occasionally need to adapt initial decisions. Thus, in line with previous research (Delen et al., 2014; Merkt et al., 2011), it could be assumed that more micro-actions were performed by learners who might not have proper strategies underlying the use of enhanced tools for effective learning. Furthermore, the frequent use of enhanced tools was not negatively related to mental effort. This might indicate that when learners frequently use task-relevant enhanced tools it does not increase their perceived effort to use these tools for fulfilling the task. Finally, a negative relationship was found for frequently used task-actions with mental load. This might indicate that students who frequently used enhanced tools perceived the material as less difficult than students who made little use of them. This is in line with our results indicating a positive relationship between frequently performed task-actions and self-assessed knowledge gain (marginal). In sum, we concluded that *task-relevant* enhanced tools in digital learning environments seem not only to support learning success, but also to reduce mental load. However, two limitations must be addressed. First, we did not perform systematic distinctions between the two enhanced tools included or between the two social learning settings. Second, the direction of causality remains a matter of interpretation in this study. We addressed these limitations in Manuscript 3.

Summary of Manuscript 3: How do Enhanced Videos Support Creative Learning and Conceptual Understanding in Individuals and Groups?

Aims of the Study and Contribution

Manuscript 2 revealed new findings on the relationship between frequently used video tools, learning success, and cognitive load. The aim of Manuscript 3 was to pursue a more situative approach (cf. Greeno & Engeström, 2015; Janssen & Kirschner, 2020) by considering (1) the effects of the different enhanced tools, (2) different social learning settings, and (3) the direction of causality between these

antecedents, processes, and the consequences of learning. More precisely, we investigated the impact of the enhanced tools, annotations and hyperlinks (i.e., *Tool-use*) – alongside a control group (i.e., no *Tool-use*) – and individual and collaborative learners (i.e., *Setting*) on learning processes (learning activity, cognitive load), and learning outcomes (creative learning and conceptual understanding). Moreover, we exploratively investigated whether learning process variables could function as possible mediators between *Tool-use* and *Setting* and the dependent variables of learning outcome.

Method

This controlled laboratory experiment comprised 209 participants. We employed a 3 x 2 study design with the factors *Tools-Use* (annotation vs. hyperlink vs. no *Tool-use*: control group) and *Setting* (individual vs. collaborative learning). In addition to the scales used in Manuscript 2, we considered *creative learning* as a further learning outcome variable by measuring the quality of the hypervideo products (i.e., HPQ) participants created as part of their task to add hyperlinks or annotations to the video. According to the situative approaches described above (see Figure 1), learning activity and cognitive load (more precisely mental load) were considered as processes of learning and "conceptual understanding", and HPQ as learning outcomes. It should be noted that no data on learning activity and HPQ could be collected for the control group, as this group was not able to engage with enhanced tools.

Results

Our results regarding learning processes (see Table 6) showed that learners in the annotation condition performed *more* macro-actions ($p = .033$) and *fewer* micro-actions compared to learners in the hyperlink condition ($p < .01$). Learners using annotations further perceived lower cognitive load than learners in the hyperlink condition ($p = .003$). No result was found for *Setting* ($p > .10$).

Table 6

Means and Standard Deviations for Learning Processes in Tool-use (Annotation vs. Hyperlink) and Setting (Individual vs. Collaborative) Conditions

	Annotation		*Hyperlink*	
Learning Activity	*Individual M (SD)*	*Collaborative M (SD)*	*Individual M (SD)*	*Collaborative M (SD)*
Micro-actions	1.41 (.7)	1.42 (.7)	3.38 (1.5)	3.04 (.9)
Macro-actions	1.83 (.7)	1.66 (.6)	1.50 (.7)	1.40 (.7)
Cognitive Load (Scale: 1-7)	3.73 (1.3)	3.77 (1.2)	4.58 (1.3)	4.39 (1.0)

The results on learning outcomes (see Table 7) revealed, first, that learners in the hyperlink condition produced hypervideo products of higher quality than learners using annotations ($p < .01$). Moreover, a marginal significant result for *Setting* was found ($p = 061$), indicating that collaborative learners slightly outperformed individual learners in their HPQ. Second, a general increase in conceptual understanding after learning was found in all conditions ($p < .001$). However, results indicated that the control group outperformed the other conditions in conceptual understanding ("concept interrelations:" $p = .002$; "transfer knowledge:" $p = .016$). No results were found for *Setting* ($p > .10$). An analysis of self-assessed knowledge gain further yielded significance ($p = .017$), indicating that learners who used annotations experienced a higher self-assessed knowledge gain than learners who used hyperlinks. No results were found for *Setting* ($p > .10$).

Mediation analyses revealed that frequently performed macro-actions mediated the effect of *Tool-use* on HPQ, $ab = -.119$, 95%-CI[-.294, -.011]. Moreover, the perception of *less* cognitive load

mediated the effect of *Tool-use* on conceptual understanding, *ab* = -1.027, 95%-CI[-1.738, -.391].

Table 7

Means and Standard Deviations for Learning Outcomes in Tool-use (Annotation vs. Hyperlink vs. Control Group) and Setting (Individual vs. Collaborative) Conditions

	Annotation		*Hyperlink*		*Control*	
Creative Learning	*Individual M (SD)*	*Collaborative M (SD)*	*Individual M (SD)*	*Collaborative M (SD)*	*Individual M (SD)*	*Collaborative M (SD)*
HPQ (grade: 1-6)	4.41 (.5)	4.53 (.5)	4.84 (.4)	5.09 (.4)	-	-
Conceptual Understanding						
"Understanding of Concepts" (max. 8 points)	5.67 (1.6)	5.71 (1.3)	5.96 (1.3)	5.23 (1.4)	6.38 (1.4)	5.91 (1.1)
"Understanding of Interrelations" (max. 8 points)	5.07 (1.8)	4.46 (1.4)	4.62 (1.9)	4.48 (1.4)	5.71 (1.7)	5.71 (1.6)
"Transfer Knowledge" (max. 4 points)	2.78 (.9)	2.82 (.8)	3.04 (.9)	2.96 (.8)	3.33 (.9)	3.25 (.6)
Self-assessed knowledge gain (scale: 1 – 5)	3.81 (.8)	3.84 (.6)	3.58 (.7)	3.41 (.4)	3.67 (.8)	3.70 (.7)

Discussion and Conclusion

The purpose of this study was to address current research gaps on how different enhanced video tools can support creative learning and conceptual understanding in individuals and groups. We

found that learners using hyperlinks produced hypervideo products (HPQ) of higher quality than learners who used annotations. Since participants in the hyperlink condition also performed more micro-actions and fewer macro-actions than participants in the annotation condition, we concluded that high-quality hypervideo products depend on the sparse but target-oriented use of enhanced tools that require multiple interactions with basic video control tools in advance (e.g., multiple skipping in the video to place a hyperlink correctly). This assumption is also in line with our results, indicating a partial mediation of *fewer* performed macro-actions on the effect between *Tool-use* and HPQ. This differentiated our assumption discussed in Manuscript 2, where we assumed that a lack of strategies underlying the use of enhanced tools might be the reason for learners to use more micro-actions (see above). Moreover, we found that collaborative learners designed hypervideo products of higher quality (marginal) than individuals. This is in line with previous research (Kolloffel et al., 2011; Sinha et al., 2015). According to earlier approaches on learning through design and generative learning, successfully designing own information structures should also foster conceptual understanding (Fiorella & Mayer, 2016; Kafai & Resnick, 1996; Krathwohl, 2002; Wittrock, 1992). However, in contrast to this assumption, no superiority was found for the hyperlink condition or collaboration in conceptual understanding. Results even indicated the superiority of the control group, which was not able to engage in generative activities with enhanced video tools. This result might be explained by recent research, suggesting that the use of “e-tasks” supports neuroplasticity in those parts of the brain that are responsible for long-term memory (Kassymova et al., 2020). This is in line with Mayer's (2005) cognitive theory of multimedia learning, indicating that knowledge acquisition with multimedia material develops over time. Another explanation might be that participants in the control group had higher results in conceptual understanding as they were able to concentrate exclusively on the learning content without putting additional strain on their working memory through the use of enhanced tools (Baddeley, 1992; Maj, 2020). This could enable them to better remember what they had learned in the subsequent post-

experimental knowledge test. However, when additionally considering cognitive load, the results revealed that learners using annotations perceived the lowest cognitive load. Lower perceived cognitive load was further found to mediate the effect between *Tool-use* and conceptual understanding. Together with the result indicating that frequently performed macro-actions lead to lower perceptions of mental load, as discussed in Manuscript 2, we assumed that the active use of enhanced tools (more often occurring in the annotation condition) can support conceptual understanding but only when mental load is low. This was underlined by the finding that learners in the annotation condition perceived higher self-assessed knowledge gain than both the other conditions. Moreover, in contrast to previous related work on animation and games (Bol et al., 2012; Kirschner et al., 2011; Liao et al., 2019; Retnowati et al., 2016), we could not find a superiority of groups over individuals in conceptual understanding. This might be explained by the fact that both individuals and dyads showed very similar learning processes which might indicate that the digital learning environment used in this study supported individual and collaborative learning equally (Janssen & Kirschner, 2020). We concluded that this study emphasizes the importance of considering learning processes when investigating the effects of enhanced video tools on learning.

General Discussion

Fostering interest and learning in science topics is important not only for learners' educational and work performance, but also for their daily lives (e.g., He et al., 2021). Providing interesting digital learning environments that help learners to understand these topics seems to be a promising approach in this regard (e.g., Noetel et al., 2021; Qureshi et al., 2020; Wang & Hannafin, 2005). However, for such environments to promote learning effectively, they must be designed to promote the cognitive processes that are relevant to learning (Mayer, 2005). Over the course of the three manuscripts, we examined the effects of two digital learning environments that were designed to promote both essential

processing, by facilitating the *selection* of essential information for transfer from sensory memory to working memory, and generative processing, by supporting the processes of *organizing* and *integrating* this information in working memory (see Figure 1). The first overarching research question addressed the effect of *aesthetically designed* interface designs in a learning app (a *game-style* variant vs. an *industrial-style* variant) on teenagers' aesthetic experience, interest, and learning in science. According to the *emotional design hypothesis* (cf. Moreno, 2007; Um et al., 2012) and research on aesthetic design (cf. Norman, 2004; Thielsch et al., 2019), we assumed that appealing learning information in aesthetic designs captures learners' attention so that the material is preferably selected from sensory memory (i.e., *essential processing*, Mayer, 2005) and that such designs additionally promote learners' motivation to engage extensively with the material, which promotes organizing and integrating processes in working memory (i.e., *generative processing*, Mayer, 2005),

The second overarching research question addressed the effect of enhanced video-based learning environments *designed to foster generative learning* on learning processes and outcomes in individuals and groups. According to Wittrock's (1992) model of generative learning and Mayer's (2005) select-organize-integrate model, we assumed that enhanced video tools, such as annotations and hyperlinks, support learning by promoting generative activities that, in turn, facilitate the cognitive processes relevant to effective learning.

To find answers to these research questions, we conducted a field study and a laboratory experiment and reported the results in three manuscripts. To obtain a fundamental understanding of learning with digital learning environments, all manuscripts followed a situative approach to investigate learning holistically, according to previous work (cf. Greeno & Engeström, 2015; Janssen & Kirschner, 2020). We simultaneously investigated different antecedents of learning (aesthetic designs, enhanced video tools, social learning settings), processes (aesthetic experience, learning activity, cognitive load), and consequences of learning (interest, self-assessed and objective learning outcomes, self-created

information structures). Figure 1 gives an overview of the theories we refer to in this thesis. In the next section, we discuss the scientific and practical implications based on the findings of the three manuscripts.

Implications

Regarding the impact of *aesthetically designed* digital learning environments (RQ 1, Manuscript 1), we found that appealing and learning-supportive aesthetic designs (*game-style* and *industrial-style* variants, see Figure 2) are able to increase scientific knowledge. In addition, our results indicate that the *game-style* variant, which was higher rated in terms of its *surface structures* ("expressive aesthetics"), also led to higher situational interest to engage with the interface and the topic, and to higher individual interest in the topic (marginal). This is in line with the *emotional design hypothesis* (cf. Moreno, 2007; Um et al., 2012) and approaches taken from aesthetic art experience (Leder et al., 2004), indicating that appealing information is preferably selected from sensory memory (see *essential processing*, Mayer, 2005) and that some aesthetic design features increase motivation to engage with the learning material. However, in contrast to these approaches and to previous research on emotional and aesthetic design (Brom et al., 2018; Thielsch et al., 2019; Wong & Adesope, 2021), we could not confirm that a more appealing and more interest-generating design also promotes the cognitive processes in working memory more than a less appealing and interesting design (see *generative processing*, Mayer, 2005). Or, to put it in terms of our results, the *game-style* did not lead to higher learning success compared to the *industrial-style* variant. This seems to confirm our assumption that previous research that compared aesthetic vs. unaesthetic (Thielsch et al., 2019) or emotional vs. neutral designs (Brom et al., 2018; Wong & Adesope, 2021) did not clearly distinguish between appealing aesthetic features and instructional design features when manipulating the designs variants. Thus, aesthetic or emotional designs – compared to their unaesthetic or neutral counterparts – could have led to higher learning success not

only because they elicited higher positive emotions in learners but also as a result of beneficial effects resulting from instructional manipulations (e.g., through a signaling effect, Mautone & Mayer, 2001). Moreover, we considered *deeper perceptual processes* of aesthetic experience resulting from an active engagement with the aesthetic interfaces (cf. Leder et al., 2004; Marković, 2012). We found that designs that triggered higher positive "emotions" in learners led to higher situational interest to engage with the app and the topic. In addition, designs that were rated higher in "cognitive stimulation" led to increased individual interest in the topic and higher self-assessed knowledge. Or, in other words, the more stimulating, involving, and exciting the interaction with the aesthetic interface of the app, the more interested the students were in the topic (also in the long term, cf. Harackiewicz & Hulleman, 2010) and the higher they rated their knowledge of the topic.

Given these results, we conclude that while appealing and emotion-enhancing designs can promote short-term interest in science topics (Ekman, 1992; Harackiewicz & Hulleman, 2010), cognitively stimulating designs can also promote longer-lasting concepts such as individual interest and learning. However, special care should be taken to ensure that aesthetic designs do not also foster the extraneous processing of appealing but not learning-relevant information (see seductive-details effect, Mayer, 2019). This is underlined by our results, which suggest that high perceived "cognitive stimulation", triggered by aesthetic designs, might also hinder knowledge acquisition. In line with situative approaches (Greeno & Engeström, 2015; Janssen & Kirschner, 2020), this work underlines the importance of considering aesthetic experience when intending to obtain a fundamental understanding of the way in which aesthetic designs of digital learning environments can support scientific interest and learning.

Regarding the impact of video-based digital learning environments *designed to foster generative learning with enhanced video tools* (RQ 2, Manuscripts 2 and 3), we found in Manuscript 2 that frequently performed macro-actions (resulting from the use of annotations or hyperlinks) were

positively related to conceptual understanding. In accordance with approaches on generative learning (Fiorella & Mayer, 2016; Wittrock, 1992), this result might indicate that the frequent use of task-relevant enhanced video tools might support an active generation of meaning by priming cognitive processes in working memory (Mayer, 2005). Our results further suggested that frequently using task-relevant enhanced tools does not increase mental effort and might even lead to lower perceptions of mental load. However, although a distinction between different enhanced tools would be important to gain insights into the conditions under which they can effectively support learning, in this study we did not distinguish between the included tools, annotations and hyperlinks. Furthermore, we did not consider the direction of causality in this work (e.g., learners who understood the topic more easily might have had more capacity available to use more enhanced tools). Additionally, although participants either learned individually or collaboratively in the study, we analyzed the data at the individual level and made no comparisons between these conditions.

Hence, we expanded our focus in Manuscript 3 following a more situative approach (cf. Greeno & Engeström, 2015; Janssen & Kirschner, 2020). Accordingly, we investigated the effects of the antecedents *Tool-use* (annotations vs. hyperlinks vs. no *Tool-use*: control group) and *Setting* (individual vs. collaborative learning) on the learning processes, learning activity (micro- and macro-actions) and cognitive load, and on learning outcome (conceptual understanding). We also examined hypervideo product quality as a further important learning outcome (i.e., *creative learning*). The results revealed that participants in the hyperlink condition created hypervideo products of higher quality than participants in the annotation condition. In accordance with approaches on learning through design (Kafai & Resnick, 1996; Krathwohl, 2002), we concluded that hyperlinks support learners in creating own information structures. According to approaches on generative learning (Fiorella & Mayer, 2016; Wittrock, 1992), such self-constructed interpretations should, in turn, also foster the deep processing of concepts and, thus, increase conceptual understanding (see also Rickley & Kemp, 2020). However, our

results suggested that this is not necessarily the case. More precisely, while a general increase in conceptual understanding after learning was found in all conditions, which is in line with previous research on the effects of (enhanced) videos (Evi-Colombo et al., 2020; Poquet et al., 2018) and on collaborative learning (Liao et al., 2019), no superiority of the hyperlink condition over the other conditions was found. In fact, the control group, which was not able to engage in generative activities by using enhanced tools, outperformed the two *Tool-use* conditions in conceptual understanding. Reasons for this result might be that the effects of enhanced video tools only develop over time (Kassymova et al., 2020) and that participants in the control group had more capacity in working memory compared to the *Tool-use* conditions (Baddeley, 1992; Maj, 2020). However, when taking a closer look at cognitive load, a more differentiated picture emerges. Our results indicated that participants in the annotation condition reported the lowest cognitive load compared to the other conditions. Moreover, we found that low perceived cognitive load mediated the effect of *Tool-use* on conceptual understanding. We, therefore, conclude that self-written annotations can support generative processing in working memory (Mayer, 2005, 2011), leading to a deeper conceptual understanding (see also Zahn et al., 2012). This is also underlined by our result that learners using annotations rated higher self-assessed knowledge gain after learning compared to the other conditions (see Table 7 for descriptive results). However, this effect only appears if learners do not consider the material too complex (e.g., Kirschner et al., 2018; Krauskopf et al., 2014).

But why is it that using annotations is more likely to lead to a deeper understanding of the topic than using hyperlinks, which encourage the creation of high-quality information structures? To understand this, we need to clarify again that annotations and hyperlinks have different purposes, or rather encourage learners to perform in different tasks, which affect their learning processes and outcomes differently. While hyperlinks encourage learners to organize and integrate *existing* material (matching predefined text information with appropriate video material, cf. Rickley & Kemp, 2020; Stahl

et al., 2006; Zahn, 2017), annotations encourage learners to reflect, organize, and integrate information in order to produce *own* material (Lawson & Mayer, 2021). Hence, the tools themselves trigger different foci in learners: either learning by meaningfully structuring existing learning material or learning by writing own summaries in order to expand on the video. The different foci between conditions were also reflected in learners' interactions with the tools. Specifically, we found that learners in the hyperlink condition used more micro-actions, but fewer macro-actions compared to learners in the annotation condition. This result indicates that learners pursued different specific strategies to use the enhanced tools for learning, depending on the purposes of the tools. Learners who focused on creating information structures by using hyperlinks, repeatedly skipped back and forth to find appropriate places in the video to add the hyperlinks. Accordingly, the creation of high-quality hypervideo products seems to depend on the sparse but target-oriented use of enhanced tools that require multiple interactions with basic video control tools in advance. This assumption is underlined by our result, indicating that the effect of *Tool-use* on HPQ was partially mediated by the performance of *fewer* macro-actions. In contrast, learners in the annotation condition used macro-actions extensively according to their focus to write own texts (cf. logged macro-action "changing annotation text" in Table 3). Thereby, they seemed to neglect a meaningful matching of the summaries they produced with relevant parts of the video, resulting in lower hypervideo product quality.

Moreover, in line with related work on animation and games (Bol et al., 2012; Kirschner et al., 2011; Liao et al., 2019; Retnowati et al., 2016), we found a marginal superiority of collaborative over individual learners in hypervideo product quality, indicating that collaboration fosters the creation of hypervideo structures (see also Zahn et al., 2010, 2012). However, similar to our results on hyperlinks, we could not find any superior effect of collaborative learning on conceptual understanding. Here, too, a possible explanation can be found by taking a closer look at the learning processes: we could not find any differences in learning processes between collaborative and individual learners. We thus argue that

the enhanced video-based environment used in this study, including well-instructed and task-relevant enhanced tools, supported learning for both settings equally (cf. Janssen & Kirschner, 2020). However, further research is needed.

In sum, we conclude that annotations and hyperlinks are both useful tools to encourage individual as well as collaborative learners to engage in generative activities that support the learning of science topics with digital learning environments. The consideration of learning processes, in the context of a situative perspective on learning (Greeno & Engeström, 2015; Janssen & Kirschner, 2020), allowed us to gain a deeper understanding on how learners use such enhanced tools to learn (cf. Fiorella & Mayer, 2016). More precisely, we conclude that annotations and hyperlinks might impact learners' focus on learning in enhanced video-based environments, leading to different strategies for using these tools that affect cognitive processes in working memory differently. This, in turn, seems to result in different learning consequences, i.e., a higher ability to learn *creatively* by constructing own information structures or a deeper conceptual understanding.

Limitations

In line with situative perspectives on learning (cf. Greeno & Engeström, 2015; Janssen & Kirschner, 2020), the presented manuscripts suggest that simultaneous investigations of different antecedents, processes, and consequences of learning might shed light on how and when digital learning environments can support learning effectively. However, several important limitations need to be addressed.

First, in Manuscript 1, we investigated the effects of two equally learning-supportive aesthetic design variants. However, because the designs differed not only in single aesthetic features, but rather in their *Gestalt* (cf. Bae & Watson, 2014), and thus differed in multiple aesthetic features, we were not able to rule out all factors that might have influenced learning. For example, the different design

manipulations of the interfaces also affected the information graphics displayed (see Figure 2). Thus, some graphic elements in one design variant could have been more easily processed by learners than in the other design. Additionally, the two designs reflected different life worlds of the students. While the *game-style* variant represented the look and feel of a mobile game, the *industrial-style* variant was oriented towards a classical schoolbook. Thus, effects of the variants could be confounded by various additionally influencing factors. For example, the industrial-style variant could trigger learning context associations in learners more, resulting in facilitated learning, or more game-experienced learners could have benefited more (or less) from the *game-style* variant for learning. Increased attention should be paid to such influencing factors in the future.

Second, by treating micro- and macro-actions separately in Manuscripts 2 and 3, we were only able to make initial assumptions about learners' strategies when using enhanced video tools for learning. However, our results indicated a close relationship between the two interactivity levels. Future research should investigate this in more depth by combining micro- and macro-actions into meaningful behavior sequences associated with learning strategies (cf. Mirriahi & Vigentini, 2017). We have already started investigations in this direction using our own data set and have developed a tool that enables a qualitative investigation of behavior sequences in enhanced video-based environments (Niederhauser et al., 2021; Ruf. et al., 2021; Ruf et al., submitted).

Third, in all manuscripts, we focused only on short-term measures. However, the constructs of (individual) interest and learning might develop and change over time. It is, thus, of the utmost importance to consider long-term measures in future research.

Fourth, although we pursued a situative approach by including different aspects of learning, many other variables may play decisive roles. For example, student characteristics, such as the ability for self-regulated learning processes or group interdependence in collaborative settings, should increasingly be addressed in future research (Janssen & Kirschner, 2020).

Finally, the major gap between female and male learners when it comes to science topics (Wang & Degol, 2017) was not considered over the course of all manuscripts. However, this should be addressed in future research by investigating different interest-fostering aspects between female and male learners in digital learning environments as well as in science topics themselves.

Conclusion

Understanding science-related topics is key to everyday life as it raises awareness of and willingness to engage in global issues and is central to good decision-making based on sensible arguments. Digital learning environments seem promising in terms of cultivating scientific interest and learning. The research presented in this thesis pursued two possible ways of fostering cognitive learning processes according to two different design approaches. We intended to foster scientific learning through a learning application with an *aesthetically appealing design* and through an enhanced video-based environment *designed to foster generative learning*. First, we found that aesthetic designs in digital learning environments can foster short-lasting interest in science topics when they provoke positive emotional experiences in learners and are designed in a fascinating, original way (i.e., the expressive aesthetics of designs). When designs additionally elicit engaging and exciting experiences in learners (i.e., cognitively stimulating designs), they further impact long-lasting interest in the learning topic, which might result in higher learning outcomes over time. Second, we found that enhanced video tools, such as annotations and hyperlinks, foster generative learning relevant for scientific learning, but in different ways. While hyperlinks support creative learning, i.e., the creation of own information structures, annotations foster conceptual understanding of these topics - but only when the learning material is not perceived as too complex. Creative learning was further found to be fostered through collaboration. In all studies, we could show that considering learning processes is of crucial significance to understand how learners interact with digital learning environments and how they perceive this

interaction and, in turn, how this affects their learning. This emphasizes the importance of also considering situative perspectives on learning in addition to cognitive perspectives, and of understanding learning holistically as a construct that is shaped by multiple aspects. I hope this thesis adds to the understanding of how scientific interest and learning can be fostered through different design approaches in digital learning environments and inspires future research in this important field.

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Appendix

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2. Ruf, A., Leisner, D., Zahn C., & Opwis, K. (2021). Impact of learners' video interactions on learning success and cognitive load. In C. Hmelo-Silver, B. de Wever, & J. Oshima (Eds.), 14th International Conference on Computer-Supported Collaborative Learning – CSCL 2021 (pp. 3-10). International Society of the Learning Sciences, 2021
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Aesthetic design of app interfaces and their impact on secondary students' interest and learning

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ABSTRACT

Interest in science topics is an important prerequisite for science learning and achievement. Here, as part of a field experiment, we studied whether teenagers' interest and learning of physics topics would be influenced by the aesthetics of a multimedia learning app. More specifically, we investigated with the example of learning about energy (types of power plants) how different interface designs of a multimedia learning app would influence aesthetic experience, interest, and learning outcome. In our study Swiss high school students (N = 108) were assigned to one of two conditions (i.e., *game-style* vs. *industrial-style*) differing in various aesthetic features. Results indicate that high-quality interfaces support learning and expressive aesthetic design features additionally foster interest in order to engage with the topic. Moreover, our findings on aesthetic experience suggest that *deep perceptual processes*, such as emotion and cognitive stimulation induced by interfaces, further impact interest and learning. Thus, our study gives implications for the design of interest-generating and learning-supporting science apps for teenagers and emphasizes the significance to consider aesthetic experience in future research.

1. Introduction

Interest in science and understanding science topics is key in everyday life to raise awareness and willingness to engage with global issues and current public debates, such as climate change [49,51], and in order to stand up and take responsibility [4]. It is also central for good decision-making based on sensible arguments. For instance, science literacy was proven to significantly decrease the likelihood of people believing in health rumors [21]. However, interest in science topics is steadily declining [50] – science-related topics are often perceived as difficult, boring, and challenging to learn, provoking negative emotions and a lack of interest [5,71]. Thus, finding timely ways to foster positive emotions and interest in science topics is important. If students could learn science topics in ways that are considered fun, this could help increase their overall science literacy and, moreover, in the long run help foster more future science careers [1,58].

One possibility to help cultivate scientific interest and learning is to create interesting computer-supported learning environments, such as multimedia learning apps [10,27]. As interest is a crucial component of intrinsic motivation [25,79], such environments could be seen as a first step in increasing motivation to learn more [e.g., 59], which in turn should increase learning performance [62] and scientific literacy [13].

Yet, what is considered "interesting" for teenage students? Research indicates that interface aesthetics plays an important role in fostering interest, positive emotions, engagement, and enthusiasm in computer-supported classrooms [26,74]. Three recently published meta-analyses provide empirical evidence that appealing aesthetic interfaces of learning environments can have impacts on emotional and interest-related factors and facilitating effects on learning [7,68,78]. These effects particularly occurred when learners interacted with mobile devices and software applications [68] and were stronger in K-12 (primary and secondary students) than in post-secondary students [7,78].

Thus, aesthetic interfaces can enhance interest in science-topics. However, few studies on the effects of aesthetic design were conducted with secondary students [7,78], even though this age group was found to be a critical life period in which orientations in science can

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successfully be encouraged [1,58]. The present research uses a field study and measures of learners' aesthetic experience to investigate the influence of two differently designed appealing and learning-supportive app interfaces on secondary school students. In the next section we will first clarify the terms aesthetic design and aesthetic experience in relation to learning. Then, we will provide a summary of related research on emotional design and its effects on scientific interest and learning, before finally emphasizing important research gaps and ending the section with the goals, research questions, and hypotheses of the present study.

1.1. Aesthetic design and aesthetic experience in HCI research

Aesthetic design is a construct that can be described as any design (e.g., websites, interactive systems) that immediately increases the appeal and attractiveness of an object for its observer [e.g., 45,67]. Although the term still lacks a consistent definition [68], the literature provides evidence that single aesthetic features, such as color [e.g., 52,65], familiarity [e.g., 32,57], expressivity [e.g., 30], and visual complexity [e.g., 65,69], have an impact on the perceived attractiveness of an object [22,34] and increase visual appeal, which is "an immediate pleasurable subjective experience that is directed toward an object and not mediated by intervening reasoning" [p. 690, 45]. This is in line with the Model of Aesthetic Art Experience by Leder et al. [31]. In their model, viewers pass through several stages when they contemplate an aesthetic object, such as artwork: perceptual analyses (e.g., complexity of an object), implicit memory integration (e.g., prototypicality of an object), explicit classification (e.g., style of the object), cognitive mastering (e.g., self-related interpretation), and evaluation (e.g., cognitive and affective state). The latter two are closely related in the form of a feedback-loop: successful cognitive mastering leads to a positive evaluation and successful understanding of the aesthetic object that, in turn, positively influences affective states, resulting in pleasure or satisfaction. These experiences of viewers while contemplating an aesthetic object are also closely related to the characteristics that define aesthetic experience as stated by Marković [35]. Marković [35] identified the following aspects as crucial and distinctive: (1) a *motivational, orientational*, or *attentive* aspect of aesthetic experience, defined as a state of intense attention, engagement, or high vigilance of the viewer, (2) a *cognitive* aspect, defined as the viewer's appraisal of an aesthetic object as part of a symbolic (or 'virtual') reality and the transcendence of their everyday uses and meanings, and (3) an *affective* aspect, defined as a strong and clear feeling of unity with aesthetic appraisal.

Research on human-computer interaction (HCI) has applied these definitions to digital interfaces (e.g., websites, online environments) as an important component of user experience [e.g., 11,22] and assumes that aesthetic interfaces are able to improve users' experience of aesthetics [45]. However, there have been few validated instruments measuring viewers' *aesthetic experience* that have been developed so far, and those that have been developed have mainly been for website evaluation [6,30,45,68]. One of the most prominent ones is the Visual Aesthetics of Websites Inventory (VisAWI). It is based on the assumption that users experience the aesthetics of websites according to four facets (i.e., aesthetic features) that are known to have an impact on attractiveness and visual appeal [e.g., 65,69]. The four facets are simplicity, variety, colourfulness, and craftsmanship [45].

Additionally, the advantages of aesthetic design to support learning and task performance have been recognized. This is reflected in the considerable amount of HCI research that examines the impact of a wide range of single aesthetic features [for an overview see 67,68]. In their meta-analysis, Thielsch et al. [68] examined studies that investigated the impact of aesthetic and unaesthetic designs on learning and task performance and found a significant – albeit small ($g = 0.12$) – effect for appealing aesthetic designs. Furthermore, this effect was found to be stronger when users interacted with mobile devices and software applications, which is in keeping with research on computer-supported collaborative learning [10]. However, Thielsch et al. [68] mentioned several limitations of these studies. Many studies did not sufficiently report which aesthetic features (e.g., color, texture etc.) were manipulated and in what way, and used unstandardized or not validated scales for measuring viewers' *aesthetic experience* to assign the design variants to the experimental conditions (aesthetic vs. unaesthetic) or for manipulation check. Hence, Thielsch et al. [68] concluded that it often remained untraceable how appealing or unappealing the designs actually were and how they differed from each other. Yet, positive affective states resulting from a successful aesthetic experience seem to still increase learning performance: in consideration of Norman's Affect Mediation Theory [cf. 46,47], Thielsch et al. [68] argued that aesthetic designs can provoke positive emotions, leading to a better working cognitive system, which results in improved performance. This is in line with the related research field of *emotional design*, which is discussed in the following section.

1.2. Emotional design, learning, and interest in science

Research on *emotional design* is based on the Cognitive Affective Theory of Learning with Media [39,41], which assumes an increase of motivational and affective factors through specific aesthetic features that, in turn, facilitate cognitive processing and, thus, interest and learning [55,56]. Historically, research on emotional design has focused primarily on examining its impact on (natural) science subjects, with limited research in other subjects, such as humanities [76,78]. One reason for this is that these subjects themselves do not usually evoke positive emotions in learners, unlike other subjects, such as poetry, music, or the arts [cf. 76]. Therefore, research on emotional design aims to artificially evoke positive emotions in learners through the provision of emotional design features. Building on the pioneering work of Um et al. [72], the features *color* [e.g., 54,72] and *facial anthropomorphisms in non-human graphical elements* [e.g., 54,64] have been widely investigated [7,78]. In fact, two recent meta-analyses revealed significant effects of emotional designs – compared to neutral designs (i.e., colorless; no facial anthropomorphisms) – on intrinsic motivation, liking/enjoyment, positive affect, and on learning performance [7,78]. Moreover, although the majority of the investigated studies were conducted with post-secondary learners, even stronger effects were found with younger K-12 participants [78]. *Emotional designs* seem to provide an effective way to foster scientific literacy, as they not only facilitate learning but also are able to increase interest in science topics [7,78], which, in turn, could encourage students to pursue a science career in the future.

Since fostering interest is of crucial importance for the present study, we briefly elaborate on the definition and conceptualization of the term in the following: a prominent definition categorizes interest as a critical motivational variable, as well as a psychological state, that influences learning and achievement, which occurs during interactions between persons and their objects of interest [23,24,29]. Thus, interest describes two different experiences: *situational* and *individual interest*. On one hand, *situational interest* is defined as a momentary experience triggered by an object and characterized by increased affect, effort, and attention. In research on science learning, recent work has demonstrated that young learners' *situational interest* in STEM topics could be fostered by providing mobile devices for learning [27]. On the other hand, *individual interest* is described as a more prolonged experience, characterized by a persistent willingness to return to a certain object or topic over time [see 20, for more information]. Theoretical and empirical work suggests that both experiences are closely related [e.g., 24,33]. For example, Romine et al. [62] found that individual interest in science facilitates situational interest. This, in turn, positively impacts science learning. While research on *emotional design* focuses merely on situational interest, both experiences were considered separately in the present study (see section 2.3).

1.3. Current research gaps

It becomes apparent from the theoretical background described above that aesthetic and emotional designs have the ability to positively impact scientific interest and learning [7,68,78]. However, there are still knowledge gaps in the scientific literature that we aim to address in the current study (see section 1.4 for study goals). Firstly, as stated by Thielsch et al. [68], in previous work regarding aesthetic design it is often untraceable how aesthetic or unaesthetic the compared interfaces actually were. This raises the question of whether the effects on learning occurred due to differently manipulated aesthetics between the design variants or due to beneficial or detrimental effects resulting from different implementations of multimedia design principles. Sweller's (66) Cognitive Load Theory and Mayer's (37) Cognitive Theory of Multimedia Learning, two well-established approaches from instructional psychology, incorporate several principles that should be applied when developing computer-supported learning environments to ensure an optimal learning support. The importance of considering these principles when examining the effects of aesthetics on learning is illustrated by the following example: using color – a frequently used design manipulation in research on aesthetic and emotional design [7,68,78] – may, on one hand, induce positive affects in learners, but may, on the other hand, also highlight important parts of the learning material, due to the so-called signaling effect [cf. 36]. In other words: a colorful design (in contrast to a black-and-white design) could not only be beneficial for learning because it triggers higher positive affects, but also because color could function as a learning-supportive instructional design feature.

Secondly, while measurements of viewers' *aesthetic experience* generally remained unconsidered in research on emotional design, it has been embraced by research on aesthetic design (see section 1.1). Nevertheless, in-depth investigations and impacts of the construct on interest and learning are still missing [see section 1.1 and 68]. Hence, only superficial parts of viewers' perceptions provoked by the designs' *surface structures* were investigated, such as perceptions of color or complexity [see VisAWI; 45]. However, in line with earlier approaches on aesthetic art experience, we assume that *aesthetic experience* derives not only due to the perception of *surface structures*, but also due to *deeper perceptual processes* resulting from an active engagement with and exploration of an aesthetic object that might be related to interest and learning [12,31,35]. More precisely, we assume that the experience of aesthetics – especially when it comes to digital interactive environments – is not limited only to perceptions of (static) surfaces of aesthetic interfaces, but is also influenced by the active engagement and interaction with them [see also 8]. Measures considering such *deeper perceptual processes* can be found in related research on general user experience [for an overview see 28] and aesthetic art experience, and are described, for example, as "cognitive stimulation" [19], "intrinsic motivation" [e.g., 25,31], "pleasurable interaction" [30], "learning related boredom" [53], and "involvement" [48]. However, an instrument measuring aesthetic experience by considering both *surface structures* and *deeper processes* of learners who actively engage with aesthetic designs is still missing.

Thirdly, young K-12 learners have rarely been investigated as subjects of research on aesthetic and emotional design [7,68,78] – although findings suggest that effects may be even stronger for younger learners than for post-secondary students [78]. Also, early intervention to spark students' interest is critical, not only in terms of fostering scientific literacy [73], but also because developing science aptitudes in middle school was found to be positively associated with pursuing a science career in the future [1,58].

1.4. Goals of the present study

Consequently, with the present work, we aimed to deepen our understanding of how aesthetic design can foster teenagers' interest and learning in science and how the experience of aesthetic *surface structures* and *deeper perceptual processes* further influence these outcomes.

More precisely, we pursued three main objectives. The first objective was to provide new insights into the effects of aesthetic design on interest and learning in science. In contrast to fundamental research on aesthetic (see section 1.1) and emotional design (see section 1.2), we were less interested in investigating differences of aesthetic vs. unaesthetic or emotional vs. neutral designs than we were in investigating the effects of differently designed appealing interfaces that were equally supportive of learning using systematic and conceptual consideration of multimedia design principles [similar to approaches from instructional psychology, see 37,66]. This new focus allowed us to examine the construct aesthetics (cf. section 1.1) more *holistically* by manipulating multiple aesthetic features in each of the designs. Furthermore, we were able to incorporate principles from the Gestalt Theory [e.g., 3,60] and interpret interfaces as a *Gestalt* that constitutes "a functional unit with properties not derivable by summation of its parts" [p. 187, 3]. Hence, we created two high-quality interface designs of a learning application that oriented towards different life worlds related to the target group (i.e., teenage students) and played with expectations: a *game-style* variant that represented the look and feel of a mobile game and an *industrial--style* variant that was designed in a more technical way and more strongly resembled a classic school book (cf. section 2.2 and Fig. 1, for detailed information). We thereby clearly distinguished between design features that are supportive for learning (i.e., instructional design: committed to be similar between the design variants) and address the target group equally, and appealing aesthetic features that might elicit positive affect in learners but do not directly influence learning due to beneficial or detrimental effects (i.e., *Interface Aesthetic*: permitted to deviate between the design variants, see Table 1). Note that we used physics (more precisely *energy*) as science topic for three main reasons. First, learning physics was found to foster students' scientific literacy through transferring knowledge about scientific products, processes, and attitudes [9,15]; it enables students to make connections between the learned material and their daily lives (e.g., where does the electricity come from?). Second, it involves learning complex processes that can be facilitated by aesthetic designs (see sections 1.1 and 1.2) and by multimedia learning environments as they are able to minimize cognitive load [37]. Third, it has been shown that taking a physics class in high school highly correlates with deciding on a science career in the future [18].

The second objective was to further investigate the effects of aesthetics by examining (explorative) the impact of aesthetic experience on interest and learning performance using a more holistic perspective of the process occurring when a viewer is exposed to and interacts with an aesthetic interface design [31,35]. We therefore investigated the impact of different dimensions of aesthetic experience, including both *surface structures* (i.e., "expressive aesthetics") and *deeper perceptual processes* (i.e., "emotion" and "cognitive stimulation") on interest and learning. For this purpose and by considering measures from closely related research on aesthetic art design and general user experience (see section 1.3), we developed and validated an appropriate instrument at our university that was used in the present study (see section 2.4 for more information).

The third objective was to contribute new results concerning the impact of visually aesthetic designs of a tablet-based learning application on aesthetic experience, interest, and learning of *middle school teenage students* and continue the tradition of research on aesthetic and emotional design [7,68,78]. The study was conducted directly in the classroom.

1.5. Research questions and hypotheses

In order to achieve our study goals (see section 1.4) and fill the above mentioned research gaps (see section 1.3), our study was guided by the following research questions and hypotheses:

Research Question 1. Do the two interface designs (*game-style* vs. *industrial-style*) differ in students' aesthetic experience?

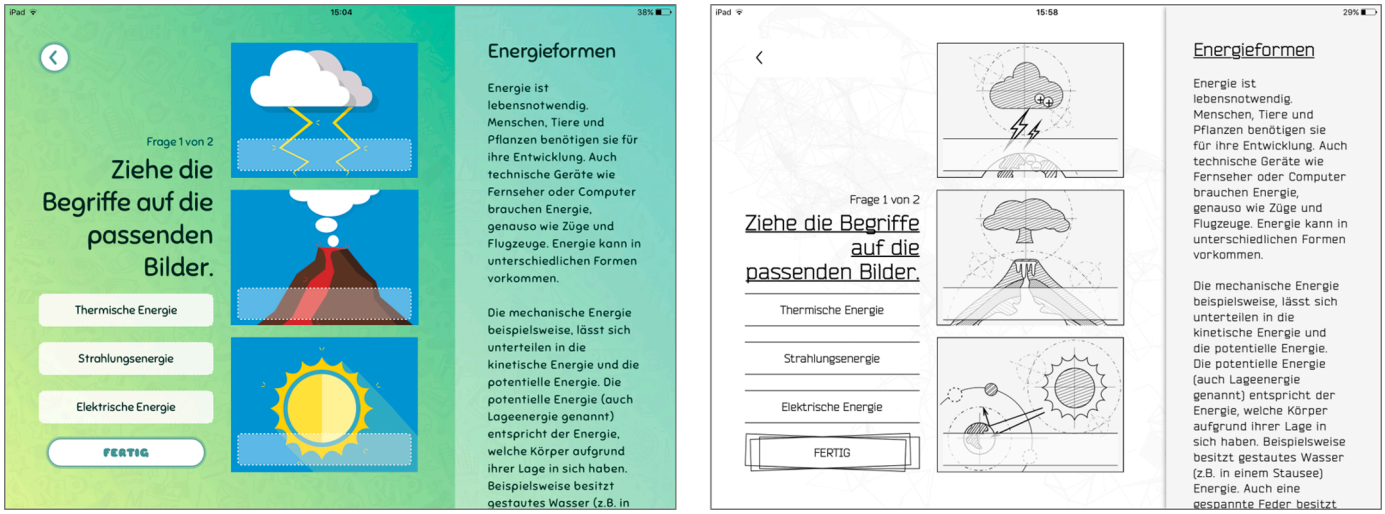

Fig. 1. The figure displays the two interface designs; on the left side the *game-style* design and on the right side the *industrial-style* design (i.e., *Interface Aesthetic*).

Based on research described in sections 1.1 and 1.2, we expected that students learning with the *game-style* design would rate (H1a) *surface structures* (visual aesthetics: VisAWI) and (H1b) *aesthetic experience* (i.e., holistic consideration of *surface structures* and *deeper perceptual processes*) higher than students learning with the *industrial-style* design.

Research Question 2. Do the two interface designs (*game-style* vs. *industrial-style*) differ in their impact on students' situational and individual interest?

Based on interest theories and research on emotional design described in section 1.2, we hypothesized that the *game-style* design would lead to a higher increase in students' (H2a) situational and (H2b) individual interest compared to the *industrial-style* design. Furthermore, we expected that both (H2c) situational and (H2d) individual interest would increase after learning for both designs.

Research Question 3. (explorative) Does aesthetic experience (*surface structures* and *deep processing*) have an impact on situational and individual interest?

According to Research Question 2 and earlier approaches on art experience [31,35], we hypothesized that aesthetic experience (i.e., "expressive aesthetics," "emotion," "cognitive stimulation") and usability would have an impact on (H3a) situational and (H3b) individual interest.

Research Question 4. (explorative) Do the two interface designs (*game-style* vs. *industrial-style*) differ in learning performance?

Although the two designs were created in such a way that they differed only in aesthetic features that were not detrimental for learning (by considering multimedia design principles, see Mayer [37], Sweller [66] and usability, see Moshagen et al. [43]), we hypothesized, based on theories on aesthetic and emotional design [7,68,78], that the two interface designs would have a different impact on learners' affects and, thus, on (H4a) objective and (H4b) self-assessed learning performance. Moreover, we expected a general increase in (H4c) objective and (H4d) self-assessed knowledge after learning for both designs.

Research Question 5. (explorative) Does aesthetic experience (*surface structures* and *deeper perceptual processes*) have an impact on learning performance?

According to the Research Questions 1 and 4, and in line with related research on aesthetic art experience and user experience (see second research gap in section 1.3), we expected that aesthetic experience (i.e., "expressive aesthetics," "emotion," "cognitive stimulation") and usability would have an impact on (H5a) objective and (H5b) self-assessed learning performance.

To answer these research questions and hypotheses, we set up a field study (1) to investigate the effects of two different learning app designs on interest and learning performance and (2) to investigate the effects of three aesthetic experience dimensions on these dependent variables. In the next section, the method of the present study is described in detail.

2. Method

2.1. Participants and design

A total of 108 secondary school students (Switzerland) participated in the experiment as part of a pre-holiday school project during regular teaching hours. The ethical standards were set through the institutional ethics committee of our institution. The participants had no previous experience with the topic of study in the experiment at the time of the study and were randomly assigned to one of two conditions using different interface designs for a learning app: the *game-style* (n = 53) and the *industrial-style* design variant (n = 55), in the following referred to as *Interface Aesthetic* (see Fig. 1). The sample consisted of 53 female and 55 male teenagers (M = 13.3 years, SD = 0.53, range = 12 -15). The experimental design was mixed two-factorial, with *Interface Aesthetic* as between factor (interface design variants *game-style* vs. *industrial-style*) and *Time of Measurement* as within factor (pre-post-test). The primary dependent variables were interest (situational and individual) and learning performance (objective knowledge and subjective self-assessments). In addition, aesthetic experience was measured by a validated questionnaire to assess the impact of aesthetic experience (i.e., "expressive aesthetics," "emotion," "cognitive stimulation") on the dependent variables.

2.2. Materials

The learning material addressed the topic of *energy* (physics) and covered three subtopics that are typically part of the school curriculum for secondary school: energy forms (e.g., electrical energy), energy sources (e.g., sun, wind), and power plants (e.g., biomass power plant). The learning app included a geographic map showing a culture trail on industrial history – well known in the region were the study was conducted. On this trail, there is an option to visit historic buildings (e.g., a historic power plant). The app "virtually" guided students through three locations and offered context and background information about the spots, as well as further texts about energy forms, energy sources, and

power plants. Additionally, short quizzes were integrated to foster a playful interaction with the learning app, which has been found to positively impact learning [e.g., 16]. Note, these quizzes were separate to the learning performance questionnaire (see section 2.3). The app was developed by a professional designer and was run on the iPad Air 2.

To create the design variants, a pilot study was conducted that followed several steps. First, a focus group was conducted, which included an expert discussion held with seven specialists from different interdisciplinary fields: contemporary design practices and aesthetic (art) design (two experts), user experience (one expert), interface- and interaction design (one expert), interactive media technologies (one expert), and instructional design (two experts). The goals of this workshop were to understand the concept of aesthetics based on the different expert opinions and the derivation of several criteria on the basis of which the interface variants were created. This involved criteria which had to be consistent in the design variants (i.e., usability and instructional design), in order to ensure optimal learning support and criteria, which were allowed to differ between the variants, i.e., aesthetic features not directly impacting learning through instructional advantages (referred to as *Interface Aesthetic*, see Table 1). Second, based on these criteria, a professional designer created four different interface designs that oriented towards different life worlds (see first study objective in section 1.4). Third, the four design variants were rated by the same group of experts with regard to the preassigned criteria: apart from the multimedia design principles and the criterion on custom design – for each of which it was necessary to indicate whether they were demonstrated in the design or not – the criteria were rated on a Likert scale from 1 to 7: from little to very (e.g., conceptual basis of text and figures in the design variants: little discernible to very well discernible) or on a scale with opposites (e.g., illustrations: very realistic to very abstract). Additionally, open responses of the experts to the criteria were considered qualitatively. Fourth, by means of descriptive analyses (due to the small number of participants) two interface designs were chosen for the present work that differed the least in their instructional design, their general quality, and their customization to the target group and the most in their *Interface Aesthetic* (i.e., aesthetic features that do not directly impact learning). For example, color was used in one of the design variants to increase appeal and attractiveness (see section 1.1), but did not directly support learning due to a signaling effect [cf. 37]. We contrasted a *game-style* design variant with an *industrial-style* variant (see Fig. 1). Note, outcomes from the focus group were also taken into account in the development of the aesthetic experience questionnaire (see section 2.4).

2.3. Measures

The number of items, ranges of Likert scale scores of all measurements, and their usage in pre- and post questionnaires can be seen in Table 2. Note, we describe our questionnaire for measuring aesthetic experience in a separate section (see section 2.4).

To measure *surface structures* with a validated (Cronbach's $\alpha = 0.76$) and well-known instrument, we used a short version of the Visual Aesthetics of Website Inventory [VisAWI-S, see 44].

Interest. In order to measure (1) situational and (2) individual interest (cf. section 1.2 for a definition), several scales were used: (1) situational interest was quantified using two measures that were identified as momentary experiences triggered by the learning environment: first, the sum of three absolute single-items measuring pre- and post-experimental interest to engage with each of the three learning topics [2]. Second, the intrinsic/enjoyment subscale of the short German version of the intrinsic motivation inventory (IMI) [77] was used to measure pre- and post-experimental interest to engage with the app (Cronbach's $\alpha = 0.89$).

To measure (2) individual interest, three measures were used that were characterized by a more long-lasting interest, probably leading to a persistent willingness to continue to study the learning material in the future: first, an absolute one-item scale measuring pre- and post-experimental general interest in physics, second, pre- and post-experimental interest in physics compared to other school subjects, and third, a post-experimental single item, where students could self-assess the change in their interest in physics after learning with the app [2].

Learning performance was measured with three types of tasks, according to Moreno and Mayer [42]: matching tasks, retention tasks, and transfer tasks. Matching tasks were available for each of the three learning topics (i.e., energy forms, energy sources, and power plants). The purpose of these tasks was to identify four out of 16 correct items related to the topic (e.g., the correct items for the topic power plants were pumped-storage power plant, generator, turbine, and biomass power plant). The matching tasks had a score between 0 and 16 points, depending on how many of the 16 items were correctly classified. Each correct item classification as "right" or "wrong" was counted. The internal consistencies of the scales (48 items used in the pre-test and post-test for measuring prior knowledge and matching tasks) were performed according to Everitt and Skrondal [17] and all items with a correlation value less than 0.3 were dropped. After exclusion of 12 low consistency items, the final test version included 36 items covering the three learning topics for the matching tasks. Cronbach's alphas for the 36 items were 0.97 (pre-test) and 0.93 (post-test). Retention and transfer tasks were conducted together with an expert in the field and consisted of six multiple choice questions with four answering options, each administered during post-test (3 questions with multiple correct answers and 3 questions with only one correct answer). The questions had a score range between 0 and 1 points; the questions with a single possible answer awarded either 1 (for correct) or 0 points (for incorrect answers), questions with several possible answers awarded 0, 0.5, or 1 points. Due to the small numbers of items, no measurement of the internal consistency was conducted.

Finally, *self-assessed knowledge* was measured by three single items about pre- and post-experimental self-assessed knowledge for each of the three learning topics (i.e., energy forms, energy sources, power plants) [2]. For further analyses, we summed the values of the three pre- and post-test variables to one pre- and one post-test variable. Hence, a total score of 18 points could be achieved in the pre- and post-test scores for self-assessed knowledge.

To test our hypotheses, we used these scales to (1) conduct (multivariate) analyses of variance and (2) multiple regression analyses. The conditions for the statistical tests were checked in advance.

2.4. Aesthetic experience questionnaire

In order to measure aesthetic experience with an instrument that considered both *surface structures* and *deeper perceptual processes*, we developed a questionnaire [61]. The questionnaire was previously validated with teenage students of our age of interest (N = 160, 43.13% female, age: $M = 13.7$, $SD = 1.04$) who learned with aesthetically appealing learning apps. The statistical validation (PAF, Promax) of the questionnaire (Cronbach's $\alpha = 0.86$-0.91) confirmed three dimensions of *aesthetic experience*: "expressive aesthetics" (Cronbach's $\alpha = 0.68$-0.86), "cognitive stimulation" (Cronbach's $\alpha = 0.83$-0.86), and "emotion" (Cronbach's $\alpha = 0.68$-0.86). Simultaneously, a short "usability" scale was validated within the same experiment (Cronbach's $\alpha = 0.74$-0.84). Separately from this, the questionnaire also involved the control item "I can solve the learning task with the learning app" which we used as a manipulation check (see section 3.1). The questionnaire was developed (1) based on relevant related research (e.g., "expressive aesthetics": [30]; "cognitive stimulation": [19], [25], [48]; "emotion": [30], [53]; and for usability see [40], [63]) and (2) in consideration of the results from the focus group described in section 2.2. Following earlier approaches by Leder et al. [31] and Marković [35], for the present study we assigned the dimension "expressive aesthetics" to *surface structures* and the dimensions "cognitive stimulation" and "emotion" to

deeper perceptual processes to measure post-experimental aesthetic experience provoked by the interaction with one of the two design variants. Note, although the questionnaire considered measures of general user experience (cf. section 1.3), we assume that the term "aesthetic experience" is more appropriate for the newly developed questionnaire for two main reasons: (1) our focus was on the investigation of learners' experience resulting from their engagement and interaction with an "aesthetic" design (stimulus = appealing app interface) by means of a correspondingly validated instrument, and (2) the development of the design variants and the questionnaire was based on qualitative research methods, such as a focus group and expert group discussions, particularly focusing on measuring aesthetic experience (see also section 2.2).

2.5. Procedure

The study took place in June 2017 and was conducted on-site in class in a school in Switzerland and in German language. Overall, the experiment lasted about 90 minutes (two school lessons). The different phases of the procedure are summarized in more detail in Fig. 2. In the pre-experimental phase, students were welcomed and informed of the content of the study and received information according to the ethics standards approved by the ethics committee of our institution (15 min). Next, they were invited for pre-testing in their classrooms and worked individually on one desk. Students were guided through the pre-test questionnaire (paper-and-pencil), including demographics and prior interest and knowledge (10 min). Just before learning, students received a brief tutorial of the learning app and the task (10 min), before being randomly assigned to one of the two designs of the learning app (*Interface Aesthetic: game-style* vs. *industrial-style*). In the experimental phase, students had about 30 minutes to learn the three topics with the app (10 min for each learning topic). Although the time of the experiment was limited due to the embedding of the study directly in the classroom (within school schedule), students had enough time to complete learning. Finally, in the post-experimental phase that followed a 15-minute break, students were invited to answer the paper-and-pencil post-test questionnaires (20 min) before they were thanked and released.

3. Results

All data analyses were performed using SPSS.

3.1. Results of between-group comparisons and manipulation check

Chi-square test for gender and *t*-tests for age and prior media experience yielded no significant differences between conditions ($p > 0.10$).

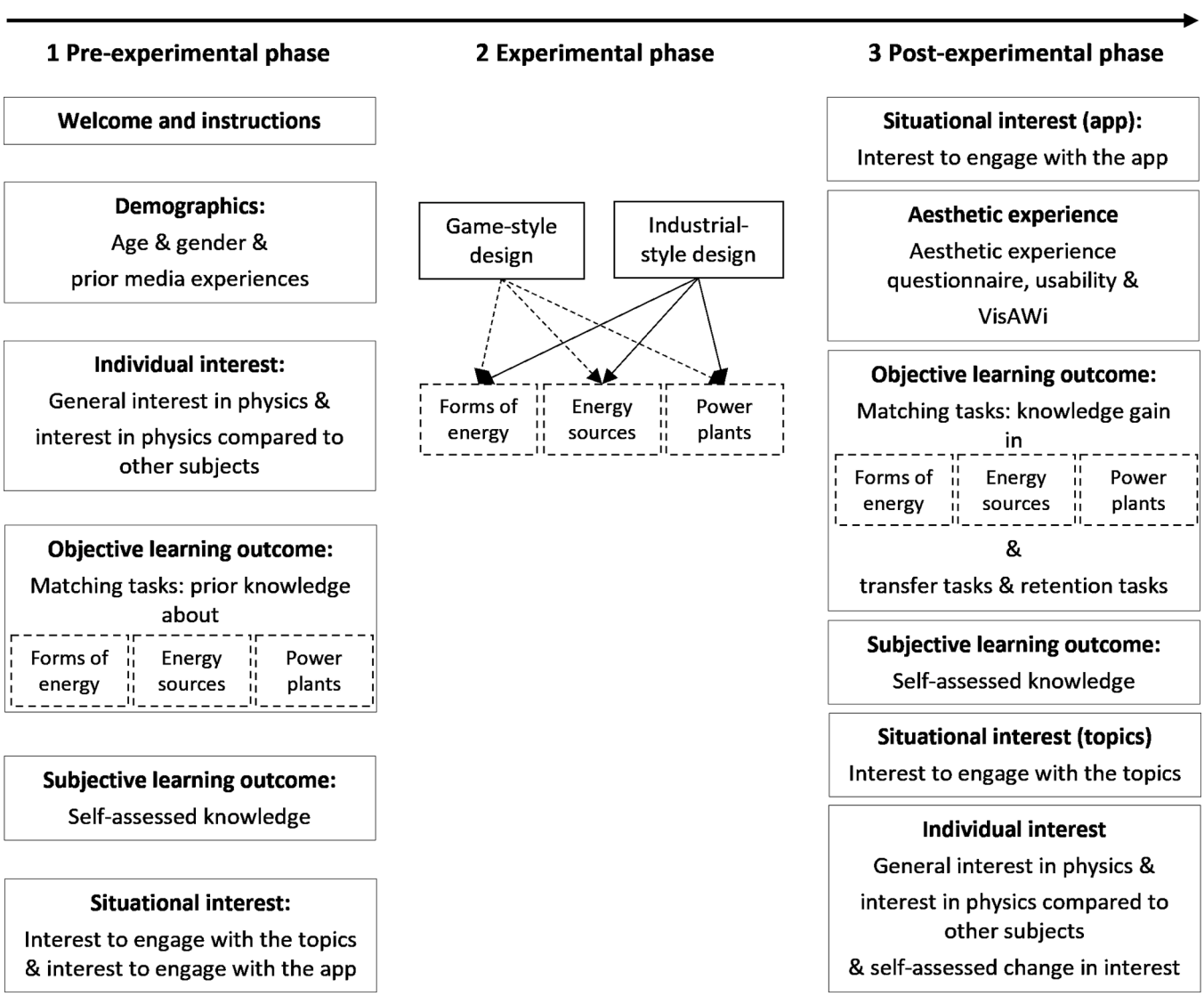

Fig. 2. The figure describes the procedure of the study.

Moreover, multivariate analysis of variance (MANOVA) with *Interface Aesthetic* (*game-style* vs. *industrial-style*) as between-subjects factor and prior knowledge and prior interest as dependent variables did not reach significance ($p > 0.10$). Hence, groups were comparable on these variables. In order to ensure the usability (see Table 2 for details) between the designs was equal and that we only varied *Interface Aesthetic* (*game-style* vs. *industrial-style*), a *t*-test for independent samples was conducted, revealing no significant difference between the design variants on usability, $t(106) = -0.06$, $p = 0.953$, $d = -0.01$. This indicated that students in both conditions experienced the app on about the same levels of usability (*game-style* variant: $M = 4.57$, $SD = 0.50$; *industrial-style* variant: $M = 4.57$, $SD = 0.49$). Moreover, results from a *t*-test for independent samples revealed no significant differences between the conditions regarding the control item "I can solve the learning task with the learning app", $t(105) = 0.80$, $p = 0.425$, $d = 0.16$. This indicates that students in both conditions found the app similarly suitable for completing the given task.

3.2. Interface aesthetic and aesthetic experience (RQ 1)

In order to investigate Research Question 1, we focused on the differences between the two designs (*Interface Aesthetic: game-style* vs. *industrial-style*) on aesthetic experience (see Table 3 for descriptive data).

To test Hypothesis 1a, whether learning with the *game-style* design would result in higher scores in *surface structures*, an independent sample *t*-test was conducted with mean scores of the VisAWI-S as dependent variable. The *t*-test revealed a significant result, $t(106) = -3.92$, $p < 0.01$, $d = 0.71$, indicating that (as expected) the students who learned with the *game-style* design rated the app significantly higher in its *surface structures* ($M = 5.45$, $SD = 1.02$) than students who learned with the *industrial-style* design ($M = 4.65$, $SD = 1.10$).

To test Hypothesis 1b, whether learning with the *game-style* design would result in higher scores of *aesthetic experience* (see Fig. 3), a MANOVA with the three dimensions of *aesthetic experience* (i.e., "expressive aesthetics," "emotion," "cognitive stimulation") as dependent variables was conducted and revealed no significant results ($F(3, 104) = 1.825$, $p = 0.147$; Wilks Lambda = 0.950). Yet, univariate post-hoc tests revealed a significant effect on "expressive aesthetics," $F(1, 106) = 3.998$, $p = 0.048$, $d = 0.38$, suggesting students who learned with the *game-style* design experienced higher "expressive aesthetics" ($M = 3.64$, $SD = 0.82$) than students who learned with the *industrial-style* design ($M = 3.31$, $SD = 0.90$).

3.3. Interface aesthetic and interest (RQ 2)

To investigate Research Question 2, whether the two interface designs (*game-style* vs. *industrial-style*) differ in their impact on students' situational and individual interest, several analyses were conducted (see Table 4 for descriptive data).

In order to investigate effects for situational interest (H2a, H2c), two mixed ANOVAs with *Interface Aesthetic* as between- and measuring time as within-subjects factor and either interest to engage with the topics or with the app as dependent variable were conducted. As expected (H2a), a significant effect was found for *Interface Aesthetic* regarding interest to engage with the topics ($F(1, 100) = 3.03$, $p = 0.0425$, Wilks Lambda = 0.971), indicating that students learning with the *game-style* design had a

Table 1
Criteria for designing the learning application .

Criteria committed to be similar (equal learning support)	Criteria permitted to deviate (Interface Aesthetic)
Instructional design	**Surface structures**
Principles of multimedia Learning	Color
Usability	Expressivity (classical to creative)
General application quality	Typography
General composition	Illustrations (realistic to abstract)
Craftsmanship	Gestalt
Conceptual basis	Orientation (playful to technical)
Text content and structure	
Target group	**Deeper perceptual processes**
Zeitgeisty	Expectable experience
Addressing preferences of target group	Cognitive stimulation
Custom Design	Emotional stimulation

Table 2
Index variables, measures, items and score of the used questionnaires.

Measure	Sample Items	Scores	Pre/ Post
Surface Structures			
VisAWI	4 items e.g.: "The layout is pleasantly varied"	1 (strongly disagree) - 7 (strongly agree)	post
Aesthetic Experience			
Surface structures and deeper processes			
Expressive aesthetics	3 items e.g.: "The special effects in the app are well done"	1 (strongly disagree) - 5 (strongly agree)	post
Cognitive stimulation	6 items e.g.: "I would love to explore the topic further with the app."		
Emotion	4 items e.g.: "Using the app is fun."		
Usability	3 items e.g.: "It is easy to navigate in the learning app."	1 (strongly disagree) - 5 (strongly agree)	post
Interest			
Situational interest			
Interest to engage with the learning topics	1 item for each learning topic: "It is important to me, to know what is behind X"	1 (strongly disagree) - 6 (strongly agree)	pre/ post
Interest to engage with the learning app	3 items e.g.: "I think I will enjoy/I enjoyed learning the topics with the app"	1 (strongly disagree) - 5 (strongly agree)	pre/ post
Individual interest			
General interest in physics	1 item: "To what extend are you interested in physics?"	1 (not at all) - 6 (very much)	pre/ post
Interest compared to other subjects	8 items e.g. "If you had to decide, what do you think, which of the school subjects do you like better?"	1 (subject 1) - 6 (subject 2)	pre/ post
Self-assessed change in interest	1 item: "In the first questionnaire we asked you about your interests and your opinion about physics. How has this opinion changed?"	-3 (rather worse) - 3 (rather improved)	post
Learning Performance			
Objective learning outcome			
Matching Tasks	16 items for each learning topic e.g.: "Please tick the terms which you would most likely assign to the topic XXX. Multiple answers may be checked."	16 terms per topic, of which 4 were respectively correct	pre/ post
Retention Tasks	4 items e.g.: "What type of power plant was the Kappelerhof power plant?"	4 answer options, 1 or multiple correct answers	post
Transfer Tasks	2 items e.g.: "A conventional electric oven... (answer:) converts the electrical energy into thermal energy."		post
Subjective learning outcome			
Self-assessed knowledge	1 item for each learning topic: "I know what X is/ are"	1 (strongly disagree) - 6 (strongly agree)	pre/ post

Table 3
Means and standard deviations for interface designs (*industrial-style* vs. *game-style*) for aesthetic experience.

	Industrial-style design	*Game-style* design
Surface Structures	M (SD)	M (SD)
VisAWI	4.65 (1.10)	5.45 (1.02)
Aesthetic Experience		
Cognitive Stimulation	3.12 (0.75)	3.18 (0.81)
Expressive Aesthetics	3.31 (0.90)	3.64 (0.82)
Emotion	3.95 (0.68)	3.93 (0.68)

Note: See Table 2 for score ranges.

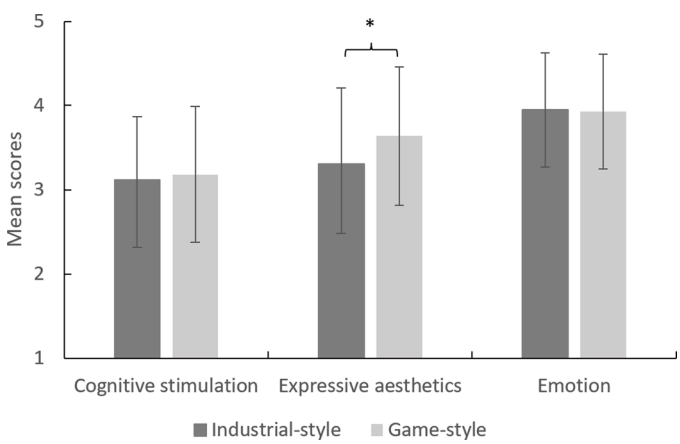

Fig. 3. Comparison between *game-style* and *industrial-style* on the three dimensions of aesthetic experience. * *game-style* design significantly assessed higher in "expressive aesthetics" than *industrial-style* design.

Table 4
Means and standard deviations for interface designs (*industrial-style* vs. *game-style*) for situational and individual interest measures.

	Industrial-style design		*Game-style* design	
	pre	post	pre	post
Situational interest	M (SD)	M (SD)	M (SD)	M (SD)
Interest to engage with the learning topics	3.47 (1.29)	3.59 (1.33)	3.29 (1.16)	3.76 (1.30)
Interest to engage with the learning app	3.55 (0.60)	3.80 (0.69)	3.44 (0.69)	3.63 (0.86)
Individual interest				
General interest in physics	3.71 (1.25)	3.83 (1.24)	3.91 (1.23)	3.98 (1.29)
Interest compared to other subjects	3.19 (0.87)	3.21 (0.89)	2.97 (0.78)	3.00 (0.79)
Self-assessed change in interest		0.66 (0.92)		1.02 (1.04)

Note: See Table 2 for score ranges.

higher increase in situational interest after learning than students learning with the *industrial-style* design. However, no between-subjects effect was found for interest to engage with the app ($p < 0.10$). Furthermore, according to expectations (H2c), significant effects for measuring time were found for both interest to engage with the topics ($F(1, 100) = 7.889$, $p < 0.01$, Wilks Lambda = 0.927) and interest to engage with the learning app ($F(1, 105) = 16.503$ $p < 0.01$, Wilks Lambda = 0.864), indicating an increase of situational interest after learning for both designs (see Table 4).

Regarding individual interest (H2b), a *t*-test for independent samples with the post single item self-assessed change in interest as dependent variable revealed a marginally significant effect, $t(103) = -1.877$, $p = 0.063$, demonstrating that students with the *game-style* design stated more positive change in individual interest after using the app than students who learned with the *industrial-style* design. However, mixed ANOVAs with *Interface Aesthetic* (*game-style* vs. *industrial-style*) as between- (H2b) and measuring time (H2d) as within-subjects variable and general interest in physics and interest in physics compared to other subjects as dependent variables did not reach statistical significance ($p < 0.10$).

3.4. Aesthetic experience and interest (RQ3)

To examine Research Question 3, if *aesthetic experience* has an impact on situational and individual interest, we took a closer look at the three dimensions "emotion," "cognitive stimulation," and "expressive aesthetics," and their relation with situational and individual interest. It is important to note that we additionally considered usability within the following analyses.

First, two multiple regression analyses with the three dimensions of aesthetic experience and usability as predictors, and the different values of the situational interest measures (H3a, interest to engage with the app and the topics) as dependent variables were computed. Both analyses revealed significant regression equations: interest to engage with the app: $F(4,102) = 4.341$, $p = 0.003$ with $R^2 = 0.145$, interest to engage with the topics: $F(4,46) = 3.451$, $p = 0.015$ with $R^2 = 0.231$. For both, the dimension "emotion" was found to predict significant change in interest (engage with the app: $B = 0.289$, $p = 0.007$; engage with the topics: $B = 2.091$, $p = 0.018$). These results indicate that students who experienced more positive emotions through design had a greater positive change in situational interest.

Similar multiple regression analyses with the dependent measures of individual interest (H3b) were then conducted. The analysis with students' self-assessed change in interest in physics as a dependent variable revealed a significant result ($F(4,100) = 5.692$, $p < 0.001$ with $R^2 = 0.182$): the more "cognitive stimulation" was experienced by the learners, the more positive was their self-assessed change in interest in physics ($B = 0.570$, $p < 0.001$). Multiple regression analyses with general interest in physics and interest in physics compared to other subjects did not reveal significant results ($p > 0.10$).

3.5. Interface aesthetic and learning performance (RQ4)

To investigate Research Question 4, regarding the effects of *Interface Aesthetic* (*game-style* vs. *industrial-style*) on objective (post-test: transfer, retention; pre-post-test: matching tasks) and self-assessed learning performance (pre-post-test), several tests were conducted.

To test hypotheses 4a and c, regarding objective learning performance, two analyses were run. First, a mixed 2x2 ANOVA with *Interface Aesthetic* as between- and measuring time as within-subjects factor with pre- and post-measurements of matching tasks was conducted. This showed a significant result for measuring time, $F(1,106) = 98.175$, $p < 0.001$, $d = 1.09$. According to expectations (H4c), this result indicates that students scored significantly higher in the post- ($M = 28.68$, $SD = 7.68$) than in the pretest ($M = 17.72$, $SD = 11.84$). No significant results were found for *Interface Aesthetic* ($p > 0.10$). Second, since transfer and retention tasks were highly correlated (Pearson: $B = 0.317$, $p = 0.001$), a MANOVA with *Interface Aesthetic* as a between-subjects factor was conducted. However, contrary to expectations (H4a), no main effects of *Interface Aesthetic* or any interaction effects concerning these measures yielded significance ($p > 0.10$).

In order to test hypotheses 4b and d, dealing with self-assessed knowledge, a mixed 2x2 ANOVA with self-assessed knowledge as dependent and *Interface Aesthetic* as between- and measuring time as within-subjects factor was conducted. The analysis yielded a highly significant effect for measuring time, $F(1, 106) = 215.819$, $p < 0.001$ Wilks Lambda = 0.329, indicating an increase in self-assessed knowledge (as expected H4c). Contrary to our expectations (H4d), no effect for *Interface Aesthetic* was found ($p > 0.10$).

3.6. Aesthetic experience and learning performance (RQ5)

In order to investigate Research Question 5, which regards the effects of aesthetic experience on learning performance, we inspected the effects of the dimensions "expressive aesthetics," "emotion," and "cognitive stimulation," as well as usability on objective and self-assessed learning performance. To determine the effects on objective learning performance (H5a), several multiple regression analyses with transfer, retention, and the difference value of matching tasks as dependent variables were conducted. The analysis computed on transfer tasks revealed a significant regression equation, $F(4,94) = 2.662$, $p = 0.037$, with $R^2 = 0.102$. However, while the dimensions of aesthetic experience showed no significant result, usability significantly predicted outcome in transfer tasks ($B = 0.107$, $p = 0.003$). This result indicates that the higher the usability of the app, the better transfer task outcomes. Moreover, the regression equation of matching tasks showed a significant result, $F(4,94) = 2.618$, $p = .040$ with $R^2 = 0.100$. It was found that "cognitive stimulation" significantly predicted outcome in matching tasks ($B = -.897$, $p = 0.011$). Interestingly, this result indicates that the *less* "cognitive stimulation" was perceived, the better the students' knowledge gains in matching tasks. Finally, the analysis conducted on retention tasks did not reach significance ($p > 0.10$).

To investigate effects of the aesthetic experience dimensions and usability on self-assessed knowledge (H5b), a multiple regression analysis was conducted with subjective knowledge after learning with the app (post-test) as the dependent variable. The analysis revealed a significant regression equation, $F(4,92) = 7.613$, $p < 0.001$ with $R^2 = 0.237$. It was found that "cognitive stimulation" ($B = 0.349$, $p < 0.001$) and usability ($B = 0.546$, $p = 0.010$) significantly predicted self-assessed knowledge: the more cognitive stimulating and the higher the usability of the app was perceived, the higher were ratings in self-assessed knowledge.

3.7. Interim summary of results

Before the results are discussed in detail, they are briefly summarized in the following. First, our results indicate that learning with both designs led to higher situational interest and higher self-assessed and objective learning performance immediately after learning.

Second, regarding the effects of appealing and learning-supportive interface designs (first study objective, cf. section 1.4), we found that *Interface Aesthetic* had an impact on perceived *surface structures* (VisAWI and dimension "expressive aesthetics" of aesthetic experience) in such a way that the *game-style* design was rated higher than the *industrial-style* design. Learning with the *game-style* design further led to a higher increase in situational and individual interest (marginal) compared to learning with the *industrial-style* design. However, *Interface Aesthetic* had no direct impact on self-assessed or objective learning performance.

Third, regarding the effects of students' aesthetic experience (second study objective, cf. section 1.4), our results suggest that higher experience of "emotion" led to higher situational interest, while higher "cognitive stimulation" led to higher individual interest. Finally, concerning learning performance, our findings show that effects of "cognitive stimulation" were conflicting; while higher "cognitive stimulation" seems to improve self-assessed knowledge, higher results in objective learning performance (matching tasks) are related to *less* "cognitive stimulation." Moreover, a positive relation of perceived usability with higher scores in self-assessed and objective learning performance (transfer tasks) was found.

4. Discussion

By pursing the three following objectives, we intended to shed light onto the effects of aesthetic designs on interest and learning in science and the role of aesthetic experience. We aimed to systematically and holistically investigate the aesthetic construct by comparing two aesthetic interface designs of a learning application that both optimally supported learning (*Interface Aesthetic: game-style* vs. *industrial-style*). We also aimed to investigate (explorative) the impact of aesthetic experience on interest and learning by considering *surface structures* and *deeper perceptual processes* with the three dimensions "expressive aesthetics," "emotion," and "cognitive stimulation." Additionally, by focusing on teenagers, we intended to contribute new results on the effects of aesthetic designs in young participants with whom science literacy can be promoted particularly well [73] and where students' orientation regarding science topics can successfully be encouraged [1,58].

To achieve these objectives, a controlled field study in the classroom context was conducted. We examined the effects of two interface design variants on interest and learning and investigated relations between three dimensions of *aesthetic experience* (i.e., *surface structures*: "expressive aesthetics;" *deeper processes*: "emotion," "cognitive stimulation") and these dependent variables. The study had its limitations, which we will outline in detail below (cf. section 4.4). Nevertheless, our data revealed interesting results that will be discussed in the following sections.

4.1. Aesthetic experience of interface designs

Our data demonstrates that students learning with the *game-style* design rated the design higher in *surface structures* (VisAWI and dimension "expressive aesthetics" of aesthetic experience) than students learning with the *industrial-style* design. This result is in line with previous research indicating that aesthetic features such as color [e.g., 52] and expressivity [30] impact perceived attractiveness of an object (see section 1.1). However, no differences between the designs concerning *deeper perceptual processes* of aesthetic experience such as "emotion" and "cognitive stimulation" could be found. A possible explanation for this result is the following. Our definition of *aesthetic experience* was mainly based on approaches relating to the experience of artwork [31,35]. In contrast, our object of investigation was the interface design of learning applications. In fact, aesthetics and the resulting experiences, such as "emotion" and "cognitive stimulation" play a more important role in museums than in traditional learning settings, since such experiences are the main goal of art enthusiasts and museum visitors. On the contrary, when it comes to learning applications, *deeper processes* related to an aesthetic object may only play a minor role. However, in the next sections, it becomes clear that *deeper processes* are important when more goal-oriented constructs such as interest and learning performance are involved.

4.2. Impact of interface aesthetic and aesthetic experience on interest

Our results show that *Interface Aesthetic* has a direct effect on situational interest in such a way that the *game-style* design leads to a higher increase in situational interest than the *industrial-style* design. This finding indicates that interface designs that lead to positive experiences of *surface structures* (VisAWI and "expressive aesthetic") of the learning application (higher in the *game-style* design) influence the momentary experience that is reflected in teenagers' situational interest [20]. This result is also in line with research on emotional design [7,78]. Moreover, our results suggest that situational interest is related to the *deep perceptual process* "emotion" – the higher the emotional experience, the higher the situational interest to engage with the learning topics and the app. This is in line with Hidi and Renninger [24], indicating that the higher the affect elicited by the experience, the higher the perceived interest.

In contrast, we could not confirm that one of the two interface designs led to higher individual interest (direct effect of *Interface Aesthetic*). While self-assessed change in interest was descriptively higher in the *game-style* than in the *industrial-style* design condition, students were not more interested in the learning topic in general. However, the *deep*

perceptual process "cognitive stimulation" was positively related to individual interest. Individual interest – characterized as a persistent willingness to return to a certain object (such as the learning topic and application) over time [see 20] – is thus mainly dependent on the stimulation, involvement, and excitement of the aesthetic learning environment. These results further highlight the importance of considering aesthetic experience – especially *deeper processes* – as they provide evidence that a successful processing of aesthetics according to Leder et al. [31] is able to increase interest.

Furthermore, contrary to our results regarding situational interest, individual interest did not increase after learning. This is, however, not surprising, since it takes a long time for individual interest to develop and change and those changes are not measurable directly after the experiment. Further and reiterated experiments could address this point (see also section 4.4).

But how do the different results between situational and individual interest come about? According to Ekman [14], emotions are characterized by a short duration – as is situational interest [20]. It is therefore not surprising that these concepts are related. Moreover, our results indicate that *surface structure* features (such as color) of interface designs also tend to be related to such short-lasting states. In contrast, interface design and "emotion" did not have a direct impact on long-lasting individual interest. It can be argued that stimulating and involving interfaces that lead to "cognitive stimulation" have a more long-term impact on interest (i.e., individual interest), while designs that evoked more positive experiences of *surface structures* and lead to higher emotional experience have a more short-term impact on interest (i.e., situational interest).

4.3. Impact of interface aesthetic and aesthetic experience on learning performance

Research on emotional design [78] suggests that specific aesthetic related aspects are responsible for aesthetics, positively affecting motivation and interest and subsequently learning. According to this research, we could confirm with our study that aesthetics has an impact on interest (more precisely on situational interest, cf. section 3.3), but not on objective or subjective learning performance. One explanation for this result could be that we manipulated several aesthetic features not necessarily defined as emotional designs (cf. Table 1). Another possible reason could be found in the design standards of our interfaces: the designs – both high-quality designs – were constructed so that they differed only in aesthetic features not detrimental for learning [successful manipulation check and equal consideration of multimedia design principles, see 37,66] and therefore offered an environment that equally supported learning in both designs. This is supported, on one hand, by our results demonstrating that higher perceived usability predicted transfer knowledge and self-assessed knowledge scores (see section 3.6), and, on the other hand, by our results showing that subjective and objective learning performance increased after learning with both interface designs. The two designs differed in *surface structures* (VisAWI and "expressive aesthetics"), but did not trigger *deeper perceptual processes* in learners (such as "emotion" and "cognitive stimulation"). Hence, we assume two related explanations: (1) interface designs that are not detrimental for learning are experienced differently, but the experience is confined to objective *surface structures* (such as color, cf. section 1.1), which are known to have a positive impact on appeal and attractiveness, and in turn, possibly on interest (cf. sections 1.1 and 1.2); (2) such designs do not have a direct impact on *deeper processes* (such as "emotion" and "cognitive stimulation") that may be related to learning performance (cf. section 3.6).

A further reason for this result can be found in the fact that the *industrial-style* design more closely resembled to a classical school book and the *game-style* design was more inspired by gaming apps. Therefore, the *industrial-style* variant probably triggered the learning context associations in learners more, whereas the *game-style* design triggered a leisure context. Learning could, therefore, be facilitated in the *industrial-style* design, since the design was a familiar stimuli in this context, whereas the *game-style* design was a non-familiar stimuli and more likely led to an orienting response compared to the familiar stimuli [70]. Positive motivational factors induced by the *game-style* design that possibly had influenced learning performance could thereby be diminished. This assumption is also in keeping with our results showing that less stimulation, involving, and excitement (i.e., "cognitive stimulation") induced by the learning environment led to higher results in objective learning performance. Students perceiving a higher "cognitive stimulation" induced by the learning environment are probably more occupied with processing the interface than the learning material. Important to note here is also the so-called seductive details effect, suggesting a negative impact of appealing but irrelevant information on learning [38]. However, on the contrary, students who perceived high "cognitive stimulation" rated their self-assessed knowledge higher. This result may be related with our findings concerning the positive relation of "cognitive stimulation" and individual interest, since self-assessed knowledge may be more related to stimulation and excitement – similar to interest – than to objective knowledge.

4.4. Limitations and future work

To investigate our study goals, we conducted a field study directly in the classroom – the familiar learning environment of the students. However, this approach is also accompanied by some limitations. Firstly, possible confounders applying in the field could not be excluded (e.g., students sharing learning information in the break, see section 2.4). Secondly, for organisational and resource reasons, the study was carried out in a single school and thus had a limited number of students participating. Therefore, future research should consider either involving multiple schools in the investigations or replicating the study in a more controlled laboratory environment. Furthermore, we intended to holistically investigate the effect of the construct aesthetic by the systematic investigation of two high-quality design variants that were both designed to optimally support learning. The designs were based on different themes and metaphors that reflected different life worlds of the students: a variant orientating towards mobile games (i.e., *game-style* variant) and one that represented the look and feel of a classical school book (i.e., *industrial-style* variant). Learning might, therefore, have been influenced by learners' personal experiences with similar designs. For example, game-experienced learners might have benefited more (or less) from the *game-style* design. It might be interesting to consider such student characteristics in future research. Moreover, through the holistic approach, an investigation of the overall expression of a design and its influence on interest and learning is difficult to grasp, due to the complexity of all influencing factors. The extent to which approaches from Gestalt theory can provide answers has been investigated in related research [3,60] and should be addressed in more detail in future research. Additionally, when simultaneously manipulating various aesthetic features, it is difficult to trace back effects of single features. For example, it remains unclear whether the different amount of contrast between the variants resulting from color variations (i.e., isoluminant) possibly led to interaction/bias effects between aesthetics and usability. Moreover, the design of the interfaces also affected the displayed information graphics in the apps (e.g., representation of electrical energy, see Fig. 1). Therefore, it cannot be completely excluded that the graphics of one design variant could be better processed by the learners than the graphics of the other design. Furthermore, the present study focused only on short-term measures of interest and learning performance. However, both concepts – especially individual interest – develop and change over time. It is, therefore, of utmost importance to additionally involve long-term measures in future research. Our results on individual and situational interest should further be interpreted with caution as we mainly used not-validated single-item scales. Future studies should use standardized and validated scales specifically created

to measure individual and situational interest. Moreover, although our study gives first evidence underlining the importance of considering aesthetic experience when investigating effects of aesthetic design on learning and interest, future research should increasingly include such measurements to further investigate the concept and its relevance for this research field. Also, physics, the chosen science topic in the present study, is very multifaceted. Thus, future work should consider conducting additional experiments involving formulas or more abstract concepts to investigate which aesthetic characteristics of interfaces better convoy and make the understanding of the topic easier. Finally, there is a major gap between female and male learners in science topics [e.g., 75], which was not considered in this study. Research should address this gender gap by investigating possible different interest-fostering aspects between female and male learners in aesthetic design and also science topics themselves, while being mindful to consider educational and cultural biases.

5. Conclusion

There is still a need to foster teenagers' interest in science. This can not only foster scientific literacy to increase students' awareness and willingness to engage in globally important issues, but can also encourage students to pursue a future career in the sciences. With the present field study, we aimed to find ways to foster teenage students' interest and learning of science with a systematic investigation of the impact of two appealing and learning-supportive aesthetic interface designs of a learning application. Moreover, we intended to provide new insights into the construct aesthetic experience by examining experiences of *surface structures* (i.e., color, complexity) and *deeper perceptual processes* (i.e., "emotion" and "cognitive stimulation") and investigate impact on interest and learning. Our study revealed that interface aesthetics can influence interest and learning in differently designed learning app variants, even when these variants provide an equally optimal learning support. More precisely, our results suggest that designs with high rated *surface structures* can positively impact interest to engage with the learning topic. Thus, important implications for the design of learning apps focusing on science can be derived. Moreover, we found that *deeper perceptual processes* – such as "emotion" and "cognitive stimulation" induced by the aesthetics of the design – are related to interest, as well as to self-assessed and objective learning performance. This highlights the importance of considering aesthetic experience, particularly such deeper processes, in future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Impact of Learners' Video Interactions on Learning Success and Cognitive Load

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Abstract: Enhanced video-based learning environments provide new tools (e.g., hyperlinks) – along with the well-known basic video control tools (e.g., play, pause, rewind) – that afford learners' enhanced interaction with videos. With these tools, learners can actively transform existing videos into their own hypervideo structures by adding hyperlinks and own materials. Unlike research on basic control tools that has revealed positive impacts on learning, research on enhanced tools is still rare and conflicting. It is thus open, whether the tools support generative interested learning or put too much extrinsic cognitive load onto learners. In the present study, we investigated the effects of video annotation and hyperlinking tools on learning success and cognitive load by analyzing tool-related interaction behavior data of 141 university students. Results indicated that the frequent use of enhanced video tools positively predicted learning success and a decrease in cognitive load. Implications of these results are discussed.

Keywords: interactive learning environments, video-based learning, interaction behavior.

Introduction and related work

Video is a popular, effective, and timely medium for supporting learning – and has been for a long time (for a review see Poquet, Lim, Mirriahi, & Dawson, 2018). Streaming media platforms such as YouTube contribute to a continuous increase of students' access to digital video-based material (Poquet et al., 2018). Previous approaches emphasized that such dynamic audiovisual media support learning (both factual and procedural) when designed according to concrete guidelines (Mayer, 2005). Besides, the possibility to *interact* with such media plays a further decisive role in fostering learning processes: for example, Schwan and Riempp (2004) investigated the effects of basic control tools – such as play, pause and rewind – on learning nautical knots of varying difficulties and could show that learners successfully used these tools for strategic interactions. Further research suggested that the active use of basic control tools correlated significantly with knowledge acquisition (Zahn et al., 2004) as they allow learners to learn at their own pace which – in turn – minimizes the risk of cognitive overload (Cattaneo et al., 2015) – or as Schwan and Riempp (2004) put it: to adapt information flow to internal cognitive needs.

Today, *enhanced video-based environments* provide tools that additionally allow to annotate (e.g., with hyperlinks or annotations for self-written summaries), comment, discuss, and edit videos alone or in groups (e.g., Leisner, Zahn, Ruf, & Cattaneo, 2020; Sauli, Cattaneo, & van der Meij, 2018; Yousef, Chatti, Danoyan, Thüs, & Schroeder, 2015; Zahn, 2017). With such *enhanced interaction tools*, learners are able to actively transform existing video representations into their own enriched information structures (Schwartz & Hartman, 2007; Yousef et al., 2015) and, therefore, actively generate meaning (Wittrock, 1992) by designing their own learning content (e.g., Kafai & Resnick, 1996; Papert, 1994). Such an active participation of learners in constructing information is crucial for conceptual understanding and fosters deep processing and re-organization of concepts (Kafai & Resnick, 1996; Papert, 1994; Wittrock, 1992). Delen, Liew, and Willson (2014) provided evidence that using enhanced tools for generative note-taking was superior to working with basic control tools regarding learning success. Besides, Zahn, Pea, Hesse, and Rosen (2010) and Zahn, Krauskopf, Hesse, and Pea (2012) found that designing a hypervideo structure is suitable for successfully learning complex history topics. However, research on enhanced tools is conflicting (see Sauli, Cattaneo, & van der Meij, 2018): for instance, Merkt et al. (2011), who investigated the impact of a table of contents in videos, found no effects on learning success. Two possible explanations for these conflicting results are discussed as follows: first, learners may be overwhelmed by the complexity of enhanced tools (Krauskopf et al., 2014; Zahn et al., 2012), which may be manifested in an increase of extraneous cognitive load (Kirschner et al., 2018; Paas, 1992). Second, some previously investigated enhanced tools were more intended to be *optional supporters* for facilitating video interaction (e.g., table of contents, see Merkt et al., 2011), than tools that are *necessary to complete the learning task* (e.g., note-taking, see Delen et al., 2014). Learners seem to have a lack of strategies underlying the use of *optional* tools and therefore hardly use them (Merkt et al., 2011), which probably results in an increased extraneous cognitive load as learners need

cognitive resources to process them as part of the learning environment but not necessarily need them to complete the task (Kirschner et al., 2018; Paas, 1992; Zahn et al., 2012). These issues could be solved when learners are provided with clear instructions about how to use enhanced tools efficiently and how to include them as part of a concrete learning task (Shin & Jung, 2020; Zahn et al., 2012). According to Sweller's (1999) Cognitive Load Theory, such *task-relevant* enhanced tools can reduce intrinsic cognitive load by helping learners to disaggregate the difficulty of the learning material by actively creating their own hypervideo structures (Kafai & Resnick, 1996; Papert, 1994; Wittrock, 1992; Yousef et al., 2015). This is also in line with constructivist approaches suggesting that learning is not a consequence of offering tools, but, after all, depends on internal processes associated with tool use – that is: concrete learning activities in a constructive learning process (Clark, 1994; Kozma, 1994).

It becomes clear from the research described above that investigating learners' interaction with videos is promising to understand how video tools can successfully be used for learning. This potential has been addressed by the research field on *learning analytics*, which suggests to measure learning behavior using logged interaction data (e.g., Mirriahi & Vigentini, 2017). Accordingly, the use of basic control tools or enhanced tools can be measured using log files that provide logged users' (inter-)actions – such as pressing buttons – in form of tabular representations. Thereby, it is important to note that the use of basic control tools (e.g., pressing the pause button to pause the video) is often reflected in a single logged action (e.g., logged action: pause), whereas the use of enhanced tools is usually reflected in multiple logged actions related to it: for example, a hyperlink can be added to the video timeline of the video, or moved within the timeline, or deleted from the timeline. Previous approaches further suggested to distinguish between different *levels of interactivity* resulting from the use of basic control or enhanced tools (Delen et al., 2014; Merkt et al., 2011). Accordingly, the use of basic control tools (e.g., play, pause, rewind) can be subsumed under the term *micro-level interactivity* and the use of enhanced tools (e.g., table of contents, hyperlinks, annotations) under the term *macro-level interactivity* (see Delen et al., 2014; Merkt et al., 2011). In line with these approaches, in the present study we summarized single learners' actions resulting from the use of basic control tools under the term "micro-actions". In addition, and as stated above, we further classified enhanced tools as either *optional supporters* for facilitating learning with videos (e.g., table of contents, Merkt et al., 2011) or as important and *necessary parts of a concrete learning task* (e.g., note-taking, Delen et al., 2014). Consequently, we summarized learners' actions resulting from the use of *task-relevant* enhanced tools under the term "task-actions".

The present study aims to add new original findings to the corpus of existing research on the effects of enhanced tools in video-based environments on learning by pursuing the two following research objectives: first, in consideration of the previously described conflicting results concerning enhanced tools and learning success (Delen et al., 2014; Merkt et al., 2011; Sauli et al., 2018; Zahn et al., 2012), we investigate the effects of learners' performed micro- and task-actions (i.e., actions resulting from *task-relevant* enhanced tools: annotations and hyperlinks) on learning success using frequencies of learners' actions (cf. Hung & Zhang, 2008) and, second, in order to address possible overwhelming situations provoked by enhanced tools, we additionally consider cognitive load by investigating both mental load and mental effort (Kirschner et al., 2018; Paas, 1992; Zahn et al., 2012). The study is guided by the following hypotheses:

(1) *Learning success*: frequently performed (H1a) micro-actions and (H1b) task-actions are positively related to learning success (i.e., objective learning success and self-assessed knowledge gain).

(2) *Cognitive load*: frequently performed (H2a) micro-actions and (H2b) task-actions reduce cognitive load (i.e., mental load and mental effort).

In the next section, we give a description of the study context, the data set, and the measures used.

Method

Study context and description of the data set

To answer our hypotheses, we used a subsample (N = 141) from a data set consisting of 209 Swiss University students (75% female, M = 24.30 years, SD = 6.70) who learned a complex learning topic from natural sciences (i.e., synaptic plasticity) with an enhanced video-based environment (i.e., *FrameTrail*, see Figure 1). The ethical standards of the controlled laboratory experiment were set through the institutional ethical committee of our institution. Participants received course credits for participation and had no or marginal experience with the learning topic prior to participation. They were randomly assigned to the experimental conditions of a 3 x 2 study plan where the first factor concerned the video-related learning task (adding hyperlinks vs. adding annotations for self-written summaries vs. considerate-watching) and the second factor related to the learning setting (individual vs. dyadic collaborative learning). After instructions concerning the task and the usage of the tools, participants learned the topic individually or in groups of two by adding either (1) hyperlinks containing further thematic

information from prepared written texts (see *Further information texts* in Figure 1) or (2) self-written annotations based on these texts directly into the video, or (3) they received further information texts but were not able to add them into the video (i.e., considerate-watching condition). Participants learned at their own pace, so that they had the chance (1) to fully understand the learning topic, (2) to complete the task, and (3) to compensate for possible effects of extraneous cognitive load triggered by the (initially unfamiliar) learning environment and tools.

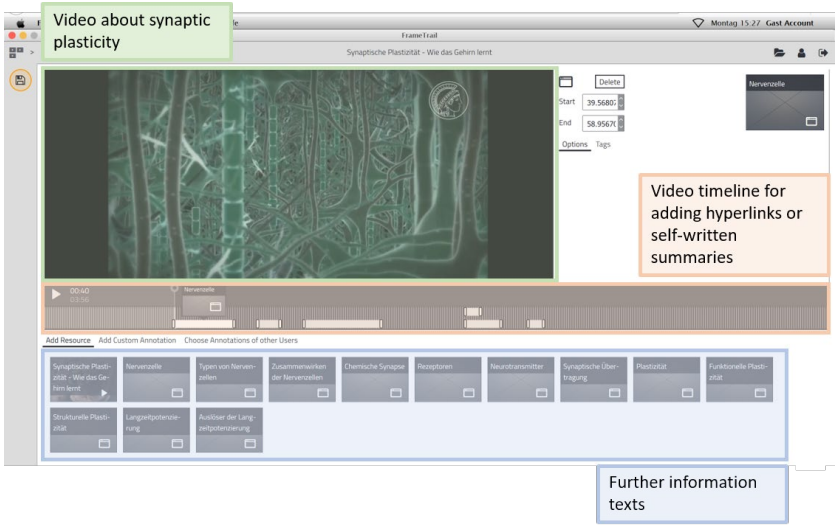

Figure 1. Enhanced video-based learning environment *FrameTrail* (see https://frametrail.org).

For the present study, only data from participants learning in the two "enhanced" learning task conditions (i.e., hyperlink and annotation) were considered, because only they had the possibility to perform task-actions with necessary tools according to their learning task. Thus, from the 209 datasets, 74 were excluded and the remaining data sample consisted of 141 participants (75% female, 79% psychology students, M = 24.27 years, SD = 6.70). Thereof, 53 participants learned in an individual learning setting and 88 learned collaboratively in 44 dyads. Furthermore, 71 used annotations and 70 used hyperlinks to complete the learning task. It is important to note that although only one set of interaction data was collected for dyads, because groups worked together on a shared desktop computer, dyad interaction data was used for the present study as *individual data* for the purpose of comparison between groups. With this, we refer to literature on *joint attention*, which revealed that interactions of collaborative dyads are closely coupled (Barron, 2003; Schneider & Pea, 2013). Moreover, two analysis of variance (ANOVAs) with micro- or task- actions as dependent variables and learning setting (individual vs. collaborative) as between-subject factor did not reach significant levels (p > .05). Thus, individuals and collaborative learners were comparable on these variables. This approach further allowed us to examine effects of video interaction on individual learning success and subjective perceptions of knowledge gain and cognitive load.

Measures

Learners' video interactions were collected with log files provided by the enhanced video-based environment used in the study (see https://frametrail.org). Table 1 lists the collected actions. As mentioned above, we summarized actions resulting from basic control tools into *micro-actions* and actions resulting from the use of enhanced tools (annotations and hyperlinks) into *task-actions*. The circumstance that participants learned at their own pace was reflected in a remarkable spread of variance for both *absolute learning time* (M = 42.17 min, SD = 15.22) and *absolute frequencies of performed actions* over all participants (micro-actions: M = 88.96, SD = 47.10; task-actions: M = 67.53, SD = 41.21). Therefore, we considered *relative values of actions* (division of absolute interaction frequencies of micro- and task-actions by learning time in minutes) to address individual learning pace (micro-actions per minute: M = 2.31, SD = 1.30; task-actions per minute: M = 1.58, SD = 0.65). Although we conducted analyses for both absolute and relative values of performed micro- and task-actions, for the purpose of this contribution as well as its substantive relevance (through the consideration of learning time), we only focused on relative values here.

Table 1: Collected micro-actions and task-actions

Micro-actions	Task-actions
Play	Adding hyperlink or annotation into video
Pause	Change annotation text
Jump backwards	Change displayed time of hyperlink or annotation on video timeline
Jump forward	Delete hyperlink or annotation from timeline

To measure *learning success*, participants were, first, asked to answer an objective knowledge test with 20 questions (post-experimental) developed with an expert of biopsychology at our institution. The questionnaire consisted of 15 multiple choice (four answer options with one correct answer) and five open short-answer questions. Out of these, eight questions addressed understanding of concepts (e.g., "What are vesicles?" referred to the understanding of the concept "vesicle"), eight related to understanding of concept interrelations (e.g., "What role do calcium ions play in synaptic transmission?" referred to the understanding of the concepts "calcium ion" and "synaptic transmission" and their interrelation), and four measured transfer knowledge (transferring learning information to other situations or circumstances, see Rebetez, Bétrancourt, Sangin, & Dillenbourg, 2010). The distinction between concept and concept interrelation was crucial with regard to our learning task conditions as the use of annotations is assumed to foster relations between prior knowledge and new information, and thus understanding of concepts (Zahn et al., 2010, 2012), and the use of hyperlinks is assumed to foster relations among concepts (Stahl, Finke, & Zahn, 2006). Participants received one point for a correct and zero points for an incorrect answer. Cronbach's α for the final test was .76 (note: this analysis was conducted with the full data sample, N = 209). Second, we measured self-assessed knowledge gain (post-experimental) with a one-item scale (i.e., "How much do you think your knowledge in synaptic plasticity has improved?") from 1 (not at all) to 5 (very much).

To measure *cognitive load*, we focused on Paas (1992) and De Jong (2010) and analyzed both concepts *mental load* (imposed by instructional parameters such as task structure) and *mental effort* (capacity assigned to instructional demands) separately to consider the large variety of definitions of the construct: first, mental load was measured according to Kalyuga, Chandler, and Sweller (1999). Participants rated the item "Please estimate how easy or how difficult you found the learning material." from 1 (very easy) to 7 (very difficult). Second, in order to measure mental effort, we took a closer look into the subscale *effort/importance* of the short version of the Intrinsic Motivation Inventory (KIM, Wilde et al., 2009, see Table 2). Note that the items of this scale were originally validated by Wilde et al. (2009) in German language and were translated from German to English for the purpose of this contribution. The participants rated the subscale from 1 (totally disagree) to 5 (totally agree) on three items. A reliability analysis (conducted with the subsample, N = 141 of the present study) for this subscale revealed $\alpha = .457$. However, when item 1 (i.e., "Editing the video in the learning environment was a considerable effort for me.", see Table 2) was excluded from the scale, Cronbach's α changed to .755. We consequently concluded that item 1 measured the actual "effort" while items 2 and 3 were more related to perceptions of "importance". Item 1 was proximately used to measure mental effort and was extracted from the original subscale. Both scales were measured post-experimental.

Table 2: Subscale effort/importance of the short version of the Intrinsic Motivation Inventory (KIM)

Subscale	Cronbach's α	Nr.	Item
Effort / Importance	.457	1	Editing the video in the learning environment was a considerable effort for me.
		2	I tried to do my best.
		3	It was my personal concern to perform well at editing the video in the learning environment

To answer the hypotheses described above, several multiple and multivariate multiple regression analyses were conducted with micro- and task-actions as predictors and measures regarding learning success and cognitive load as dependent variables.

Results

For data preparation, we first investigated the correlation of micro- and task-actions using Pearson correlations and found no significant result ($p > .05$). When conducting regression analyses, predictor variables are ideally

independent to minimize the risk of suppressor effects (Bortz, 2005). Hence, we concluded that both predictor variables (micro- and task-actions) could be examined independently. Second, we calculated a Pearson correlation with the dependent variables mental effort and mental load and found no significant results ($p > .05$). Therefore, we examined these variables independently in two multiple regression analyses. For the statistical tests, an α-level of .05 was used.

Effects of interaction frequencies on learning success (H1)

To answer our hypotheses on learning success (H1), a multivariate multiple regression analysis with the three scores of objective learning success (understanding of concept, understanding of concept interrelations and transfer tasks) as dependent variables and micro- and task-actions as predictors was conducted (see Table 3). A significant regression equation was found for understanding of concepts for task-actions ($F(1,132) = 5.31$, $p = .023$). As expected, (Hb), this result indicates that the more task-actions were performed the higher were learning success outcomes in understanding of concepts. However, no other result reached a significant level ($p > .05$). Hence, we could not confirm a positive relation between micro-actions and objective learning success (H1a).

Table 3: Results on the impact of micro- and task-actions on objective learning success

	Concept				Concept interrelations				Transfer			
Predictors	β	SE β	R^2	ΔR^2	β	SE β	R^2	ΔR^2	β	SE β	R^2	ΔR^2
Micro-actions	.023	.107	.039	.024	-.088	.136	.003	-.012	.022	.062	.004	-.011
Task-actions	.493*	.214	.039	.024	-.044	.273	.003	-.012	.081	.125	.004	-.011

Moreover, a multiple regression analysis with self-assessed knowledge gain as dependent variable (see Table 4) yielded significance ($F(2,132) = 6.38$, $p = .002$). However, in contrast to our assumption (H1a), this result indicates that the more micro-actions were performed the lower was self-assessed knowledge gain ($\beta = -.148$, $p = .004$). Besides, a marginal significant effect was found for task-actions ($\beta = .193$, $p = .056$), indicating, according to expectations (H1b), that frequently performed task-action increased self-assessed knowledge gain.

Table 4: Results on the impact of micro- and task-actions on self-assessed knowledge gain

	Self-assessed knowledge gain			
Predictors	β	SE β	R^2	ΔR^2
Micro-actions	-.148*	.050	.088	.074
Task-actions	.193	.100	.088	.074

Effects of interaction frequencies on cognitive load (H2)

To answer the hypotheses on cognitive load (H2), two multiple regression analyses were conducted that addressed mental load and mental effort separately (see Table 5). First, we conducted an analysis with mental load as dependent variable and micro- and task-actions as predictors. The analysis showed a significant result ($F(2,131) = 3.94$, $p = .022$). A closer look at the predictors revealed that task-actions significantly predicted mental load ($\beta = -.435$, $p = .021$). As expected, (H2b), this result indicates that frequently performed task-actions reduce mental load. However, contrary to our expectations (H2a), no effects were found for micro-actions ($p > .05$).

Second, a similar analysis with mental effort as dependent variable did not reach significance ($p > .05$). Thus, we could not confirm our assumptions for mental effort (H2a, H2b).

Table 5: Results on the impact of micro- and task-actions on mental effort and mental load

	Mental load				Mental effort			
Predictors	β	SE β	R^2	ΔR^2	β	SE β	R^2	ΔR^2
Micro-actions	.134	.092	.057	.042	-.092	.068	.018	.003
Task-actions	-.435*	.186	.057	.042	-.113	.137	.018	.003

Discussion

The main goal of this study was to understand how learners' video interactions are related to learning success and cognitive load in natural science learning. To address this goal, we differentiated between micro- and task-actions and analyzed log file data of students' interactions with an enhanced video-based environment.

Our data indicates that frequently performed task-actions predict objective learning success. Following earlier considerations (Zahn et al., 2012), we therefore conclude that meaningful enhanced tools that are an integral and explicit part of the learning task can substantially foster learning processes. This conclusion is in line with related research suggesting that note-taking in enhanced videos is able to increase learning success (Delen et al., 2014) and that designing a hypervideo structure can foster learning of complex topics (Zahn et al., 2010, 2012; Zahn, 2017). The frequent use of enhanced video tools seems to help learners to design their own information structures (e.g., Clark, 1994; Kafai & Resnick, 1996; Yousef et al., 2015) and to actively generate meaning (Wittrock, 1992), which in turn is reflected in actual learning success. However, this could only be confirmed for understanding of concepts, whereas results on other measures (understanding of concept interrelations and transfer knowledge) did not yield significance. Thus, it is arguable that task-actions that are connected to annotations are more involved in fostering understanding of concepts than task-actions that are related to hyperlinks (see Stahl et al., 2006; Zahn et al., 2012, 2010). Future research should consider this by explicitly investigating differences between annotations and hyperlinks and their related actions.

Moreover, in contrast to earlier research (Zahn et al., 2004), we could not confirm a positive relation of frequently performed micro-actions with objective learning success and even found a negative relation with subjective knowledge gain. One possible explanation for these results may be that not the frequent but rather the target-oriented use of basic control tools (manifesting in performed micro-actions) is crucial when learning a complex learning topic (synaptic plasticity) with an enhanced video-based environment. For example, learners who first completely watch the video before starting with the task (interacting with enhanced tools) may need less micro-actions to complete the task than learners who directly start with the task and occasionally need to adapt initial decisions (e.g., skipping through the video to find appropriate places to add an annotation). Hence, frequently performed micro-actions in enhanced video-based environments might not necessarily be related to a deep engagement with the content of the learning material which, in turn, may be reflected in objective learning success and subjective perception of knowledge gain. This example further shows that micro- and task-actions are closely related – not in the sense of a correlation (see results above) – but rather in such a way that basic control tools are often used by learners to *meaningfully* use enhanced tools (e.g., rewind (= micro-action) the video to find an appropriate place to add a hyperlink (= task-action)). Thus, a learner's intention to use an enhanced tool not only includes task- but also micro-actions. Behavior sequence analyses could provide deeper insights into such intentions: learners' micro- and task-actions can be combined into meaningful sequences that can be associated with learning strategies. Such analyses have – although rarely – been considered in previous research on interactive videos (see Sinha, Jermann, Li, & Dillenbourg, 2014). Future research should increasingly exploit the potential of behavior sequence analyses for learning with interactive (video) environments.

Furthermore, we investigated cognitive load (by analyzing both mental load and mental effort) and found a negative relation of task-actions with mental load, indicating that students who frequently performed task-actions perceived the learning material as less difficult than students who made little use of them. In consideration of the above described research (Wittrock, 1992; Zahn et al., 2010, 2012; Zahn, 2017), we conclude that frequently performed task-actions can lead to a deeper understanding of concepts, which in turn can lead to a lower mental load. This could also explain our result suggesting that more performed task-actions increased self-assessed knowledge gain (marginal). However, it is important to note that these findings might also be interpreted in the other direction (e.g., learners who understand the topic more easily have more capacity available to use the enhanced tools meaningfully, which is reflected in a higher number of task-actions). The direction of causality should therefore be specifically considered in future work. Moreover, our results showed that enhanced video tools that are an important and necessary part of the learning task seem not to negatively impact mental effort (no relations found for micro- and task-actions with mental effort). However, these results should be interpreted with caution, as we used a not validated single-item scale. Subsequent studies should use standardized and validated scales specifically created to measure mental effort. Also, to get further insights into the effects of video interaction on cognitive load, future research should consider measurements for intrinsic, extraneous and germane load (with validated instruments, see for example Klepsch et al., 2017).

In sum, we conclude from our results that designs for enhanced video-based learning environments should include tools that are *task-relevant* and explicitly important to the learning task, instead of being optional. The frequent use of such tools seems not only to support learning, but also to reduce cognitive load.

Conclusion

The present study examined the impact of video interactions (micro- and task-actions) of learners who interacted with an enhanced video-based learning environment on learning success and cognitive load. Our results suggest that frequently performed task-actions – that are related to the use of *task-relevant* enhanced tools – not only positively impact learning success but also cognitive load. In summary, our study sheds light on the scientific knowledge about the effects of video tools on learning and leads to important practical implications for designing enhanced video-based learning environments concerning questions of how task instructions and video tools should be integrated. Future research should consider behavior sequence analyses of interaction behavior data for additional in-depth analyses of learning strategies by an equal investigation of micro- and task-actions and their impact on learning success and cognitive load. We hope this contribution will inspire future research in this important area.

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How do enhanced videos support creative learning and conceptual understanding in individuals and groups?

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How do enhanced videos support creative learning and conceptual understanding in individuals and groups?

Abstract

Videos are an increasingly popular medium for supporting learning in various educational settings. Nowadays, newly designed video-based environments contain enhanced tools that allow for specific interactions with video materials (such as adding annotations and hyperlinks) which may well support creative learning and conceptual understanding. However, to exploit the potentials of such enhanced tools, we need to gain a deeper understanding on the learning processes and outcomes that go along with using these tools. Thus, we conducted a controlled laboratory experiment with 209 participants who were engaged in learning a complex topic by using different enhanced video tools (annotations vs. hyperlinks vs. control group) in different social learning settings (individual vs. collaborative). Findings revealed that participants who learned with hyperlinks and participants in collaborative settings created hypervideo products of higher quality than learners in other conditions. Participants who learned with annotations assessed their knowledge gain higher and had higher results in conceptual understanding when they experienced low cognitive load. With our study we contribute new original work to advance cognitive research on learning with enhanced video learning environments. Limitations and recommendations for future research are discussed.

Keywords: video-based learning, enhanced tools, collaborative learning, hypervideos

Introduction

How can we support effective learning? Answering this question is of utmost practical and scientific interest, as it is key for successful educational and work performance. In times of digital transformation - recently boosted through the challenges occurring from the COVID-19 crisis - effective learning with digital tools and new digital classroom settings gained in importance (Marinoni et al., 2020; Yan et al., 2021). Especially digital videos were recognized by educational institutions to be a promising opportunity to tackle challenges of such settings since they can be provided asynchronously and remotely (Noetel et al., 2021) and have been shown to foster learning (e.g., Tiernan, 2015).

Nowadays, *enhanced video-based environments* provide *enhanced video tools* that allow learners not only to *watch* videos, but to *interact* with the video materials and re-structure them according to their own needs. In other words: videos can be used in more flexible and creative ways. For instance, learners can use *annotations* to place their own comments and remarks or self-written summaries into videos, or they can add *hyperlinks* to connect video objects to additional pieces of information. Moreover, learners can collaboratively work in enhanced video-based environments - discuss or edit the material in learning groups (Author, 20xxa; Sauli et al., 2018). In this sense, enhanced video tools can be seen as socio-cognitive tools for learning that support advanced learning activities beyond knowledge acquisition, learning activities like “analyze”,

“evaluate” or “create” according to Bloom`s taxonomy (Anderson & Krathwohl, 2001; Krathwohl, 2002). However, there is no consensus in the literature on whether and how enhanced tools really support individual and collaborative learning or are rather cognitively overwhelming (Evi-Colombo et al., 2020; Sauli et al., 2018). A *holistic* view on learning might shed light into this question. Situative approaches from cognitive research on learning and computer-supported collaborative learning (CSCL) suggest to study learning by a simultaneous consideration of different aspects that shape learning (Greeno & Engeström, 2015; Janssen & Kirschner, 2020): *antecedents* of learning, such as subjects (individuals or groups), objects (topics and tasks learners work on), and resources (e.g., tools learners use to transform the object to a desired outcome), *processes of learning*, and *consequences of learning*. For an overview, see Figure 1.

In the present work we systematically investigated in a controlled laboratory experiment the effects of different enhanced video tools (*Tool-use*: annotations vs. hyperlinks) - alongside with a control group (no *Tool-use*) - and different social learning *Settings* (individual vs. collaborative learning) on learning processes (i.e., learning activity and cognitive load) and outcomes (i.e., creative learning and conceptual understanding). In the following sections, we introduce related research on enhanced video-based learning and on individual and collaborative learning. The introduction closes with the aims of the present work.

Fig. 1

The relationship between antecedents, processes, and consequences of learning, based on situative approaches

From learning with videos to enhanced video tools

Videos are used to support learning in many domains as they allow to depict objects, situations, and movements (also those that cannot easily be watched with naked eyes) and are able to visualize abstract information processes (Overbaugh, 1995). Even before the COVID-19 pandemic, the use of videos had a long tradition in educational institutions around the globe (for a review see Poquet et al., 2018). However, the rather passive viewing of videos - although it is very easy (Salomon, 1984) - can result in little engagement, mental effort or reflection of learners, which may impede the construction of their own understanding of a topic (Shin et al., 2018). Thus, the possibility for learners to *interact* with the video material was emphasized to be of crucial importance (Hasler et al., 2007). By using *basic video control tools*, such as play, pause, or rewind, learners are able to actively engage and interact with the material and, thus, to adapt the learning information to their own cognitive needs (Schwan & Riempp, 2004).

Today, *enhanced video-based environments* go beyond these basic interactions and allow learners to use *enhanced video tools* to actively generate meaning by transforming existing video presentations into own enriched information structures (for an overview, see Schwartz & Hartman, 2007). According to Bloom’s taxonomy (Krathwohl, 2002), such an active creation of own learning structures is important, since knowledge acquisition is not only a product of "understanding", but also of "creating" (see also *learning through design approach*: Kafai & Resnick, 1996). This is in line with Wittrock's (1992) model of generative learning and

Mayer's (2009) select-organize-integrate (SOI) model, suggesting that *generative activity* – that can be fostered by enhanced video tools - promotes generative processing in the working memory, i.e., the organizing and integrating of new learning material with prior knowledge (see Figure 1, cf. Fiorella & Mayer, 2016). Examples of enhanced tools include *annotations*, i.e., self-written notes or summaries (Chiu et al., 2018), *hyperlinks*, i.e., supplementary material that includes predefined texts or pictures (Meixner, 2017), or *in-video quizzes*, i.e., questions that directly appear during video watching (Cattaneo et al., 2019).

Enhanced video tools have received a growing interest in education (Noetel et al., 2021) and research reported overall positive effects on learning (for a review, see Evi-Colombo et al., 2020). For example, learners were found to perform better on knowledge tests when they used annotations to learn about first aid (Chiu et al., 2018) or physics (Delen et al., 2014) than when they learned with common video material without enhanced tools. Moreover, rare existing research on hyperlinks (cf. Evi-Colombo et al., 2020) has shown that the creation of own hypervideo structures supports learning of complex history topics (Author, 20xxb,; 20xxc). In addition, research on in-video quizzes revealed positive effects on learning performance (Haagsman et al., 2020; Rice et al., 2019), engagement (Cummins et al., 2016), and motivation (Author, 20xxd). However, many studies also reported conflicting results (for an overview, see Sauli et al., 2018). Thomas et al. (2016), for instance, found that learners who used annotations to learn a history topic underperformed learners who learned with common videos. Merkt et al. (2011), who investigated the effects of a common video, an enhanced video with a table of contents, and an illustrated textbook, also found that learning with a common video was more useful to learn history topics than learning with an enhanced video. They argued that performing so-called micro-level activities (resulting from the use of basic video control tools) is unproblematic for learning, while performing macro-level activities (resulting from the use of enhanced tools) caused problems for learners.

From reviewing the empirical results, we assume that general statements about the effectiveness of enhanced tools are difficult for the following reasons. First, different enhanced tools support learning differently, which, in turn, is reflected in learning outcomes. For example, the act of writing promoted by annotation tools stimulates the cognitive processes of reflecting, organizing, and integrating of information (Lawson & Mayer, 2021), which, in turn, supports the understanding and evaluation of individual concepts and the creation of own (new) ideas (Author 20xxa). In contrast, hyperlinks support the integration of related pieces of information and their re-structuring, which promotes the understanding of interrelations between concepts (Rickley & Kemp, 2020; Stahl et al., 2006). Last, in-video quizzes support self-assessment of own knowledge by pointing out still existing knowledge gaps (Panadero et al., 2017). These examples illustrate the importance of considering different impacts on learning processes and outcomes when examining the effects of enhanced tools. Although direct comparisons of enhanced tools could help determine how different tools might successfully support learning in concrete learning situations, there is still little research in this regard. To the authors' knowledge, only three studies have directly compared different enhanced tools. However, the focus in these studies has been less on learning outcomes but more on the development of enhanced learning

environments (Kim et al., 2021), learning processes, such as cognitive load (Van Sebille et al., 2018), or intentions and influencing factors that determine when learners use such tools (Mirriahi et al., 2021).

Second, enhanced tools need to be clearly instructed and included as a *necessary part* of the learning task (Author, 20xxa; Rice et al., 2019). So far, however, enhanced tools have been offered rather as *optional supporters* for learning. Previous research suggests that learners may not develop appropriate learning strategies to use optional tools for learning (Merkt et al., 2011) and that they may cognitively overwhelm learners rather than support them in effective learning (Krauskopf et al., 2014).

In sum, we conclude that comparisons of different *task-relevant* enhanced tools could provide new insights into the conditions under which they can effectively support learning. Thereby, a simultaneous investigation of the effects of enhanced tools on learning processes and learning outcomes, following previous approaches (see Figure 1, cf. Greeno & Engeström, 2015; Janssen & Kirschner, 2020), is crucial. Accordingly, incorporating investigations of learning processes help to understand (1) how learners use enhanced tools for learning (i.e., micro- and macro-level learning activities, cf. Merkt et al., 2011) and (2) how these tools influence learners' cognitive load (Author, 20xxd; Rice et al., 2019). Furthermore, both *creative learning* (cf. generative learning e.g., Fiorella & Mayer, 2016; Kafai & Resnick, 1996; Krathwohl, 2002) and *conceptual understanding* should be considered as learning outcomes to account for different supportive roles of enhanced tools in concrete learning situations (Author 20xxa; Stahl et al., 2006).

Individual vs. collaborative video-based learning

It becomes obvious from previous literature that research on enhanced video-based environments has been conducted primarily with individual learners. Besides, although computer-supported collaborative learning (CSCL) has received considerable attention in the last decades – especially in higher education (see e.g., Janssen & Kirschner, 2020; Jeong et al., 2019) - research on *video-supported collaborative learning* is still lacking (Ramos et al., 2019). Therefore, it is hardly surprising that direct comparisons between social settings (i.e., individual and collaborative learners) are missing in the research field on enhanced video-based learning. However, related research on learning with animations did such comparisons and found that collaborative learning is superior to individual learning in problem solving (Kirschner et al., 2011; Retnowati et al., 2016), retention, interpretation, explanation (Bol et al., 2012), and transfer tasks (Rebetez et al., 2010). Rebetez et al. (2010) for example, examined the impact of different multimedia instructions that varied regarding their level of interactivity (static vs. animated material) on learning a science topic and found that participants who learned with animations were overall superior in retention tasks, but only collaborative learners benefited from animations in transfer tasks. In a study by Kirschner et al. (2011), the authors examined the impact of different instructional formats (worked examples vs. equivalent problem solving) on individual and collaborative learning outcomes in biology and could show that studying worked examples was better performed by individuals but problem solving tasks were easier for collaborative learners. A more recent study by Liao et al. (2019) further found that collaborative learning combined with instructional videos supports learning achievement and reduces extraneous load in a digital game-based learning context.

In sum, research on animations and game-based learning indicates that collaborative learning fosters learning outcomes for complex tasks. In the present work, we aim to fill the gap of simultaneous investigations of individual and collaborative learners in enhanced video-based learning.

Aim of the present study

According to the literature described above, we assume that enhanced video tools can be used to foster generative activities, which, in turn, should support creative learning and conceptual understanding (Mayer, 2009; Wittrock, 1992). However, systematic comparisons of the effects of different enhanced tools and individual and collaborative learning settings on video-enhanced learning are still very rare. However, given the high and still growing relevance of videos in educational institutions (Noetel et al., 2021), we aim to tackle these research gaps and contribute new original work to advance cognitive research on learning with interactive videos. In doing so, we follow previous approaches (Greeno & Engeström, 2015; Janssen & Kirschner, 2020) and pursue a holistic approach by systematically and simultaneously examining different antecedents (enhanced tools and social learning settings), processes, and consequences of learning in a co-located face-to-face context.

More precisely, we pursue the following research question: how does learning in different *Tool-use* (annotations vs. hyperlinks vs. control) and different *Setting* conditions (individual vs. collaborative learning) impact learning processes (H1), outcomes (H2), and their relations (H3)? The following hypotheses are derived from this: first, regarding the effects on learning processes, we expect (H1a) differences in *Tool-use* and (H1b) *Setting*. Second, regarding *learning outcomes*, we expect (H2a) an overall knowledge gain after learning over all conditions, (H2b) differences in *Tool-use*, and (H2c) a superiority of collaborative over individual learners (i.e., *Setting*). Third, we exploratory investigate (H3) if learning processes can function as possible mediators between the independent variables *Tool-use* and *Setting* and the dependent variables of learning outcome.

Methods

Participants and study design

Overall, 209 participants were part of this experiment (74.6% female, M = 24.30, SD = 6.7) which took place in a controlled laboratory setting at a Swiss University. Figure 2 includes detailed information on the study design and sample size. The ethical standards were met as is confirmed by the ethical review board of our institution. Each participant received either course credits or CHF 20.- for participation. Participants were randomly assigned to the experimental conditions of a 3 x 2 study plan. The first factor (*Tool-use*) determined whether participants were allowed to use enhanced tools and/or which tools they were allowed to use to perform the task: *annotations* of self-written summaries, *hyperlinks*, or no option to use enhanced tools (no *Tool-use* = control group). The second factor concerned the social learning *Setting*: participants learned either alone (individual condition) or collaboratively in dyads (collaborative condition).

Fig. 2

Study design and procedure

Procedure

The experimental procedure lasted approximately one and a half hours and followed four phases (see Figure 2). In the pre-experimental phase, participants were welcomed and asked to complete questions about their demographics (gender, age, educational level), their prior experience with digital media for learning, prior self-assessed and objective knowledge, and prior topic-related interest. Next, in the preparation phase, participants were instructed to their task to learn about *synaptic plasticity* for a post-experimental questionnaire either by using enhanced tools (*Tool-use*: annotations vs. hyperlinks) or without the possibility to use enhanced tools (control group) and were asked to familiarize themselves with the environment by a tutorial video. In the design phase, participants were then asked to accomplish the task either individually or in dyads working on a shared desktop computer (= *Setting*). Participants in the *Tool-use* conditions were additionally asked to use enhanced tools to create a high-quality hypervideo product that should also help other students to learn in the future. Participants in the control group were asked to watch the video considerately. The design phase took on average 35.83 minutes (*SD* = 16.8). Participants could invest as much time as they needed. This should ensure that they were able to fully understand the content, to compensate for effects of cognitive load, and to complete the given task. In the post-experimental phase participants were finally asked to complete the post-questionnaires before they were thanked and released.

Materials

The exemplary video used as learning material for the experiment addressed the neuroscience topic *synaptic plasticity of the human brain*. It was originally produced as high-quality instructional learning material by the Max Planck Society and lasts 3:56 minutes. The video was embedded in the enhanced video-based environment *FrameTrail* (see Figure 3). This environment additionally included topic-related in-depth information in form of prepared text snippets directly available below the video. These texts were developed together with an expert in the field of neurobiology. While participants in the annotation condition were asked to read these texts and then write own summaries (i.e., annotations) to add them into the video, participants in the hyperlinks condition could grab these text snippets and add them directly into the video at appropriate places (per drag and drop). In both conditions, the display time of the hyperlinks or annotations could be manually changed to adapt the additional learning material to the relevant part of the video. Participants in the control group were asked to simply watch the video and read the text snippets (i.e., common video learning).

Fig. 3

Illustration of the enhanced video-based environment *FrameTrail*

Measures

Measures and scores of the dependent variables on learning processes and outcomes are summarized in Table 1.

To measure *learning processes*, we, on the one hand, collected participants' *learning activities* by using log-file protocols provided by *FrameTrail*. These files included information about video interaction for each individual and dyad (i.e., actions such as clicking on the "play" button). According to previous research (Delen et al., 2014; Merkt et al., 2011), learning activity was measured by distinguishing between (1) micro- and (2) macro-actions. While micro-actions included logs of interactions with basic video control tools, i.e., play, pause, skipping forward and backward, macro-actions covered interactions with enhanced tools, i.e., adding or deleting hyperlinks or annotations, changes of the display time on the video timeline, and changes of self-written annotation texts. The fact that participants learned at their own pace was reflected in a spread of variance for both the absolute learning time (M = 42.17 min, SD = 15.2) and the absolute frequencies of performed actions over all participants (micro-actions: M = 88.96, SD = 47.1; macro-actions: M = 67.53, SD = 41.2). We thus considered relative values of these actions (absolute performed actions divided by total learning time in minutes) to take account of varying total learning times (micro-actions per minute: M = 2.31, SD = 1.3; macro-actions per minute: M = 1.58, SD = 0.7). Although analyses for both absolute and relative values were conducted, we focus on relative values hereafter. On the other hand, we measured *cognitive load*, according to previous definitions of the concept (Jong, 2010; Paas, 1992), with the one-item scale "Please estimate how easy or how difficult you found the learning material" from 1 (very easy) to 7 (very difficult) according to Kalyuga et al. (1999).

To collect *learning outcomes*, we were guided by the above-mentioned literature (Fiorella & Mayer, 2016; Krathwohl, 2002; Wittrock, 1992) and investigated both (1) *creative learning*, by measuring the quality of self-created hypervideo products, and (2) *conceptual understanding* of the topic. First, *hypervideo product quality* (HPQ) was measured by the ratings of two experts with 10% of the products rated by both experts (Cronbach's alpha: .96). The experts evaluated several quality indicators based on a grading system developed for this study: (1) knowledge transformation (correctness of content and use of own words instead of "copy/paste"), (2) information structuring (correct placement the enhanced tools, completeness of content, meaningful change of display time), (3) formal criteria (text length, correct grammar, use of titles), and (4) knowledge development (additional information provided by the learners based on their prior knowledge). Additionally, experts rated (5) an overall impression of the products. To compare HPQ of the annotation and hyperlink condition, we developed a weighted grading system (total points achieved * 5 divided by max. score) from 1 (lowest grade) to 6 (top grade). Note, while all categories could be addressed in the annotation condition, the hyperlink condition could only be evaluated via (2) information structuring and (5) overall impression. Thus, we conducted separate analyses with "information structuring", which was equally measured in both conditions. A maximum of 300 points could be scored (see Table 1).

Second, *conceptual understanding* was measured using a post-experimental questionnaire including eight questions that addressed 'understanding of concepts' (6 MC- and 2 short answer questions, e.g., "what are vesicles?" referring to understanding the concept of vesicles), eight questions that addressed 'understanding of interrelations' between concepts (6 MC- and 2 short answer questions, e.g., "what role do calcium ions play

in synaptic transmission?" referring to an understanding of the interrelation of calcium ions and synaptic transmission), and four questions that addressed 'transfer knowledge' (3 MC- and 1 short answer questions intended to measure the ability to transfer learned information to other situations or circumstances, see Rebetez et al., 2010). Learners received one point for a correct and zero points for an incorrect answer. The Cronbach's alpha of the full test was .76. Moreover, we randomly selected two questions each of 'understanding of concepts' and 'understanding of interrelations' and one 'transfer knowledge' question that we integrated in the pre-experimental questionnaire. These five questions were used to check for between-group comparisons and to measure *objective knowledge gain*.

Table 1 Measures and scores of dependent variables on learning processes and outcomes

Dependent variables	**Measures/items**	**Scores/scales**
Learning processes		
Learning activity		
Micro-actions (basic video control tools)	Logs of play, pause, skipping forward, skipping backward	relative values of actions per min
Macro-actions (enhanced video tools)	Logs of adding, deleting, or changing display time of annotation/hyperlink and changes of annotation text	
Cognitive load	One-item scale: "Please estimate how easy or how difficult you found the learning material"	1 (very easy) - 7 (very difficult)
Learning outcomes		
Hypervideo product quality (HPQ)	Knowledge transforming	*Grading system:* 1 (lowest grade) - 6 (top grade) *Information structuring*: max. 300 points
	Information structuring	
	Formal criteria	
	Knowledge development	
	Overall impression	
Conceptual understanding	Understanding of concepts, 8 questions (2 included in prior knowledge test)	8 points
	Understanding of interrelations, 8 question (2 included in prior knowledge test)	8 points
	Transfer knowledge, 4 questions (1 included in prior knowledge test)	4 points
Self-assessed knowledge gain	One-item scale: "How much do you think your knowledge of synaptic plasticity has improved?"	1 (not at all) - 5 (very much)

Third, we collected *self-assessed knowledge gain* using a post-experimental one-item scale. Participants were asked to specify how much they think their knowledge about synaptic plasticity has improved after learning from 1 (not at all) to 5 (very much). Note, to justify the use of one-item, we refer to previous research (Gogol et al., 2014).

Data analysis

Regarding the data analysis of the present study, the following should be noted: the first focus of the present study lied on the impact of different enhanced tools on learning processes and outcomes. For this reason, we included measures that could not be collected for the control group (i.e., macro-actions and HPQ). Consequently, the control group was not considered in all analyses. Analyses that could be conducted with the control group were performed both with and without the control group. The second focus of this study lied on the impact of different social settings on learning processes and outcomes. Hence, 132 participants learned and performed the task in dyads on a shared desktop computer (= 66 dyadic settings). As a result, measures on learning activity and HPQ were only available at the group level while other measures were available at the individual level. Hence, to compare the different settings with analyses of variance, data from learners in groups were aggregated (by averaging group means). With this, we refer to previous research, suggesting interdependence of students working in one team (Kenny et al., 2006). Still, we additionally performed multilevel analyses by using HLM (Raudenbush & Bryk, 2002) and found similar effects. Moreover, standard deviations between individual and collaborative learners were found to be relatively similar (see Tables 2 – 5 below). Therefore, we considered our measures to be independent.

To test our hypotheses, we used the following analyses. First, regarding H1 (learning processes), we conducted a two-way multivariate analysis of variance (MANOVA) with micro- and macro-actions (i.e., learning activity) as dependent variables. The control group was not considered. Moreover, a two-way analysis of variance (ANOVA) was conducted with cognitive load as dependent variable.

Second, regarding H2 (learning outcomes), we conducted a two-way repeated-measures ANOVA for objective knowledge gain (H2a). Furthermore, two similar two-way ANOVAs with either HPQ or information structuring as dependent variables were conducted (H2b, H2c). The control group was not considered. Also, a two-way MANOVA was performed with the variables ‘understanding of concepts’, ‘understanding of interrelations’, and ‘transfer knowledge’ (i.e., conceptual understanding) as dependent variables. Last, we conducted a two-way ANOVA with self-assessed knowledge gain as dependent variable.

Third, we intended to exploratory investigate effects of learning processes as pre-supposed mediators between the independent variables *Tool-use* and *Setting* and the dependent variables on learning outcomes in H3. Therefore, we checked for assumptions to conduct mediation analyses, on one hand, provided by the findings demonstrated in our analyses on learning processes (H1) and outcomes (H2), and, on the other hand, by running a series of bivariate correlations (Pearson) between the mediators and the dependent variables (Baron & Kenny, 1986). The assumption checks are discussed separately in the results section below. The mediation analyses were then conducted using the regression-based approach for conditional process modeling using the

SPSS-macro PROCESS (Hayes et al., 2017). The control group was not considered in these analyses because no data on macro-actions and HPQ were available. For all analyses, requirements were checked in advance referring to relevant literature (e.g., Blanca et al., 2017; Finch, 2005; Kenny et al., 2006).

Results

Between-group comparisons and manipulation check

The analyses for gender (chi-square test), age, educational level, prior experience with digital media for learning, prior self-assessed knowledge, and prior interest in the learning topic (ANOVAs) yielded no significant differences in *Tool-use* (annotations vs. hyperlinks vs. control, $p > .10$) nor *Setting* (individual vs. collaborative, $p > .10$). Hence, groups were comparable on these variables. For manipulation check, the hypervideo products of the annotation and hyperlink condition were compared by an expert using log data of learners' interaction to confirm that participants in the *Tool-use* conditions only performed the task they were assigned to. Results revealed that participants in the annotation condition only added annotations, participants in the hyperlink condition only hyperlinks, and that no enhanced tools were used in the control group.

Impact of *Tool-use* and *Setting* on learning processes (H1)

Learning activity (see Table 2): MANOVA revealed a statistically significant effect for *Tool-use* (as expected in H1a), $F(2,88) = 41.709$, $p < .01$, partial $\eta^2 = .487$, Wilk's $\Lambda = .513$. Additionally conducted post-hoc ANOVAs revealed that participants that learned with annotations performed significantly *more* macro-actions (annotation: $M = 1.75$, $SD = .6$; hyperlink: $M = 1.45$, $SD = .7$, $F(1,89) = 1.978$, $p = .033$, partial $\eta^2 = .050$), and significantly *fewer* micro-actions than participants that learned with hyperlinks (annotation: $M = 1.41$, $SD = .7$; hyperlink: $M = 3.22$, $SD = 1.3$, $F(1,89) = 74.116$, $p < .01$, partial $\eta^2 = .440$). No significant effect was found for *Setting* (H1b, $p > .10$).

Table 2 Descriptive data (Mean, SD) of learning activity

Tool-use	Annotations		Hyperlinks	
Setting	Individual	Dyad	Individual	Dyad
Micro-actions	1.41 (.7)	1.42 (.7)	3.38 (1.5)	3.04 (.9)
Macro-actions	1.83 (.7)	1.66 (.6)	1.50 (.7)	1.40 (.7)

Cognitive load (see Table 3): results yielded significance for *Tool-use*, $F(1,92) = 9.000$, $p = .003$, partial $\eta^2 = .089$ (as expected in H1a), indicating that learners in the annotation condition perceived a significant *lower* cognitive load ($M = 3.75$, $SD = 1.2$) than learners in the hyperlink condition ($M = 4.49$, $SD = 1.2$). No effects were found for *Setting* (H1b, $p > .10$). A similar analysis that considered the control group revealed no additional significant results ($p > .10$).

Table 3 Descriptive data (Mean, SD) on cognitive load

Tool-use	Annotations		Hyperlinks		Control group	
Setting	Individual	Dyad	Individual	Dyad	Individual	Dyad
(Scale from 1-7)	3.73 (1.3)	3.77 (1.2)	4.58 (1.3)	4.39 (1.0)	3.83 (1.2)	4.02 (1.0)

Impact of *Tool-use* and *Setting* on learning outcome (H2)

Hypervideo product quality (see Table 4): results revealed a significant main effect for *Tool-use* (as expected in H2b), $F(1,88) = 24.414$, $p < .01$, partial $\eta^2 = .216$, $d = 1.01$, indicating that learners in the hyperlink condition produced hypervideo products of higher quality ($M = 4.96$, $SD = .4$) than learners in the annotation condition ($M = 4.47$, $SD = .5$). Moreover, a marginal significant effect for *Setting* was found, $F(1,88) = 3.605$, $p = .061$, partial $\eta^2 = .039$, $d = 0.36$, indicating that dyads ($M = 4.82$, $SD = .6$) slightly outperformed individuals ($M = 4.63$, $SD = .5$), as expected in H2c. An analysis with information structuring revealed similar results: a significant effect for *Tool-use*, $F(1,88) = 52.36$, $p < .01$, partial $\eta^2 = .373$, $d = 1.47$, with a superiority of the hyperlink condition (hyperlink: $M = 243.16$, $SD = 25.0$; annotation: $M = 199.99$, $SD = 33.3$), and a marginally significant effect for *Setting*, $F(1,88) = 3.485$, $p = .065$, partial $\eta^2 = .038$, $d = 0.32$, with higher scores for dyads (dyads: $M = 228.16$, $SD = 38.5$; individuals: $M = 216.68$, $SD = 33.9$). These results, too, confirm H2b and c.

Table 4 Descriptive data (Mean, SD) of HPQ and information structuring

Tool-use	Annotations		Hyperlinks	
Setting	Individual	Dyad	Individual	Dyad
HPQ (grades from 1-6)	4.41 (.5)	4.53 (.5)	4.84 (.4)	5.09 (.4)
Information structuring (max. 300 points)	198.15 (33.0)	202.09 (34.4)	234.47 (24.2)	253.04 (22.4)

Conceptual understanding (see Table 5): as expected in H2a, results yielded significance, $F(1,93) = 119.47$, $p < .001$, Wilks' Lambda = .438 (M_{prior}= 2.44, SD_{prior}=1.3; M_{post}= 3.91, SD_{post}=1.0), indicating an objective knowledge gain after learning over all conditions. No significant differences were found between the conditions (all $p > .10$). An equal analysis considering the control group revealed similar results (knowledge gain: $F(1,137) = 210.57$, $p < .001$, Wilks' $\Lambda = .394$; M_{prior}=2.47, SD_{prior}=1.3; M_{post}= 3.99, SD_{post}=1.0; no differences between the conditions, all $p > .10$). Moreover, in contrast to our assumptions in H2b and H2c, no significance differences were found for *Tool-use* or *Setting* on the combined dependent variables 'understanding of concepts', 'understanding of interrelations', and 'transfer knowledge' (all $p > .10$). A similar analysis that

considered the control group, however, yielded significance for *Tool-use*, $F(6,270) = 2.87$, $p = .010$, partial $\eta^2 = .060$, Wilk's $\Lambda = .884$. Post-hoc univariate ANOVAs revealed significance for the variables 'understanding of interrelations', $F(2,137) = 6.530$, $p = .002$, partial $\eta^2 = .087$, and 'transfer knowledge', $F(2,137) = 4.294$, $p = .016$, partial $\eta^2 = .059$, both indicating that the control group outperformed the two other conditions (Tukey post-hoc analyses: 'understanding of interrelations': control > annotation, $p = .022$ (Mdiff = .91, 95%-CI[.11,1.71]); control > hyperlinks, $p = .003$ (Mdiff = 1.15, 95%-CI[.35,1.96]; 'transfer knowledge': control > annotation, $p = .010$ (Mdiff = .50, 95%-CI[.10,.90])). Results on *Setting* were not significant (H2c, $p > .10$).

Self-assessed knowledge gain (see Table 5): a significant effect for *Tool-use* was found, $F(1,93) = 5.907$, $p = .017$, partial $\eta^2 = .60$, indicating (as expected in H2b) that learners using annotations had experienced a higher knowledge gain ($M = 3.83$, $SD = .8$) than learners using hyperlinks ($M = 3.50$, $SD = .6$). No effects were found for *Setting* (H2c, $p > .10$). A similar analysis additionally considering the control group did not reveal further significant effects ($p > .10$).

Table 5 Descriptive data (Mean, SD) of conceptual understanding

Tool-use	Annotations		Hyperlinks		Control group	
Setting	Individual	Dyad	Individual	Dyad	Individual	Dyad
Understanding of concepts (max. 8 points)	5.67 (1.6)	5.71 (1.3)	5.96 (1.3)	5.23 (1.4)	6.38 (1.4)	5.91 (1.1)
Understanding of interrelations (max. 8 pints)	5.07 (1.8)	4.46 (1.4)	4.62 (1.9)	4.48 (1.4)	5.71 (1.7)	5.71 (1.6)
Transfer knowledge (max. 4 points)	2.78 (.9)	2.82 (.8)	3.04 (.9)	2.96 (.8)	3.33 (.9)	3.25 (.6)
Self-assessed knowledge gain (scale from 1-5)	3.81 (.8)	3.84 (.6)	3.58 (.7)	3.41 (.4)	3.67 (.8)	3.70 (.7)

Assumption checks for mediation analyses

Before conducting the mediation analyses, we, first, took a closer look at the results found for H1 and H2. The results showed that no or only marginal effects were found for the independent variable *Setting*. Thus, we subsequently focused on *Tool-use* as independent variable for the following mediation analyses. Second,

Pearson correlations were performed with learning process variables (pre-supposed mediators) and variables relating to learning outcome (see Table 6). Significant correlations were found between learning activity and HPQ, information structuring, and self-assessed knowledge gain. Moreover, results revealed that cognitive load positively correlated with 'understanding of concepts', 'understanding of interrelations', and 'transfer knowledge'. The analyses further revealed (1) that micro- and macro-actions did not correlate, wherefore they were included as separate mediators in the following analyses, (2) that the three dependent variables on conceptual understanding correlated, whereas we combined these variables into the single variable "conceptual understanding" (by sum) for further analyses, and (3) significant correlation between macro-actions and cognitive load, indicating that the less macro-actions were performed by learners, the lower was perceived cognitive load.

In sum, based on the results found regarding H1 and H2 and the Pearson correlations, the following mediation analyses were conducted with *Tool-use* as independent variable: (1) learning activity (micro-, and macro-actions) as mediator for HPQ and information structuring, (2) learning activity as mediator for self-assessed knowledge gain, and (3) cognitive load as mediator for "conceptual understanding".

Mediating effects of learning processes on learning outcomes (H3)

Learning activity, HPQ, and information structuring (see Figures 4 and 5): the mediation analysis with HPQ as dependent variable revealed a significant *c* path, indicating a total effect of *Tool-use* on HPQ ($\beta = .49$, $t = 4.78$, $p < .001$). Moreover, both *a* paths of learning activity were significant, indicating an effect of *Tool-use* on the performance of micro- ($\beta = 1.75$, $t = 8.25$, $p > .001$) and macro-actions ($\beta = -.34$, $t = -2.56$, $p = .012$). Moreover, while the *b* path from macro-actions to HPQ was significant ($\beta = .19$, $t = 2.54$, $p = .013$) the *b* path for micro-actions was not ($p > .10$). Last, the direct effect of *Tool-use* on HPQ controlling for learning activity was still significant (path *c'*; $\beta = .61$, $t = 4.07$, $p < .001$), suggesting a partial mediation. We found that the relationship between *Tool-use* and HPQ is mediated by the amount of less performed macro-actions, *ab* = -.119, 95%-CI[-.294, -.011], but not by the amount of performed micro-actions, *ab* = -.091, 95%-CI[-.389, .227]. A mediation analysis with information structuring as dependent variable revealed similar results (macro-actions: *ab* = -4.381, 95%-CI[-10.115, -.577]; micro-actions: *ab* = -1.124, 95%-CI[-10.43, 8.429]).

Fig. 4

Mediation analysis *Tool-use*, learning activities, and HPQ

Fig. 5

Mediation analysis *Tool-use*, learning activities, and information structuring

Learning activity and self-assessed knowledge gain (see Figure 6): the mediation analysis revealed a significant *c* path, indicating a total effect of *Tool-use* on self-assessed knowledge gain ($\beta = -.42$, $t = -3.24$, $p = .002$). Furthermore, both *a* paths for learning activity were significant, indicating an effect of *Tool-use* on micro-

(β = 1.81, t = 8.45, *p* > .001) and macro-actions (β = -.30, t = -2.22, *p* = .03). However, the *b* paths and the *c'* path were not significant (*p* > .10). This suggests that the relationship between *Tool-use* and self-assessed knowledge gain is not mediated by learning activity.

Fig. 6

Mediation analysis *Tool-use*, learning activities, and self-assessed knowledge gain

Cognitive load and "conceptual understanding" (see Figure 7): the mediation analysis revealed no significant *c* path, indicating that there was no total effect of *Tool-use* on "conceptual understanding" (β = -.083, t = -.13, *p* > .10). However, following previous approaches (Rucker et al., 2011; Zhao et al., 2010), we continued with the analysis. A significant *a* path was found, indicating an effect of *Tool-use* on cognitive load (β = .740, t = 3.05, *p* = .003). Moreover, the *b* path was found to be significant, indicating an effect of cognitive load on "conceptual understanding" (β = -1.388, t = -5.05, *p* < .001). Last, the relationship between *Tool-use* and "conceptual understanding" was found to be mediated by cognitive load, *ab* = -1.027, 95%-CI[-1.738, -.391].

Fig. 7

Mediation analysis *Tool-use*, learning activities, and "conceptual understanding"

Discussion

The present work aimed to close current research gaps to the question *how different enhanced video-tools can support creative learning and conceptual understanding in individual and groups?* We intended to provide new original findings on how learning with an interactive video in different *Tool-use* conditions (annotations vs. hyperlinks vs. no *Tool-use*: control group) and in different social *Settings* (individual vs. collaborative learning) impact learning processes (H1) and learning outcomes (H2) in a co-located face-to face-context. Since our results indicate a close association between learning processes and outcomes (H3), we discuss them, first, in terms of *creative learning*, followed by *conceptual understanding*. The discussion closes with limitations and recommendations for future work.

The impact of *Tool-use* and *Setting* on creative learning (HPQ)

Our results indicate (H2b) that the hypervideo products of learners who were asked to use hyperlinks were of better quality according to experts than of learners who were asked to use self-written annotations. To explain this result, we need to take a closer look at our instrument for measuring hypervideo product quality (HPQ). The instrument considered the different foci of the two *Tool-use* conditions: since learners of the hyperlink condition were asked to learn by expanding the video material with predefined text snippets, their focus was primarily on a meaningful structuring of the material. Therefore, they were primarily evaluated

Table 6 Pearson correlations among mediators and dependent variables (note: aggregated means were used for dyads)

	Variables	*M*	*SD*	N	1	2	3	4	5	6	7	8	9
1	Micro-actions	2.33	1.4	93	-								
2	Macro-actions	1.60	0.7	93	-0.01	-							
3	Cognitive load	4.12	1.2	96	0.16	-,253*	-						
4	Understanding of concepts	5.65	1.4	97	0.06	0.20	-,467**	-					
5	Understanding of interrelations	4.68	1.6	97	-0.06	-0.06	-,406**	,454**	-				
6	Transfer knowledge	2.90	0.8	97	0.04	0.03	-,271**	,436**	,366**	-			
7	“Conceptual understanding”	13.23	3.1	97	0.01	0.07	-,502**	,818**	,837**	,666**	-		
8	Self-assessed knowledge gain	3.66	0.7	97	-,280**	,218*	-0.02	0.03	0.03	0.00	0.03	-	
9	Hypervideo product quality (HPQ)	4.72	0.5	92	,288**	0.08	0.01	0.02	0.13	0.04	0.09	-0.07	-
10	Information structuring	222.04	36.4	92	,409**	0.05	0.07	-0.02	0.03	0.05	0.02	-0.13	,918**

* = $p < .05$

** = $p < .01$

according to the quality of their information structuring. In contrast, learners of the annotation condition were additionally asked to expand the video material with *self-written content*. These learners were, thus, also evaluated according to the quality of their writing activities. The different focus between the conditions was also reflected in different learning activities: more micro-actions but less macro-actions were performed in the hyperlink compared to the annotation condition (H1a). From this we conclude the following: a high quality of information structuring seems to depend on a sparse but target-oriented use of enhanced tools that requires multiple interactions with basic control tools in advance. In other words: learners use basic video control tools (i.e., skipping forward and backward, pressing play and pause) to correctly place and adapt hyperlinks to relevant parts of the video. This is also reflected in our results, (1) indicating that the effect of *Tool-use* on HPQ was partially mediated by the performance of *less* macro-actions (H3) and (2) by a positive correlation of micro-actions with HPQ (see Table 6). Hence, it appears that learners in the hyperlink condition, who were able to focus more on information structuring, were able to create hypervideo products of higher quality, which is in line with previous research (Author, 20xxa; Schwartz & Hartman, 2007). In contrast, learners in the annotation condition did not seem to distribute their focus evenly between the two tasks information structuring and writing but focused mainly on the latter. This was reflected in more performed macro-actions and resulted in poorer hypervideo products. Our results further revealed that dyads (marginally) designed hypervideo products of higher quality than individuals (H2c). In line with previous research, we, thus, argue that enhanced environments support socio-cognitive processes (Schwartz & Hartman, 2007) and enable collaborative learners to jointly engage with the material (Sinha et al., 2015).

As stated by earlier approaches on learning though design (cf. Kafai & Resnick, 1996; Krathwohl, 2002) a high quality of own constructed learning material should also foster conceptual understanding, deep processing, and re-organizing of concepts (see also Rickley & Kemp, 2020; Wittrock, 1992). Hence, according to our results, it could be assumed that learners in the hyperlink condition and in collaborative settings should also have higher outcomes in conceptual understanding. However, our results suggest that this is not necessarily the case. This is discussed in the next section.

The impact of *Tool-use* and *Setting* on conceptual understanding

Our results indicate a general knowledge increase after learning with the enhanced video-based environment over all conditions (H2a). This is in line with previous research on video learning (Evi-Colombo et al., 2020; Poquet et al., 2018) and with research on collaborative learning (Janssen & Kirschner, 2020; Liao et al., 2019). However, we could not find differences in conceptual understanding for *Tool-use* (H2b) or *Setting* (H2c). Our results even demonstrate a superiority of the control group. This result could be explained by the fact that participants in the control group were able to focus exclusively on learning the topic. Thus, the capacity of their working memory may have been higher, leading to better results in conceptual understanding (cf. Baddeley, 2010; Maj, 2020). Moreover, in contrast to previous assumptions (e.g., Krathwohl, 2002; Rickley & Kemp, 2020), we could not show that successful information structuring (high-quality hypervideo products) led to deeper conceptual understanding. More precisely, we could not find a significant relationship between high-

quality hypervideo products and conceptual understanding and we found that learners in the hyperlink condition, who created hypervideo products of higher quality compared to learners in the annotation condition, did not achieve higher results in conceptual understanding. A possible explanation is that the present study focused on short-term memory effects. According to Kassymova et al. (2020), the usage of 'e-tasks' support the proper function of the brain's limbic system that increase neuroplasticity of these parts in the brain that are responsible for long term memory (see also Zull, 2004). Therefore, the effect of constructing own information structures by using enhanced tools on knowledge acquisition could develop over time.

However, when additionally considering learning processes the following picture appears: our results indicate that not learners in the control group, but learners in the annotation condition perceived the lowest cognitive load (H1a). Lower cognitive load was further found to be related with higher outcomes in conceptual understanding and to mediate the effect of *Tool-use* on conceptual understanding (H3). Moreover, our results suggest that lower cognitive load is related to frequently performed macro-actions. Hence, we conclude that an active and frequent use of enhanced tools, which occurs more often in the annotation condition (H1a), can support conceptual understanding, but only when low cognitive load is perceived. In other words: if learners using annotations did not perceive the learning material too complex, annotations could help them build conceptual understanding. This assumption is underlined by the fact that participants in the annotation condition reported higher self-assessed knowledge gain compared to participants in other conditions.

Moreover, we found that collaborative learners did not perform better in conceptual understanding than individual learners (H2c), which is in contrast to related research (Kirschner et al., 2011; Retnowati et al., 2016). Results on learning processes revealed that learning activity and cognitive load appeared to be relatively similar between individuals and dyads (H1b). Thus, considering previous work (cf. Janssen & Kirschner, 2020), we conclude that the used environment supported learning in such a way that not only individuals, but also collaborative learners could benefit.

In sum, by considering different antecedents of learning and learning processes, as suggested by situative approaches (Greeno & Engeström, 2015; Janssen & Kirschner, 2020), we were able to gain a deeper understanding of how (individual and collaborative) learners use enhanced tools to learn (cf. Fiorella & Mayer, 2016) and found that enhanced tools impact learners' focus on learning in enhanced video-based environment, leading to different strategies to use these tools for learning, which results in different learning outcomes.

Limitations and future work

This study has several limitations, which we will discuss here, along with recommendations for future research. First, to investigate our study goals, we conducted an experimental laboratory study in a co-located face-to-face context. Thus, high internal validity could be achieved because several disturbing variables could be excluded or controlled. However, especially regarding intrinsic and extrinsic motivation, learning in the laboratory cannot be compared with learning in everyday contexts (cf. motivational processes, Mayer, 2014). Hence, future research should conduct field studies as they allow for reasonable generalizations by implying high situational representativity and, thus, external validity (Rack & Christophersen, 2009). Second, the success

of computer-supported (collaborative) learning depends on many different aspects (e.g., Janssen & Kirschner, 2020). Although we pursued a holistic approach by including different aspects that shape learning, many other variables play a decisive role: for example, student characteristics, such as the ability for self-regulated learning processes (Janssen & Kirschner, 2020). Future research should increasingly address such aspects and their mutual influence on learning processes and outcomes. Third, our results on learning outcomes (i.e., creative learning and conceptual understanding) suggest, on one hand, that investigating long-term effects of learning with enhanced video environments could provide new insights, which should be addressed in future work. On the other hand, further methods to measure quality of hypervideo products – for example by deeply considering text quality of annotation texts – are recommended for future research. Forth, concerning learning processes, we suggest addressing the close relationship between micro- and task-actions in future research, for example by conducting behavior sequence analyses (see for example, Sinha et al., 2014). Last, cognitive load should be considered by using measurements for intrinsic, extraneous, and germane load with validated instruments (e.g., Klepsch et al., 2017) and by focusing on collaborative load (e.g., Kontogiorgos & Gustafson, 2021).

Conclusion

Enhanced video-based environments could provide answers to the question of how we can support *effective* learning. In the present work, we aimed to tackle the conflicting results on whether enhanced tools support creative learning and conceptual understanding in individuals and groups. The scientific relevance of this study lied on a holistic approach to investigate learning. We systematically and simultaneously investigated the effects of different antecedents of learning (different enhanced tools: annotations vs. hyperlinks; different settings: individual vs. collaborative learning) on learning processes (i.e., learning activity and cognitive load), learning outcomes (i.e., hypervideo product quality and conceptual understanding), and their relations. Our results suggest that hyperlinks are more suited to create own information structures of the learning material (i.e., hypervideo products) compared to annotations. Results further indicate that this depends on a frequent use of basic video control tools (such as play, pause, and rewind). In contrast, annotations foster self-assessed knowledge gain and help learners to deepen their conceptual understanding of the learning material – but only when they perceive the learning material not too difficult. Moreover, we found a marginal superiority of collaborative over individual learnings in constructing hypervideo products, indicating that creative learning might be fostered through collaboration. Our study sheds light into the different aspects that shape learning and highlights the importance to investigate them holistically.

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Figures used in Manuscript 3

Figures and figure captions used in Manuscript 3. Figures were uploaded as supplemental files for submission.

Fig. 1 The relationship between antecedents, processes, and consequences of learning, based on situative approaches

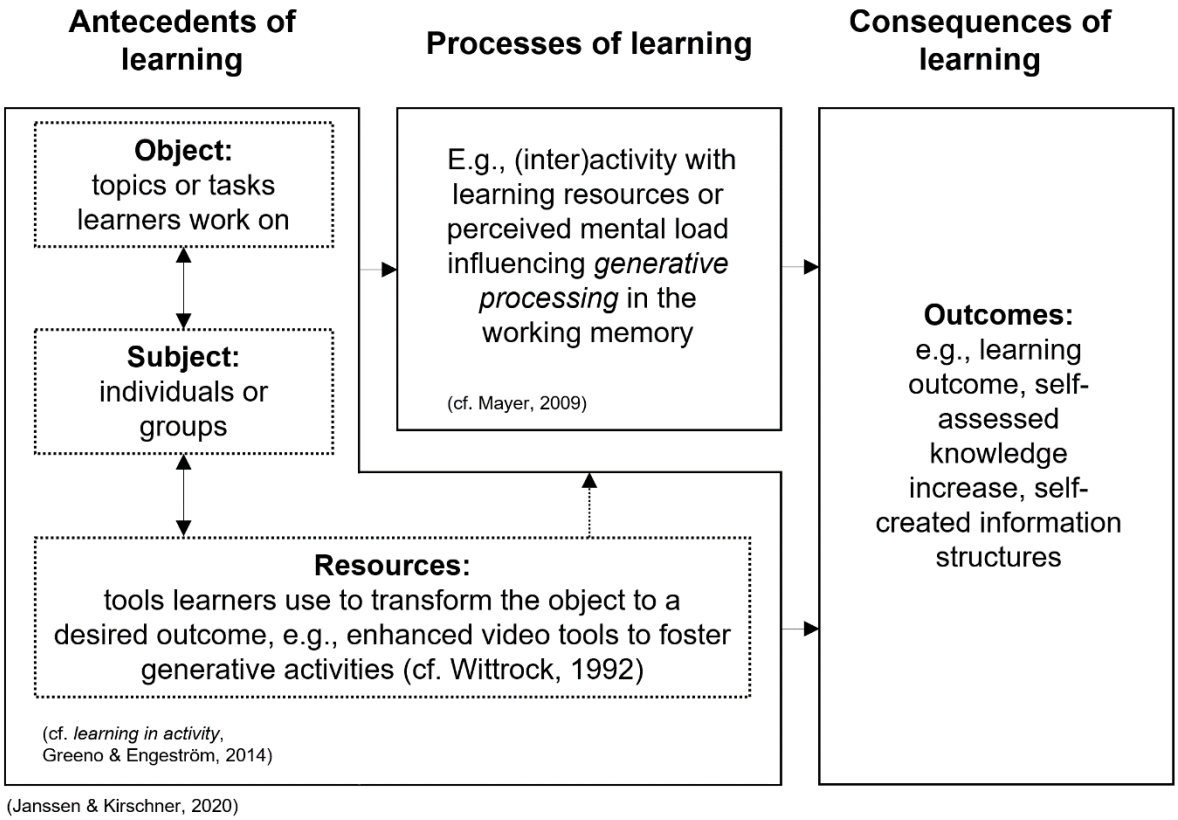


Fig. 2 Study design and procedure

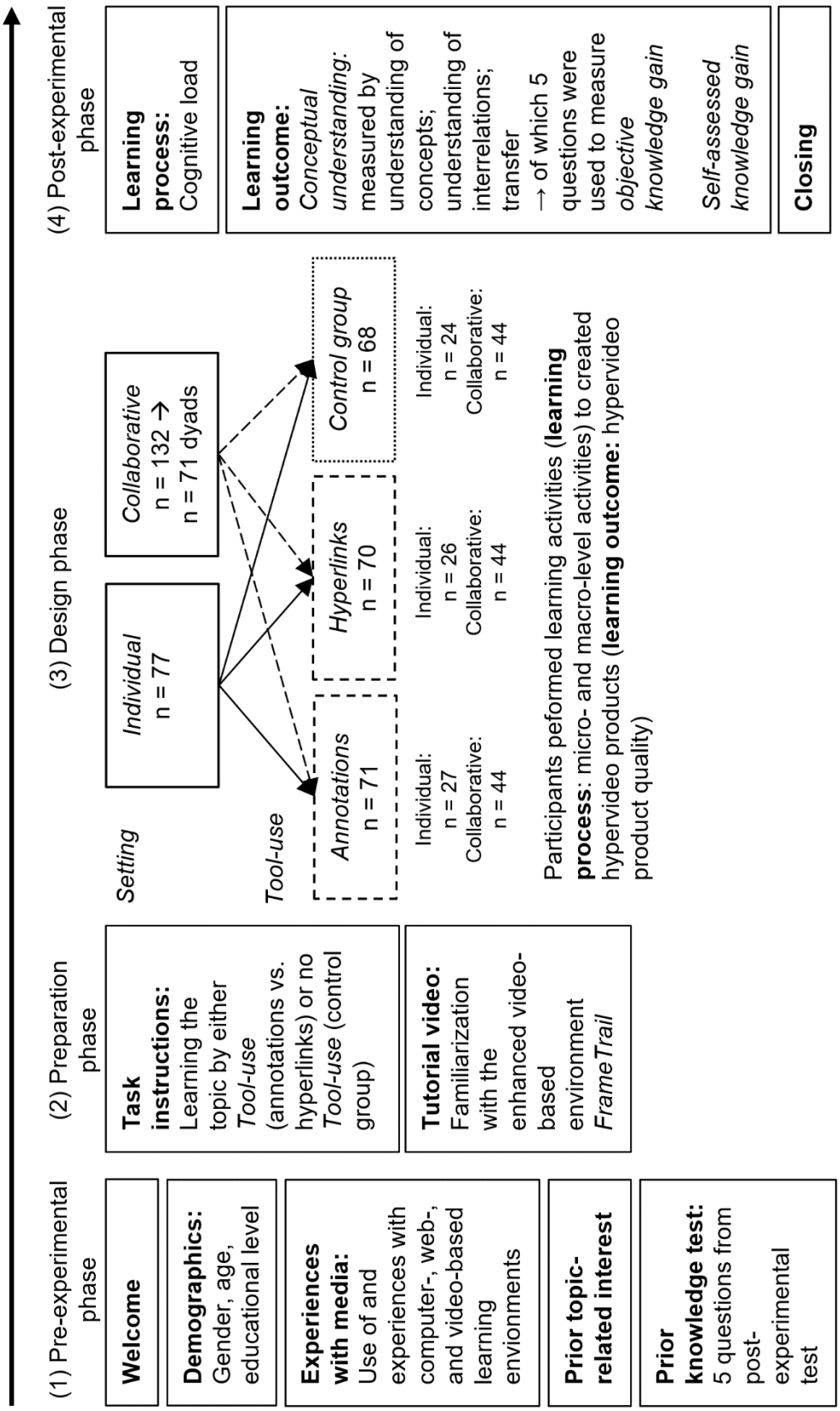


Fig. 3 Illustration of the enhanced video-based environment *FrameTrail*.

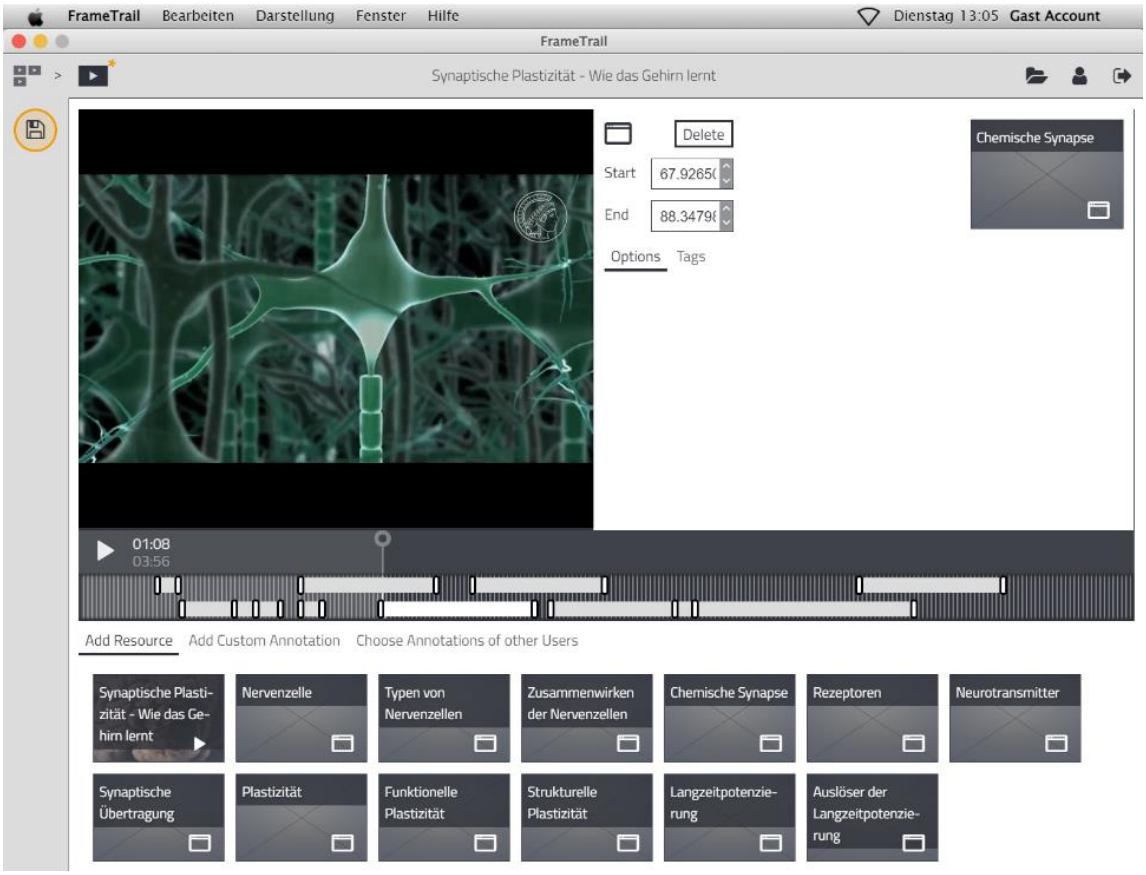


Fig. 4 Mediation analysis *Tool-use*, learning activities, and HPQ

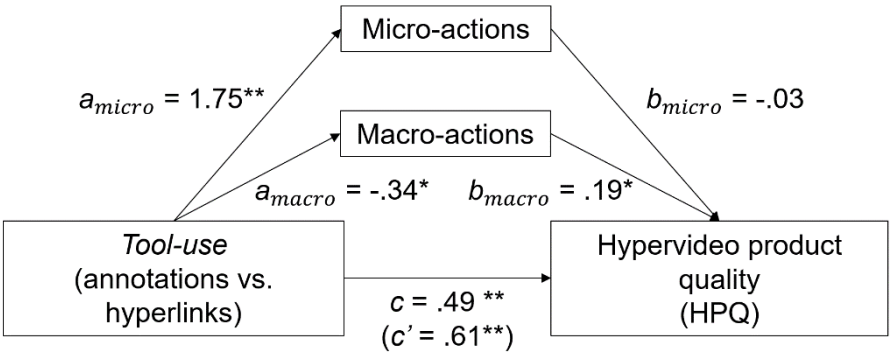


Fig. 5 Mediation analysis *Tool-use*, learning activities, and information structuring

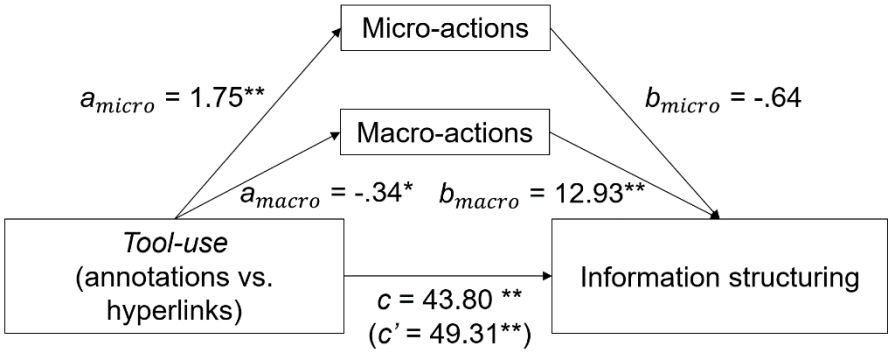


Fig. 6 Mediation analysis *Tool-use*, learning activities, and self-assessed knowledge gain

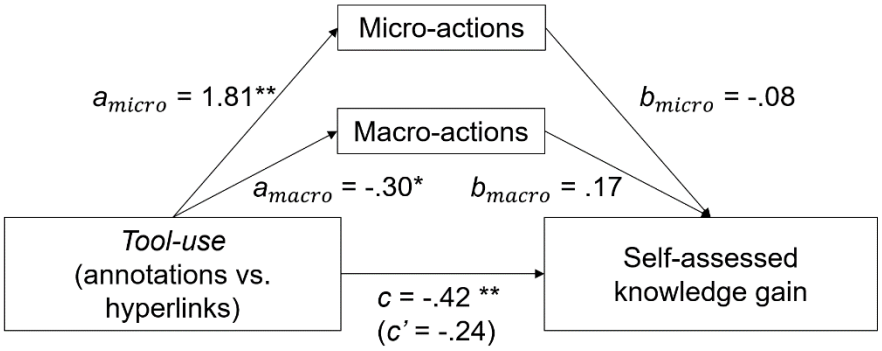
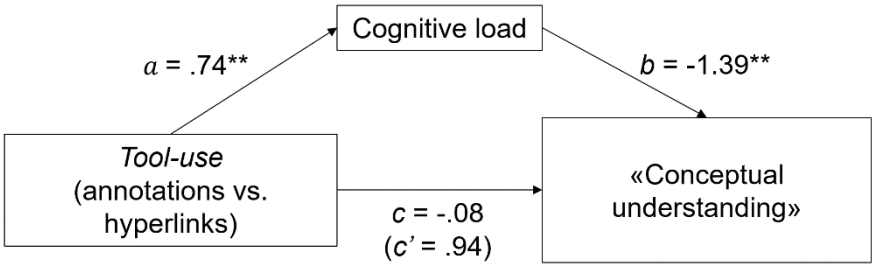


Fig. 7 Mediation analysis *Tool-use*, learning activities, and "conceptual understanding"



Curriculum Vitae

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2018-2022 PhD Dissertation at the Human-Computer Interaction Research Lab,
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Faculty of Psychology, University of Basel, Switzerland.

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2010-2013 Bachelor of Science in Psychology, University of Basel, Switzerland.

Employment

2016 – 2021 Research Assistant at the School of Applied Psychology, FHNW, Olten, Switzerland.

Internships

2015 User Research Internship in the YouTube Ads UX Teams, YouTube, Zurich,
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2015 Research Internship at the School of Applied Psychology, FHNW, Olten, Switzerland.

2013 Research Internship in the Centre of Chronobiology at the University of Psychiatric
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Publications

2022 **Ruf, A**., Zahn, C., Roos, A., & Opwis, K. (submitted). How do digital video tools
support conceptual understanding and creative learning in individuals and groups?

Ruf, A., Niederhauser, M., Jäger, J., Zahn, C., & Opwis, K. (submitted). An exploratory approach to investigate learning strategies in enhanced video-based environments.

Jeitziner, L. T., Roos, A. L., **Ruf, A.**, & Zahn, C. (submitted). University students' emotional experience in online versus onsite exams.

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2015 **Ruf, A.** (2016) *Short- and Long-Term Modality Effect in Multimedia Learning*. Wiesbaden: Springer Fachmedien. doi:10.1007/978-3- 658-12430-4.

2014 **Ruf, A.**, Seckler, M., & Opwis, K. (2014). Long-term modality effect in multimedia learning. In Proceedings of the *8th Nordic Conference on Human Computer Interaction: Fun, Fast, Foundational* (pp. 963-966).