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Exploring the development and impact of learning styles: An empirical investigation based on explicit and implicit measures

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ABSTRACT

It is still controversial whether learning styles are unchangeable dispositions or flexible characteristics. Research on the development of learning styles is therefore in high demand. We suggest a conceptual model that describes both explicit and implicit cognitive processes involved in processing instructional material. We also propose an implicit association test (learning styles IAT). In a first study (N = 126), we evaluate the stimulus material for the IAT. In a second study (N = 104), we investigate the correlations between the implicit and explicit measures used. We further examine interactions between learning styles and learning outcomes as well as cognitive load. Two versions of a computer-based learning program (verbal vs. visual presentation of information) were used. The results reveal that matching learning styles and learning materials neither leads to better learning outcomes nor to a lower cognitive load. Additionally, neither implicit nor explicit measures were able to predict learning outcomes.

1. Introduction

Digital multimedia technologies have become an integral part of our everyday life. They provide a variety of opportunities for learners as they offer easy access to information and comprehensive learning resources. Further, multimedia learning environments allow instructors to present information in different ways, including text, pictures, animations, audio files, etc. This provides them with ample opportunities to respond to learners' individual needs and preferences, and allows learners to focus on those representations which they deem most efficient (Ainsworth, 2008; Sadler-Smith & Smith, 2004; Richardson, 2001). The meshing hypothesis (also known as matching hypothesis or aptitude-treatment interaction hypothesis) postulates in this respect that learners who prefer visual learning material (so-called Visualizers) achieve better learning outcomes when learning with visual material (pictures, animations, etc.), while learners who prefer verbal material (Verbalizers) are more successful when learning with verbal material (text; Kirby, Moore, & Schofield, 1988; Leutner & Plass, 1998; Massa & Mayer, 2006; Mayer & Massa, 2003; Pashler, McDaniel, Rohrer, & Bjork, 2008; Richardson, 1977; Riding & Watts, 1997).

A renewed assessment of the meshing hypothesis seems reasonable due to 1) the conflicting opinions on the advantages of matching a learning style with relevant learning materials, and 2) the fact that the meshing hypothesis is still widely accepted in educational scientific areas and practical domains irrespective of the conflicting opinions (Cassidy, 2004; Kirschner, 2017; Pashler et al., 2008). Thus, a closer investigation of the meshing hypothesis under clear experimental conditions is one of the objectives of this research. Via aptitude-treatment interactions, we aim to answer the question of whether matching learning styles and learning materials leads to better learning outcomes.

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Additionally, the genesis of learning styles is a matter of interest in the present paper. It is still controversial if learning styles are fixed, biologically determined, and inflexible dispositions, or if they are dynamic, adaptable, and flexible characteristics (Cassidy, 2004). Another objective of this research is therefore to examine to what extent different cognitive aspects of verbal and visual information processing influence learning in multimedia learning environments. It can be assumed that learning styles are influenced by several external and internal factors, e.g., cognitive resources or the design of learning environments (Alloway, Banner, & Smith, 2011; Riding, Grimley, Dahraei, & Banner, 2003). It is yet to be clarified, however, how spontaneous cognitions influence learning styles and to what extent learners are aware of their own learning styles (Coffield, Moseley, Hall, & Ecclestone, 2004; Kirschner & van Merriënboer, 2013). Against this background, we present a model which 1) assumes an interaction between external and internal factors, and 2) integrates both explicit and implicit processes. To this end, we have developed and applied an adapted implicit learning style test based on the Implicit Association Test (IAT; Greenwald & Banaji, 1995). This measure takes into account possible unconscious processes of cognitive information processing of verbal and visual learning material.

1.1. Objectives and research questions

Consequently, the first main objective of the present paper is to develop and evaluate a learning styles IAT. Accordingly, the first question addresses the following issue:

1) To what extent can implicit attitudes towards text and picture material be demonstrated?

Furthermore, another main goal of the present research is a closer examination of the meshing hypothesis under controlled experimental conditions. This implies the use of aptitude-treatment-interactions (ATI). Thus, the following question is adressed:

2) To what extent can the meshing hypothesis be confirmed when learners are presented with either visual or verbal learning material?

Via a computer-based learning program, presenting either verbal or visual content, the ATI method is applied to answer that question.

2. Learning styles – a new model for a controversially discussed issue

People differ in many ways, including the type of instruction that is assumed to be most suitable for them. This assumption has gained increasing popularity in (multimedia) learning research and practice (Cassidy, 2004; Coffield et al., 2004; Pashler et al., 2008). Individual differences are often summed up in terms like *learning types* (Vester, 1975), *learning styles* (Jonassen & Grabowski, 1993), or *learning preferences* (Mayer & Massa, 2003). These concepts assume that learners cognitively process information presented in different ways differently and/or prefer different kinds of representations of information. A multitude of approaches and taxonomies of learning styles have been described in the literature since research on learning types first started (e.g. Vester, 1975). These often complex and multidimensional approaches frequently include comprehensive questionnaires for assessing learning styles in which learners are asked to review and report their learning habits (e.g. Dunn & Dunn, 1992; Kolb, 1985). Coffield et al. (2004) differentiate five families of learning styles and present them on a continuum (see Fig. 1). This continuum describes to what extent learning styles are seen as biologically determined dispositions with a strong genetic influence or as flexible characteristics with a strong influence of personal and environmental factors. The left side of the continuum presents models which assume that learning styles are fixed dispositions while the right-hand side of the continuum shows models which consider learning styles to be flexible and dynamic strategies.

The discussion around the question of whether learning styles are stable or flexible characteristics is fraught with controversy (Richardson, 2010). While there is some empirical evidence supporting the assumption that learning styles are flexible and dynamic structures, there seems to be less evidence in favor of theories which assume that learning styles are inflexible and biologically

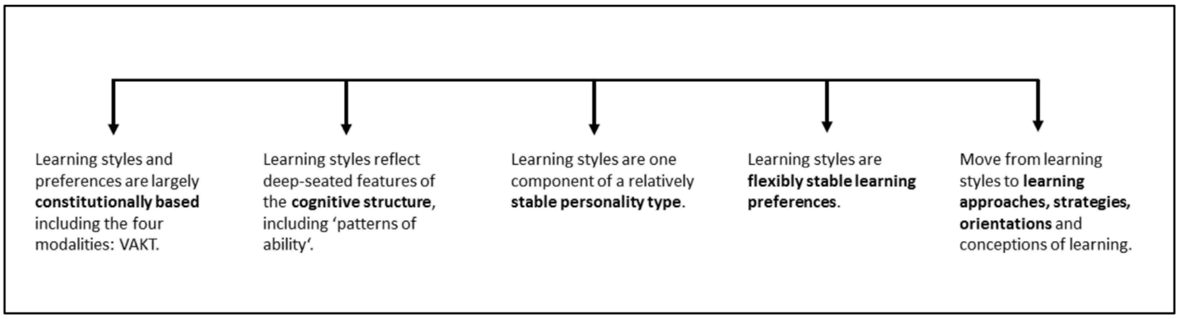

Fig. 1. Families of learning styles (according to Coffield et al., 2004).

determined (Cassidy, 2004; Coffield et al., 2004).

Additionally, it might be problematic to regard learning styles as a trait and, thus "label" learners and put them into a specific category. This might lead to stereotyped behavior. Consequently, learners run the risk of not being able to react adequately in some learning situations. Coffield et al. (2004) emphasize that various external factors can influence and strengthen learning habits, e.g., previous experiences with different kinds of learning material, exchange with other learners or colleagues, behavior of instructors etc. As a consequence, if learning styles and learning success are influenced by different factors, then the question arises to what extent learners are able to reflect their own learning habits. Measures like questionnaires, which include self-reports of learners might be problematic in this regard (Kirschner & van Merriënboer, 2013; Kirschner, 2017; Pashler et al., 2008). Spontaneous, implicit and automatic cognitions, and emotions play a relevant role here. Based on the previous assumptions, below we introduce a model that 1) takes into account both internal and external factors that might influence the genesis of learning styles, and 2) integrates both well-considered attitudes/behaviors and implicitly activated cognitions.

2.1. A Learning Styles Genesis Model

The Learning Styles Genesis Model (LSGM) suggested here describes the development of learning styles as result of a person's repeated confrontation with different learning material and learning situations. It is based on models that also take into account explicit as well as implicit processes within a person's cognitive structure (e.g., the General Aggressive Model; Anderson & Bushman, 2001). The model, to our opinion, does not take into account all aspects of learning, but rather deals with the development of a person's particular learning behavior, i.e., learning styles. While a person is usually in control and aware of explicit processes, implicit processes are automatic, introspectively inaccessible, and people are unaware of them (Greenwald & Banaji, 1995). Based on related literature (e.g., Coffield et al., 2004), we assume that learning styles are influenced by different factors. Thus, the underlying assumption of the LSGM is that learning styles are shaped by learners' experiences in varied learning situations. Generally, the repeated encounter with input material influences a person's internal processing (Anderson & Bushman, 2001). With regard to learning styles, the LSGM (see Fig. 2) thus postulates that there is an interaction between external (e.g., behavior of instructors or design of learning material) and internal factors (internal state of the learners and processing of the learning situation including affect, cognition, arousal) during learning. The internal processing (e.g., particular attitudes or emotions including frustration during learning situations or aversion towards the learning material), in turn, influences appraisal and decisions on how to handle the learning situation. Besides carefully considered thoughts (e.g., evaluating the suitability of specific learning materials for a specific context), the model also takes into account spontaneous cognitions without any context-related thoughts. Thus, the LSGM integrates both explicit and implicit information processing. Previous appraisal and decision processes influence implicit and explicit information processes and emerging behaviors (e.g., the amount of effort learners devote to their learning). Positive or negative learning outcomes resulting from these processes may influence learners' evaluation of future learning situations and related internal processing, and in turn influence prospective learning behavior. Although the LSGM is based on explicit and implicit cognitions, it is important to note that they are not mutually exclusive and neither of the two is the "real" or "true" attitude. We should rather assume that both operate in parallel and interact with each other (Nosek, Greenwald, & Banaji, 2007).

The aforementioned assumptions lead us to question the extent to which implicit and explicit learning processes develop over time. The General Aggression Model (Anderson & Bushman, 2001) assumes long-term effects and changes due to repeatedly experienced situations. In terms of learning styles, such a cyclical process might also lead to a "self-fulfilling prophecy" where previous (positive or negative) learning experiences determine learners' cognitions and attitudes which, in turn, cause similar future learning behavior. This may lead to the development of whole behavioral scripts for specific learning situations. A negative experience with verbal learning material, for example, might lead to a negative attitude towards textbooks. Some similar experiences might lead to a

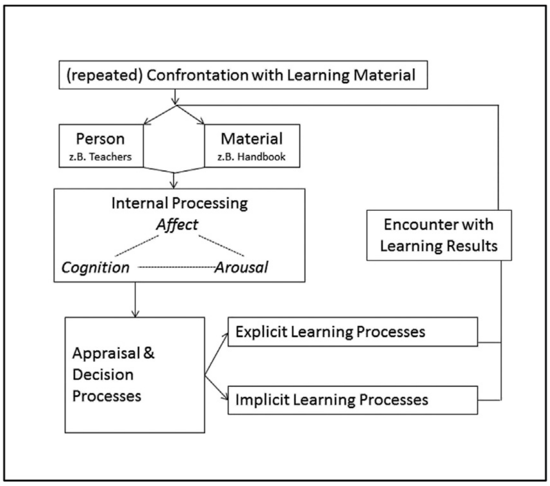

Fig. 2. Learning styles genesis model.

certain kind of self-concept: If a learner thinks he or she performs better when learning with visual learning materials than with verbal materials, this opinion might influence his or her attitudes towards texts in the long run, leading to a lasting negative appraisal of textbooks. This attitude might subsequently lead to low self-efficacy regarding verbal material and lower processing of textual information resulting in lower learning outcomes. These negative learning outcomes would then strengthen the learner's idea of being a visual learner and so on. Explicit and implicit attitudes may change in a relatively short time but only long-term processes result in sustainable change.

Taken together, the above-mentioned processes can foster the adoption of a certain learning behavior. As mentioned before, different kinds of learning styles and learning style families are described in relevant literature. For the purpose of this paper, we focus on an aspect which is closely related to multimedia learning: visual and verbal learning styles.

2.2. Visual and verbal learning styles

Learning styles in multimedia learning frequently focus on the categorization of learners as *Visualizers* and *Verbalizers* (Kirby et al., 1988; Mayer & Massa, 2003; Richardson, 1977; Riding, 1991). The Visualizer-Verbalizer hypothesis states that visual learners, or Visualizers, tend to construct visual (pictorial) mental representations, while verbal learners, or Verbalizers, more often rely on verbal (textual) mental representations (Riding & Watts, 1997). Multimedia learning can support this information processing and facilitate learning by engaging the corresponding senses. Thus, it is assumed that Visualizers prefer visual instruction (pictures, graphics, animations, etc.) while Verbalizers prefer verbal instruction (written or spoken text; Felder, 2010; Kirby, 1993; Mayer & Massa, 2003; Richardson, 1977, Riding & Watts, 1997). These assumptions are based on theories of cognitive psychology that focus on cognitive information processing of different representations of information, e.g. Dual Coding Theory (Paivio, 1971) or Cognitive Theory of Multimedia Learning (Mayer, 2005). A closer examination of visual and verbal learning styles has gained new relevance due to the increasing implementation of new media in educational settings.

Concepts like Richardson's (1977) approach of the Visualizer-Verbalizer dimension, Riding's model (1991), Felder und Silverman's (1988) Index of Learning Styles (ILS), or Fleming and Mills's (1992) VARK-model differentiate between visual and verbal learners. Related research states that visual-verbal learning styles constitute a multi-dimensional concept. In a comprehensive study, Mayer and Massa (2003) describe three facets of verbal and visual learners within a comprehensive study: 1) cognitive ability, 2) cognitive style, and 3) learning preference (see also Astwood, Landsberg, Mercado, & Van Buskirk, 2011). Choi and Sardar (2011) have demonstrated a relation between these dimensions: greater spatial abilities predicted a visual learning style which, in turn, predicted visual learning preferences. Higher verbal capacities (vocabulary tasks) correlated with a higher possibility for a verbal cognitive style but did not correlate with higher verbal learning preference.

The above leads to the assumption that matching learning styles and learning environments should lead to better learning outcomes. Current empirical findings related to the meshing hypothesis are, however, inconsistent and contradictory (see also Kirschner, 2017). Some research confirms this assumption (Chen & Sun, 2012; Kirby et al., 1988; Pazzaglia & Moè, 2013; Riding & Ashmore, 1980; Riding & Douglas, 1993; Thomas & McKay, 2010). On the other hand, some researchers' results confirmed the hypothesis only in part (Höffler, Prechtel, & Nerdel, 2010; Leutner & Plass, 1998; Mehigan, Barry, Kehoe, & Pitt, 2011; Mendelson & Thorson, 2004; Plass, Chun, Mayer, & Leutner, 1998; Schofield & Kirby, 1994). Finally, some authors even disproved the assumptions of the meshing hypothesis (Constantinidou & Baker, 2002; Homer, Plass, & Blake, 2008; Jaspers, 1994; Jonassen & Grabowski, 1993; Kollöffel, 2011; Massa & Mayer, 2006; Ozier, 1980).

With regard to common ways of differentiating between Verbalizers and Visualizers, one can find subscales in more general and comprehensive learning styles questionnaires, e.g. VARK (Fleming & Mills, 1992), but also questionnaires specifically tailored to the Verbalizer-Visualizer dimension, e.g. VVQ (Verbalizer-Visualizer Questionnaire; Richardson, 1977; Kirby et al., 1988) or the SBLSQ (Santa Barbara Learning Styles Questionnaire; Mayer & Massa, 2003). All of these questionnaires group learners according to their self-reported visual or verbal learning styles. Computer-assisted methods have been developed to categorize learners while reducing reliance on self-reports. The CSA (Cognitive Styles Analyses; Riding, 1991), for example, records the time learners need to solve several verbal and visual tasks and assesses differences between them. However, this method seems to be problematic in terms of its reliability (Peterson, Deary, & Austin, 2003) and validity (Massa & Mayer, 2005). Leutner and Plass (1998) reported greater success in predicting learning outcomes by using the Visualizer/Verbalizer Behavior Observation Scale (VV-BOS). Methods using observation of learners during learning were, however, unable to predict underlying cognitive or motivational processes. According to the LSGM, implicit processes might be involved in the development of learning styles. Subconscious preferences, attitudes, affects, and emotional states play a role in learning behavior. Thus, besides explicit methods, implicit measures are also relevant in order to paint a comprehensive picture of the development of learning styles. One of the goals of the present work is to develop a method that categorizes visual and verbal learners without being dependent on self-reports of learners, and measures cognitive and/or affective attitudes. A frequently used method of measuring implicit information processing is the Implicit Association Test (IAT; Greenwald, McGhee, & Schwartz, 1998).

3. Measuring implicit attitudes

One of the most prominent methods of assessing implicit information processing is the Implicit Association Test (IAT). The IAT was introduced in 1998 by Greenwald, McGee and Schwarz in order to measure and examine individual differences in implicit cognition. The theoretical rationale for the IAT is grounded in the concept of spreading activation as described in the Activation Theory of Semantic Processing (Collins & Loftus, 1975). This theory assumes that many mental concepts are connected with each other. Thus, the activation of one mental concept will in turn lead to the activation of closely related mental concepts. The IAT is a priming method based on reaction time measurement that assesses automatically activated associations between mental representations of memorized concepts. During the IAT procedure, participants are asked to assign stimuli to dichotomous categories. Closely related categories lead to faster performance than unrelated categories. The stronger the categories are mentally connected, the faster the performance should be: "[…] if two concepts are highly associated, the IAT's sorting tasks will be easier when the two associated concepts share the same response than when they require different responses" (Greenwald & Nosek, 2001, p. 85). The difference in reaction times indicates the relative strength of associations (IAT effect).

Implicit attitudes can sometimes predict behavior in a more reliable way than self-reported attitudes as a person might lack the ability to introspect correctly (Brunel, Tietje, & Greenwald, 2004). Furthermore, both emotional and cognitive aspects can be accessed using the IAT (Blümke & Friese, 2006; Fiedler, Messner, & Blümke, 2006). Thus, the IAT is used for various reasons: "[…] it can be adapted to measure positive or negative associations about any types of concepts" (Smith & Nosek, 2010, S. 804).

The IAT is a method that is used in various fields of research such as social psychology or cognitive psychology, e.g., in relation to self-concept, prejudice, or stereotypes. In addition to emotional concepts, it also permits the assessment of cognitive associations (Blümke & Zumbach, 2007). Smith and Nosek (2010) point out that the IAT "[…] can be adapted to measure positive or negative associations about any types of concepts" (Smith & Nosek, 2010, p. 804). A classic application of the IAT is the assessment of race preferences (Greenwald et al., 1998).

One advantage of using the IAT in order to measure learning styles is that it allows us to examine whether some learning materials provoke positive or negative reactions learners might not be aware of. Thus, implicit measurement of learning styles in addition to explicit measurement might provide a more comprehensive overview of a person's learning preferences. Within the present research, we assessed learners' implicit and explicit learning preferences. Furthermore, we provided either visual or verbal learning material in order to address the meshing hypothesis. In addition to a closer examination of learning outcomes, cognitive load will also be assessed in relation to learning styles and learning materials.

4. Method

The following chapter describes the development, application, and assessment of the learning styles IAT as well as the examination of the relation between learning styles and learning outcomes via ATI.

4.1. Participants and design

Via aptitude-treatment interactions (Cronbach & Snow, 1977), we aim to investigate the influence of learning styles (measured both explicitly and implicitly) on learning outcomes and cognitive load. As independent variable, we varied the codality of information (visual or verbal computer-based learning environment). Dependent variables are learning outcomes, cognitive load, and mental effort. Learning style as well as pre-knowledge were included as co-variates. Participants were 126 Austrian university students (85 female students, 28 males, 13 students did not report gender) aged between 19 and 66 years ($M = 25.17$; $SD = 6.96$).

4.2. Material

4.2.1. Explicit measurements

We used two explicit self-report measurement methods to identify participants' learning styles: the Verbal-Visual Learning Styles Questionnaire (VVQ revised; Kirby, Moore, & Schoenfeld, 1988; Mayer & Massa, 2003; Richardson, 1977) and the Santa Barbara Learning Styles Questionnaire (SBLSQ; Mayer & Massa, 2003). Both questionnaires were administered online. The VVQ consists of ten items related to verbal information processing (e.g., "I enjoy work that requires the use of words") and ten items related to visual information processing (e.g., "I find maps helpful in finding my way around a new city"). Participants indicated agreement or disagreement with the statements on a 7-point Likert scale (1 = totally disagree, 7 = totally agree). Both subscales showed acceptable internal consistency ($\alpha = 0.69$ for the verbal subscale and $\alpha = 0.73$ for the visual subscale). The SBLSQ consists of six items related to the individual's personal perception of his or her own learning styles (e.g., "I am a visual learner"). Again, participants used a 7-point Likert scale for agreement or disagreement. The subscales showed high internal consistency ($\alpha = 0.80$ for the verbal subscale and $\alpha = 0.83$ for the visual subscale). Mean values for visual items were subtracted from mean values for verbal items in each questionnaire and participants were categorized accordingly (see also Mayer & Massa, 2003). Participants needed a maximum of 15 min to make their statements.

4.2.2. The implicit association test

In order to determine participants' implicit learning styles, we developed and applied a learning styles IAT (Greenwald et al., 1998). Within the scope of this procedure, participants do not make explicit self-reports but perform a latency-based computer-supported sorting-task. It allows assumptions about a person's implicit attitudes or cognitions that exist outside of conscious awareness or control and that accumulate through everyday experiences (Smith & Nosek, 2010). With regard to visual and verbal learning styles, such concepts may exist for visual and verbal learning material due to the associative mental network created.

4.2.2.1. Evaluation of the visual material used for the IAT. The IAT procedure requires distinctive visual stimulus material (Nosek et al., 2007). It was therefore important to choose appropriate examples for each IAT category. We developed and evaluated new stimulus material for the learning styles IAT, consisting of either predominantly pictorial or predominantly verbal content. The stimulus material (21 slides) used in this study varied in textual and visual content. To avoid affective reactions to the pictorial material, we used pictures from the International Affective Picture System (IAPS; Lang, Bradley, & Cuthbert, 2008) which were deemed neutral in terms of their ability to evoke positive or negative emotions. As texts can likewise provoke different affective reactions (Bradley & Lang, 2007), we used a short dummy text in order to avoid distraction from the essential task. To ensure the distinctiveness of our materials, we conducted a pre-study. 164 participants (142 women, 20 men; mean age: 24.46 years; $SD = 6.35$) were asked to rate the stimulus material on semantic differential scales for three aspects: 1) content (textual or pictorial), 2) difficulty (hard or easy to learn), and 3) degree to which hypothetical learning success with the slides would be attributable to the learning material (external attribution) or to the learners' own learning efforts (internal attribution). Furthermore, participants reported on their learning styles using the VVQ ($\alpha = 0.69$ for the verbal subscale; $\alpha = 0.64$ for the visual subscale) and the SBLSQ ($\alpha = 0.80$ for the verbal subscale; $\alpha = 0.83$ for the visual subscale). Due to the large volume of slides available, participants were randomly assigned to one of two versions of the online-questionnaire, each containing about half of the slides in order to keep the time frame adequate (version 1: $n = 82$; version 2: $n = 82$; participants took about 30 min to fill in the questionnaires).

1) Textual and pictorial material:

We carried out a principal component factor analysis with varimax rotation (questionnaire version 1: KMO = 0.75, Bartlett's = 0.000; questionnaire version 2: KMO = 0.81, Bartlett's = 0.000). The stimuli were divided into textual and pictorial categories. Slides with more than 50% pictorial content were assigned to the pictorial category, slides with more than 50% textual information were assigned to the textual group. The slides were integrated into the IAT as dichotomous categories – text and picture material. We found no significant differences between Verbalizers and Visualizers in this evaluation (VVQ version 1: $F(1,80) = 1.08$, $p = .120$, $\eta^2 = 0.03$; SBLSQ version 1: $F(1,70) = 0.02$, $p > .05$, $\eta^2 = 0.00$; VVQ version 2: $F(1,71) = 1.31$, $p > .05$, $\eta^2 = 0.02$; SBLSQ version 2: $F(1,63) = 0.06$, $p > .05$, $\eta^2 = 0.00$).

2) Appraisal

Again a principal component factor analysis with varimax rotation was computed (questionnaire version 1: KMO = 0.86, Bartlett's = 0.000; questionnaire version 2: KMO = 0.77, Bartlett's = 0.000). Results showed that textual material was rated as rather difficult to learn, while visual material was rated as easier to learn. Significant differences between Verbalizers and Vizualizers were found (VVQ version 1: $F(1,80) = 8.49$, $p = .005$, $\eta^2 = 0.10$; SBLSQ version 1: ($F(1,70) = 14.66$, $p < .001$, $\eta^2 = 0.17$; VVQ version 2: ($F(1,71) = 15.02$, $p < .001$, $\eta^2 = 0.18$; SBLSQ version 2: ($F(1,63) = 6.42$, $p = .054$, $\eta^2 = 0.06$). Visualizers rated text slides as harder to learn than Verbalizers, while Verbalizers rated pictorial material as slightly harder to learn than Visualizers.

3) Internal and external attribution of learning success

A principal component factor analysis with varimax rotation (questionnaire version 1: KMO = 0.88, Bartlett's = 0.000; questionnaire version 2: KMO = 0.89, Bartlett's = 0.000) showed for pictorial material that participants attributed learning success to the learning material, while learning success for textual material was attributed to participants' own learning efforts. No differences were found between Verbalizers and Visualizers (VVQ version 1: $F(1,80) = 0.12$, $p = .727$, $\eta^2 = 0.00$); SBLSQ version 1: $F(1,70) = 0.41$, $p > .05$, $\eta^2 = .01$; VVQ version 2: $F(1,71) = 1.49$, $p > .05$, $\eta^2 = 0.02$; SBLSQ version 2: $F(1,63) = 0.46$, $p > .05$, $\eta^2 = 0.01$).

The above described evaluation reveals that the slides can be used during the IAT procedure as they represent two dichotomous categories (textual and pictorial material). Additionally, no differences regarding this categorization between Visualizers and Verbalizers were found. This is important as differences in perception possibly could result in biases during the IAT procedure. The results of the pre-study further indicate that there might be differences between Verbalizer and Visualizer regarding the appraisal towards the learning material, which in turn might lead to different learning behavior as previously stated in the LSGM.

4.2.2.2. The IAT procedure. The IAT reveals individual preferences via the interpretation of differences in reaction times related to the activation of associations between mental concepts. The test uses examples (stimuli) of dichotomous categories participants must sort as fast as possible using two response keys on a keyboard. During the initial training tasks, stimuli of two dichotomous target categories or two dichotomous attribute categories appear on screen and participants are asked to rapidly classify them by pressing one of the two related keys. Double-discrimination tasks require participants to sort stimuli into the according target categories and the attribute categories, respectively. It is assumed that congruent tasks, i.e., categories participants evaluate as highly related, can be solved faster than incongruent tasks, i.e., concepts participants evaluate as different. This means that it is easier for participants to classify two strongly related concepts via one keyboard key than two unrelated concepts. As a result, the IAT effect, i.e., the difference between congruent and incongruent tasks, allows us to draw conclusions about spontaneous, automatic, or unconscious processes. In our case, during the learning styles IAT procedure, participants are asked to sort the stimulus materials of the target categories, i.e., verbal or textual material, and attribute materials, i.e., positive or negative words, according to their characteristics, via keyboard keys. Participants assign all stimuli to their respective categories in five sequences. In sequences 3 and 5, target and attribute categories appear at the same time, i.e., if two connected categories share the same key, then a faster reaction is to be expected than if two unconnected categories shared one key. Faster responses when pairing “text” and “positive” (or “picture” and “negative”) than when pairing “text” and “negative” (as well as “picture” and “positive”) therefore indicate a greater association of a more positive valuation with textual material than with pictorial material. This is called the IAT effect. The sequence of congruent and incongruent conditions is crucial for the interpretation of the IAT effect (Gawronski & Conrey, 2004). As participants in the pre-study predominantly reported to be visual learners, we assumed the condition of "picture/positive and text/negative" to be the congruent condition and presented it in sequence 5. Participants with negative IAT effect values were classified as visual learners, participants with positive values were assumed to be verbal learners. The IAT showed acceptable internal consistency (α = 0.74). On average, participants completed the IAT within 10 min.

4.2.3. Educational software: "plate tectonics"

A key aim of this research was to test the meshing hypothesis in more detail by means of aptitude-treatment interactions. For this purpose, we designed and applied computer-based instructional multimedia material that was presented to participants either in a predominantly visual version (mostly pictures) or in a predominantly verbal version (mostly text). Participants were randomly assigned to either the visual or verbal version until we could find at least 20 persons of each learning style working with the verbal or the visual program. The computerbased learning program is about plate tectonics as this topic lends itself to presenting varied information both visually and by means of text. Following a general introduction to plate tectonics, the program provides information about the development of the theory, earth's internal structure, types of plate boundaries, continental thrift, and driving forces as well as consequences of plate motion. Furthermore, volcanism is addressed and a link between natural catastrophes like earthquakes and plate motion is established. Wherever possible, this information is presented either via pictures or via text. In the visual version, aspects of effective multimedia presentation are taken into account (e.g. spatial contiguity of pictures and related text, see Mayer, 2009). Learners can work through the program at their own pace by clicking on the 'next page' or 'previous page' buttons (learning time: 15 min). In order to achieve a certain level of interactivity, the program further allows learners to display information by clicking on several predefined buttons.

4.2.4. Knowledge test

Knowledge related to plate tectonics was assessed via paper-based pre- and post-tests. The test consisted of 13 multiple choice questions and five open questions. The questions of the knowledge test were related to the information presented either visually or verbally. One point was awarded for correct answers to the multiple choice questions, two to four points were awarded for the open questions. Overall, participants could reach 27 points. Increase in knowledge was assessed by computing the difference between the pre- and the post-test. On average, participants needed 10–15 min to complete the test.

4.2.5. Cognitive load and mental effort measures

In order to assess cognitive load as well as perceived mental effort, two short paper-based questionnaires were used after the learning phase: NASA-TLX (Task Load Index; Hart & Staveland, 1988) and Mental Effort Rating Scale (MERS; Paas & van Merriënboer, 1994). The NASA-TLX measures cognitive load via six statements relating to the dimensions of mental demand, physical demand, temporal demand, performance, effort, and frustration level. Participants indicated their agreement or disagreement with the statements on a 5-point Likert scale (1 = totally disagree, 5 = totally agree). After analyzing its reliability, we excluded the performance item and the remaining five items achieved an internal consistency of α = 0.75. For further analysis, we recoded the items in such a way that higher values indicated a higher load. An adapted version of the MERS with two (instead of one) statements was used by participants to report on the amount of effort made during learning (5-point Likert scale; 1 = no effort at all, 5 = very high effort). The internal consistency was $\alpha = 0.73$. It took participants a maximum of 5 min to make their statements.

4.3. Procedure

The study took place in the university's media lab, which is equipped with six computers. Following a welcome and a short introduction, participants filled in the online versions of the self-report measures on learning styles, the VVQ, and the SBLSQ before taking the knowledge pre-test. Then the implicit measurement (IAT) was applied. For the learning program, participants were randomly assigned to either the visual or the verbal version, and spent about 15 min working with the program. After the learning phase, participants completed the knowledge post-test, and the questionnaires related to cognitive load and mental effort.

5. Results

5.1. Relation between implicit and explicit measures

According to the results, most participants regarded themselves as visual learners. The VVQ classified 82 people as Visualizers, 42 people as Verbalizers, and two people with no difference on the subscales. The SBLSQ categorized 73 Visualizers, 40 Verbalizers and 13 participants with no difference on the subscales. The IAT resulted in 70 Visualizers, 47 Verbalizers, and nine missing values.

Relations between explicit and implicit measurements were examined via a two-sided correlation analysis according to Pearson. The results showed a mediocre relation between VVQ and SBLSQ ($r = 0.43$, $p < .001$). The IAT (operationalized as IAT effect) slightly but significantly correlated with the VVQ ($r = 0.20$, $p = .031$). No correlation was found for IAT and SBLSQ ($r = 0.05$, $p = .576$).

Table 1
Means of independent variables.

	Minimum	*Maximum*	*M*	*SD*	*N*
NASA-TLX	1.50	4.60	2.94	0.78	126
MERS	1.50	5.00	3.59	0.77	126
Pre-test	0.00	19.00	7.81	4.56	126
Post-test	8.00	26.00	18.73	3.25	126
Knowledge growth	2.00	20.50	10.91	3.99	126

5.2. Correlations between dependent variables

On average, participants achieved 7.81 ($SD = 4.56$) points in the knowledge pre-test and 18.73 ($SD = 3.25$) in the knowledge post-test (see Table 1). This difference is significant ($t(125) = -30.68$, $p < .001$). Thus, participants showed an average increase of 10.91 ($SD = 3.99$) points from pre-test to the post-test.

There was a significant correlation between the pre- and the post-test ($r = 0.52$, $p < .001$; see Table 2). Furthermore, knowledge growth correlated with prior knowledge ($r = -0.72$, $p < .001$), indicating that deeper prior knowledge led to greater knowledge growth. Additionally, knowledge gain correlated significantly with MERS ($r = 0.18$, $p = .039$) but not with NASA-TLX ($r = 0.01$, $p = .880$). Thus, higher mental effort resulted in greater learning success, while higher cognitive load had no effect. Mental effort showed a weak correlation with cognitive load ($r = 0.20$, $p = .025$). The correlation between cognitive load (NASA-TLX) and the knowledge post-test was negative ($r = -0.25$, $p < .001$), that with mental effort (MERS) was positive ($r = 0.19$, $p = .037$).

5.3. Influence of learning styles on learning outcomes and learning behavior

Descriptive differences in terms of knowledge acquisition are shown in Table 3. These results reveal that Visualizers and Verbalizers benefit more from the verbal program than from the visual program, regardless of their assumed learning style and learning style measure.

The descriptive values reveal that the assumptions of the meshing hypothesis were only confirmed by the VVQ questionnaire and only for Verbalizers. In order to test the meshing hypothesis for significant differences, analyses of variances were computed to identify interaction effects between learning style and learning material. Contrary to the assumptions of the meshing hypothesis, no significant interactions were found between the different learning style measures and the learning material for the knowledge post-test and cognitive load as measured via the NASA-TLX and MERS (VVQ: $F(3,89) = 0.22$, $p = .881$; SBLSQ: $F(6,180) = 1.15$, $p = .337$; IAT: $F(3,89) = 0.22$, $p = .882$). Descriptive values for cognitive load and mental effort are presented in Table 4.

In order to verify whether learning styles might act as mediator variables for knowledge acquisition, a repeated measurement MANCOVA was computed with the codality condition (verbal or visual) as an independent variable. In addition, the results of NASA-TLX, MERS, and increase in knowledge, operationalized as the difference between the knowledge post- and pre-test, were used as dependent variables. With regard to learning styles, the results from the VVQ, SBLSQ, and IAT scores were included as co-variates to verify whether there was any significant influence of learning styles on learning outcomes.

The results of the MANCOVA showed no significant main effect of the treatment ($F(3,107) = 1.81$, $p > .05$, $\eta^2 = 0.03$). Furthermore, no significant influence was found regarding learning styles (VVQ: $F(3,107) = 0.85$, $p > .05$; $\eta^2 = 0.02$; SBLSQ: $F(3,107) = 0.88$, $p > .05$, $\eta^2 = 0.02$; and IAT ($F(3,107) = 1.12$, $p > .05$, $\eta^2 = 0.03$). Only prior knowledge showed a significant influence ($F(3,107) = 43.97$, $p = .00$, $\eta^2 = 0.55$). This influence relates to cognitive load, but with a low effect size ($F(1,109) = 3.45$, $p = .03$, $\eta^2 = 0.03$), and to the results for knowledge growth ($F(1,109) = 112.73$, $p = .00$, $\eta^2 = 0.27$). No significant influence of prior knowledge was found by means of the MERS ($F(1,109) = 0.16$, $p > .05$, $\eta^2 = 0.00$).

Finally, a multiple regression analysis was performed in order to examine those factors which significantly predict learning outcomes. Knowledge gain was included as an endogenous variable and the results of the pre-test, VVQ, SBLSQ, IAT, as well as NASA-TLX and MERS were included as exogenous variables. After a Boxplot analysis, 12 persons were excluded as outliers and 114 participants were included in a regression analysis. The results reveal an explanation of variance of 59% ($R^2 = 0.59$, $F(6,114) = 26.16$, $p = .000$). Prior knowledge, MERS, and NASA-TLX showed significant influence on knowledge acquisition (Prior knowledge and NASA-TLX showed a negative influence on knowledge gain). The learning style measurements (VVQ, SBLSQ, and IAT)

Table 2
Correlations between scales (correlation coefficient r).

	NASA-TLX	MERS	Knowledge growth	Pre-test	Post-test
NASA-TLX	1	.20*	.01	-.19*	-.25**
MERS		1	.18*	-.03	.19*
Knowledge growth			1	-.72**	.22*
Pre-test				1	.52**
Post-test					1

Level of significance: *$p < .05$; **$p < .01$.

Table 3
Means (and standard deviations) of knowledge post-test for Visualizers and Verbalizers according to the different learning style measurements and learning conditions.

		Visual program	Verbal program
VVQ	Visualizer	18.66 (3.80)	18.77 (3.18)
	Verbalizer	18.12 (2.58)	19.35 (2.75)
SBLSQ	Visualizer	18.92 (3.76)	19.07 (2.96)
	Verbalizer	17.40 (2.10)	18.97 (2.90)
IAT	Visualizer	18.41 (3.17)	18.90 (2.98)
	Verbalizer	19.07 (3.72)	19.15 (3.15)

Table 4
Means (and standard deviations) of cognitive load for Visualizers and Verbalizers according to the different learning style measurements and learning conditions.

		NASA-TLX		MERS	
		Visual program	Verbal program	Visual program	Verbal program
VVQ	Visualizer	3.00 (0.84)	2.88 (0.72)	3.62 (0.74)	3.53 (0.85)
	Verbalizer	3.02 (0.72)	2.74 (0.82)	3.62 (0.84)	3.57 (0.66)
SBLSQ	Visualizer	2.96 (0.79)	2.88 (0.72)	3.59 (0.81)	3.46 (0.86)
	Verbalizer	3.07 (0.75)	2.73 (0.87)	3.50 (0.65)	3.68 (0.69)
IAT	Visualizer	3.07 (0.77)	2.95 (0.81)	3.73 (0.71)	3.60 (0.66)
	Verbalizer	2.86 (0.82)	2.86 (0.67)	3.46 (0.88)	3.50 (0.90)

did not predict learning outcomes. Detailed values are presented in Table 5.

6. Discussion

The first aim of the present study was to develop and apply a new implicit learning style measurement, i.e., a learning styles IAT related to the Verbalizer-Visualizer dimension. To this end, we took a closer look at the relationship between explicit and implicit learning style measures. Secondly, we intended to shed light on the controversy around the meshing hypothesis, which states that Verbalizers achieve better learning outcomes with verbal materials, while visual learners achieve better learning outcomes with visual materials. In order to do so, we developed both a visual and a verbal computer-based learning program, and used aptitude-treatment interactions for analysis.

In a first study (see section 5.2.2.1), we developed and evaluated the stimulus materials for the IAT. No differences between self-reported Verbalizers and Visualizers were found in terms of the categorization of visual and verbal material. Thus, we were able to use the materials further in order to assess participants' implicit positive or negative reactions towards our learning material in a second study. The test showed acceptable internal consistency. For external validation, two standard explicit questionnaires (VVQ and SBLSQ) were applied, and relations between implicit and explicit questionnaires were examined. A small but significant correlation was found between the IAT and the VVQ, but not between the IAT and the SBLSQ. This was attributable to the different notions of the two explicit questionnaires. The SBLSQ requires participants to make clear statements about their learning styles ("I am a verbal learner"), while the VVQ mostly asks about habits and/or feelings when dealing with multimedia material ("I enjoy work that requires the use of words"). Thus, the level of explicitness in the statements with regard to visual and verbal learning styles seems to be different between the questionnaires: The SBLSQ requires absolute statements, while the VVQ requires relative ones. This difference in conceptual correspondence between the two explicit measures and the IAT might lead to different results regarding the correlation with implicit measures (Hofmann, Gawronski, Gschwendner, Le, & Schmitt, 2005). We assume that learning styles represent cognitive processes according to Mayer and Massa (2003), but are nevertheless contextual and flexible like preferences. According to the LSGM, these dimensions cannot be clearly separated. However, learning preferences seem to be more easily

Table 5
Results of multiple regression analysis.

	B	SE	β
Pre-test	-.65	.06	-.74**
MERS	.99	.34	.18**
NASA_TXL	-.81	.35	-.15*
SBLSQ	.02	.03	.06
VVQ	-.02	.05	-.02
IAT	.00	.00	.10

Level of significance: *$p < .05$; **$p < .001$.

accessible and describable for a person. The VVQ relates to both cognitive processes during learning and preferences of learning material. Participants are more likely to be able to make statements related to their learning preferences than about their cognitive processing. Additional correlations with other explicit measures would be of advantage in future studies.

The results further indicate that both explicit (related to a person's experiences) and implicit (subconscious) learning styles exist within a person. These results are consistent with the assumptions of Nosek (2007) that both explicit and implicit cognitions are part of a person's cognitive structure, and are unlikely to show total congruence. In addition, this confirms the assumptions of the LSGM that both explicit and implicit information processing take place during learning.

However, correlations between explicit and implicit measures are rather difficult to interpret. Weak correlations between both kinds of measures, as found in the present study, are quite usual because the IAT assesses automatic mental associations that are difficult to gage with explicit self-report measures (Bluemke & Zumbach, 2012; Hofmann et al., 2005). Furthermore, the discussion whether explicit and implicit measures refer to two distinct or similar constructs is fraught with controversy (Greenwald et al., 1998, 2003). We assume in this respect that the differences between implicit and explicit measures of learning styles might be due to a number of reasons: First of all, the above-mentioned differences between cognitive processing and learning preferences could be a potential cause for low correlations. Greater conceptual correspondence between explicit and implicit measures leads to stronger correlations (Hofmann et al., 2005). Another explanation can be seen in the influence of moderating variables, e.g., the ability or motivation of participants to control and introspect their own attitudes and/or behaviors (Gawronski & Conrey, 2004). Subsequent investigations might also take into account motivational factors and other aspects that influence learning processes, e.g., self-efficacy.

In the course of the second investigation, we also examined the meshing hypothesis. Participants were randomly assigned to either a visual or a verbal computer program on plate tectonics. Knowledge was assessed via pre- and post-tests, cognitive load and mental effort were assessed after learning. Knowledge acquisition in the post-test showed strong correlations with prior knowledge, which is in line with prior research (Hattie, 2009; Kalyuga, 2007). Analyses of variance lead to the rejection of the meshing hypothesis. Visual learners did not achieve greater learning success when learning with a visual computer program and verbal learners did not achieve better learning outcomes when learning with verbal material. Learning styles as co-variates also showed no significant influence on learning outcomes. What is more, no differences in cognitive load and mental effort were found. Thus, no interaction between learning style and cognitive performance was found (e.g., Alloway et al., 2011; Riding et al., 2003).

These findings support research on the meshing hypothesis that could not find any advantages of matching learning style and learning material (e.g., Constantinidou & Baker, 2002; Kirschner, 2017; Pashler et al., 2008). Massa and Mayer (2006) concluded in their study: “There was no strong support for the hypothesis that verbal learners and visual learners should be given different kinds of multimedia instruction” (p. 1). We consider a possible compensatory effect that might come into play here (Salomon, 1979). Deficient verbal or visual abilities might be counterbalanced through the presentation of such kinds of information. Furthermore, these results support the idea of flexible learning styles. Individuals seem to apply the strategies that are required by the task (see Constantinidou & Baker, 2002; Richardson, 1977). In relation to the above, Cassidy (2004) states: “[…] that the structure is, to some degree, responsive to experiences and the demands of the situation (process) to allow change and enable adaptive behavior” (p. 421).

Regression analysis supports these findings. Prior knowledge, cognitive load, and mental effort are significant predictors for knowledge acquisition. Learners with rather low prior knowledge or low cognitive load showed higher knowledge gain. What is more, greater mental effort led to greater knowledge gain. Learning styles did not show significant effects on knowledge gain.). This is in line with statements such as Kollöffel’s (2011) assumption that learners should not choose learning materials according to their learning style as other factors have a greater influence on learning success (see also Ford & Chen, 2001 or; Muijs & Reynolds, 2005).

These findings support the ideas of the LSGM related to the genesis of learning styles as flexible and adaptive characteristics. The LSGM takes into account many context- and person-related factors that play a role here. However, several limitations of the present research must be addressed. First of all, the learning task at hand might have influenced the above-mentioned results. Advantages of matching learning styles and learning material might be more obvious in transfer tasks than in retention tasks as used in the present study (see Riding et al., 2003). Furthermore, the sample size used was rather small and the gender distribution was not equal. However, we included at least 20 Verbalizers and Visualizers for each condition (measured by each of the instruments), which represents an adequate number of participants overall. In addition, we investigated a rather short intervention. A longer learning intervention might lead to a higher impact on learning outcomes. We did not investigate long-term effects that result from feedback about the learning outcomes, etc., either. However, the present study represents a sound analysis and valuable steps towards answers to open questions related to the genesis of learning styles and their impact on learning outcomes.

7. Conclusion

In line with the findings of the present paper, we may assume that both explicit and implicit measures allow for a distinction between verbal and visual learning styles. This is in accordance with the Verbalizer-Visualizer hypothesis of Massa and Mayer (2006). However, neither explicit nor implicit measurements show prognostic validity with regard to learning outcomes. Learning styles seem to have no impact on knowledge acquisition, cognitive load, or mental effort. Given these results, the findings are in accordance with claims against the use of learning styles in educational practice, e.g., “[…] there presently is no empirical justification for tailoring instruction to students' supposedly different learning styles” (Rohrer & Pashler, 2012, p. 636) or “[…] there is quite a difference between the way that someone prefers to learn and that which actually leads to effective and efficient learning” (Kirschner, 2017, p. 1). The findings of our study make an important contribution to basic research in the area of multimedia learning: It is yet to be examined whether learning styles are flexible or stable characteristics (Cassidy, 2004; Richardson, 2010). With the LSGM, we present an approach that rejects the assumption of stable characteristics in favor of flexible and changeable characteristics. External factors are taken into account in a cyclic process that can affect implicit and explicit learning style beliefs. Within this study, visual and verbal learning styles were investigated, as they represent a basic and clear example of different styles. Although the LSGM represents a general approach, relations with other kinds of learning styles should be investigated further and a closer look should be taken on external factors and long-term effects.

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