How the design and complexity of concept maps influence cognitive and motivational learning processes

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Abstract

Concept Maps are assumed to enhance learning as their inherent structure makes relations between information more salient. Nevertheless, research on how to design concept maps as conducive to learning as possible is still rare. In particular, the salience of spatial arrangement of thematically related concepts within the map as well as the complexity of the map were found to be central design elements that influence learning. This study aimed to examine how the structure (i.e., the salience of the spatial relationship between individual concepts) and the complexity (number of nodes per sub concept) influence learning. Accordingly, a 2 (low vs. high salience of map structure) x 2 (few vs. many nodes) between-subject design was used (N = 122) to measure cognitive and motivational processes. No significant learning and motivation group differences were found. Concepts maps with a low salience of map structure increased perceptions of disorientation. A serial mediation with the learning performance as a dependent variable revealed that the salience of the map structure is significantly associated with disorientation and extraneous cognitive load perceptions. By this, current attempts to measure extraneous cognitive load are questioned.

1 Introduction

When learning complex information, it is primarily important to be able to transfer the various components into a coherent model. When learners struggle to create such relations mentally, learning may be hindered. In particular, learners with rather low prior knowledge often need further help to internalize knowledge which consists of interconnections. Hereby, different instructional methods offer the possibility to structure and present information in an easy-to-understand way. One way to organize knowledge hierarchically in a rather simple and compact way are concept maps (Cañas et al., 2015; Novak, 1990). In contrast to texts, concept maps represent visualized relationships between thematically-related information units. Therefore, the aim of this study was to gain deeper insights into how the salience of the map structure and the number of nodes per sub concept affect cognitive and motivational processes.

1.1 Learning with Concept Maps

A concept map is defined as “a node-link diagram in which each node represents a concept and each link identifies the relationship between the two concepts it connects” (Schroeder et al., 2018, p. 431) while concepts are illustrated in boxes or oval-shaped forms (Novak et al., 2008). To specify the relationship between two or more concepts, connecting lines are used that can be labeled to further define this connection (Cañas et al., 2015). For instance, the concepts “Facebook” and “Mark Zuckerberg” could be linked with the label “founded by”. The modern idea to structure information in a concept map originates from Novak and colleagues in the 1970s (Novak & Gowin, 1984). In the literature similar designations like knowledge maps (O’Donnell et al., 2002), node-link maps (Blankenship & Dansereau, 2000), or mind mapping (Buran & Filyukov, 2015) can be found which deal with the graphical representation of information. Theoretical foundations for the benefit of concept maps can be found in the *assimilation theory of meaningful learning* (Ausubel, 1963). In line with this cognitive theory, meaningful learning only occurs when new ideas and concepts are integrated into already existing knowledge structures (see also Kalyuga, 2009). Since then, concept maps have been examined in numerous learning settings to determine the extent to which they offer an advantage over comparable instructional methods.

The learning-promoting effect of concept maps is meta-analytically supported (Nesbit & Adesope, 2006; Schroeder et al., 2018). In a recent meta-analysis by Schroeder and colleagues (2018), the learning-beneficial effect could be confirmed with a moderate effect size ($g+ = 0.58$). Hereby, creating concept maps ($g = 0.72$) offered a bigger benefit for learning than studying concept maps ($g = 0.43$). Concept maps can be seen as an effective learning strategy for two main reasons (Schroeder et al., 2018): First, concept mapping promotes meaningful learning. In line with Kalyuga (2009), integrating and organizing new elements into the learner's knowledge structures can be defined as knowledge elaboration. This process is supported by the inherent structure of concept maps. Therefore, the concept and sub-concept look of concept maps (e.g., Europe – Germany – federal states – Saxony) illustrates subordinate and superordinate relationships in a more comprehensible way. Compared to texts involving its grammatical structure, concept maps emphasize the macrostructure of the information more clearly (O'Donnell et al., 2002). In this vein, meta-analytical findings from Nesbit and Adesope (2006) revealed that students with low prior knowledge benefitted most from learning with concept maps. Second, the inherent structure of concept maps makes it possible to distribute the cognitive load across the verbal and visual channels of information processing. Thus, a cognitive overload can be avoided (Schroeder et al., 2018; Sweller et al., 2019). Moreover, it is assumed that concept mapping reduces extraneous cognitive processing due to its simpler structure than is the case when studying or writing texts. Concept maps are therefore also beneficial for learners with a low verbal ability (Haugwitz et al., 2010).

1.2 Cognitive Processes while Learning with Concept Maps

While learning several processes take place within the learner. The most important are cognitive processes which determine learning success in a crucial manner. In this vein, the *cognitive load theory* (CLT, Sweller et al., 2019) tries to reconcile human working memory characteristics and the instructional design of multimedia learning environments. Cognitive load can be defined as the cognitive burden which is caused by the learning material in dependence on learners' prior knowledge (Feldon et al., 2019). Cognitive load subsumes two additive types: intrinsic and extraneous cognitive load (Jiang & Kalyuga, 2020; Sweller et al., 2019). Intrinsic cognitive load (ICL) is determined by task complexity (i.e., the element interactivity) and moderated by learners' domain-specific prior knowledge (Kalyuga, 2011). The complexity of the learning material is described with the element interactivity on a continuum between low and high. In line with Sweller (2010, p. 124) an element can be defined "as anything that needs to be or has been learned, such as a concept or a procedure". On the other hand, the prior knowledge may influence the ICL (Chen et al., 2017) as learners with high expertise have already formed schemata, which helps them to solve a problem without a high working memory load. Due to its relevance for learning the ICL can be equated with productive load (Kalyuga & Singh, 2015). In contrast, extraneous cognitive load (ECL) is the burden triggered by information-seeking processes that are caused by a non-optimal design and format of the learning material (Sweller, 2010). Extraneous processing may be also caused when the information is spatially or temporally distributed or not presented in a comprehensible order (van Merriënboer & Ayres, 2005). If working memory resources are already consumed by ECL processes, not enough resources are available to deal with the intrinsic load. The ECL can be changed actively within the design phase of the learning material (Leahy & Sweller, 2016). In line with Kalyuga and Singh (2015) extraneous processing is not relevant for learning and therefore unproductive.

Instructional materials, such as concept maps, also induce a certain amount of cognitive load. Orientated to previous research in the field of educational psychology, it is primarily important to avoid extraneous processing while learning with concept maps to keep free enough working memory capacities for managing the inherent task difficulty (Paas et al., 2003). In line with Tergan (2005), easily comprehensible concept map structures can reduce searching processes, which are detrimental to learning. In this vein, learning with concept maps can suffer from cognitive overload as well as navigational disorientation (Bleakley & Carrigan, 1994). Orienting on Ahuja and Webster (2001), Amadieu and colleagues (2009) as well as Cress and Knabel (2003), disorientation hinders learning processes in different ways: (1) The learner cannot capture how various concepts within the map are connected; (2) It is more difficult to recognize semantic relationships between the concepts, i.e., which concept is subordinate and which concept is superordinate; (3) The learner is hindered in identifying a path that will function as a guide through the map; and (4) It is sometimes tough to find already read information again. Tergan (2005) assumes that learning scenarios with "ill-structured" content required additional tools to foster learning. One approach is providing a visible hierarchical structure within the concept map (Amadieu et al., 2015). In line with principles of reducing extraneous processing while learning (e.g., *spatial contiguity principle* to prevent learning-hindering split-attention effects; Schroeder & Cenkci, 2018), a visible hierarchical structure within the concept map should lead to better learning performances (DeStefano & LeFevre, 2007; Puntambekar & Goldstein, 2007). Hierarchy results in a high-quality concept map and was thus expected to support learning (Cañas et al., 2015). For this study, an easily identifiable navigation path (in line with Amadieu et al., 2009) characterizes a salient structure within the map. Therefore, a logical and comprehensible navigation through the learning material is fundamentally conducive to learning, not only in concept maps (Dias & Sousa, 1997).

Another possibility is the implementation of signaling (highlighting relevant information within the learning material; for a meta-analysis see Schneider et al., 2018) which is based on the CLT. For example, Aguiar and Correia (2016) could show that adding colors into the concept map, in order to group similar information, reduces extraneous cognitive load. However, empirical evidence in which way the cognitive load facets can be influenced through various design options is not fully experimentally examined. In contrast, reducing the intrinsic cognitive load is only possible when the knowledge provided by the map is simplified or when the learner's prior knowledge is changed (Kalyuga, 2011).

1.3 Motivational Processes while Learning with Concept Maps

Motivation is a hypothetical construct, which cannot be observed directly or immediately. In general, motivation can be defined as the activating alignment to a positively evaluated target state (Vollmeyer & Rheinberg, 2018). Motivation is regarded as a crucial factor that moderates learning success whereby it is positively related to mental effort and learning outcomes (Paas et al., 2005). Learners are driven by a range between intrinsic and extrinsic motivation (e.g., Ryan & Deci, 2000). When intrinsically motivated, individuals freely engage in an activity, task, or challenge. Thus, people take part because of enjoyment, excitement, pleasure, challenge, or interest (Deci & Ryan, 1985). Nevertheless, people can also be motivated by external factors defined as extrinsic motivation. Extrinsic motivation is defined as acting for reasons that are not related to the fulfillment of inner satisfaction (Ryan & Deci, 2020). For learning it is assumed that in particular intrinsic motivation leads to higher engagement, interest, and learning outcomes (e.g., Froiland & Worrell, 2016). Depending on learners' motivation, cognitive commitment can be increased or reduced and thus contribute to learning success (Moreno & Mayer, 2007). In consequence, educational designers and teachers should also take motivational variables into account when designing effective concept maps. A study by Schaal (2010) examined the impact of digital concept maps on learning performances and motivation. The main feature of the study was that students were allowed to learn with a concept map including continuative learning materials over 14 weeks (sessions). In accordance with the hypothesis, the motivational factors interest/enjoyment, competency, and usefulness were correlated positively with the frequency of use. Therefore, with increasing use of concept maps motivation to learn is boosted. In this vein, it is also interesting to examine whether learning with concept maps triggers motivational processes within a shorter time.

2 The Present Study

Concept maps were found to have positive effects on motivation and learning (Nesbit & Adesope, 2006; Novak, 1990; Schaal, 2010; Schroeder et al., 2018). However, empirically documented recommendations on how concept maps should be optimally designed are still rare (Schroeder et al., 2018). This study examined how the inherent design of concept maps can be improved in order to support cognitive and motivational processes while learning. Hereby, the effectiveness of concept maps depends to a large extent on the spatial arrangement of the individual sub-concepts, respectively the structure of the entire map. Also, a hierarchically structured concept map, in which related information is arranged spatially close to each other, should lead to lower disorientation and ECL perceptions. In contrast, when the concept map is designed in a confusing manner (i.e., corresponding sub concepts are not recognizable as such), learners' intrinsic motivation could suffer accompanied by a reduced mental effort in learning, which in turn leads to lower learning success. To summarize, the following hypotheses were formulated:

Providing a concept map with a high salience of the map structure leads to …

H1a: better learning performances

H1b: lower ECL perceptions

H1c: higher intrinsic motivation

H1d: lower perceived disorientation

than providing a concept map with a low salience of the map structure.

In line with findings concerning element interactivity (Kalyuga, 2011), it is assumed that each node of the map can be understood as an element. When thematically and spatially related nodes within the map are assembled to one node, this leads to a lower quantity of elements. When learners are confronted, for example, with three instead of six nodes, they might consider the whole sub-concept as a lower load. The aim is to reduce the element interactivity artificially since the amount of information to be learned remains the same. Just the presentation changes across the factor levels. In a concept map with a higher number of nodes, more separated elements must be connected and learned. Consequently, aggregating thematically related nodes should lead to better learning outcomes. Moreover, when learners are forced to learn with a lower number of nodes, the perceived ICL should decrease because of the reduced element interactivity (Sweller, 2010). As the learning material is perceived as less complex in a more compact form (with a lower number of nodes), students should be more intrinsically motivated to deal with it. Besides, intrinsic motivation perceptions are indirectly positively related to learning performances via engagement (Froiland & Worrell, 2016). In terms of disorientation, a lower number of nodes facilitates learning since additional integrating processes of related nodes are reduced. To sum up, the following hypotheses were formulated:

A lower number of nodes within sub concepts of a concept map leads to …

H2a: better learning performances

H2b: lower perceived ICL

H2c: higher intrinsic motivation

H2d: lower perceived disorientation

than a higher number of nodes within sub concepts.

Moreover, a mediation model is proposed under the premise that explicitly the salience of the map structure is associated with the learner's navigational disorientation (DeStefano & LeFevre, 2007; Puntambekar & Goldstein, 2007; Tergan, 2005). Since disorientation is negative for learning it is hypothesized that this perception leads to higher ECL ratings. Following the proposed path, extraneous processing leads to worse learning performance. For this analysis, the retention and comprehension scores were subsumed to the variable learning performance.

H3: The effect of the salience of the map structure on learning performance is serially mediated by disorientation and extraneous cognitive load.

3 Methods

3.1 Design and participants

This experiment is based on a two (salience of the map structure; low vs. high) x two (number of nodes; few vs. many) between-subjects factorial design. An a-priori power analysis (using G*Power; Faul et al., 2007) was conducted with a two-factorial between-subject design with two-factor levels each, a moderate effect size of $f = .25$ (based on meta-analytical findings regarding concept maps and spatial contiguity; Schroeder & Cenkci, 2018; Schroeder et al., 2018), a test power of $1\text{-}\beta = .80$ and an error probability of $\alpha = .05$. This analysis recommended a minimum sample size of $N = 128$. Overall, 130 students from XXX, who received either one-hour course credit or the possibility to participate in a voucher lottery, took part in this experiment. Due to technical problems, eight participants had to be excluded. The remaining 122 students (71.3 % female; age: $M = 23.01$; $SD = 3.04$) were considered for statistical analyses. Each participant was randomly assigned to one of the four aforementioned groups. Mean prior knowledge was 1.33 ($SD = 1.19$) out of 7 points what can be seen as rather low prior knowledge.

3.2 Instructional materials

Two web pages were prepared for the study. The first webpage introduced the participants to the learning content with some general information about the cell and the question of how many cells in the human body exist. By clicking on the forward button, the participants were directed to the second webpage where the concept map was displayed. The concept map dealt with biological facts on the cell. More specific, the map presented components of animal and plant cells (eukaryotes) including their formation and functions. Also, prokaryotic cells were briefly stated whereby in particular, the difference between animal and plant cells was emphasized. The concept map was titled “The Cell”. All concept maps comprised of the same amount of information, only the way of presentation was varied across the experimental conditions. To avoid possible *emotional design* effects (Brom et al., 2018), the map was presented on a white background and the font color was black. Just the centrally placed title was displayed in a beige box. Based on the two experimental factors, participants randomly received one map dependent on their condition.

In terms of the first independent variable, the salience of the structure of the concept map was manipulated. Specifically, a clearly arranged structure should be visible in one condition and an unclear structure in the other condition. The map with the salient structure can be compared with a hierarchical structure (Amadieu et al., 2009). This leads to easier navigation through the map and to a better understanding of the major and minor components and their semantic relationship. Accordingly, the structure serves as an attention guidance assistant. Lucidly presenting information makes it easier to maintain a meaningful reading order through the concept map. On the other hand, if the map has a less salient structure, it is hardly recognizable how the sub-concepts relate to each other. This is mainly favored by the fact that the individual nodes were distributed as randomly as possible across the map. As a consequence, thematically different nodes are no longer recognizable as such. The learner has to mentally structure the map himself accompanied by many search processes.

Regarding the second independent variable, the two-factor levels differed in the total number of nodes. Concept maps are characterized by the fact that for each node one idea or element is presented. In this study, in the few nodes condition, thematically related nodes (which contains related information) were combined to one node (see Fig. 1) by summarizing corresponding nodes leading to the dissolution of individual nodes. For instance, the concept “regulation of the internal cell pressure” is connected with the two sub-concepts “turgor” (linked via “is also known as”) and “stabilization of the plant” (link via “leads to”). These two sub-concepts can also be combined in one node due to their thematic proximity. By integrating any nodes that belong together, the total number of nodes could be reduced by 35 % (see Table 1).

3.3 Measures

For each measure, the reliability indicator Cronbach’s α was calculated (Cronbach, 1951) to ensure the internal consistency of the used measurements.

Prior knowledge. Learners’ prior knowledge was measured because of its empirically proven influence on cognitive load perceptions and learning performances (Chen et al., 2017). Two different task types were used to capture this concept. First, the open-answer question “What is the difference between eukaryotic and prokaryotic cells?” was given to the participants. A list with correct answers was prepared for evaluation which was conducted by two independent raters. The inter-rater reliability (κ = .92) was almost perfect (McHugh, 2012). The learners could achieve a maximum of three points. For the second task, the participants were asked to assign the following cell organelles to the correct cell type in which they occur: vacuoles, mitochondria, chloroplasts, and Golgi apparatus. Accordingly, four additional points could be reached, whereby a maximum of seven points was awarded in the prior knowledge test. Here, no inter-rater reliability was calculated since only one answer per item was correct.

Disorientation. For deeper insights on whether the learners were able to navigate through the concept map, modified items of the disorientation scale from Ahuja and Webster (2001) were used (see Table 2). In its original version, this scale is designed to assess the effectiveness of web designs. For this experiment, seven items (α = .93) were adapted for the use of concept maps. Participants had to rate items like “The navigation between the concepts was a problem” on a 7-point scale ranging from (1) “does not apply at all” to (7) “applies completely”.

Cognitive load. In order to evaluate the impact of the manipulated experimental conditions on learners' cognitive processes, cognitive load was assessed with a questionnaire from Klepsch and colleagues (2017). In detail, the German subscales of intrinsic cognitive load (ICL; two items, α = .77, e.g. “For this task, many things needed to be kept in mind simultaneously”) and extraneous cognitive load (ECL; three items, α = .88, e.g., “During this task, it was exhausting to find the important information”) were chosen for this experiment. Each item was rated on a 7-point scale ranging from (1) “not applicable at all” to (7) “fully applicable”.

Motivation. Due to its importance for successful learning, the learner's motivation was measured with the Situational Motivational Scale (SIMS; Guay et al., 2000). For the purpose of this study, the dimensions intrinsic motivation (four items; α = .85) and external regulation (four items; α = .87) were chosen. Participants were given the question “Why were you engaged with the previous study?” with corresponding pre-set answers like “Because I think that this activity is interesting” (for intrinsic motivation) or “Because I don't have any choice” (for extrinsic regulation). These answers had to be rated on a 7-point scale ranging from (1) “corresponds not at all” to (7) “corresponds exactly”.

Learning performance. In order to measure the participants' learning performance, two tests (retention and comprehension) were conducted. For retention, which can be defined as remembering (Mayer, 2014), 14 multiple-choice questions were created (α = .74), that questioned knowledge that was explicitly mentioned in the learning material. All questions consisted of four reply options. The number of correct answers differed among all tasks, however, at least one answer was correct. In consequence, the participants got a point if they recognized an item as correct. Besides, one point was awarded when a false item was not selected. For example, the question “What are the functions of the endoplasmic reticulum (ER)?” was given with the answer options (a) “formation of proteins”, (b) “translation of fatty acids”, (c) “signal transmission”, and (d) “storage of genetic information”. Per question, participants could receive a maximum of four points. Overall, 56 points could be maximally achieved by the participants in the retention test.

To measure comprehension, four open-format questions were formulated (α = .62). In line with Hulin and colleagues (2001), this value can be seen as acceptable. The comprehension tasks served to check to what extent learners understand the learning content. Accordingly, information learned had to be applied (Mayer, 2014). For example, two sketchy representations (an animal cell and a bacterial cell) were presented to the participants. Learners had to apply their knowledge of cell structure and components to identify the correct cell type. In another task, learners were asked to explain the possible consequences of a defective cell membrane. To be able to answer this question correctly, participants had to apply their knowledge of the functions of this cell organelle. In sum, 13 points could be reached in the comprehension test.

Instructional efficiency. In order to track how efficiently learners used their learning time, efficiency scores were calculated with the following formula (van Gog & Paas, 2008):

$$\text{Efficiency} = \frac{zP - zT}{\sqrt{2}}$$

Learning time (T) and learning performance (P) were z-standardized. After calculation, the efficiency scores ranged from − 2.08 to 1.57 (higher values encode a higher learning efficiency).

3.4 Procedure

Due to the Covid-19 pandemic and related social distancing interventions, the experiment was conducted online via the open-source web conferencing system *BigBlueButton*. Before the experiment, participants got an email with a link to the online room. At the beginning of the experiment, the instructor informed them about the purpose of the study, asked for informed consent, and instructed participants to share their screen. This screen sharing was implemented to check whether participants continuously worked with the learning material and the questionnaires and did not check other websites. No personal data was viewed or recorded. Also, participants were instructed to close all tabs except the study website. During the entire experiment, students were able to contact the experimenter either by microphone or chat message in case of problems. The experiment started with the prior knowledge test. After that, students were directed to the website with the learning material. On this website, participants could freely divide their time. Learning time was logged to analyze possible differences. The average duration was 531.34 s (*SD* = 339.05 s). After participants' finished learning, the dependent variables were measured in the following order: (1) disorientation, (2) cognitive load, (3) motivation, and (4) learning tests. In line with ongoing debates that multimedia learning provides rather short-term learning effects in lab experiments (Mayer, 2017), this study tries to examine if the learned information can still be retrieved after an intervention. For this purpose, three filler tasks with rather low cognitive load were implemented. The participants had to name the capitals of different countries, solve geometrical problems and sort confused letters into words. These filler tasks lasted about five to ten minutes. Afterward, the learning performance was measured. At the end, the participants were asked to provide demographic information such as age, gender, and study subject. Overall, the entire experiment took between 35 and 45 minutes.

4 Results

IBM SPSS Statistics 27 was used to analyze group differences. To investigate possible mediations, the SPSS macro process, written by Hayes (2013), was used. For data analyses, multivariate analyses of variance (MANOVAs) and univariate analyses of variance (ANOVAs) were conducted to check for group differences. Follow-up ANOVAs were only calculated if the previously performed MANOVA produced significant effects (Cramer & Bock, 1966). For all variance analyses, the group variables, *salience of the map structure* (low vs. high) and *number of nodes* (few vs. many) were used as independent variables. Prior knowledge was not included as a covariate since the four groups showed no significant differences ($p = .17$). Besides, there were no significant differences between the four treatment groups in terms of age ($p = .30$) and learning time ($p = .756$). Chi-squared tests revealed no differences with regard to gender ($p = .95$) and subject of study ($p = .64$). Effect sizes for group differences were only reported if they reached statistical significance. Partial eta-squared

(η_p^2) was used as effect size measure with the conventions .01 for a small, .06 for a moderate, and .14 for a large effect (Cohen, 1988).

4.1 Analyses of variance

Learning performance. To investigate possible effects of the independent variables on learning performances, a MANOVA was conducted using retention and comprehension as dependent variable. A significant main effect was found for the number of nodes, Wilk's Λ = .94, $F(2, 117) = 3.829$, $p = .025$, $\eta_p^2 = .06$. The main effect for salience of the map structure ($p = .381$) and the interaction ($p = .270$) did not reach significance. In terms of retention, a follow-up ANOVA was not able to detect a significant effect for the number of nodes ($p = .252$). For comprehension, the effect for the number of nodes was also not significant ($p = .155$). Consequently, hypotheses 1a and 2a had to be rejected.

Cognitive load. For the cognitive load types, a MANOVA was conducted with ICL and ECL as dependent measures. Here, no significant main effect for the salience of the map structure ($p = .119$), the number of nodes ($p = .627$) and for the interaction ($p = .954$) was found. Thus, hypotheses 1b and 2b were also rejected.

Motivation. In order to examine the perceived motivation while learning, a MANOVA was calculated with the intrinsic motivation and external regulation as dependent variables. The main effects for the salience of the map structure ($p = .909$) as well as the number of nodes ($p = .336$) failed to reach significance. Moreover, the interaction was not significant ($p = .323$). Hypotheses 1c and 2c had to be rejected.

Disorientation. For perceived disorientation, while learning, an ANOVA was calculated. This analysis found a significant effect of the salience of the map structure; $F(1, 118) = 8.938$, $p = .003$, $\eta_p^2 = .07$. Accordingly, students in the condition with low salience of the map structure reported their disorientation while learning significantly higher than students in the condition with high salience. This result is in accordance to hypothesis 1d. The effect for number of nodes ($p = .899$) as well as the interaction of both factors were not significant ($p = .560$). Accordingly, hypothesis 2d must be rejected.

Instructional efficiency. To analyze learning efficiency, an ANOVA was calculated. Hereby, a significant main effect was found for the salience of the map structure; $F(1, 118) = 4.208$, $p = .042$, $\eta_p^2 = .03$. It indicates that students confronted with a low salience of structure were more efficient in terms of learning time. The main effect for the number of nodes ($p = .956$) and the interaction failed to reach significance ($p = .100$).

4.2 Mediation model

More complex models, such as serial mediation, can include more than one mediator (Hayes, 2013). In this case, two mediators (disorientation and ECL) were assumed. For this study, a serial mediation was calculated since the two constructs were measured with different questionnaires (Kane & Ashbaugh, 2017). Accordingly, the mediators are in a causal relationship with a hierarchical character. The serial mediation analysis showed that the salience of the map structure had a significant effect on disorientation (a_1; $\beta = -0.53$, $SE = 0.28$, $p = .003$). Disorientation, in turn, had a significant effect on extraneous cognitive load (d; $\beta = 0.80$, $SE = 0.06$, $p < .001$) and on learning performance (b_1; $\beta = -0.37$, $SE = 0.69$, $p = .007$). In addition, the effect of the salience on extraneous cognitive load (a_2; $\beta = 0.04$, $SE = 0.21$, $p = .722$) was not significant.

Moreover, the path from extraneous cognitive load to learning performances was not significant as well (b_2; β = -0.12, *SE* = 0.61, *p* = .371). The total effect of the salience on learning performances did not reach significance (c; β = -0.13, *SE* = 1.50, *p* = .489). Interestingly, the direct effect of salience of the map structure on learning performances, controlling for disorientation and extraneous cognitive load was significant (c', β = -0.37, *SE* = 1.39, *p* = .031), suggesting that the inclusion of the two path variables impacts the effectiveness of the salience of the map structure in terms of learning outcomes. This serial mediation represents a causal chain between salience of the map structure, disorientation, extraneous cognitive load, and learning performances can only be partially confirmed as the foundation of the serial mediation.

5 Conclusion

5.1 General discussion

The central aim of this study was the experimental verification of two design interventions that play a significant role in the design of concept maps. For this purpose, four different versions of a concept map dealing with a biological topic were given to the participants. These maps differed in terms of the salience of structure and the number of nodes per sub-concept.

Regarding retention and comprehension, the absence of statistically significant effects of the independent variables indicates that it is irrelevant for learning whether the concept map is presented with a low or high salience of the structure or with few or many nodes. From a descriptive point of view, there is hardly any difference between the four groups in terms of the two factors. In terms of the cognitive load facets and motivation, the same conclusion can be drawn, since significant effects could not be observed. However, the assumed negative effect of perceived disorientation could be confirmed. When participants were confronted with a difficult-to-encode map (low-salience), they felt more disorientated while learning. Besides the statistical significance of this effect, the explained variance of 7 %, which corresponds to a medium effect size, indicates that the map structure affects perceived disorientation notably. Furthermore, navigating between the concepts was complicated by the low salience of the map structure. The number of nodes does not influence perceived disorientation. Concerning the efficiency, learners with the rather unstructured concept map (low salience) were more efficient than learners with a high salience meaning learners took less learning time to achieve the same performance in the test. Possibly the learning tests were too easy so that even short learning times led to good performances.

Also, the mediation model showed that a low salience of the map structure significantly affects perceived disorientation. In line with findings from hypertext research (e.g., DeStefano & LeFevre, 2007; Kim & Hirtle, 1995) rather unstructured concept maps caused feelings of disorientation. Problems mainly occur when a high level of disorientation leads to a cognitive overload while learning with concept maps. Following the causal chain, disorientation leads to significantly higher perceptions of the ECL. The high beta coefficient of .80 underlines the strength of this effect. It can be deduced that both disorientation and extraneous processing are a consequence of an inadequate structure within the concept map.

5.2 Implications

After analyzing and interpreting the results of this study, some theoretical and practical implications can be drawn. This study gives some practical insights into designing concept maps in educational settings.

Instructional designers should place a primary emphasis on creating concept maps in a way that does not cause feelings of disorientation for the learner. It is particularly important to support learners to find a meaningful reading order through a concept map (Amadieu & Salmerón, 2014). If this prerequisite is met, learners will be able to construct a mental model of both the concept map inherent physical structure as well as the semantic representation (Payne & Reader, 2006). When learning with graphical visualization tools such as concept maps or mind maps, it should be also possible for learners with low prior knowledge to understand how the individual concepts interact.

On the theoretical side, this study gives a first impulse that disorientation can be regarded as a meaningful supplement of our current understanding of extraneous cognitive load. The current prevailing assumption is that this source of cognitive load is affected by relatively unspecific unfavorable instructional processes and design realizations. Mainly, extraneous load perceptions are recorded in experimental studies using questionnaires. Over time, several validated instruments were developed for measuring the different types of cognitive load along with the ECL (Eysink et al., 2009; Klepsch et al., 2017; Leppink et al., 2013). However, these measurements capture extraneous processing while learning relatively unspecific.

Just the measurement from Eysink and colleagues (2009) distinguishes the ECL into the dimensions: *navigation*, *design of the learning task*, and *accessibility of information* in order to address the different sources of learning-disrupting factors. Nevertheless, this instrument measures navigation with the question if working within the learning environment was rather easy or difficult. Whether the learner’s navigation impressions while learning are sufficiently captured with an unspecific single item is questionable. Under the premise that navigation within the material can be seen as a fundamental prerequisite for successful learning, this factor should get more attention in future research. While empirical findings regarding the influence of the structure on concept map effectiveness are still lacking, several studies from the field of hypertext research already examined in which way structure affects learning (e.g., Dee-Lucas & Larkin, 1995; McDonald & Stevenson, 1998). Moreover, disorientation and extraneous cognitive load correlate very highly with each other. The structure in which information is organized crucially affects learning and can be changed by the instructional designer in order to prevent disorientation perceptions while learning. In this vein, the learners perceived navigational disorientation (Amadieu & Salmerón, 2014) could be measured when learning materials display knowledge in a certain spatially and semantic arrangement. For instance, one or more of the following items could be useful, but require factor-analytical examinations:

- “It was difficult to get an overview of the structure of the learning material.”
- “The structure within the learning material made it difficult for me to deduce how the individual pieces of information are related”.
- “While learning I had the feeling of getting lost in the learning material.”
- “It was difficult to put the individual pieces of information together to form a big whole.”
- “The structure made it difficult to find important information quickly.”

5.3 Limitations and further directions

From a methodological point of view, it must be underlined that the sample is not representative in its composition since participants were mostly female and enrolled in a media-oriented study course. A generalization to other educational settings (e.g., types of schools, school subjects, or students at a different age) is hardly possible and needs replications.

Besides, the learning material was learner-paced meaning that participants were free in their allocation of learning time. In this vein, a system-paced learning environment could have a higher impact on the examined effects (Rey et al., 2019).

It must be noted that the concept maps caused high intrinsic loads since a high amount of information was presented. Above all, the condition with many nodes could create a feeling that learners need to internalize as much as possible of the nodes. To be able to accomplish this, sufficient working memory capacities are required. Since this variable was not measured in this study, it cannot be used as an explanatory factor. Further studies should measure the participants working memory capacity when the learning material uses memorization tasks (Wilhelm et al., 2013).

Declarations

All procedures were performed in full accordance with the ethical guidelines of the German Psychological Society (DGPs, https://www.dgps.de/index.php?id=85). Since the experiment constitutes non-medical low risk research, no special permission by an ethics committee was required for psychological research in the Institute for Media Research of the faculty of humanities of the Chemnitz University of Technology as well as in Germany. At the beginning of the study, participants were informed that the data of this study will be used for research purposes only and that all data are collected anonymously. Thus, no identifying information was collected.

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Tables

Table 1.

Number of nodes for sub-concept of the concept map by condition.

Name of sub-concept	Many nodes condition	Few nodes condition
Eukaryotic cells	5	5
Prokaryotic cells	6	4
Nucleus	8	8
Golgi apparatus	4	3
Endoplasmic reticulum	12	6
Ribosomes	6	4
Vacuoles	10	5
Cell membrane	9	6
Chloroplasts	9	5
Mitochondria	8	4
Total number of nodes	77	50

Table 2.

Modified Disorientation Scale (Ahuja & Webster, 2001) used in the experiment.

Original item in English	Translated item in German	Adapted item in German	Adapted item in English
I felt lost.	Ich fühlte mich verloren.	Ich fühlte mich beim Lesen der Concept Map verloren.	I felt lost while reading the concept map.
I felt like I was going around incircles.	Ich fühlte mich, als ob ich mich im Kreis drehen würde.	Während ich die Concept Map las, fühlte ich mich, als ob ich mich im Kreis drehen würde.	As I read the concept map, I felt like I was going around in circles.
It was difficult to find a page that I had previously viewed.	Es war schwierig, eine Seite zu finden, die ich zuvor angesehen hatte.	Es war schwierig, ein Konzept zu finden, welches ich zuvor angesehen hatte.	It was difficult to find a concept that I already looked at before.
Navigating between pages was a problem.	Die Navigation zwischen den Seiten war ein Problem.	Die Navigation zwischen den Konzepten war ein Problem.	The navigation between the concepts was a problem.
I didn't know how to get to my desired location.	Ich wusste nicht, wie ich zu meinem gewünschten Ort gelangen konnte.	Innerhalb der Concept Map wusste ich nicht, wie ich zu meinem gewünschten Standort gelangen konnte.	Within the concept map, I didn't know how to get to my desired location.
I felt disoriented.	Ich fühlte mich desorientiert.	Ich fühlte mich desorientiert beim Lesen der Concept Map.	I felt disorientated while reading the concept map.
After browsing for a while I had no idea where to go next.	Nachdem ich eine Weile geblättert hatte, wusste ich nicht, wohin ich als Nächstes gehen sollte.	Nachdem ich die Concept Map eine Weile gelesen hatte, wusste ich nicht, wohin ich als Nächstes gehen sollte.	After reading the concept map for a while, I did not know where to go next.

Note: These items were answered on a 7-point Likert scale ranging from 1 (“does not apply at all”) to 7 (“applies completely”).

Table 3

Correlations between all dependent variables and prior knowledge.

Variables	1	2	3	4	5	6	7
1. Prior knowledge	–						
2. Disorientation	-.226*	–					
3. Intrinsic Cognitive Load	-.297**	.545***	–				
4. Extraneous Cognitive Load	-.219*	.789***	.556***	–			
5. Intrinsic motivation	.240**	-.240**	-.242**	-.305***	–		
6. External regulation	-.131	.272**	.256**	.282**	-.422***	–	
7. Comprehension	.355***	-.247**	-.179*	-.253**	.264**	-.089	–
8. Retention	.192*	-.437***	-.244**	-.381***	.143	.037	.544***

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

Table 4
Mean scores and standard deviations of all dependent variables by experimental group.

	Experimental groups							
	Low salience of the map-structure				High salience of the map-structure			
	Few Nodes ($N = 31$)		Many Nodes ($N = 29$)		Few Nodes ($N = 31$)		Many nodes ($N = 31$)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Disorientation (1-7)	4.25	1.74	4.38	1.64	3.56	1.58	3.36	1.32
Intrinsic Cognitive Load (1-7)	5.29	1.25	5.03	1.43	4.94	1.55	4.81	1.17
Extraneous Cognitive Load (1-7)	4.75	1.76	4.68	1.87	3.99	1.85	4.10	1.62
Intrinsic Motivation (1-7)	3.98	1.30	4.00	1.33	3.72	1.16	4.36	1.02
External Regulation (1-7)	4.28	1.76	4.09	1.61	4.20	1.62	3.90	1.67
Prior knowledge (0-7)	1.04	1.13	1.38	1.24	1.22	0.98	1.69	1.35
Retention (0-56)	39.58	6.03	36.66	5.27	37.65	6.24	38.00	6.95
Comprehension (0-13)	5.24	3.16	5.90	2.99	4.40	2.56	5.32	3.38
Learning time	501.51	260.26	496.00	307.93	577.68	339.47	547.87	433.06

Note. The minimum and maximum of each scale are given in parentheses. Learning time is stated in seconds.

Figures

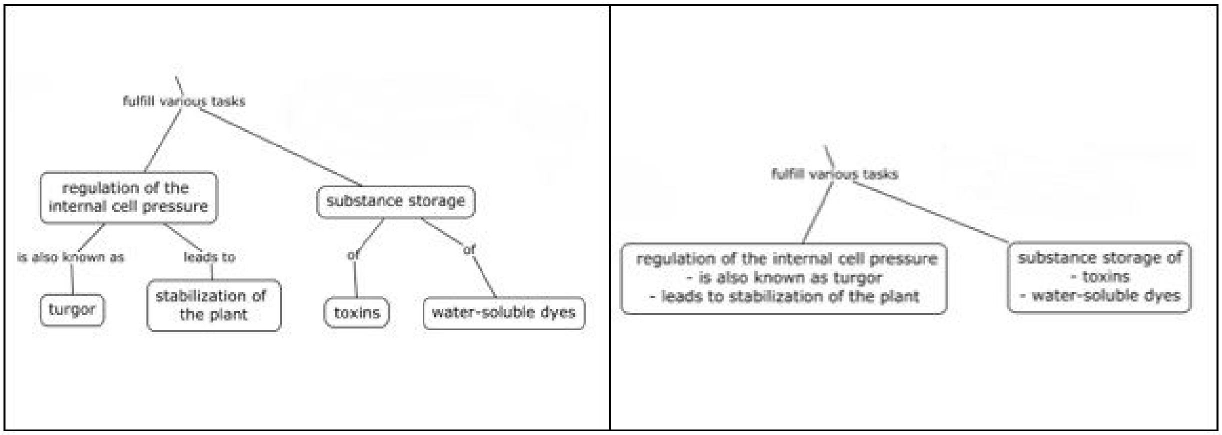

Figure 1

Extract from the concept map (left: many nodes, right: few nodes). Note. Instructional material was translated from German to English for this example.

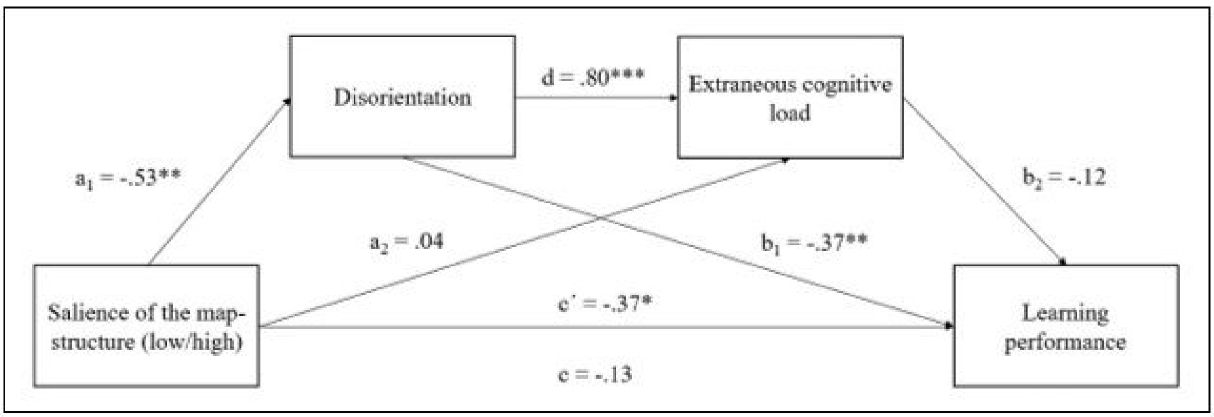

Figure 2

Standardized beta coefficients of the serial mediation analysis paths for the mediating effect of disorientation and extraneous cognitive load on the effect of salience of the map structure and learning performance. Note. *p < .05. **p < .01. ***p < .001.

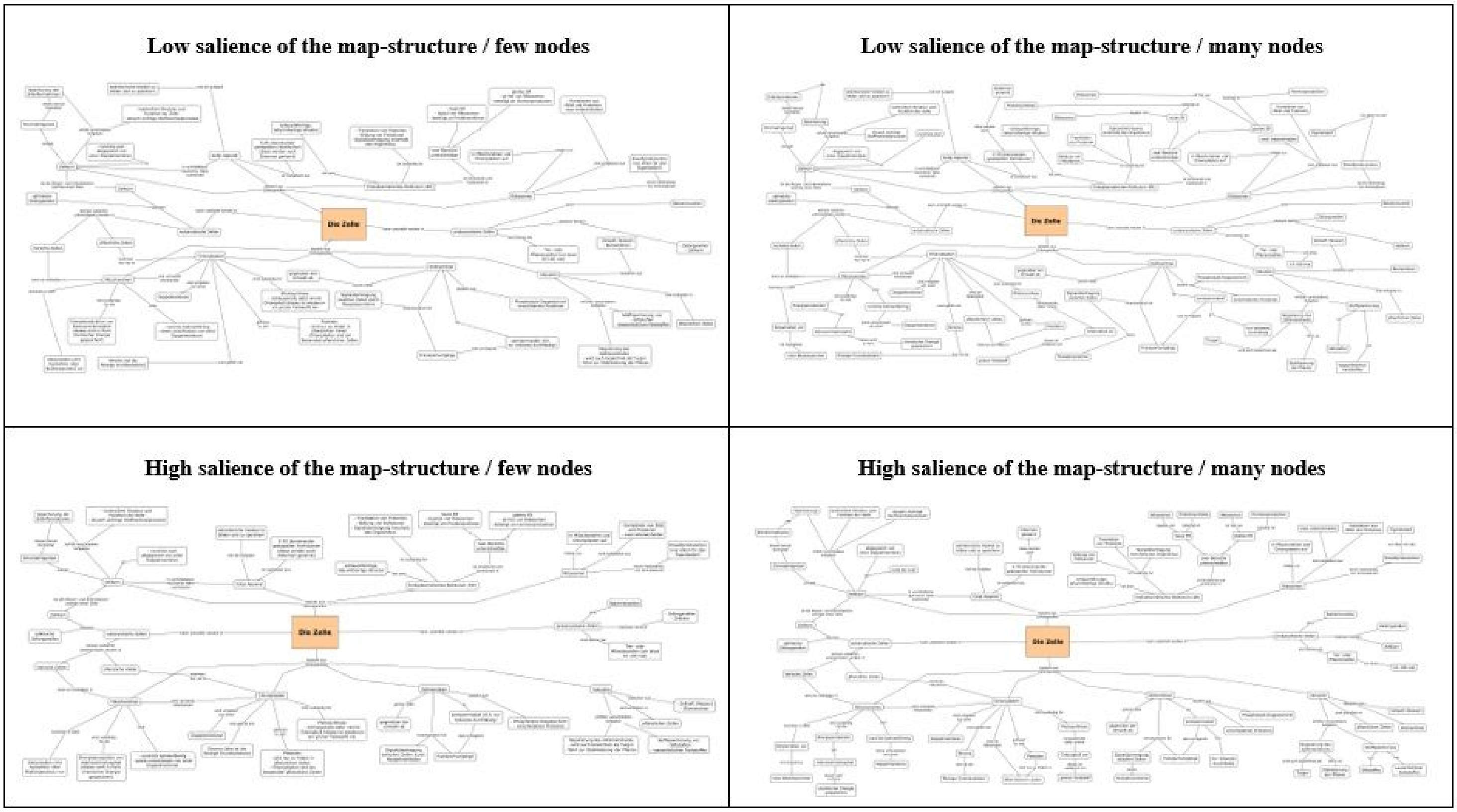

Figure 3

Overview of the four concept maps (conditions) used in the experiment.