Chapter 2
Learning How to Use a Digital Workbench: Guided or Explorative?

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2.1 Introduction

In the digital age, more and more processes are digitized to support people in their work and professional tasks. Consequently, many new tools and applications are developed with this in mind. The challenge for developers and instructional designers is to ensure that people can use these applications and are willing to use them in the everyday work situation (e.g., Venkatesh et al., 2003). How learning to use a new digital tool or application works best is still an open question.

One tradition in educational psychology and educational research argues in favor of guided approaches that provide learners with supportive information to not overload their cognitive capacities. The effectiveness of such approaches, e.g., learning with worked-out examples or direct instruction, was demonstrated in many empirical studies (Kirschner et al., 2006; Sweller et al., 2007). However, researchers criticize that guided instruction is beneficial for structured problems and content but not for other learning objectives like affective outcomes or the invention of ideas beyond the obvious solution (Hmelo-Silver, 2004; Kapur, 2008).

Here, the other tradition comes in and argues in favor of instructional approaches with more degrees of freedom for learners. Such approaches are known as explorative learning, in which learners discover content on their own and find personalized solutions to given problems. As a consequence, motivational and affective learning objectives or learning objectives other than retention are addressed and promoted more deeply (Hmelo-Silver et al., 2007; Newman & DeCaro, 2019).

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In practice, most learning environments are complex and aim to facilitate different learning objectives. Hence, it is necessary to investigate which instructional approaches facilitate which learning objectives. In this study, we investigate this question and report the results of an intervention, in which participants in a workshop either learned how to use a digital workbench through a guided or an unguided instructional approach.

2.2 Theoretical Background

2.2.1 Guided Instruction

The idea of guided instruction is based on the theoretical assumptions outlined in cognitive load theory (CLT). CLT is an instructional design theory grounded on the human cognitive architecture with a limited working memory and an infinite long-term memory. Hence, the aim of instruction is to process the to be learned information in working memory and transfer it into long-term memory where it can be stored. Stored information can then be used in working memory, for example, when new tasks have to be solved (Sweller et al., 1998, 2019). The transfer of new information from working memory to long-term memory is dependent of a cognitive load imposed: high cognitive load can hinder transfer and thus learning (Sweller, 2020). As several decades in CLT research show, the learning environment, the characteristics of the learners, and the learning task influence cognitive load (Choi et al., 2014; Paas & van Merriënboer, 2020). For example, learners with little prior knowledge in a domain do not benefit from unguided instructional approaches like pure discovery or explorative learning. For them, searching for the right strategy to solve given tasks is cognitively overwhelming, time-consuming, and not better for learning performance compared to guided approaches (Kirschner et al., 2006; Sweller et al., 2007). In guided instructional approaches, learners get support from their teachers, for example, via feedback, or instructional materials like worked examples (Lazonder & Harmsen, 2016). Worked examples are elaborated samples of problems leading step by step to the solution to the problem. Novices can use them to follow an expert's approach, and as their level of expertise increases, they can detach themselves from the supportive materials (Atkinson & Renkl, 2007). Theoretically, worked examples reduce the unproductive cognitive load (extraneous cognitive load) while freeing up working memory capacities for the productive cognitive load (intrinsic cognitive load) resulting in better learning (Kalyuga & Singh, 2015).

Guiding students learning with the help of worked examples is one of the strongest CLT effects supported by plenty of empirical evidence (Sweller, 2020; Wittwer & Renkl, 2010). However, most of the CLT studies on worked examples address highly structured problems with a focus on the acquisition of domain-specific knowledge. In practice, learning environments are more complex including various learning activities with different learning objectives (Kalyuga & Singh, 2015). As a consequence, different learning objectives may need different instructional approaches. For example, exploring new solutions to a problem beyond the restrictive structure provided by worked examples might be better in learning environments with less guidance (Kapur, 2008).

2.2.2 *Explorative Learning*

The concept of explorative learning is a constructivist-inspired instructional approach where learners first discover content on their own followed by more teacher-led methods (Newman & DeCaro, 2019). In the literature, there are several terms describing such a procedure like productive failure or problem-solving first (Kapur, 2016; Likourezos & Kalyuga, 2017). The effectiveness of such approaches is grounded in the idea of active learning and hands-on experiences helping learners in constructing knowledge and facilitating lifelong learning skills (Hmelo-Silver, 2004). From a CLT perspective, two different assumptions with regard to explorative learning are discussed: On the one hand, explorative learning can overwhelm learners, especially beginners in a domain, because the complex tasks involved in explorative learning cognitively overload working memory capacity and thus hinder learning (Kirschner et al., 2006; Sweller et al., 2007). On the other hand, the cognitive load imposed during exploration can activate learners prior knowledge, make them aware of possible knowledge gaps, and thus boost productive cognitive processing (Kapur, 2008, 2016). For example, in Likourezos and Kalyuga (2017), learners in an unguided condition reported higher cognitive load, but no differences in learning outcomes compared to a worked examples group were found. The authors explain the result with a possible moderating effect of affect: Learners in the unguided condition accepted the more difficult task as a challenge, which in turn compensated for the higher cognitive load (Likourezos & Kalyuga, 2017, p. 214). The result is also in line with the idea presented above: different learning objectives need different instructional approaches (Koedinger et al., 2012). The promotion of interest, motivation, or attitude is a valuable aim in education, and explorative approaches of instruction might be better suited to achieve them (Newman & DeCaro, 2019). In addition, explorative learning can support students inventing new ideas and reaching learning objectives that are beyond the constructed learning scenario (Hmelo-Silver, 2004; Kapur, 2008).

2.3 The Present Study

Based on the findings above, we investigated in this study how a fully guided and an unguided explorative approach affected different learning objectives, cognitive load, and attitudes in an authentic learning environment. We situated our study within the ASPE[1] (= assessment for professional exams) project in which the team at our lab developed a so-called digital workbench. The digital workbench is an online tool based on the content management system Drupal (see Drupal.org). In the future, the workbench will support teachers and research assistants in the creation of examination tasks in vocational education. For example, a teacher can use the workbench to create text-based tasks with tables, figures, and a description of the authentic context where the tasks take place (e.g., in a transport company: cancel a purchase order because there was a problem with the delivery).

During a workshop we presented the workbench to the participants for the first time, with the possibility to test the existing functionalities and to learn how to use it. It is important to mention here that the used workbench in the workshop was a first prototype. In the meantime, the workbench has been significantly enhanced and is available in a different version.

Achieving the following learning objectives was the goal of the workshop:

- The first learning objective concerns the creation of the sub-parts for exams in vocational education. Each exam consists of several parts that, when put together, make up the final exam. Learning objective 1 was to design as many of these parts as possible. Learning objective 1 is therefore referred to as a quantitative learning objective. Since the procedure for creating the parts can be considered structured, the following first hypothesis is formulated for learning objective 1:

  The guided group will score better on learning objective 1 compared to the explorative group (H1).

- The second learning objective concerns the quality of the designed tasks. For example, every task needs a solution written in an extra text field. Again, learning objective 2 can be considered structured; thus, we test the following hypothesis 2:

  The guided group will score better on learning objective 2 compared to the explorative group (H2).

- The third learning objective concerns the functionalities of the workbench. Participants can explore a lot of functions that are beyond the traditional design of vocational exams. This task is less structured than the others; consequently the following hypothesis 3 is investigated:

  The unguided explorative group will test more functionalities of the workbench than the guided group (H3).

Furthermore, we collected data on participants' cognitive load and attitudes toward the workbench and tested the following hypotheses:

[1] ASPE is the acronym for assessment for professional exams. In this project, a digital workbench is used to support and facilitate the creation of examination tasks in vocational education and training and to set up a model of how final examinations should become more competence-based in the future.

For cognitive load, we predict in hypothesis 4 that the guided group will report lower cognitive load compared to the unguided group (H4).

For attitudes, we predict in hypothesis 5 that the guided group will report more positive and less negative attitudes toward the workbench use compared to the unguided group (H5).

2.4 Method

2.4.1 Participants and Sampling

A total of 31 participants (4 women, 22 men, 5 did not specify) with an average age of 50.6 years (SD = 8.9 years) participated in the study. The participants work as teachers and research assistants for vocational schools and a state organization for nationwide examinations in vocational education and training. The study was conducted during a workshop where the participants were able to test the workbench for the first time. With the help of colored markers on the name tag, 16 participants were randomly assigned to the fully guided worked examples group (FG) and 15 to the unguided exploratory group (UG).

2.4.2 Research Design

The independent variable in this study was the instructional approach: In the fully guided (FG) worked examples group, learners used step-by-step instructions to complete the prepared tasks. In the unguided (UG) exploratory group, participants received only a handout describing the task; no other learning materials were given. The dependent variables were the quantity (learning objective 1) as well as the quality (learning objective 2) of the completed tasks, functionalities of the workbench explored (learning objective 3), perceived cognitive load, and attitudes toward the workbench use.

2.4.3 Material

2.4.3.1 The Digital Workbench

Within the framework of the ASPE project, a digital workbench was developed to support the participants of this study in their future creation of examination tasks. In this study, the first prototype was tested for the first time. An examination in vocational education and training consists of several parts, all of which can be created in the digital workbench. For example, participants describe a so-called situational context that situates a given task; this can be a mathematical calculation, to an authentic professional context. In combination, the task and the situational context form an exam that will be presented to the students. The participants in this study had the task to create each element of an exam at least once in the same way as they would do it for a real one. The more elements created, the better for the score on learning objective 1.

In addition, each element of an exam needs certain information. For example, a solution has to be provided to every task created. If the solution is missing, the created element is of lower quality than another one. Consequently, complete elements positively influence the score on learning objective 2.

Furthermore, the workbench provides functionalities that go beyond the traditional design of vocational exams. For example, the teachers can upload tables and pictures that might help the students to understand the task. If participants used these additional functionalities, it affects the score on learning objective 3.

The prototype of the workbench allowed the research team to access all content created. The evaluation of the influence of the instructional approach on learning objectives 1–3 is based on this content.

2.4.3.2 Worked-Out Example

To guide the participants in the FG group, we designed a worked-out example with step-by-step instructions for each element of an exam. The manual consists of text-image combinations and was given to the FG group participations only in paper-based form.

2.4.4 Instruments

2.4.4.1 Learning Objectives 1–3

As mentioned above, learning objectives 1–3 were measured via the workbench. Higher values indicate higher achievement levels for all three learning objectives.

2.4.4.2 Cognitive Load

To assess cognitive load, we used the NASA Task Load Index (NASA-TLX). The NASA-TLX is a self-reporting questionnaire with six subscales (Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, Frustration) answered on a scale of 0 (low) to 20 (high) (Hart, 2006; Hart & Staveland, 1988). In contrast to one-dimensional scales, the NASA-TLX is a multidimensional instrument to measure cognitive load and is therefore used frequently in cognitive load studies (de Jong, 2010; Grier, 2015). The participants answered the NASA-TLX after the intervention, *Cronbach's alpha* = .70.

2.4.4.3 Attitudes

To evaluate participants' attitudes toward the use of the workbench, we used a modified version of the personal digital assistants attitude survey (Cheng, 2017). This self-reporting survey has four subscales: Usability (four items; e.g., "The workbench is easy to use"; *Cronbach's alpha* = .90), Usefulness (four items; e.g., "The workbench supports my work"; *Cronbach's alpha* = .90), Concerns (three items; e.g., "Using the workbench was boring"; *Cronbach's alpha* = .60), and Intention to Use (three items; e.g., "I want to use the workbench in the future"; *Cronbach's alpha* = .70). The participants answered the attitude survey after the intervention on a 5-point Likert scale from 1 (do not agree at all) to 5 (totally agree).

2.4.5 Procedure

Based on the colored marker on the name tag, participants were randomly assigned to either the FG group or the UG group. For both groups separate rooms were prepared in which the participants met in small groups and worked out the tasks with the help of the workbench on notebooks. Every small group received a printed sheet with a description of the tasks to complete. Additionally, the instructional manual was given to the FG group participants. The testing of the workbench with the completion of the tasks took about 1 h. Afterward, the research instruments were answered. An overview of the research procedure is presented in Fig. 2.1. The elements created were automatically and anonymously saved by the workbench.

2.5 Results

For data analysis purpose, we first extracted all of the participants' activities from the workbench. This included data on quantity, e.g., how many of the tasks we set were completed; quality, e.g., how many of the tasks were completed in full; and exploration of functionality, e.g., which additional functions were used when creating the examination elements. All scales and subscales of the NASA-TLX and the attitude survey were aggregated using mean values. Data analysis was done in SPSS 26. The descriptive statistics for all dependent variables in this study is presented in Table 2.1. Effect sizes are interpreted according to Cohen (1992).

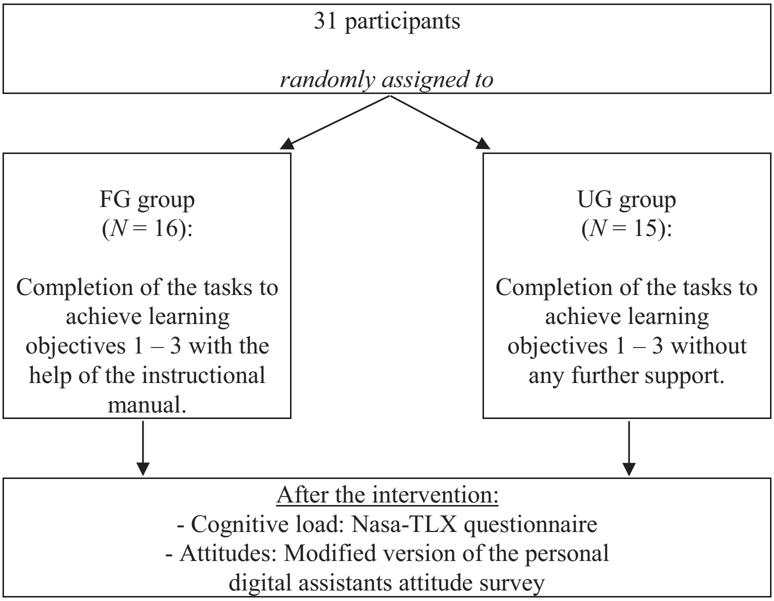

Fig. 2.1 Overview for the research procedure

2.5.1 Does the Guided Group Score Better on Learning Objective 1?

The descriptive data in Table 2.1 supports the first hypothesis as the FG group (M = 3.50, SD = 1.38) completed more tasks than the UG group (M = 1.71, SD = 0.95). To test if this difference is significant, we calculated an independent t-test. The result reveals that the FG group created significantly more elements compared to the UG group, $t(11) = -2.76$, $p < .05$, $d = 1.50$. The corresponding effect size is large.

2.5.2 Does the Guided Group Score Better on Learning Objective 2?

For the learning objective 2, the quality of the created elements in the workbench, the data in Table 2.1 supports the second hypothesis. The FG group (M = 6.50, SD = 5.68) scored higher compared to the UG group (M = 4.00, SD = 3.00). However, as the result of an independent t-test shows, the difference is not statistically significant, $t(11) = -1.02$, $p = .33$, $d = 0.37$. The effect size is small.

Table 2.1 Descriptive statistics with means and standard deviations for all variables

	FG (n = 16)		UG (n = 15)	
Variable	*M*	SD	*M*	SD
Learning Obj. 1—quantitative	3.50	1.38	1.71	0.95
Learning Obj. 2—qualitative	6.50	5.68	4.00	3.00
Learning Obj. 3—functions	8.00	5.40	10.00	6.90
Cognitive load				
Mental Demand	10.06	5.13	10.53	5.84
Physical Demand	5.12	6.12	4.40	3.23
Temporal Demand	4.00	3.76	8.92	4.73
Performance[a]	8.50	4.65	12.20	4.78
Effort	8.00	5.48	8.33	4.98
Frustration	6.25	5.62	8.80	5.67
Overall CL	6.99	3.31	8.85	3.05
Attitudes				
Usability	3.14	0.46	2.98	0.50
Usefulness	3.09	1.11	3.68	1.16
Concerns	1.46	0.47	1.58	0.56
Intention to use	3.65	0.93	3.98	0.92
Overall attitude	2.83	0.44	3.00	0.46

Note: [a]Scale performance is reverse coded. Lower values reflect a stronger belief in one's own ability to perform

2.5.3 Does the Unguided Group Score Better on Learning Objective 3?

In hypothesis 3 we predicted that the unguided group would explore more functions within the workbench. The data in Table 2.1 supports this assumption as the UG group ($M = 10.00$, SD = 6.90) scored higher than the FG group ($M = 8.00$, SD = 5.40). An independent t-test found that this difference is not significant, $t(11) = 0.57$, $p = .58$, $d = 0.35$. The effect size is small.

2.5.4 Does the Guided Group Report Lower Cognitive Load?

To test hypothesis 4, we calculated an independent t-test with the NASA-TLX subscales and the overall cognitive load as dependent variables. For the subscales Mental Demand ($p = .81$), Physical Demand ($p = .67$), Effort ($p = .86$), and Frustration ($p = .22$), no significant differences between the two groups were found. Also, the FG group and the UG group do not significantly differ in terms of the overall cognitive load ($p = .12$).

Table 2.2 Significant results of the independent *t*-test to test hypothesis 4

Variable	FG *M*	FG SD	UG *M*	UG SD	*t*(29)	*p*	Cohen's *d*
Temporal Demand	4.00	3.76	8.92	4.73	3.12	0.004	1.21
Performance[a]	8.50	4.65	12.20	4.78	2.18	0.037	0.78

Note: [a]Scale performance is reverse coded

Significant differences were found for the subscales Temporal Demand ($p < .01$) and Performance ($p < .05$) with large effect sizes for both (see Table 2.2). This means that the FG group perceived the completion of the task in the workbench less temporally demanding and participants were more confident in their ability to solve the tasks than the participants in the UG group.

2.5.5 *Does the Guided Group Show More Positive Attitudes Toward the Workbench?*

The descriptive data in Table 2.1 only partially supports hypothesis 5. For example, the FG group participants (M = 1.46, SD = 0.47) are less concerned than the UG group participants (M = 1.58, SD = 0.56). In contrast, the usefulness of the workbench is rated higher by participants of the UG group (M = 3.68, SD = 1.16) compared to the FG group (M = 3.09, SD = 1.11). In sum, the values collected are similar in both groups. An independent *t*-test confirms this impression as we found neither for one of the subscales nor for the overall attitude significant differences between the FG and the UG group.

2.6 Discussion

In this study, we compared a fully guided group with an unguided explorative group when learning how to use a new digital workbench to create vocational examination tasks. We predicted that different instructional approaches are better for different learning objectives. In hypotheses 1 and 2, we assumed benefits for the group guided through a worked-out example how to fulfil the more structured tasks given. For learning objective 1, the quantity of created tasks, the data confirms our hypothesis: the participants in the guided group significantly performed better compared to the unguided group, and the effect size is large. This result is in line with the theoretical assumptions of CLT where more guidance is beneficial for structured tasks. Furthermore, the descriptive data verifies the second hypothesis: the guided group did not only create more tasks but also with a higher quality than the control group participants. However, the difference did not reach statistical significance. A possible explanation for this is the small sample size. In a future study, a replication of the experiment is necessary with a larger sample to validate our findings. For learning objective 3, we predicted benefits for the unguided group. Here, the descriptive data confirms the assumption: the unguided group explored more functionalities in the workbench than the guided group. Again, the difference is not statistically significant, and the effect size is small. A possible explanation here might be that the participants in both groups were curious about the first use of the workbench. Hence, all participants tried to explore as much as possible in the workbench to provide feedback to the research team for the further development of the workbench. This would confirm the moderating role of affect and emotion during guided and unguided instructional approaches like mentioned in Likourezos and Kalyuga (2017).

In hypothesis 4 we predicted that the participants in the guided group report lower cognitive load than the unguided group. For the overall cognitive load and the subscales Mental Demand, Physical Demand, Effort, as well as Frustration, we found no significant differences. We found significant differences for the subscales Temporal Demand and Performance in favor of the guided group. First, this means that the participants in the guided group did not feel a strong sense of time pressure during their learning how to use the workbench. The control group without any guidance felt significantly more stressed, which can also explain the lower performance in both quantity and quality learning objectives. In addition, the guided group had more time and was therefore able to compensate the predicted lower performance with regard to the learning objective of exploring the functionalities of the workbench. More time helped the participants to create more tasks, in a high quality, and to explore as much functionalities as the control group. This is in line with CLT as guided instructional approaches are less time-consuming, better for structured learning objectives, and as good as unguided approaches for more unstructured learning objectives (Kirschner et al., 2006; Sweller et al., 2007). Second, participants in the guided group felt more self-confident to fulfill the tasks, which also resulted in a significantly better performance on learning objective 1, a better performance on learning objective 2, and almost the same good performance on learning objective 3 compared to the unguided group. This result confirms the assumption of the CLT regarding the positive effect of worked-out examples especially for beginners. As our participants saw the digital workbench in the workshop for the first time, the worked-out examples were perceived as supportive by them like shown in other CLT studies (e.g., Wittwer & Renkl, 2010).

Interestingly, we found no differences regarding the attitudes toward the use of the workbench between the two groups. Worth mentioning might be that the Usefulness and Intention to Use values are higher in the unguided group compared to the guided group. The difference is not significant, but this result needs to be further investigated by other researchers. The result is in line with the assumptions of explorative learning, whereas more freedom can address learning objectives beyond the traditional ones. Here, we found a tendency that the more affective learning objectives of Usefulness and Intention to Use the workbench in the future are slightly better addressed through exploration than guidance.

2.7 Limitations and Future Research

A limitation of this study is the small sample not allowing us to draw general conclusion about the investigated topic. The experiment also took place under real-world conditions, which is good for the ecological validity, but a further study should replicate the findings in a laboratory study. As mentioned before, future studies should also further investigate the influence of the two instructional approaches on affective learning outcomes. For example, in teacher training it would be helpful to know which instructional approach leads to more positive attitudes toward the use of a specific tool or application. Other studies should also include more modern forms of worked-out examples, e.g., video tutorials or virtual simulations of how to perform certain tasks. Here, instead of the learning how to use a digital workbench, also how to use and implement more contemporary educational technologies like augmented and virtual reality into teaching need further investigation.

2.8 Conclusion

In conclusion, the study shows that a fully guided instructional approach with worked-out examples was better able to teach participants how to use the digital workbench to solve given tasks. The guided group performed better regarding the quantity and the quality of the tasks and similar in terms of a more explorative learning objective. Furthermore, the guided instructional approach was less time-consuming, and the participants felt more self-confident when guided by the worked-out example. For the more affective learning objective of attitudes toward the use of the workbench, we were not able to find significant differences. However, we found a tendency that supports the idea of explorative learning, according to which more freedom might better address emotional and affective learning outcomes. Here, more research is needed with other forms of worked-out examples for learning how to use contemporary (educational) technologies.

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References

Atkinson, R. K., & Renkl, A. (2007). Interactive example-based learning environments: using interactive elements to encourage effective processing of worked examples. *Educational Psychology Review, 19*(3), 375–386. https://doi.org/10.1007/s10648-007-9055-2

Cheng, K.-H. (2017). Reading an augmented reality book: An exploration of learners' cognitive load, motivation, and attitudes. *Australasian Journal of Educational Technology, 33*(4), 53–69. https://doi.org/10.14742/ajet.2820

Choi, H.-H., van Merriënboer, J. J. G., & Paas, F. (2014). Effects of the physical environment on cognitive load and learning: towards a new model of cognitive load. *Educational Psychology Review, 26*(2), 225–244. https://doi.org/10.1007/s10648-014-9262-6

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*(1), 155–159. https://www.ime.usp.br/~abe/lista/pdfn45sGokvRe.pdf

Grier, R. A. (2015). How high is high? A meta-analysis of NASA-TLX global workload scores. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 59*(1), 1727–1731. https://doi.org/10.1177/1541931215591373

Hart, S. G. (2006). NASA-Task Load Index (NASA-TLX); 20 years later. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 50*, 904–908.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. *Advances in Psychology, 52*, 139–183. https://doi.org/10.1016/S0166-4115(08)62386-9

Hmelo-Silver, C. E. (2004). Problem-based learning: What and how do students learn? *Educational Psychology Review, 16*(3), 235–266. https://doi.org/10.1023/B:EDPR.0000034022.16470.f3

Hmelo-Silver, C. E., Duncan, R. G., & Chinn, C. A. (2007). Scaffolding and achievement in problem-based and inquiry learning: A response to Kirschner, Sweller, and Clark (2006). *Educational Psychologist, 42*(2), 99–107. https://doi.org/10.1080/00461520701263368

de Jong, T. (2010). Cognitive load theory, educational research, and instructional design: Some food for thought. *Instructional Science, 38*(2), 105–134. https://doi.org/10.1007/s11251-009-9110-0

Kalyuga, S., & Singh, A.-M. (2015). Rethinking the boundaries of cognitive load theory in complex learning. *Educational Psychology Review, 28*(4), 831–852. https://doi.org/10.1007/s10648-015-9352-0

Kapur, M. (2008). Productive failure. *Cognition and Instruction, 26*(3), 307–313. https://doi.org/10.1080/07370000802212669

Kapur, M. (2016). Examining productive failure, productive success, unproductive failure, and unproductive success in learning. *Educational Psychologist, 51*(2), 289–299. https://doi.org/10.1080/00461520.2016.1155457

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist, 41*(2), 75–86. https://doi.org/10.1207/s15326985ep4102_1

Koedinger, K. R., Corbett, A. T., & Perfetti, C. (2012). The knowledge-learning-instruction framework: Bridging the science-practice chasm to enhance robust student learning. *Cognitive Science, 36*(5), 757–798. https://doi.org/10.1111/j.1551-6709.2012.01245.x

Lazonder, A. W., & Harmsen, R. (2016). Meta-analysis of inquiry-based learning: Effects of guidance. *Review of Educational Research, 86*(3), 681–718. https://doi.org/10.3102/0034654315627366

Likourezos, V., & Kalyuga, S. (2017). Instruction-first and problem-solving-first approaches: Alternative pathways to learning complex tasks. *Instructional Science, 45*(2), 195–219. https://doi.org/10.1007/s11251-016-9399-4

Newman, P. M., & DeCaro, M. S. (2019). Learning by exploring: How much guidance is optimal? *Learning and Instruction, 62*, 49–63. https://doi.org/10.1016/j.learninstruc.2019.05.005

Paas, F., & van Merriënboer, J. J. G. (2020). Cognitive-load theory: Methods to manage working memory load in the learning of complex tasks. *Current Directions in Psychological Science, 29*(4), 394–398. https://doi.org/10.1177/0963721420922183

Sweller, J. (2020). Cognitive load theory and educational technology. *Educational Technology Research and Development, 68*(1), 1–16. https://doi.org/10.1007/s11423-019-09701-3

Sweller, J., Van Merriënboer, J., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review, 10*(3), 251–296.

Sweller, J., Kirschner, P. A., & Clark, R. E. (2007). Why minimally guided teaching techniques do not work: A reply to commentaries. *Educational Psychologist, 42*(2), 115–121. https://doi.org/10.1080/00461520701263426

Sweller, J., van Merriënboer, J., & Paas, F. G. W. C. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review, 31*(2), 261–292. https://doi.org/10.1007/s10648-019-09465-5

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified. *MIS Quarterly, 27*(3), 425–478.

Wittwer, J., & Renkl, A. (2010). How effective are instructional explanations in example-based learning? A meta-analytic review. *Educational Psychology Review, 22*(4), 393–409. https://doi.org/10.1007/s10648-010-9136-5