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Learning in Virtual Reality

The Relationship Between Cognitive Load, Interactivity, and Learning Outcomes

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Abstract: This study aimed to gain an understanding of what makes learning effective in educational virtual reality (VR) experiences. By integrating insights from cognitive load theory and the limited capacity model of motivated mediated message processing, we investigated the role of different dimensions of cognitive load as potential predictors (i.e., intrinsic and extraneous load) and outcomes (i.e., germane load) of interactivity and consequently learning. A one-group pretest-posttest laboratory experiment was conducted among young adults (N = 102). The results show that intrinsic load hinders learner-content interactions, whereas extraneous load hinders overall interactivity. However, interactivity did not affect germane load, nor was germane load found to predict learning scores. Taken together, these findings call for refinements in cognitive load theory to account for the interplay between the different types of cognitive load in VR learning environments. Furthermore, the results suggest that instructional designers should be cautious in assuming that more interactions will necessarily lead to better learning outcomes. Instead, the focus should be on facilitating high-quality learner-content interactions that are directly aligned with learning objectives.

Keywords: virtual reality, interactivity, learning, cognitive load

From training medical experts to teaching history in museums, immersive technologies like virtual reality (VR) are increasingly used as educational tools (e.g., Andersen et al., 2023; Shen et al., 2019; Sungur et al., 2024; Van Berlo & Stikos, 2023). Virtual reality owes its popularity to its unique technological affordances, which can enhance learning outcomes (Shin, 2017). Specifically, virtual reality tools can deliver highly immersive and interactive experiences, incorporate storytelling and gamification elements, and provide self-paced and personalized learning opportunities. In practice, this means that VR can be utilized to deliver specialized educational experiences about situations, places, or historical figures, in ways that would otherwise be unsafe, impractical, or simply impossible (e.g., Breves & Schramm, 2021; El Ali et al., 2023; Lee & Kim, 2021; Liu et al., 2022; Škola et al., 2020; Van Berlo et al., 2020; Wang & Liu, 2019). Considering these affordances and the increasing availability of these tools, it is expected that virtual reality will become an integral part of the learning culture in the future.

Various learning theories have been used to understand educational VR experiences, such as experiential learning, gamification, and learning-by-doing (e.g., Marougkas et al., 2023; Van Berlo et al., 2023). A common factor in these theories is the important role interactivity plays in learning (Marougkas et al., 2023). While interactivity is crucial for enhancing motivation and engagement, it is also important to note that interactivity in VR settings can be more demanding than in non-VR settings due to hardware and content-related limitations (Andersen et al., 2023). For example, simple actions like moving around and using multiple senses can be cumbersome in virtual reality. Thus, while virtual reality offers unique opportunities for interactivity, it also presents challenges related to cognitive load, including extraneous, intrinsic, and germane load (Andersen et al., 2023; Finken & Wölfel, 2023).

Recently, several studies have identified cognitive load theory as a relevant theory to explain VR learning (Albus & Seufert, 2023; Albus et al., 2021; Andersen et al., 2023; Makransky & Petersen, 2021; Sedlák et al., 2022). Even though the use of VR is typically associated with an overall increase in cognitive load (Breves & Schramm, 2019), most studies so far have not distinguished between different types of cognitive load that arise with specific qualities of VR (e.g., Frederiksen et al., 2020; Kaplan-Rakowski & Gruber, 2024) nor have they considered the relationships between these dimensions. This lack of differentiation limits our understanding of how specific types of cognitive load affect learning in VR environments, and consequently hampers the development of strategies that can optimize VR as an effective educational tool.

To address this gap, the present study sets out to examine what makes learning effective in educational VR experiences. By integrating insights from both cognitive load theory (Chandler & Sweller, 1991) and the limited capacity model of motivated mediated message processing (Lang, 2000, 2009), we study the relationship between different dimensions of cognitive load, interactivity, and learning. Concretely, we explore the role of intrinsic and extraneous load as potential predictors of interactivity and, consequently, learning. By integrating insights from the limited capacity model, germane load is considered as a mediator of the effect of interactivity on learning.

This study is relevant for researchers studying the relationship between cognitive load and learning, and for educators looking to utilize VR content in their curriculum. For instance, researchers studying fields such as educational, and media psychology can leverage the findings to deepen their understanding of how cognitive load impacts learning in virtual reality environments. Meanwhile, educators can apply these insights to create more effective and engaging VR-based learning experiences.

Learning in Virtual Reality

Interactivity is recognized as a key mechanism for effective learning (Petersen et al., 2022); however, the relationship between interactivity and learning may seem paradoxical in a virtual reality context. While on the one hand, virtual reality is typically seen as a cognitively and physically taxing medium due to factors such as its multisensory nature or straining hardware, on the other hand, it is also recognized as a medium that can be highly engaging for the users (e.g., Breves, 2023). In this study, we focus on the relationship between cognitive load and interactivity, and we expect these constructs to be related in two distinct ways: Negatively, with intrinsic and extraneous load hindering interactivity, and positively, with interactivity enhancing germane cognitive load and subsequently enhancing learning.

Cognitive Load Theory

Cognitive load theory (CLT) suggests that the human brain has a limited capacity for processing new information at any given time (for a recent overview see Sweller et al., 2019). The theory (Chandler & Sweller, 1991) distinguishes between three types of cognitive load: Intrinsic load, extraneous load, and germane load.

In the context of multimedia learning, intrinsic load relates to the inherent complexity of the learning material (e.g., learning about scientific theories or languages), extraneous load to the way the material is presented (e.g., clarity of instructions or usability of interface), and germane load to the mental effort dedicated to the process of learning and understanding (Chen et al., 2016). This means that while intrinsic and extraneous load relate more to the qualities of the information, germane load relates to the cognitive engagement with the information and therefore is believed to be beneficial to learning (Debue & Van de Leemput, 2014; Paas & Sweller, 2014). Given that cognitive resources are finite, high levels of intrinsic and extraneous cognitive load can hinder the capacity for germane load, and effectively overwhelm the learner's ability to process and assimilate new information – ultimately resulting in less effective learning.

Cognitive Load, Interactivity, and Effective Learning in Virtual Environments

Intrinsic and Extraneous Cognitive Load

In virtual reality learning environments, high intrinsic and extraneous cognitive load is expected to reduce interactivity and exploration, impacting the effectiveness of virtual reality learning experience. As with any learning experience, when the intrinsic load is high (i.e., when the study material covers a complex topic), learners must allocate a considerable portion of their cognitive resources into making sense of the information (Chandler & Sweller, 1991). This reduces the cognitive resources available for engaging in additional – and typically integral – tasks, such as exploring the virtual reality environment or interacting with its elements. Since intrinsic load is related to the complexity of the material that needs to be learned, the use of virtual reality itself is not expected to inherently lead to higher intrinsic cognitive load (Kaplan-Rakowski & Gruber, 2024).

This relationship is expected to be different for extraneous cognitive load – a type of cognitive load highly influenced by how information is presented, and the way people engage with that information. Several factors that are inherent to virtual reality environments can contribute to an increased extraneous cognitive load for learning. Specifically, the multisensory nature of virtual reality environments usually means that multiple senses are engaged simultaneously (e.g., visual, auditory, and sometimes tactile). Such a sensory overload, accompanied by the typically vivid graphics and sounds, can overwhelm or distract learners from focusing on the learning content (e.g., Frederiksen et al., 2020; Makransky & Petersen, 2021). Similarly, navigating through the virtual experience can be challenging. These characteristics can make it difficult for learners to engage in further exploration or to use interactive features effectively.

On top of this, a recent study by Breves and Stein (2023) showed that cybersickness in virtual reality environments also increases cognitive load, suggesting that simply being in virtual reality can be cognitively taxing. All in all, we expect that, when users experience high intrinsic and extraneous cognitive loads, people will engage less in interactive or exploratory activities in virtual environments, ultimately hindering effective learning. The following hypothesis was formulated:

> *Hypothesis 1 (H1)*: (a) Intrinsic and (b) extraneous cognitive load hinder interactivity in virtual environments, and (c) subsequently reduce learning effectiveness.

Germane Cognitive Load

While intrinsic and extraneous cognitive loads can hinder interactivity, we believe interactivity itself can promote germane cognitive load and ultimately promote learning effectiveness. Germane load is a reflection of the mental effort invested in understanding new information (Sweller et al., 1998) and is often measured indirectly as a learner's perception of how well a specific learning activity contributed to their comprehension (Andersen & Makransky, 2021; Klepsch et al., 2017). Interactive elements are expected to enhance germane load by fostering controlled information processing (Breves, 2023; Vandewaetere & Clarebout, 2013).

This controlled processing is explained by the limited capacity model of motivated mediated message processing (Lang, 2000, 2009), which provides a framework for understanding how active learning can increase germane load. Similar to cognitive load theory (Chandler & Sweller, 1991), the model suggests that people have a finite amount of cognitive resources that can be allocated when processing mediated information. According to the limited capacity model, learners engage in both automatic (effortless) and controlled (intentional) processing, with the latter handling deeper understanding (Fisher et al., 2018).

In virtual reality environments, interactive elements direct learners' attention to the material, promoting controlled processing of this information (Fisher et al., 2018). Since these elements are often directly tied to the learning content, the active engagement with the material is believed to ensure that learners are not just passively receiving information but are instead actively constructing and organizing meaningful knowledge – facilitating germane cognitive load. Ultimately, this active engagement enhances learning efficiency, leading to more robust knowledge structures and improved overall learning outcomes.

> *Hypothesis 2 (H2)*: Interactivity has (a) a positive effect on germane cognitive load and (b) subsequently increases learning effectiveness.

Methods

Participants and Design

To test how cognitive load and interactivity in VR environments are associated with learning, we have conducted a one-group pretest-posttest laboratory experiment with 117 students from the University of Amsterdam. For participation, they received either research credits or monetary compensation. Following the inclusion criteria, 102 participants were included in the final analyses (M_{age} = 21.07, SD_{age} = 2.27, 86 women, 16 men). This means 15 participants were omitted from the analysis: 6 did not complete the survey, 2 withheld consent, 3 spent insufficient time in the virtual environment, and 4 had failed screen recordings. The study received ethical approval (2022-YME-15706) from the Ethics Review Board of the Department of Communication Science, University of Amsterdam.

Stimulus Material

The stimulus used in the study was an award-winning educational VR experience: *Breaking Boundaries in Science* (2019). This experience focuses on the lives and discoveries of women scientists such as Marie Curie and Grace Hopper (*Breaking Boundaries in Science*, 2019). The experience immerses users in the laboratories of these scientists and aims to educate users by enabling them to interact with various objects in the virtual environment. The experience features multiple scientists, however, for the purpose of this study, Grace Hopper's experience was used, since she was the only non-European scientist featured in the experience and we assumed our participants would have less previous knowledge about her.

With the help of a controller, users can move around in the virtual environment and interact with objects (e.g., Naval cap, see Figure 1). When they point and click at certain objects with historical or personal significance, the object's name is displayed, and a narrator provides additional information about it. Grace Hopper's experience included 21 of these objects, each time a new object was found, a counter displayed the total number of objects discovered, thereby motivating users to keep searching and interacting.

Procedure

After providing informed consent, participants answered a set of multiple-choice questions to control their preexisting knowledge about the life and achievements of the American computer scientist Grace Hopper, whom the virtual experience focused on. Next, participants used an Oculus Go head-mounted display (HMD) and a

Figure 1. Example setup and stimulus materials. Participants used an Oculus Go head-mounted display (HMD) and controller. They could move around by pointing to different locations and clicking on certain objects to learn more about the scientists.

controller to navigate and interact with the VR experience. Participants were given six minutes and were instructed to experience the environment at their own pace. After spending the required time in the VR experience, participants completed the rest of the survey by answering the knowledge questions again and about cognitive load. Participants' experience in the VR environment was screen-recorded (i.e., participants' actions in the experience from their point of view). All measurements took place in the VR laboratory of the university. The study took about 20 min to complete.

Measures

Learning Scores

Learning was measured with 10 multiple choice questions that assessed the retention of information which can be gained during the VR experience (e.g., "Why did Grace Hopper have a backwards clock in her room?"). Response options consisted of one right answer, two wrong answers, and an "I do not know" option. For each correct answer participants received one point (M = 5.80, SD = 1.76).

Interactivity

Interactivity was operationalized based on the number of objects found by the participants in the VR experience. This was calculated by a content analysis of the screen-recordings of participants' actions in the VR environment. We have calculated two interactivity scores. Firstly, we calculated the total interactions by counting the number of objects found among the 21 objects that were present in the experience (M = 12.58, SD = 2.37). Secondly, we calculated the learner-content interactions. This score was calculated as the total number of objects found among a subset of 10 objects on which participants learning was assessed (M = 7.26, SD = 1.68). In other words, the learner-content interaction score reflects whether participants found the items related to the learning questions, whereas total interactivity reflected the total number of items found.

Cognitive Load

The different dimensions of cognitive load were measured with 15 items from the multidimensional cognitive load scale for virtual environments (Andersen & Makransky, 2021) using a 7-point Likert scale (1 = *Totally disagree*, 7 = *Totally agree*). The wording of the original items was slightly changed to better fit with the present study (e.g., "The topic covered in the simulation was very complex" was changed to "The topic covered in the VR exhibition was very complex").

Intrinsic load (M = 3.13, SD = 1.35, Cronbach's α = .87) was measured with two items (i.e., "The topic covered in the VR exhibition was very complex"; "The VR exhibition covered concepts and definitions that I perceived as very complex"). Extraneous load (M = 1.87, SD = 0.69, Cronbach's α = .87) was measured with 11 items relating to the experience of the instructions, interactivity, and the environment (e.g., "The instructions and/or explanations used in the VR exhibition were very unclear"; "The interaction technique used in the VR exhibition was very unclear"; "The virtual environment was full of irrelevant content"). Germane load (M = 5.80, SD = 1.76, Cronbach's α = .84) was measured with two items (i.e., "The VR exhibition really enhanced my understanding of the topics covered"; "The VR exhibition really enhanced my understanding of concepts and definitions").

Control Variables

To account for factors that might influence the outcome of our study, we included five control variables: Baseline knowledge, age, gender, VR experience, and cybersickness. Baseline knowledge was measured as the total number of correct answers given to the learning questions measured prior to the VR experience and was used as a measure (M = 0.25, SD = 0.78). Age was measured in years and for gender we asked participants to indicate which gender they identified with most. Furthermore, we measured VR experience by asking people to indicate, on a single-item 4-point scale, how much prior experience they had with VR (M = 1.78, SD = 0.64). The scale ranged from ranged from 1 = *no experience* to 4 = *using regularly and/or owning a device*. Finally, we measured cybersickness by asking participants to indicate, on a single-item measure ranging from 1 = *not at all* to 7 = *extremely*, to what extent they experienced symptoms of motion sickness (e.g., nausea, dizziness, feeling sick) during the VR experience (M = 2.49, SD = 1.37).

Results

To test our hypotheses, we ran two serial mediation models (Model 80; Hayes, 2013) predicting learning scores. Intrinsic and extraneous load served as the independent variables and interactivity, total interactions, and germane load as (serial) mediators. Baseline learning, age, gender, VR experience, and cybersickness were included as control variables. The models were specified with 95% confidence intervals (10,000 bootstrap samples). Sensitivity analyses were conducted, and we found no meaningful differences between the results with control variables included and those without, supporting the robustness of our findings. The results without control variables can be found in the Appendix. An overview of the results can be found in Table 1, and for the complete model with standardized coefficients, see Figure 2.

To facilitate the interpretation of the models, descriptives and correlations between the main variables are shown in Table 2.

Effects of Intrinsic and Extraneous Load on Interactivity and Learning

As shown in Table 1, the negative main effect of intrinsic load on learner-content interactions was significant (p = .031), whereas the effect of extraneous load was non-significant (p = .698). Notably, the findings are reversed for total interactions, where we found a non-significant (p = .995) main effect of intrinsic load, and a significant (p = .048) negative main effect of extraneous load. This means that intrinsic (but not extraneous) load hinders learner-content interactions, and extraneous (but not intrinsic) load hinders total interactions. These findings partially support H1a and H1b.

Subsequently, the results in Table 1 show a positive significant (p < .001) effect of learner-content interactions on learning. Total interactions do not seem to affect learning (p = .265). Subsequently, we found that the indirect effect of intrinsic load on learning, explained via learner-content interactions (b = −0.10, SE = 0.07, 95% CI [−0.29, −0.01]) was significant. The indirect effect of extraneous load on learning, explained via learner-content interactions (b = 0.04, SE = 0.10, 95% CI [−0.17, 0.25]) was non-significant. These findings only partially support H1c.

Effects of Interactivity on Germane Load and Learning

Contrary to our expectation, both the effects of learner-content interactions (p = .330) and total interactions (p = .136) on germane load were non-significant. This means that the number of interactions did not affect whether people perceived the VR experience to enhance their understanding of the material. Notably, the results, in Table 1, also show non-significant indirect effects of learner-content interactions and total interactions, via germane load, on learning scores. Concretely, this means that the effect of interactivity on learning is not explained by the extent to which people perceived the VR experience to enhance their understanding of the material. Overall, these findings do not support H2.

Discussion

The aim of our study was to examine what makes learning effective in educational VR experiences. We investigated the role of extraneous and intrinsic load as predictors of interactivity (learner-content interactions and total interactions) and germane load as outcome of interactivity, and subsequently its effects on learning. The results showed that virtual reality can effectively be used for learning activities, though both intrinsic and extraneous cognitive load mitigate the effectiveness of virtual learning environments. Based on our findings, we identified two distinct pathways explaining how cognitive load hinders interactivity and learning: One pathway via intrinsic load obstructing learner-content interactions and learning, and another through extraneous load mitigating the total number of interactions.

Table 1. Regression analysis for the combined serial mediation path models

	Interactivity							
Variables	Learner-content interactions (INT)		Total interactions (TIN)		Germane load (GL)		Learning (L)	
Direct effects	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI
Intrinsic load (IL)	−**0.19** (0.09)	[−0.36, −0.02]	0.001 (0.16)	[−0.32, 0.33]	−0.08 (0.07)	[−0.23, 0.07]	−0.03 (0.10)	[−0.24, 0.17]
Extraneous load (EL)	−0.08 (0.20)	[−0.31, 0.46]	−**0.73** (0.37)	[−1.46, −0.01]	−**0.55** (0.17)	[−0.87, −0.22]	−0.14 (0.25)	[−0.63, 0.35]
Learner-content interactions					−0.09 (0.09)	[−0.27, 0.09]	**0.53** (0.13)	[0.28, 0.78]
Total interactions					0.07 (0.05)	[−0.02, 0.17]	0.08 (0.07)	[−0.06, 0.21]
Germane load							0.22 (0.15)	[−0.08, 0.51]
Baseline learning	0.10 (0.17)	[−0.23, 0.42]	−0.08 (0.31)	[−0.70, 0.53]	−0.004 (0.14)	[−0.28, 0.27]	0.20 (0.19)	[−0.18, 0.58]
Age	0.05 (0.06)	[−0.07, 0.17]	−0.04 (0.11)	[−0.26, 0.18]	0.01 (0.05)	[−0.09, 0.11]	0.01 (0.07)	[−0.12, 0.15]
Gender[1]	0.06 (0.38)	[−0.69, 0.81]	−1.06 (0.71)	[−2.47, 0.34]	−0.09 (0.32)	[−0.72, 0.54]	0.11 (0.44)	[−0.77, 0.99]
VR experience	0.34 (0.20)	[−0.05, 0.73]	**0.81** (0.37)	[0.08, 1.54]	0.04 (0.17)	[−0.29, 0.37]	0.02 (0.23)	[−0.45, 0.48]
Cybersickness	−**0.25** (0.10)	[−0.45, −0.05]	0.04 (0.19)	[−0.33, 0.41]	−0.08 (0.09)	[−0.24, 0.09]	−**0.30** (0.12)	[−0.54, −0.06]

Indirect effects intrinsic load	*b* (*SE*)	95% CI	Indirect effects intrinsic load	*b* (*SE*)	95% CI
IL > INT > L	−**0.10** (0.07)	[−0.29, −0.01]	EL > INT > L	0.04 (0.10)	[−0.17, 0.25]
IL > TIN > L	< 0.001 (0.02)	[−0.03, 0.04]	EL > TIN > L	−0.05 (0.06)	[−0.22, 0.03]
IL > GL > L	−0.02 (0.02)	[−0.08, 0.01]	EL > GL > L	−0.12 (0.09)	[−0.33, 0.02]
IL > INT > GL > L	0.004 (0.01)	[−0.005, 0.02]	EL > INT > GL > L	−0.002 (0.01)	[−0.02, 0.01]
IL > TIN > GL > L	< 0.001 (0.003)	[−0.01, 0.01]	EL > TIN > GL > L	−0.01 (0.01)	[−0.04, 0.004]

Note. Regression coefficients are unstandardized. Coefficients in bold are significant at α = .05. Control variables are indicated in italics. [1]Gender was a dummy variable and coded as 1 (female) and 0 (non-female).

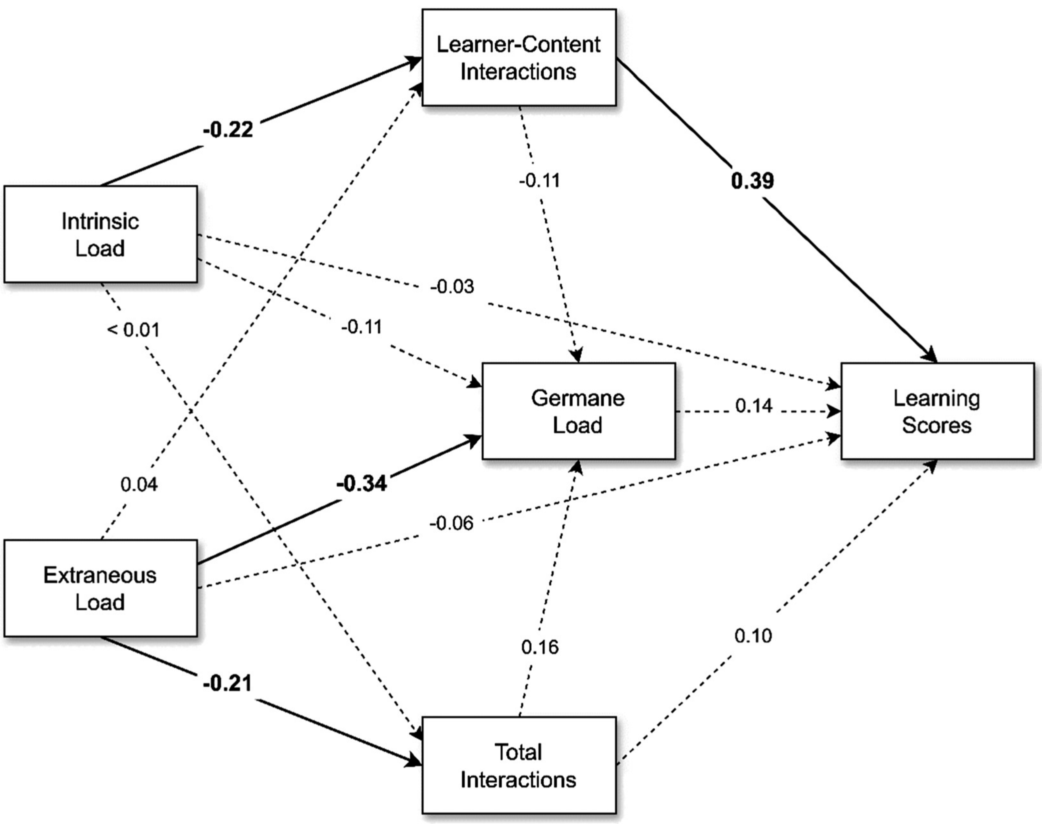

Figure 2. Combined serial mediation path models for the effects of intrinsic and extraneous load on learning, via interactivity and germane load. Regression coefficients are standardized. Coefficients in bold are significant at α = .05. Baseline learning, age, gender, VR experience, and cybersickness were included as control variables.

Table 2. Descriptive statistics and correlations of variables

Variables	*M*	*SD*	1	2	3	4	5	6
1. Intrinsic load	3.13	1.35	–	**.19**	−.19	**−.24**	.00	**−.28**
2. Extraneous load	1.87	0.69		–	**−.43**	−.13	**−.21**	**−.27**
3. Germane load	5.12	1.10			–	.07	**.21**	**.26**
4. Learner-content interactions	7.27	1.68				–	**.32**	**.56**
5. Total interactions	12.58	2.37					–	**.30**
6. Learning scores	5.80	1.76						–

Note. N = 102. Correlations presented in bold are significant at least at the .045 level.

How Learning Works in Virtual Reality

First, in line with cognitive load theory (Chandler & Sweller, 1991), we found that intrinsic load hinders learner-content interactions. This means that, when a topic is complex, learners will be less likely to interact with it in VR learning environments. Subsequently, when learners struggle to engage with the material, they are less likely to grasp the concepts effectively, leading to less effective learning outcomes.

Contrary to our expectations, germane cognitive load did not explain the effect of learner-content interactions on learning effectiveness. This is notable because, theoretically, higher germane load is associated with better learning outcomes (Paas & Sweller, 2014; Sweller et al., 2019). Empirically, however, the results have been mixed. For example, Kim and Kim (2020), in their study on health information processing, also found no relationship between germane load and knowledge acquisition and retention. What these studies have in common is that they adopt a combination of subjective cognitive load measures and performance measures for learning. This suggests that the relationship between germane load and learning outcomes might be context-dependent.

Second, the results show that extraneous load hinders total interactions. This means that learners will engage with fewer interactive elements when using the VR system is cognitively taxing. For example, because the navigation is confusing or complicated. These findings are in line with cognitive load theory (Paas & Sweller, 2014). Notably, the total number of interactions does not seem to predict learning outcomes.

Interestingly, the results show that only extraneous (and not intrinsic) load had a negative effect on germane load. This suggests that, when learners are subjected to high extraneous cognitive load, for example due to complexities related to navigating the VR environment, their cognitive resources are diverted away from germane load activities, such as understanding and internalizing the material. Or in other words, extraneous load reduces the mental capacity that can be devoted to the actual learning process. This echoes the findings by Albus and Seufert (2023), who recently showed that visual-only VR led to higher learning scores compared to audio-visual VR. On the contrary, intrinsic load, being the effort required to understand the material itself, does not seem to detract from germane load. A potential reason for this could be that this cognitive effort is related to the learning task.

Limitations and Suggestions for Future Research

In this study, we offer novel insights into the workings of cognitive load and interactivity in educational VR environments. However, this study also has several limitations, which should be considered when interpreting the results. For example, due to the cross-sectional design of the study, the results only have a limited explanatory power and cannot be used to infer causality. To explore causal relationships between cognitive load types and interactivity, we suggest a follow-up experiment in which intrinsic and extraneous load would be manipulated.

Another limitation would be the use of relatively older technology (i.e. Oculus Go) in this study. The Oculus Go offers only three degrees of freedom (3DoF), which means it tracks the rotation of the user's head in three axes: Yaw (left and right), pitch (up and down), and roll (tilting side to side). However, it does not track the user's position in space, such as moving forward or backward, up or down, or side to side, which would require six degrees of freedom (6DoF). In the context of our study, this might have influenced the results, particularly in terms of extraneous cognitive load. In this case, the restricted movement capabilities of the Oculus Go might have required participants to expend additional mental effort to navigate and interact within the VR environment, which is not directly related to the primary objectives of the study. While the study's findings are valuable, it is important to consider how these results would translate to a contemporary context with more advanced VR technologies. Future research should consider devices offering six degrees of freedom capabilities to determine if the observed effects remain consistent or if they are amplified with improved hardware. This would provide a more comprehensive understanding of the findings' applicability in the current technological landscape.

Although self-report measures, such as the scale used in the current study (Andersen & Makransky, 2021), are considered valid and reliable measures of cognitive load, they have some limitations. For example, they rely heavily on learners' subjective perceptions, which may not always accurately reflect actual cognitive processes. Also, self-reports are often collected after a task is completed, introducing the risk of memory biases or retrospective distortion. In future research, self-report measures could be supplemented with other methods, such as physiological measures (Ayres et al., 2021; Das Chakladar & Roy, 2024) for a more comprehensive assessment of cognitive load.

Furthermore, the operationalization of our dependent variable, learning, could be considered a limitation. The fact that only a small-to-medium sized correlation was found between germane load and learning scores could be considered at least notable, because, typically, higher germane load is associated with better learning outcomes (Paas & Sweller, 2014). Future research should therefore consider adopting different learning measures that might be more associated with germane load processes, such as understanding, rather than knowledge acquisition and retention. Additionally, an experimental design that pre-assesses participants' proficiency with VR technology and tailors the VR learning experience to their level of expertise could offer valuable insights into the relationship between the difference dimensions of cognitive load and learning outcomes. This approach would be particularly beneficial if task difficulty increases in alignment with the learner's growing competencies.

Additionally, future research could explore how different types of interactivity within VR environments impact cognitive load and learning outcomes. Building on this, experimental designs could be developed to directly compare the effects of different types of interactivity, such as exploratory versus guided interactions, on cognitive load and learning. Investigating further which types of interactions enhance learning and which may unnecessarily increase extraneous load, would provide valuable insights into optimizing VR-based learning experiences. Moreover, future studies could assess the effectiveness of interventions aimed at reducing cognitive load in VR environments, such as scaffolding techniques, to determine how these approaches can enhance both usability and educational outcomes in these immersive spaces.

Theoretical and Practical Implications

The current study has several implications for theory and practice. For theory, our study has three main contributions for the application of cognitive load theory in the context of VR learning environments. First, we show that, in VR learning environments, intrinsic load (the complexity of the content) hinders learner-content interactions. Second, contrary to our expectations, learner-content interactions were not associated with germane cognitive load (effort toward understanding the material). And third, extraneous load (the cognitive burden due to the way information is presented) negatively impacts both total interactions and germane load, but not learner-content interactions. Taken together, these findings call for refinements in cognitive load theory to account for the interplay between different types of cognitive load in VR learning environments.

For educators designing VR learning environments, the results suggest a need to be aware of how the inherent complexity of a topic (intrinsic load) can inhibit interactions with the material and, in turn, negatively affect learning performance. To mitigate intrinsic load, previous research (e.g., Mayer & Fiorella, 2021; Raaijmakers & Van Berlo, 2023) recommends breaking down complex topics and employing multimodal approaches tailored to learning styles.

In contrast, the findings indicate that while extraneous load does not significantly affect learner-content interactions, it does reduce total interactions – the broader set of actions a learner takes within the VR environment. Educators should focus on minimizing extraneous load, but not necessarily to enhance total interactions as total interactions do not directly contribute to learning. Instead, this could be done by eliminating unnecessary visual or auditory elements (Albus & Seufert, 2023) that do not support the learning objectives, and by ensuring that all interactive elements are related to the learning objectives (Nelson & Erlandson, 2008). For example, strategies such as scaffolding techniques could guide learners step-by-step through tasks to manage intrinsic load (Van Nooijen et al., 2024), while intuitive interfaces and streamlined navigation can further reduce extraneous cognitive strain (Reinhardt & Hurtienne, 2024).

Moreover, the results suggest that increasing the number of interactions, whether learner-content or total, does not automatically enhance germane load (the mental effort directed toward constructing knowledge and understanding). This underscores the need for instructional designs that are not only interactive but also purposefully structured to facilitate understanding. Reducing extraneous load without compromising interactivity could involve limiting irrelevant stimuli, optimizing the delivery of information, and carefully balancing the complexity of interactive elements to ensure alignment with learning goals. Furthermore, the results also show that instructional designers should be cautious in assuming that more interactions will necessarily lead to better learning outcomes. Instead, the focus should be on facilitating high-quality learner-content interactions that are directly aligned with learning objectives.

By carefully balancing these cognitive load factors – managing intrinsic load to enhance learner-content interactions and minimizing extraneous load to reduce its negative impact on germane load – educators and designers can create immersive and engaging VR environments that optimize learning outcomes.

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Zeph M. C. van Berlo, formal analysis, resources, writing – original draft, writing – review & editing, visualization; Hande Sungur, conceptualization, writing – review & editing, supervision; Fanni Margit Gyarmati, conceptualization, methodology, investigation, resources, data curation, project administration.

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Appendix

Table A1. Regression analysis for the combined serial mediation path models (without control variables)

Variables	Interactivity							
	Learner-Content Interactions (INT)		Total Interactions (TIN)		Germane Load (GL)		Learning (L)	
Direct effects	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI
Intrinsic load (IL)	−**0.26** (0.13)	[−0.51, −0.02]	0.09 (0.18)	[−0.27, 0.45]	−0.11 (0.08)	[−0.27, 0.05]	−0.14 (0.11)	[−0.36, 0.09]
Extraneous load (EL)	−0.22 (0.24)	[−0.71, 0.26]	−**0.77** (0.35)	[−1.46, −0.08]	−**0.60** (0.15)	[−0.90, −0.30]	−0.27 (0.23)	[−0.78, 0.13]
Learner-content interactions					−0.04 (0.06)	[−0.26, 0.26]	**0.50** (0.09)	[0.31, 0.68]
Total interactions					0.07 (0.05)	[−0.02, 0.16]	0.07 (0.06)	[−0.06, 0.20]
Germane load							0.26 (0.15)	[−0.05, 0.52]
Indirect effects	*b* (*SE*)	95% CI		Indirect effects	*b* (*SE*)		95% CI	
IL > INT > L	−**0.13** (0.07)	[−0.29, −0.01]		EL > INT > L	−0.11 (0.11)		[−0.35, 0.10]	
IL > TIN > L	0.01 (0.02)	[−0.03, 0.04]		EL > TIN > L	−0.05 (0.06)		[−0.21, 0.03]	
IL > GL > L	−0.03 (0.03)	[−0.10, 0.01]		EL > GL > L	−0.14 (0.10)		[−0.37, 0.01]	
IL > INT > GL > L	0.00 (0.01)	[−0.01, 0.02]		EL > INT > GL > L	0.00 (0.01)		[−0.01, 0.03]	
IL > TIN > GL > L	0.00 (0.00)	[−0.01, 0.01]		EL > TIN > GL > L	−0.01 (0.01)		[−0.04, 0.00]	

Note. Regression coefficients are unstandardized. Coefficients in bold are significant at α = .05. Baseline learning scores were included as control variable.