Behavioral Characteristics of Learning Phases: How Individual Differences Shape Learning Trajectories in a Virtual Environment

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Abstract

Procedural learning occurs in three phases—cognitive, associative, and autonomous—enabling skill acquisition across domains like medicine and sports. However, learning efficiency varies due to individual differences. While factors like cognitive abilities and learning environments influence this variability, their effects across learning phases remain understudied, particularly in Virtual Reality (VR). This study examines how cognitive abilities (memory span, mental rotation) and VR-related factors (familiarity, cybersickness) impact performance in a 3D assembly task within an immersive VR environment. Results reveal that lower VR familiarity prolongs task completion in early phases, highlighting interaction-related challenges. Higher mental rotation ability enhances performance in the autonomous phase, whereas cybersickness hinders efficiency. These findings suggest that adapting VR-based learning scenarios to individual profiles—such as early guidance for VR novices and phase-specific challenge adjustments—could optimize learning outcomes. Additionally, considering cybersickness effects in advanced phases supports the use of distributed learning approaches to mitigate discomfort.

Keywords: cybersickness; learning phases; mental rotation; user experience; working memory

Introduction

Procedural learning is a complex process through which individuals acquire, retain, and apply knowledge and skills. This process is influenced by internal (e.g., cognitive abilities) and external factors (e.g., learning environment).

Virtual Reality (VR) has emerged as a transformative tool for procedural learning, enabling learners to engage in interactive, immersive environments. While VR enhances engagement and provides adaptability in training scenarios, it also introduces new variables that may impact learning efficiency, such as the sense of presence or the susceptibility to cybersickness (Chang, Kim & Yoo, 2020; Luong et al., 2022; Makransky & Petersen, 2021). Despite numerous studies examining learning outcomes in VR (Hoareau et al., 2017; Pastel et al., 2023; Zahabi & Abdul Razak, 2020), limited attention has been given to the dynamic interplay between individual differences and the distinct phases of learning—cognitive, associative, and autonomous—as described in classic learning models (Fitts & Posner, 1967; Anderson, 1983; Ackerman, 1988).

The current study addresses this gap by analyzing how cognitive and user experience factors influence performance across these phases in a VR procedural task.

Procedural Learning and Individual Differences

Procedural learning describes the transition from the conscious processing of declarative knowledge to its automatic application, a process often characterized by three distinct phases: the cognitive, associative, and autonomous phases (Anderson, 1983; Fitts & Posner, 1967).

During the cognitive phase, learners actively interpret the task requirements, leading to slow and error-prone performance due to high cognitive load. Individual differences, such as general intelligence, working memory, and prior knowledge, play a critical role during this initial phase (Ackerman, 1988; Beaunieux et al., 2006).

In the associative phase, performance becomes more fluid as learners begin to refine their skills and correct errors. Here, procedural knowledge consolidates, and the demands on working memory decrease (Anderson, 1983). Interindividual differences at this phase can be attributed to perceptual speed (i.e., the ability to quickly identify, compare, or discriminate perceptual stimuli) and, consequently, to the efficiency with which procedural rules (productions) are compiled and applied (Ackerman, 1988; Anderson, 2009).

Finally, in the autonomous phase, task execution becomes automatic and efficient, with performance stabilizing at a high level. Differences in psychomotor abilities influence progression during this phase (Ackerman, 1988; Beaunieux et al., 2006).

In sum, progression through the three phases of procedural learning varies across individuals, with some advancing quickly initially but struggling later, while others progress more steadily after a slower start. These individual differences can be shaped by cognitive and non-cognitive factors, and influence both intra- and inter-phase learning dynamics.

In D. Barner, N.R. Bramley, A. Ruggeri and C.M. Walker (Eds.), *Proceedings of the 47th Annual Conference of the Cognitive Science Society*

Procedural Learning: Cognitive Factors

Cognitive abilities (e.g., working memory, attention, mental rotation), alongside motivation and emotions, influence how individuals learn and respond to situations, shaping the trajectory of their learning curves and predicting performance in procedural tasks both in virtual and non-virtual environments (Ackerman, Kanfer & Goff, 1995; Beaunieux et al., 2006; Burgoyne, Harris & Hambrick, 2019; Meinz et al., 2023). However, according to Meinz et al. (2023), non-cognitive factors are generally weaker or non-significant predictors of performance when cognitive ability is accounted for in the analysis.

Moreover, a limitation of existing research on learning is the comparison of individuals with varying skill levels without analyzing and breaking down the learning process itself (Langan-Fox et al., 2002; Meinz et al., 2023), a gap that Beaunieux et al. (2006) and Hubert et al. (2007) addressed by examining how individual differences manifest across distinct phases of learning, based on Ackerman's (1988) theory.

Beaunieux et al. (2006) demonstrated that certain cognitive functions have a greater impact at different learning phases, with general intelligence driving the cognitive phase, and episodic memory and executive functions playing a key role. In the associative phase, both general intelligence and psychomotor abilities influence performance, while in the autonomous phase, psychomotor skills become the primary determinant, with executive functions, particularly cognitive flexibility, linked to faster performance. Similarly, Hubert et al. (2007) identified cognitive predictors of the duration of the initial phases, associating them with non-verbal intelligence, episodic memory, perceptual processes, and executive functions. Brain data further validated these phase distinctions, showing a shift from frontoparietal to occipital and thalamic regions, signifying a transition from effortful to automated cognitive processing (Hubert et al., 2007).

Beyond cognitive factors, the speed at which individuals learn can also be influenced by environmental factors, such as the use of VR as a learning tool.

Procedural Learning in Virtual Reality: User Experience Factors

Individual differences in VR learning are largely driven by variations in User eXperience (UX; Hartson & Pyla, 2018; Mäkinen et al., 2022). The Components of User Experience (CUE) model by Thüring and Mahlke (2007) emphasizes how user experience is shaped by system properties (e.g., usability and aesthetics), user characteristics, as well as task and context. Key components of UX in Immersive Virtual Environments (IVEs), such as presence (the feeling of being in the IVE), usability, and cybersickness (also called motion sickness), can significantly impact learning performance (Hartson & Pyla, 2018; Mäkinen et al., 2022; Tcha-Tokey et al., 2018). For instance, a user-friendly interface that requires minimal effort is crucial for optimizing learning effectiveness and overall UX (Mäkinen et al., 2022; Orfanou, Tselios & Katsanos, 2015). Conversely, cybersickness, caused in particular by high-fidelity visual simulators, can limit the effectiveness of VR training by inducing nausea, and visual fatigue, which disrupt attention and learning (Fuchs, 2016; Munafo, Diedrick & Stoffregen, 2017).

The Cognitive Affective Model of Immersive Learning (CAMIL) by Makransky and Petersen (2021) further explores the impact of two key UX dimensions - presence and agency (the sense of control over actions in the IVE) - on learning outcomes. These dimensions, influenced by immersion, interaction, and realism, affect cognitive and affective processes like motivation, cognitive load, and embodiment. For instance, high agency, supported by realistic interaction, promotes embodiment (i.e., the sense of body ownership and control), which is essential for procedural learning that involves repeated task practice. However, benefits from presence and agency may be counterbalanced by excessive cognitive load, which can arise from excessive freedom of action or lack of familiarity with interactions (Faure et al., 2020; Makransky & Petersen, 2021). Familiarity with the technology is crucial, as users who are more experienced with VR tend also to experience less cybersickness (Chang et al., 2020; Luong et al., 2022).
Thus, VR's immersive and interactive features impact UX by modulating dimensions such as presence, agency, and cybersickness. These factors, along with prior technological experience, introduce additional sources of interindividual variability in learning performance.

The present study aims to enhance the understanding of the procedural learning process in VR by adopting a phase-based approach to explore the interplay between some cognitive abilities and VR-related UX factors. The memory span (working memory) and mental rotation abilities are examined as cognitive factors due to their well-known influence on learning in VR, particularly for assembly tasks (Li et al., 2020; Makransky & Petersen, 2021; Meinz et al., 2023). Additionally, IVE familiarity and cybersickness, are analyzed and grouped under the name of "UX factors" based on the work of Tcha-Tokey et al. (2018). These factors were selected because they can exert a disruptive influence on learning outcomes, regardless of task or context, particularly during repeated procedures and prolonged immersion in VE. To the best of our knowledge, no study has yet examined these factors across learning phases and their impact on VR learning performance. The study hypothesizes that cognitive factors, as well as IVE familiarity, would be particularly influential during the cognitive and associative phases, whereas cybersickness, which tends to manifest after extended immersion, would mainly affect the autonomous phase.

Methods

Participants

Forty-six participants were recruited, including 24 women aged around 23 (*SD* = 2.98, *min* = 18, *max* = 34). All participants held a bachelor's degree and had normal or corrected-to-normal vision. None had prior experience with the virtual environment used in the study or prior knowledge of the specific task.

The study was conducted in accordance with the World Medical Association's Code of Ethics (Declaration of Helsinki). All data were analyzed anonymously, and all participants gave written informed consent before participation, with the option of withdrawing from the study at any time.

Materials and Stimuli

Questionnaires and Cognitive Tasks. Participants' characteristics were assessed using a sociodemographic questionnaire and psychometric tests. The sociodemographic questionnaire gathered data on participants' familiarity with IVE, particularly the frequency of use. Responses on a 5-point Likert scale were categorized as follows: 4 for "daily," 3 for "several times per week," 2 for "several times per month," 1 for "less frequently," and 0 for "never". Simulator sickness was evaluated using the French version of the Simulator Sickness Questionnaire (SSQ; Kennedy et al., 1993), which comprises 16 items and is the most widely used tool for assessing cybersickness (Tian et al., 2022). Each item was rated on a 4-point scale: 0 for "not at all," 1 for "slightly," 2 for "moderately," and 3 for "severely". The SSQ was administered both before and after immersion in the VE to capture participants' baseline state and the effect of the immersion. The SSQ score used in the analyses was calculated as the difference between post-immersion and pre-immersion scores.

Cognitive performance was evaluated using two tasks. Working memory was assessed with the WAIS-III digit span test (Wechsler, 2001), which measured memory span through the maximum number of digits correctly recalled in both forward and backward orders. Mental rotation ability was assessed using the Vandenberg and Kuse Mental Rotation Test (1978), adapted by Albaret and Aubert (1996). Participants completed 20 items, each with two correct responses, yielding a maximum possible score of 40.

Procedural Tasks and Virtual Environments. Two Virtual Environments (VEs) were created using Unity. An HTC Vive Pro Eye headset (2800x1600 resolution, 110° field of view, and 90 Hz refresh rate) and a controller, represented in VEs (Figure 1B), were used. One VE was for familiarization with the environment and a procedure, and the other was for the experimental task of assembling a Soma cube.

Both VEs represented a simulated workshop with interactive elements, including tables, shelves, and a central switch that activated a timer and enabled interaction (Figure 1D). A panel with opaque sections displayed task steps, visible only when the controller passed through them. Instructions were presented graphically, showing previously placed pieces and highlighting the next piece to manipulate (Figure 1A). The familiarization VE featured five colored geometric pieces, while the experimental VE included the seven Soma cube pieces. To manipulate pieces, they had to press the controller’s trigger. A collision detection system highlighted overlapping pieces, with the manipulated piece turning yellow and the collided piece turning red (Figure 1C). Behavioral data were collected automatically by the VE and included: manipulation time (MT), instruction consultation time (ICT), planning time (PT), task realization time (TRT = MT + ICT + PT), number of piece manipulations (MN), instruction consultations (ICN), and incorrect actions (IAN).

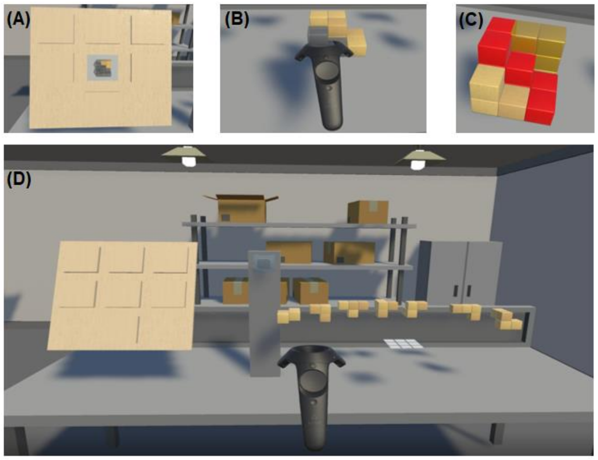


Figure 1: Experimental VE of the Soma cube.

Procedure

The experiment employed a within-subjects design, lasted approximately one hour per participant, and was conducted in individual sessions.

Before the experiment, participants were informed about their right to withdraw at any time, the confidentiality of their data, and the potential risks associated with VR. They provided informed consent by signing a form. They also completed a sociodemographic questionnaire and the SSQ (Kennedy et al., 1993).

Initially, participants completed the mental rotation and digit span tests. The experimenter then introduced the familiarization VE, providing formal instructions and demonstrating the interactions and task. Participants were equipped with a VR headset and completed two consecutive trials of a specially designed procedural task to become accustomed to the VE. Following this, participants performed the Soma cube assembly procedure ten times. A three-minute break was scheduled between the fourth and fifth trials to prevent prolonged VR immersion and mitigate potential side effects.

Finally, a debriefing discussion with the experimenter was conducted at the end of the session, during which the SSQ was also administered.

Data Analysis

The R statistical software (R Core Team, 2017) was used for data analysis. Four participants were excluded from the statistical analyses due to technical issues that occurred during the task.

Procedural Learning Assessment. A repeated measures ANOVA was conducted on all behavioral indicators collected during the Soma cube assembly task by the IVE, with trials treated as the repeated factor. When the assumption of covariance equality was violated (Mauchly's test), the Greenhouse-Geisser corrected p-value was used. Bonferroni correction was applied for post-hoc analyses to adjust the significance threshold, reducing Type I errors by dividing the alpha level by the number of tests conducted. Analyses were performed using the "stats" and "ez" packages (Lawrence & Lawrence, 2016).

Behavioral Model of Learning Phases Identification. The procedural learning phases were defined separately for each participant based on two behavioral indicators (log data): instruction consultations and incorrect actions. The phases were labeled "cognitive," "associative," and "autonomous" to align with theoretical models.

Behavioral rules were established from the literature and previous studies (Anderson, 1983; Fitts & Posner, 1967; Ganier, Hoareau & Devillers, 2013). A trial was classified as a "cognitive phase" if the number of instruction consultations was equal to or greater than the number of necessary instructions in the procedure. For example, in the Soma cube task, six out of seven instructions are considered necessary, as the last piece has only one possible position. Once instruction consultations fell below the number of necessary instructions, the trial was classified as an "associative phase", referring to the ACT theory compilation process (Anderson, 1983). A trial was classified as an "autonomous phase" when it and the preceding trial exhibited zero instruction consultations and incorrect actions. Progression between phases is unidirectional.

To assess whether these phases exhibit distinct behavioral patterns, a Linear Mixed Model (LMM) analysis was conducted on the mean data for each participant, calculated by phase, using the "lmerTest" and "stats" packages (Kunzetsova, Brockhoff & Christensen, 2017). Participants are considered as a random factor and identified learning phases as a within-subjects factor.

Individual Factors and Learning Phases. The behavioral characteristics of each learning phase were determined by calculating the mean of the trial data classified into each phase for each participant. Correlational analyses were conducted using Kendall's tau (Kendall, 1948) from the "Kendall" package for each behavioral characteristic across the three learning phases, with the following factors: memory span score, mental rotation score, SSQ score, and category related to the frequency of VE use.

Results

Procedural Learning Assessment

ANOVA revealed significant improvements in task performance across trials. The task realization time decreases with practice: *F* (9, 369) = 58.11, $p < .001$, $\eta^2_p = .53$ (Figure 2). Instruction consultations are shorter with practice (*F* (9, 369) = 62.22, $p < .001$, $\eta^2_p = .56$) and pieces manipulation is faster (*F* (9, 369) = 26.09, $p < .001$, $\eta^2_p = .33$). Planning time also decreased progressively (*F* (9, 369) = 62.48, $p < .001$, $\eta^2_p = .54$), from 143.72 seconds (*SD* = 95.05) on the first trial to 17.92 seconds (*SD* = 4.55) on the last trial.

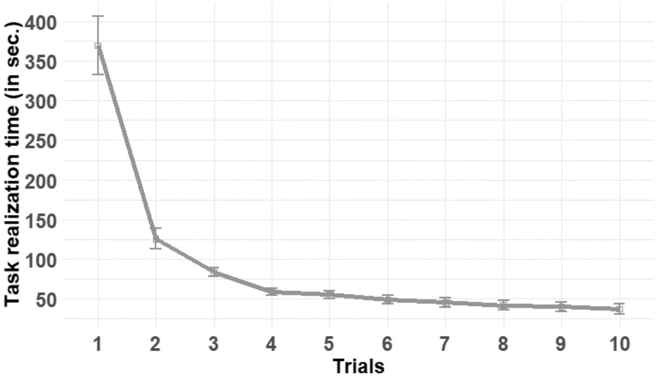


Figure 2: Learning curve (error bars corresponding to the standard error of the mean calculated for the within-participant model, Cousineau, 2005).

ANOVAs indicate that participants are more precise in their actions, with fewer incorrect actions (*F* (9, 369) = 18.89, $p < .001$, $\eta^2_p = .26$) and fewer manipulations of pieces (*F* (9, 369) = 23.51, $p < .001$, $\eta^2_p = .28$) as the trials progress. They also consulted instructions less frequently with practice (*F* (9, 369) = 53.24, $p < .001$, $\eta^2_p = .51$), dropping from around 66 consultations in trial 1 (*SD* = 53.90) to just one in trial 10 (*SD* = 3.06).

Behavioral Characteristics of Learning Phases

In the present study, the procedural task trials of each participant were divided into three learning phases — cognitive, associative, and autonomous — based on the model defined previously. On average, the number of trials in the cognitive phase was 3.35 (*SD* = 2.53), in the associative phase 3.28 (*SD* = 2.46), and in the autonomous phase 3.31 (*SD* = 2.44). There is variability in learning rhythm, with eight participants reaching the associative phase by the second trial, while most transitioned to this phase by the fourth trial. Regarding the autonomous phase, more than one-third of participants reached it within seven trials, while another third did not reach it even after 10 trials.

LMM analysis reveals performance differences between learning phases on indicators not used in the phase identification model design, with progressive improvement. Post-hoc tests show a significant improvement in the chronometric measures collected and in the number of manipulations between the cognitive phase and the other two phases ($p < .001$). There was, however, no significant difference between the associative and autonomous phases.

Individual Factors and Learning Phases

The participants obtained an average mental rotation score of 23.29 (*SD* = 6.93, *min* = 10, *max* = 39) and an average working memory span score of 15.48 (*SD* = 3.76, *min* = 9, *max* = 25). A negative cybersickness score indicates that participants felt better after the experience. Participants reported experiencing cybersickness symptoms, as assessed by comparing pre-immersion (*M* = 3.55, *SD* = 4.32) and post-immersion (*M* = 5.66, *SD* = 4.89) scores using a Wilcoxon test: *V* = 148, *p* < .001. Thus, symptoms of cybersickness may have impacted participants' learning performance (total SSQ score: *M* = 1.98, *SD* = 3.45, *min* = -5, *max* = 10). The frequency of VE use, measured on a 5-point scale, revealed that 50% of participants had never used VEs before the experiment, 10% used them several times per month, and 40% used them less frequently.

Cognitive Learning Phase. For the first phase, only a statistical trend appeared between the memory span score and manipulation time (*tau* = -.21, *p* < .08). Regarding VR-related UX factors, the significant correlations in the cognitive phase concern the IVE familiarity factor and planning time (*tau* = .26, *p* < .05) and pieces manipulation time (*tau* = -.29, *p* < .05) (Figure 3).

Associative Learning Phase. Correlations with cognitive factors and mean associative phase performance were all non-significant. Regarding VR-related UX factors, familiarity with IVEs correlated with planning time (*tau* = -.32, *p* < .05), manipulation time (*tau* = -.27, *p* < .05), and also task realization time (*tau* = -.30, *p* < .05) (Figure 3).

Autonomous Learning Phase. In the autonomous phase, the correlation between mental rotation ability and planning time is significant (*tau* = -.31, *p* < .05), as is the correlation between memory span and number of manipulations (*tau* = -.33, *p* < .05), while only a trend appears between mental rotation and task realization time (*tau* = -.26, *p* < .08). A significant correlation between the cybersickness score and the average number of incorrect actions appears (*tau* = .45, *p* < .01) (Figure 3).

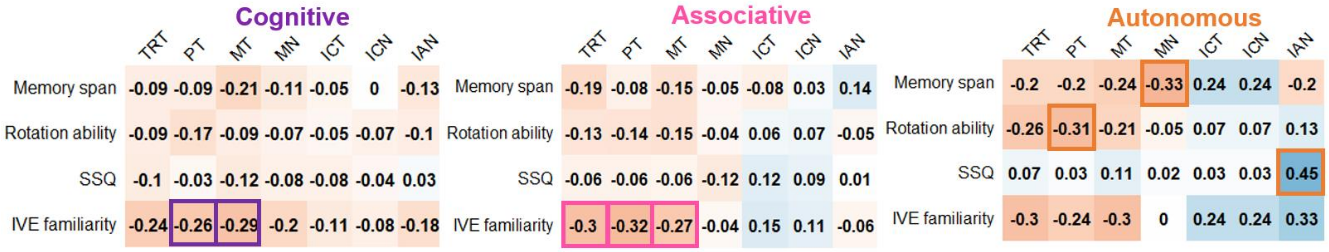
Discussion

The present study investigated the influence of cognitive factors and UX with IVE on performance during procedural learning in VR, offering a novel perspective by employing a phase-based analysis.

First of all, the results confirmed the existence of a procedural learning process for the Soma Cube assembly task in VR, as evidenced by overall performance improvements with practice (i.e., both in terms of speed and accuracy), aligning with previous studies demonstrating the feasibility of procedural learning in VEs (e.g., Ganier et al., 2013). Moreover, the cognitive and associative learning phases identified by the model show different behavioral patterns concerning indicators that were not used to identify them. The absence of significant behavioral differences between the associative and autonomous phases aligns with Tenison and Anderson's (2016) observation.

Although behavioral indicators were interdependent, significant correlations with the studied factors were not systematic, suggesting that specific factors impact particular performance dimensions. Analyzing the learning process across three phases clarified these relationships, revealing phase-specific influences of cognitive abilities and UX. Results support the notion that knowledge and skills reorganize with practice, as the factors studied have different impacts depending on the learning phase (Anderson et al., 2021).

For instance, during the cognitive and associative phases, lower familiarity with IVEs negatively influenced timing measures, underscoring the importance of the interactive dimension in procedural learning. This process relies on the practice and repetition of actions. Prior experience with new technologies affects the early phases of learning, which are already cognitively demanding, potentially generating extraneous cognitive load (Makransky & Petersen, 2021; Sweller, Ayres & Kalyuga, 2011). This influence can be attributed to the novel interaction forms introduced by VR, which may affect learners’ motor abilities. This aligns with the CAMIL model and research on UX, where interaction serves as a central dimension, influencing both agency and usability, factors that directly affect learning performance in VR (Makransky & Petersen, 2021; Tcha-Tokey et al., 2018; Thüring & Mahlke, 2007). Future studies could explore the impact of prior UX with IVEs, examining behavioral



Cognitive

	TRT	PT	MT	MN	ICT	ICN	IAN
Memory span	-0.09	-0.09	-0.21	-0.11	-0.05	0	-0.13
Rotation ability	-0.09	-0.17	-0.09	-0.07	-0.05	-0.07	-0.1
SSQ	-0.1	-0.03	-0.12	-0.08	-0.08	-0.04	0.03
IVE familiarity	-0.24	-0.26	-0.29	-0.2	-0.11	-0.08	-0.18

Associative

	TRT	PT	MT	MN	ICT	ICN	IAN
Memory span	-0.19	-0.08	-0.15	-0.05	-0.08	0.03	0.14
Rotation ability	-0.13	-0.14	-0.15	-0.04	0.06	0.07	-0.05
SSQ	-0.06	-0.06	-0.06	-0.12	0.12	0.09	0.01
IVE familiarity	-0.3	-0.32	-0.27	-0.04	0.15	0.11	-0.06

Autonomous

	TRT	PT	MT	MN	ICT	ICN	IAN
Memory span	-0.2	-0.2	-0.24	-0.33	0.24	0.24	-0.2
Rotation ability	-0.26	-0.31	-0.21	-0.05	0.07	0.07	0.13
SSQ	0.07	0.03	0.11	0.02	0.03	0.03	0.45
IVE familiarity	-0.3	-0.24	-0.3	0	0.24	0.24	0.33

Figure 3: Correlations between behavioral measures and individual factors across the three learning phases. Significant correlations are boxed in bold; color indicates strength and direction of correlation (blue: positive, red: negative).

measures collected during familiarization periods to complement subjective measures.

In the autonomous phase, higher mental rotation and working memory scores contributed to overall performance improvement, likely due to more efficient long-term memory organization. Previous research has shown that "experts" (i.e., individuals with a high level of mastery) manage to extend their working memory by optimizing the use of long-term memory, allowing for faster and more efficient retrieval (Ericsson & Kintsch, 1995; Gobet & Simon, 1996). This ability may vary according to individuals' initial cognitive capacities.

Moreover, during this final learning phase, accuracy (i.e., the number of incorrect actions) deteriorated due to the onset of cybersickness, which aligns with research on the impact of sensory-motor inconsistencies on learning performance in VR (Fuchs, 2016; Makransky & Petersen, 2021; Munafo et al., 2017). Future research could assess cybersickness using the SSQ administered after each trial or through real-time physiological measures, enabling a more precise analysis of its impact on VR learning (Chang et al., 2020).

As highlighted by Ackerman’s theory (1988) and the work of Beaunieux et al. (2006), cognitive factors should allow for more precise identification of the cognitive phase relative to other learning phases. A decrease in the importance of cognitive abilities as learning progresses should be observed. However, although the results related to cognitive factors partially explain the individual differences in learning rhythms in VR, they do not support the hypothesis that cognitive factors are more strongly associated with the first phase. This divergence could be explained by the use of a single test to assess this factor, whereas previous studies relied on multiple tests, providing a more comprehensive evaluation. Furthermore, using a spatially oriented working memory test would likely have been more relevant for assessing performance in a VR learning context, which involves graphic instructions and a 3D shape assembly task. These results nonetheless align with studies that have emphasized that, in certain tasks, these abilities remain crucial even in the later phases of learning (Bell, Gardner & Woltz, 1997; Matthews, Jones & Chamberlain, 1992).

Methodological limitations, such as sample size and the diversity of psychometric tests and questionnaires used, continue to pose challenges for comparing and generalizing results in the study of individual differences. As Ranganathan, Cone, and Fox (2022) noted in their review of individual differences in motor learning, the high variability in predicted and predictive variables limits the robustness of empirical evidence. In the context of IVE, it would also be relevant to consider implementing cognitive tests – such as mental rotation – directly within VR, to ensure greater ecological validity and alignment with the experimental setting. Furthermore, some results (e.g., the role of mental rotation) may not generalize to non-VR learning contexts or other tasks.

Unlike standardized traditional methods, VR supports personalized learning by adapting task difficulty and feedback to individual performance and preferences (Field et al., 2011; Ganier et al., 2013; Riemer et al., 2024; Riemer et al., 2024; Ropelato et al., 2018). By targeting task-specific characteristics, such as mental rotation ability (as explored in this study), and accounting for levels of technological familiarity, learning pathways can be customized to better meet learners' needs. However, current adaptive strategies often fail to account for learners' progression through the learning phases.

Integrating real-time, automated phase detection into VR systems could enhance personalization. In early phases, feedback like object highlighting could facilitate action planning, particularly for low-tech users (e.g., controller button highlights or directional arrows). As learners progress to autonomous performance, feedback should be reduced to avoid visual overload and favor proprioceptive cues (Magill & Anderson, 2010). This progression aligns with Ackerman’s theory (1988), linking the autonomous phase to psychomotor abilities. At this phase, task execution becomes automatic, and proprioception enables smoother, more efficient motor control.

Instructional strategies could likewise evolve, shifting from step-by-step guidance to goal-based prompts (e.g., for hierarchical structuring of instructions: Hoareau, Querrec & Ganier, 2015) and incorporating increased task complexity or variability to maintain challenge (Field et al., 2011). Adapting to learners’ progress and preferences could also include distributed practice strategies or rest periods (Beaunieux et al., 2006; Hong et al., 2019; Kim, Ritter & Koubek, 2013), optimizing performance and consolidating knowledge while accounting for cybersickness. This phased personalization aligns with the “challenge point framework” (Guadagnoli & Lee, 2004), emphasizing that effective learning strategies depend on the interaction between task characteristics, learner skill level, and information processing capacity. VR thus offers an opportunity to design tailored learning pathways that adapt to learners' strengths, weaknesses, and individual pace.

Conclusion

To better understand individual differences in procedural learning within VR, the present study emphasizes the role of cognitive abilities and UX dimensions across the distinct learning phases (cognitive, associative, and autonomous). By adopting a phase-based approach to the learning process, this research enriches existing theoretical models, such as the CAMIL model (Makransky & Petersen, 2021), and provides practical insights for optimizing the design of immersive learning environments. VR-based learning scenarios could benefit from considering both the learner's profile and their learning rhythms.

Future research should adopt a learning phase-based analysis approach to better understand sources of variability in IVE learning, examining diverse tasks and populations and incorporating factors such as motivation and personality.

Acknowledgements

This work was supported by French government funding managed by the ANR (National Agency for Research and Innovation), grant number ANR-21-ESRE-0030 (CONTINUUM), and also by Brest Métropole. We would like to thank Frédéric Devillers and Sébastien Levieux for development and technical support, as well as Fanny Dessaint, Carole Boezet, and Mona Le Guillou for managing the experimental sessions.

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