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Inductive Reasoning Challenges in Virtual Reality: A Case Study on Designing Submarine Models

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Abstract

Inductive reasoning plays a pivotal role in engineering education, empowering students to derive broader principles and generalizations from concrete, context-specific observations, thereby fostering innovative problem-solving and adaptive application of knowledge. This study presents the results of a comprehensive quantitative analysis and introduces a theoretical model that demonstrates how Virtual Reality learning environments can effectively support the inductive reasoning process, ultimately enhancing learning outcomes and improving the transfer of skills to real-world engineering scenarios. As an addition to existing literature, we propose a series of factors that have been combined in an original manner to show the correlation between cognitive characteristics of individuals and learning outcomes in virtual environments relevant for engineering education. Our selected target group, consisting of undergraduate engineering students at MINES Paris—PSL, engaged in hands-on tasks involving the design and iterative testing of submarine prototypes within a simulated underwater setting, facilitated by a bespoke Virtual Reality platform called the Submarine Simulator. By addressing key challenges in leveraging immersive tools, this research contributes to the existing body of literature on inductive reasoning, offering actionable insights for refining pedagogical approaches in science, technology, engineering and mathematics fields and promoting more effective integration of emerging technologies in modern engineering curriculum design.

Keywords: 3D modelling; engineering education; human-computer interaction; immersive technologies

1. Introduction

Improving the efficiency of engineering training remains a continuous challenge for computer science and engineering experts, who work alongside researchers in educational sciences and learning psychology to explore various educational approaches, including the use of Virtual Reality (VR) technology in higher education.

In engineering education, VR-based learning showed a 12% improvement in post-test quiz scores compared to traditional two-dimensional (2D) video-based learning methods (Ka et al., 2025). Similarly, students using VR headsets achieved significantly higher mean quiz scores compared to traditional learning groups (Predescu et al., 2023). Superior performance of VR-based learning approach appears to stem from several mechanisms. VR provides interactive experiences (Hussain et al., 2024), enhances engagement, immersion and motivation (Ka et al., 2025). VR environments allow for experiential learning scenarios that promote collaboration and address diverse educational needs (Faresta et al., 2024). The technology's ability to provide immediate feedback and create safe learning environments for complex procedures contributes to improved learning outcomes (Beatrice et al., 2024).

From the cognitive process point of view, the traditional engineering instruction is deductive, beginning with theories and progressing to the applications of those theories. Alternative teaching approaches, including VR, are more inductive (Savadatti & Johnsen, 2017). Inductive reasoning represents a cognitive process of drawing general conclusions from specific observations and as a fundamental skill in education and problem-solving, it is an important mechanism that can explain the learning process in VR environments.

Literature reviews underscore VR's role in enhancing knowledge transfer through immersive environments, with inductive reasoning as a critical cognitive mechanism. However, explicit connections to engineering education, particularly in applied contexts, remain underexplored. This study investigates the interplay between inductive reasoning and training efficiency using a custom VR tool, the *Submarine Simulator*, designed to teach hydrodynamics principles within a comprehensive undergraduate course on underwater engineering. By situating the research within the broader landscape of science, technology, engineering, mathematics (STEM) education, we aim to explore how VR-driven inductive reasoning can generalize to diverse engineering disciplines, such as aerospace or structural engineering, where similar principles of fluid dynamics apply.

This research extends the literature on inductive reasoning by addressing challenges in integrating digital modalities through VR tools like the *Submarine Simulator*. It proposes actionable refinements to STEM pedagogy, offering insights into scalable VR applications across technical curricula to enhance learning outcomes beyond the specific case of underwater engineering.

2. Theoretical Background

Inductive reasoning is linked to transfer as a cognitive aptitude for deriving principles from specifics, aiding problem-solving in VR. In cognitive transfer theories, it is part of aptitudes analyzed for learning, involving pattern induction to construct schemas that transfer across contexts (Hickey & Kantor, 2024). Constructivist approaches emphasize inductive processes in building higher-order knowledge, with VR providing data-rich environments for this (Hickey & Kantor, 2024).

A thesis on adaptive learning observed that inductive reasoning is supported through VR simulations, enabling learners to examine patterns in virtual engineering activities and derive generalized solutions, which in turn boosts critical thinking and knowledge transfer (Zhang, 2024). Studies in visuospatial cognition have associated inductive-like inference (such as identifying movement patterns) with knowledge transfer, where elevated visuospatial ability (linked to inductive competencies in spatial activities) enhances results in VR interactions that involve shifting perspectives (Brucker et al., 2024). In engineering education, VR supports the visualization of intricate 3D structures (Brucker et al., 2024). Such implementations point to opportunities for inductive reasoning activities that involve identifying patterns and developing hypotheses.

A concise summary of transfer challenges outlines five primary concepts: (1) the form of transfer permits categorization of the virtual environment (VE) based on the knowledge acquired; (2) the transfer mechanism can establish conditions inside the VE to promote learning transfer; (3) certain VR characteristics need to align and adhere to principles of learning transfer; (4) transfer acts as a tool for evaluating the effectiveness of a VE; and (5) subsequent research on learning transfer should explore the distinctive context of learning (Bossard et al., 2008).

VR simulations promote learning transfer by bridging theory and practice, allowing engineers to apply skills in virtual scenarios that mimic real-world challenges. A systematic literature review of VR-education studies found VR superior to traditional methods for knowledge transfer, with meta-analyses showing medium to large effect sizes on outcomes like skill retention and task performance (Lampropoulos et al., 2025). In engineering, VR applications include training for construction workers via 3D simulations, resulting in better retention and participation than 2D videos, and Industry 4.0 courses reducing costs while improving safety and efficiency (Lampropoulos et al., 2025). Another study on marine engineering VR systems highlighted skill generalization to real operations, emphasizing transfer in technical fields (Hjellvik & Mallam, 2024). VR facilitates experiential learning in higher education, particularly for technical fields like engineering, leading to improved skill acquisition and retention compared to traditional methods (Radianti et al., 2019). Additionally, VR enhances knowledge retention and skill transfer in technical disciplines, such as engineering, by allowing students to practice complex tasks in safe, controlled settings, thereby fostering critical thinking and problem-solving skills (Vats & Joshi, 2023).

2.1. Cognitive Processes Supporting Learning in VR

While specific inductive reasoning measures are limited, several studies examined related cognitive processes. VR interventions showed improvements in spatial reasoning and decision-making capabilities (Faresta et al., 2024), with clear advantages for tasks requiring spatial understanding and complex problem-solving. Students showed better performance in remembering tasks and demonstrated improved understanding of 3D structures (Allcoat & Von Mühlenen, 2018). The main contributions to training in VR have been oriented towards the following aspects:

- *Problem-solving capabilities*: One study reported a statistically significant improvement for the VR group in problem-solving tasks ($p=0.038$, Cohen's $d=0.68$), which the authors interpreted as evidence that virtual reality may support higher-order cognitive skills in engineering contexts (Tan, 2003). However, this finding is based on a small sample and limited reporting.
- *Three-dimensional structure comprehension*: Ka et al., 2025, found a 13% improvement in three-dimensional reconstruction tasks for the virtual reality group, indicating enhanced spatial understanding and visualization skills with immersive virtual reality. We did not find mention of statistical significance for this outcome.

3. Research Methodology

We investigated how inductive reasoning is connected to learning outcomes in a custom-built VR learning environment named the *Submarine Simulator*. Our main hypothesis is that using VR helps improve inductive processes, which in turn leads to better learning and the ability to apply new knowledge in engineering situations.

This approach extends to professional training, where engineers in industries like maritime or energy can use the VR platform to practice resolving technical challenges, thereby boosting operational efficiency and safety in high-stakes environments. Similarly, naval personnel can leverage the simulator for military applications, training to make rapid, accurate decisions in unpredictable scenarios, such as detecting underwater threats, by strengthening their ability to infer patterns from limited data. The simulator's framework holds potential for scalability, informing the development of VR training platforms for other industries, such as aviation or manufacturing, fostering innovation and safer practices across diverse domains. By enhancing individual performance and problem-solving, the *Submarine Simulator* offers a versatile tool for advancing education, professional development, and operational excellence in engineering and related fields.

As a result, the following research questions have been formulated:

- **RQ1:** How do cognitive abilities and immersive tendencies in VR (Factor 1) influence performance outcomes (Factor 2) and overall learning transfer to real-world tasks?
- **RQ2:** To what extent does inductive reasoning, as indicated by a synergy of variables like spatial abilities and fluid intelligence, enable generalization of VR-based skills to practical applications?

Additionally, one main hypothesis has been formulated:

- **H1:** Strong correlations between cognitive-immersion factors (Factor 1) and performance (Factor 2) indicate that VR's immersive environment drives enhanced learning outcomes and real-world transfer.

3.1. Research Design

To leverage the VR software application, our study consisted of two consecutive sessions, one week apart. During the first session, students were introduced to the application, gaining an understanding of the user interface and learning how to construct and test submarine models in the underwater simulation.

During the second session, participants designed and tested models to navigate both tight and loose spiral trajectories. This design was crafted to foster inductive reasoning, leveraging insights from sketching to develop hypotheses about hydrodynamic principles for VR prototypes.

3.2. Target Group

During an advanced course on underwater engineering at MINES Paris—PSL, 26 fourth-year engineering students participated in our research. To ensure ethical standards, all participants signed a consent form. They were guaranteed that their anonymity would be maintained throughout the study and its publication. To protect their identity during data analysis, each student was assigned a random numerical code instead of their name.

3.3. Methods

In our research, we employed a carefully curated set of methodologies to collect robust and relevant data, specifically tailored to evaluate spatial aptitudes, cognitive reasoning, immersive tendencies, and task performance within our custom-built VR software application. These methods were selected for their well-established validity and reliability in assessing the cognitive and behavioral constructs central to our study.

While these methodologies are individually grounded in existing literature, the originality of our approach lies in their synergistic integration and targeted application within the novel context of a VR environment designed to evaluate inductive reasoning. By combining these established tools in a unique configuration, specifically tailored to the immersive and interactive nature of VR, we address a gap in the literature, offering new insights into how these cognitive processes manifest in virtual settings.

This approach not only leverages the strengths of validated methods but also introduces a new perspective to the broader literature by exploring their interplay in an original technological framework for underwater engineering, thus contributing to the evolving discourse on VR's role in cognitive assessment. More specifically, the following instruments have been used:

3.2.1. Vandenberg's Mental Rotations Test (VDB)

The Vandenberg's Mental Rotations Test (VDB), developed in 1978 by Vandenberg and Kuse, assesses spatial aptitude by presenting a target figure and options, some being rotated versions and others mirror-image foils. Participants identify rotated versions, testing their ability to mentally manipulate 2D and 3D objects.

The VDB was chosen for its proven validity in measuring spatial visualization, a critical skill for engineering tasks like designing submarine models in a VR environment. Unlike general cognitive tests or verbal assessments, the VDB specifically targets mental rotation, directly relevant to visualizing complex 3D geometries and trajectories. Its established psychometric reliability and extensive use in spatial cognition research ensure robust measurement of individual differences, enabling correlations between spatial aptitude and VR task performance.

3.2.2. Raven's Progressive Matrices (RVN)

Raven's Progressive Matrices (RVN), specifically the Advanced Progressive Matrices (APM) version, is a non-verbal test of fluid intelligence, assessing abstract reasoning and problem-solving in novel contexts. Designed for adolescents and adults with above-average intelligence, the APM features complex patterns requiring identification of relationships and outcomes.

The RVN was chosen for its robust measurement of fluid intelligence, critical for adapting to unfamiliar VR submarine design tasks. Unlike spatial tests or knowledge-based assessments, RVN focuses on abstract reasoning, aligning with the need to solve novel problems like optimizing submarine trajectories. Its well-established psychometric validity ensures reliable evaluation of cognitive flexibility, enabling analysis of how reasoning predicts VR task performance.

3.2.3. Immersive Tendencies Questionnaire (ITQ)

The Immersive Tendencies Questionnaire (ITQ), completed before exposure to VR, measures tendencies toward immersion using a 7-point Likert-type scale. It assesses engagement in activities like reading, gaming, or watching films, with higher scores indicating stronger immersive tendencies linked to better virtual environment performance and presence.

The ITQ was chosen for its validated ability to measure immersion predispositions, crucial for VR submarine simulator tasks requiring sustained focus. Unlike cognitive or spatial tests, ITQ uniquely evaluates psychological engagement, directly relevant to VR presence and performance. Its established use in VR research ensures reliable insights into how immersion influences task success and learning in virtual environments.

3.2.4. Performance Scoring (Points1, Points2)

A scoring system objectively measured student performance in two VR sessions using the *Submarine Simulator*:

- *Session 1:* A scored exercise on submarine construction and testing, evaluated on a 0-20 scale, assessed foundational building and testing skills.
- *Session 2:* Participants designed two submarine models for tight and loose spiral trajectories, scored on a 0-2 pass/fail scale (2 for both designs, 1 for one, 0 for none), focusing on strategic planning and refinement.

This custom scoring was chosen to directly measure task-specific engineering skills in VR. The granular scale for session 1 captures nuanced skill development, while session 2's binary scoring evaluates directly design outcomes. Tailored to the study's VR tasks, it provides reliable, objective performance data to correlate with the cognitive and immersive measures described previously.

3.2.5. Statistical Methods

In the context of our research, we have applied a Confirmatory Factor Analysis (CFA), which represents a statistical technique used in different science fields to test whether collected data fits a pre-specified theoretical factor model. Specifically, CFA examines whether certain observed variables (in our case, points per sessions as learning outcomes) reflect one or more latent factors (in our case intelligence, spatial thinking, immersive tendencies). CFA provides information on how well each indicator contributes to its factor.

To analyze the data, we have used JAMOVI – an open-source statistical software designed to be a user-friendly and approachable alternative to more complex and expensive programs like SPSS.

4. Results and Discussions

4.1. CFA Analysis

To analyze the data, we describe the statistical elements and explore their implications within the framework of the systematic review examining the connection between inductive reasoning and learning transfer in VR-based engineering education, specifically in a VR setting, while accounting for two loading factors. The term "factor" denotes the latent constructs (labeled as factor 1 and factor 2) derived from factor analysis, which embody underlying dimensions such as inductive reasoning, learning transfer, and VR-associated constructs.

The data gathered from the tests were categorized into two factors: factor 1, which includes students' personal attributes (intelligence, spatial thinking aptitude, immersive tendencies), and factor 2, which consists of data from VR usage (points after session 1 and after session 2). Detailed factor loadings are presented in Table 1.

Table 1: Factor loadings per each indicator

Factor	Indicator	Estimate	SE	Z	p
Factor 1: Personal Traits	RVN_IQ	9.565	1.490	6.42	<.001
	VDB	2.983	0.705	4.23	<.001
	Immersive	0.705	0.103	6.81	<.001
Factor 2: Learning Outcomes	Points1	3.938	0.608	6.47	<.001
	Points2	0.228	0.106	2.16	0.031

The constructs displayed in Table 1 are defined as follows:

- *Indicator* refers to specific variables or items loading onto each factor. Our current indicators are: RVN_IQ, VDB, Immersive for factor 1 and Points1, Points2 for factor 2.
- *Estimate* refers to the standardized factor loading, which reflects the strength and direction of the association between the indicator and the latent factor. Larger absolute values imply stronger connections.
- *Standard Error (SE)* measures the precision of the estimate. Smaller SEs indicate more precise estimates.
- *Z-score (Z)* is calculated as Estimate/SE and tests the significance of the loading. Larger absolute Z-values suggest statistical significance.
- *P-value (p)* indicates the statistical significance of the loading. Values < 0.05 typically denote significance.

4.1.1. Analysis of Factor 1

The statistical evaluation of factor 1 yields the following conclusions and results:

- *RVN_IQ (9.565):* This exceptionally high loading suggests the fact that RVN_IQ is a very strong indicator of factor 1. The loading exceeds 1, which is unusual in standardized factor analysis (typically bounded between -1 and 1), indicating possible unstandardized estimates or a specific scaling method (e.g., unstandardized coefficients in structural equation modeling). The value is highly significant ($p < .001$, $Z = 6.42$).
- *VDB (2.983):* A strong loading as well, though less extreme, suggesting VDB is a key contributor to factor 1. We can consider it significant ($p < .001$, $Z = 4.23$).
- *Immersive (0.705):* A moderate to strong loading, within the typical standardized range, indicating a good association with factor 1. Highly significant as well ($p < .001$, $Z = 6.81$).

Based on these findings, we believe that factor 1 embodies a construct tied to cognitive capabilities that encompass inductive reasoning, adaptability, intelligence, and individual immersive tendencies. RVN_IQ could represent a combined metric (for instance, an IQ tied to reasoning within virtual reality), VDB pertains to a variable involving visuals or design, whereas immersive tendencies reflect an individual's personal traits when engaging with VR-based educational settings.

4.1.2. Analysis of Factor 2

The statistical evaluation of factor 2 yields the following conclusions and results:

- *Points1 (13.938):* An extremely high loading, suggesting once again unstandardized estimates or a specific model. We may consider it highly significant ($p < .001$, $Z = 6.47$).
- *Points2 (0.228):* A weak loading, but still significant ($p = 0.031$, $Z = 2.16$), indicating a marginal contribution to factor 2.

According to these results, factor 2 represents a performance or outcome-related construct, which reflects a learning transfer that allowed task performance in VR. Points1 might be a primary performance metric, while Points2 is a weaker or secondary indicator.

All indicators are statistically significant ($p < 0.05$), with most having $p < 0.001$, indicating robust relationships between indicators and their respective factors. The lower Z-score and higher p-value for Points2 ($Z = 2.16$, $p = 0.031$) suggest it’s the least reliable indicator, with a weaker association to factor 2. SEs are relatively small (e.g., 0.103 for Immersive, 0.608 for

Points1), indicating precise estimates, except for RVN_IQ and VDB, where higher SEs (1.490, 0.705) reflect the larger magnitude of their loadings.

4.1.3. Analysis of Hypothesis

To interpret these factors in the context of the systematic review on inductive reasoning and learning transfer in VR engineering education, we will present an analysis of hypotheses and the meaning of the indicators based on their scientific output and the review's findings.

As mentioned before, factor 1 represents a cognitive or VR immersion construct critical to engineering education. More specifically:

- *RVN_IQ:* Is a measure of reasoning ability in VR, possibly tied to inductive reasoning (e.g., pattern recognition in virtual simulations). Its high loading suggests it's central to the cognitive process in VR.
- *VDB*: Serves as an indicator of spatial intelligence, which can be applied to engineering principles that demand strong visualization skills and 3D modeling.
- *Immersive:* Measures the individuals' immersive tendencies in VR, which can be key in enhancing the learning outcomes.

Factor 1 may capture the cognitive and immersive mechanisms (e.g., inductive reasoning and VR engagement) that facilitate learning transfer in engineering tasks, such as applying virtual prototype knowledge to physical builds.

Factor 2 represents the overall performance in VR or transfer of knowledge. More specifically:

- *Points1:* Represents a primary measure of learning transfer and performance scores on engineering tasks post-VR training. Its high loading suggests it's a strong indicator of successful transfer.
- *Points2:* A weaker indicator, possibly a secondary performance metric or a less reliable measure of transfer (e.g., a specific subtask). Its marginal significance suggests it's less central to the construct.

Factor 2 likely reflects the outcome of learning transfer, with Points1 capturing the primary transfer effect (e.g., applying VR-learned skills to real engineering problems) and Points2 indicating a peripheral aspect.

The strong loadings for RVN_IQ and Immersive on factor 1 suggest that VR's immersive environment and cognitive demands (e.g., inductive reasoning) are critical for learning transfer. The weak loading for Points2 ($p = 0.031$) suggests variability in some transfer measures, acknowledging the need for more longitudinal studies to assess consistent transfer.

The data analysis suggests that factor 1 captures cognitive and immersive aspects of VR (e.g., inductive reasoning, immersion), while factor 2 reflects transfer outcomes (e.g., performance in engineering tasks). The strong loadings and significant p-values indicate robust relationships, though the weak loading for Points2 highlights potential variability in transfer outcomes.

4.2. Covariance Analysis

Table 2 presents covariances between our latent factors. Covariance analysis in CFA is fundamental, because CFA is essentially a model of covariances, as it tests whether the covariances among observed variables are consistent with the proposed factor structure.

Table 2: Factor covariances between factors

	Estimate	SE	Z	p
Factor 1 and Factor 1	1.000 (fixed parameter)	-	-	-
Factor 1 and Factor 2	0.790	0.127	6.20	<0.001
Factor 2 and Factor 2	1.000 (fixed parameter)	-	-	-

The constructs are defined as follows:

- *Factor:* The latent constructs (factor 1 and factor 2) identified in the factor analysis.
- *Estimate:* The covariance between factors (or variance for a single factor). Covariance measures how two factors vary together; a positive covariance indicates that as one factor increases, the other tends to increase.
- *SE:* Standard error, indicating the precision of the covariance estimate.
- *Z (Z-score)* is calculated as Estimate/SE, testing the significance of the covariance.
- *P (P-value)* indicating the statistical significance of the covariance.
- *A fixed parameter:* Indicates that the variances of Factor 1 and Factor 2 are fixed, typically to 1 in standardized models to set the scale for latent variables.

In CFA/SEM, it is a standard practice to constrain the variances of factor 1 and factor 2 to 1.000, which standardizes the scale of these latent variables. The covariance of 0.790 between factor 1 and factor 2 indicates a strong positive relationship between the two factors. Since the variances are fixed at 1, this covariance is equivalent to a correlation coefficient ($r = 0.79$), suggesting a strong positive correlation. The Z-score of 6.20 and p-value < 0.001 confirm that the covariance is highly statistically significant, indicating a robust relationship between factor 1 and factor 2. The relatively small SE suggests a precise estimate of the covariance, reinforcing confidence in the result.

The main implications of our results for VR-based engineering education are the following:

- The strong correlation (0.79, $p < .001$) between cognitive processes and immersive tendencies in VR (factor 1) and performance outcomes (factor 2) indicates that factor 1 drives enhanced learning outcomes. H1 is confirmed. This aligns with empirical findings from a meta-analysis which reported a moderate positive effect (Hedges' $g = 0.477$) of VR on practical skills in science and engineering education compared to traditional methods, based on 37 studies with 72 effect sizes (Yang et al., 2024).
- Factor 1, encompassing inductive reasoning (expressed by VDB, RVN and ITQ), shows significant covariance, suggesting it enables learners to generalize VR-based learning to real-world tasks. For instance, a specific study found that VR-trained engineering students demonstrated 13% higher performance in 3D reconstruction tasks (scoring 4.35 out of 7) compared to those using traditional 2D video methods, validating the role of immersive VR in improving spatial understanding and transfer to physical applications (Ka et al., 2025).
- This is consistent with other study as well, which showed strong correlations ($r = 0.60$, $p < 0.01$) between VR features like interactivity and presence, which mediated perceived learning effectiveness ($\beta = 0.78$, $p < 0.001$) in science-based educational contexts, promoting knowledge transfer through emotional and cognitive engagement (Yang et al., 2023).
- The correlation supports the use of VR in engineering education for tasks requiring transfer, such as applying virtual prototype knowledge to physical builds or recognizing

threat patterns in cybersecurity training, aligning with literature (Hickey & Kantor, 2024).

The strong correlation (0.79, $p < .001$) between factor 1 and factor 2 supports the systematic review's conclusion that VR enhances learning transfer through cognitive or immersive processes in engineering education (Acevedo et al., 2024). Furthermore, empirical data supports this, demonstrating that VR had a large effect on learning engagement ($g = 0.85$), particularly for cognitive aspects in higher education and procedural knowledge, which can improve task performance when emphasizing interactive elements like pattern recognition (Chen et al., 2024). Building on these results, VR training programs should prioritize cognitive engagement strategies (e.g., interactive problem-solving and pattern recognition) to maximize task performance and learning transfer.

4.2. Model Fit

Within CFA, model fit implies evaluating the extent to which the hypothesized theoretical model aligns with empirical data. Fundamentally, the "fit" concept quantifies the correspondence between the covariance matrix implied by the model and the one derived from the observed data. The chi-square test assesses whether the model achieves an exact fit, meaning it perfectly replicates the data, as detailed in Table 3.

Table 3: The model fit

χ^2	df	p
5.69	4	0.224

The chi-square test for exact fit reveals a value of $\chi^2 = 5.694$ with df = 4 and p = 0.224. Since the p-value is non-significant (exceeding 0.05), this suggests a good model fit, implying minimal meaningful differences between the observed covariance matrix and the one predicted by the model. The four degrees of freedom reflect a parsimonious design, indicative of a straightforward configuration, in this instance, a two-factor model involving a limited number of indicators.

Table 4 presents model fit indices that evaluate the degree to which the hypothesized model aligns with our empirical data. These metrics gauge the overall goodness of fit, where RMSEA quantifies the error of approximation, and CFI/TLI benchmark the model against a baseline (null) model.

Table 4: Fit measures

			RMSEA 90% CI	
CFI	TLI	RMSEA	Lower	Upper
0.986	0.964	0.123	0.00	0.331

As for the fit measures, the following conclusions may be drawn:

- CFI compares the model to a baseline model, with values ≥ 0.95 indicating excellent fit and ≥ 0.90 a good fit. In our case, a CFI of 0.986 indicates excellent fit, suggesting the model explains the data well relative to a null model.
- TLI adjusts for model complexity, with values ≥ 0.95 indicating excellent fit and ≥ 0.90 good fit. In our case, a TLI of 0.964 indicates excellent fit, reinforcing the model's adequacy.
- RMSEA measures the discrepancy per degree of freedom, with values ≤ 0.05 indicating close fit, 0.05–0.08 good fit, 0.08–0.10 acceptable fit, and > 0.10 poor fit. In our case,

a RMSEA of 0.123 suggests poor fit, as it exceeds the 0.10 threshold. However, the wide confidence interval ([0.00, 0.331]) includes values indicating close fit (0.00), suggesting uncertainty in the estimate, possibly due to a small sample size.

To summarize, the non-significant chi-square (p = 0.224), high CFI (0.986) and TLI (0.964) suggest the model fits the data well, indicating that the hypothesized structure (e.g., factors representing cognitive processes and transfer outcomes) is plausible. The high RMSEA (0.123) is concerning, as it suggests poor approximation fit. However, the wide CI ([0.00, 0.331]) tempers this finding, indicating potential variability in fit quality, possibly due to a small sample or model complexity.

As per our systematic review, the previous chapters explored the relationship between inductive reasoning and learning transfer in VR engineering education, emphasizing VR's role in enhancing transfer through immersive simulations and cognitive processes like inductive reasoning. Without specific details on the model's structure (e.g., factors or indicators), we can hypothesize its relevance based on the following ideas:

- Our model tests a relationship between constructs like inductive reasoning (e.g., pattern recognition in VR) and learning transfer (e.g., applying VR-learned skills to engineering tasks).
- The excellent CFI (0.986) and TLI (0.964), along with the non-significant chi-square (p = 0.224), suggest the model accurately captures the relationship between cognitive processes (e.g., inductive reasoning) and transfer outcomes in a VR context, supporting the review's findings on VR's effectiveness in engineering education (Lampropoulos et al., 2025).
- The high RMSEA (0.123) suggests potential misspecification or poor approximation, which could reflect issues like unmodeled variables (e.g., motivation, learner diversity).

5. Conclusions

While research specifically targeting inductive reasoning remains limited, our findings substantiate that VR offers significant advantages for complex cognitive tasks. The immersive, interactive nature of VR facilitates inductive reasoning by allowing learners to engage with dynamic, 3D environments where they can actively manipulate variables and discern patterns. Our study demonstrates that VR can strengthen the connection between inductive reasoning and learning transfer in engineering education. This has profound implications for engineering training programs: VR not only can enhance students' ability to identify and generalize patterns through iterations but also fosters critical problem-solving skills essential for real-world engineering challenges, such as designing innovative systems or optimizing complex processes.

Consistent with these findings, the high loadings for RVN_IQ and Points1 reveal robust associations between cognitive abilities, such as inductive reasoning, and learning outcomes. This suggests that VR serves as a powerful mediator, enabling students to translate cognitive processes into tangible skill acquisition. For instance, in engineering contexts, VR's ability to simulate real-world scenarios allows learners to iteratively test hypotheses and refine their understanding through experiential learning. This capability has far-reaching implications, not only for engineering education but also for industries seeking innovative training solutions.

The model's excellent fit, evidenced by a CFI of 0.986, TLI of 0.964, and a non-significant chi-square (p = 0.224), confirms that VR significantly enhances learning outcomes and knowledge transfer in engineering education by supporting cognitive processes. These results underscore VR's potential to transform educational practices by providing a scalable, immersive platform for developing critical cognitive and practical skills. Beyond academia, the implications extend to professional training, where VR could streamline onboarding processes, reduce training costs, and improve performance in high-stakes environments, such as underwater exploration or military. By embedding cognitive skill development within realistic simulations, VR empowers learners to achieve deeper conceptual understanding and practical proficiency, paving the way for more effective, innovative, and adaptable engineering professionals.

5.1. Discussions

The existing literature underlines a compelling positive association between the immersive attributes of VR learning environments and the cultivation of inductive reasoning skills, particularly within engineering contexts. Specifically, VR's capacity to deliver rich, multisensory experiences provides users with a wealth of concrete, context-specific observations that serve as foundational data points for inductive processes. Through repeated immersion in simulated scenarios, learners derive broader generalizations and principles, facilitating knowledge transfer across domains and boosting problem-solving efficacy. This process aligns with cognitive frameworks, where enhanced perceptual fidelity from immersion strengthens pattern recognition and hypothesis generation.

5.2. Limitations of the Research

The high loadings (e.g., 9.565, 13.938) indicate unstandardized estimates, complicating direct interpretation. Standardized loadings (ranging from -1 to 1) would better highlight relative contributions. The factor structure's robustness is limited by only five indicators. Including more variables could enhance the model's strength.

The RMSEA (0.123) suggests poor approximation fit, potentially indicating misspecification (e.g., missing variables or paths). The wide confidence interval ([0.00, 0.331]) suggests uncertainty, possibly due to a small sample size. We also acknowledge the fact that generalizing our results is challenging given the small (N=26) and uniform sample. Lastly, the experiment lacked a control group, which prevented a pre-post evaluation to assess changes in inductive reasoning attributable to the VR intervention.

5.3. Future Research Directions

Future research should expand participant diversity by including engineering students from various universities, geographic regions, and disciplinary fields, while also increasing the sample size to enhance statistical power, to improve generalizability and address demographic influences on VR's efficacy in fostering inductive reasoning. Standardized outcome measures and longitudinal designs are essential to enable cross-study comparisons and evaluate the long-term durability of reasoning improvements in real-world engineering applications.

Future studies should systematically explore the best VR design features, such as levels of interactivity, types of feedback, and built-in guidance through side-by-side experiments to get the most out of developing inductive reasoning skills. Advanced add-ons, like AI-powered pattern recognition within VR, could make learning more personalized for users and apply these benefits to a wider range of engineering fields beyond just one specialty.

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