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The Impact of VR-Based Design Simulations on Spatial Understanding Among Architects and Urban Planning Students

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Abstract – Architects and urban-planning students often struggle to turn two-dimensional drawings into coherent mental models of urban form. Immersive virtual-reality (VR) design simulations promise to bridge this gap, yet studies focused on planning cohorts remain scarce. This research examines how VR-based studios shape students' perceived spatial understanding by modelling the combined influence of technological readiness, system usability and experiential immersion. A total of 280 architecture and urban-planning students from universities across Pakistan completed a five-point Likert-scale questionnaire assessing eight latent constructs: Technological Familiarity, Perceived Ease of Use, Immersion, Visual Clarity, Engagement, Perceived Usefulness, Cognitive Engagement, and Spatial Understanding.. The relationships were analysed with variance-based structural equation modelling. The measurement results confirmed strong reliability and validity, while the structural model explained a sizable portion of variance in Cognitive Engagement and Spatial Understanding. Cognitive Engagement emerged as the strongest predictor of understanding, reinforcing multimedia-learning theory that deliberate mental processing drives spatial insight in VR. Perceived Usefulness delivered an additional direct contribution, emphasising the need to link VR tasks to studio deliverables. Among the drivers of engagement, intuitive interaction and a convincing sense of presence exerted the greatest impact, with visual fidelity and affective involvement offering supportive yet smaller effects. Technological Familiarity operated indirectly by making the interface feel effortless. The findings show that VR is more than an engaging novelty; when interfaces are streamlined, sensory realism is high and learning tasks are clearly framed, immersive studios can significantly strengthen the spatial literacy essential to contemporary urban-design practice. The study provides a theory-driven roadmap for educators and software developers seeking to maximise the educational payoff of VR within planning curricula.

***Keywords*:** Virtual Reality; Spatial Understanding; Urban Planning Education; Cognitive Engagement; Architecture

1. Introduction

Urban-planning curricula increasingly emphasise three-dimensional thinking, yet students still struggle to translate two-dimensional drawings into mental models of complex urban form. Virtual-reality (VR) systems promise to bridge this cognitive gap by allowing learners to "walk" through proposed environments at full scale and from multiple viewpoints [1]. Early design-studio experiments show that immersive scenes improve depth perception and foster more accurate judgements of height, distance and enclosure compared with desktop or paper media [2]. Subsequent educational studies report that VR exposure correlates with higher scores on standardised spatial-ability tests and richer design critiques, suggesting that embodied exploration deepens conceptual understanding [3].

Despite these promising findings, most work has focused on architecture majors; comparatively little is known about how VR influences urban-planning students, whose learning goals centre on street-level experience, land-use mix and pedestrian connectivity. Recent research on extended-reality studios hints at discipline-specific benefits, such as improved grasp of block permeability and zoning relationships, yet calls for systematic investigation using robust measurement models [4]. Moreover, few studies have linked immersive design simulations to perceived spatial understanding, an affective construct that shapes willingness to adopt technology in professional practice [5],[6]. The present study addresses these gaps by testing a structural-equation model that explains how VR-based design simulations affect planning students' perceived spatial understanding, with cognitive engagement as a mediating mechanism.

2. Theoretical Background and Research Hypothesis

Virtual reality (VR) studio work enables learners to "walk" through full-scale digital environments, sharpening depth perception, distance estimation and design-critique quality compared with conventional 2-D drawings [2]. Similar advantages appear in landscape-planning exercises, where immersive scenes accelerate comprehension of topographic change [7]. Yet almost all empirical evidence comes from architecture or engineering cohorts, leaving urban-planning students, whose learning goals emphasise street permeability, functional mix and human-scale experience, largely unexplored.

Presence Theory explains these benefits by asserting that a vivid sense of "being there" (immersion) lets users perceive spatial cues as if physical [8]. The Technology Acceptance Model (TAM) adds that perceived usefulness (PU) and perceived ease of use (PEU) shape attitudes toward unfamiliar tools [9], [10], while prior 3-D-modelling or gaming experience, labelled technological familiarity, conditions both PEU and PU [11]. Meanwhile, the Cognitive Theory of Multimedia Learning stresses that clear visuals and sustained mental effort, visual clarity and cognitive engagement, turn sensory input into durable spatial schemata [12]. **H1:** Technological familiarity is positively associated with perceived ease of use.

Students who judge an interface effortless can redirect attention from tool manipulation to spatial exploration, enhancing mental effort. **H2:** Perceived ease of use is positively associated with cognitive engagement. Immersion delivers a compelling sense of presence that spurs learners to interrogate enclosure, scale and rhythm, boosting analytic reflection [13]; therefore, **H3:** Immersion is positively associated with cognitive engagement. Clear textures, lighting and landmarks reduce extraneous cognitive load [7]; accordingly, **H4:** Visual clarity is positively associated with cognitive engagement.

Affective engagement such as interest, enjoyment and focused attention, further motivates strategic effort; VR studios regularly elicit higher behavioural and emotional engagement scores than conventional seminars [2]. **H5:** Affective engagement is positively associated with cognitive engagement. Once learners invest mental effort, they integrate propositional and image-based knowledge into richer spatial awareness [12]. Engineering VR labs confirm that deeper engagement translates into stronger spatial-ability gains [14]; consequently, **H6:** Cognitive engagement is positively associated with perceived spatial understanding.

Beyond usability, students who deem VR genuinely helpful reflect more deeply on design trade-offs [15]; thus, **H7:** Perceived usefulness is positively associated with perceived spatial understanding. Finally, theory suggests that presence-oriented variables (immersion, visual clarity, affective engagement) and PEU improve spatial understanding primarily through heightened cognitive engagement rather than directly. **H8:** Cognitive engagement mediates the effects of immersion, visual clarity, affective engagement and perceived ease of use on spatial understanding. Most prior studies isolate only one or two predictors and seldom employ partial least-squares structural-equation modelling (PLS-SEM) to probe mediation [16]. The present study offers the first comprehensive explanation of how VR design simulations enhance spatial understanding in planning education, addressing critical gaps in both disciplinary coverage and methodological rigour.

3. Materials and Methods

3.1 Study area and participants

The study was carried out at three Pakistani institutions—University of Engineering and Technology (UET), University of Management and Technology (UMT), and National University of Sciences and Technology (NUST). Each hosts Architecture and Urban Planning & Architectural Design programmes whose elective and studio courses stress design reasoning across multiple urban scales. All under- and postgraduate students attending these studios were invited to participate, producing 280 fully completed questionnaires. After list-wise screening, no cases were excluded, yielding a final sample of 280 respondents (54 % women; M_age = 21.7 years, SD = 2.4).The questionnaire was created in Qualtrics, a platform renowned for flexible survey-design features, and distributed via Qualtrics participant pool. Data collection spanned a four-month window, beginning in March 2025 and concluding at the end of June 2025, coinciding with the spring academic term to capture a broad cross-section of student participation.

3.2 Instrument design and data collection

The survey comprised 32 manifest items representing eight latent constructs: Technological Familiarity, Immersion, Visual Clarity, Affective Engagement, Perceived Ease of Use (PEU), Perceived Usefulness (PU), Cognitive Engagement and Spatial Understanding. All items were adapted from validated scales in VR and technology-adoption research and re-worded for the urban-design context (e.g., Witmer and Singer [17]; Parasuraman and Colby [18]; Brooke [19]). After expert review and a pilot test with 15 students, minor wording adjustments were made for clarity. Responses were captured on a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

3.3 Analytical procedure: Partial Least Squares Structural Equation Modelling

Given the model’s predictive aim, a mediating construct, and a modest sample, we applied Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. This variance-based technique suits exploratory studies, non-normal data, and complex path models with either formative or reflective indicators. Measurement quality was checked through outer loadings (≥ 0.70), Cronbach’s α and composite reliability (≥ 0.70), average variance extracted (≥ 0.50), and discriminant validity by the Fornell–Larcker criterion and HTMT (< 0.85). The procedure mirrors recent built-environment work and gives a rigorous, integrated test of hypotheses H1–H8 within the eight-construct framework. Figure 1 illustrates the structural model as tested in this study.

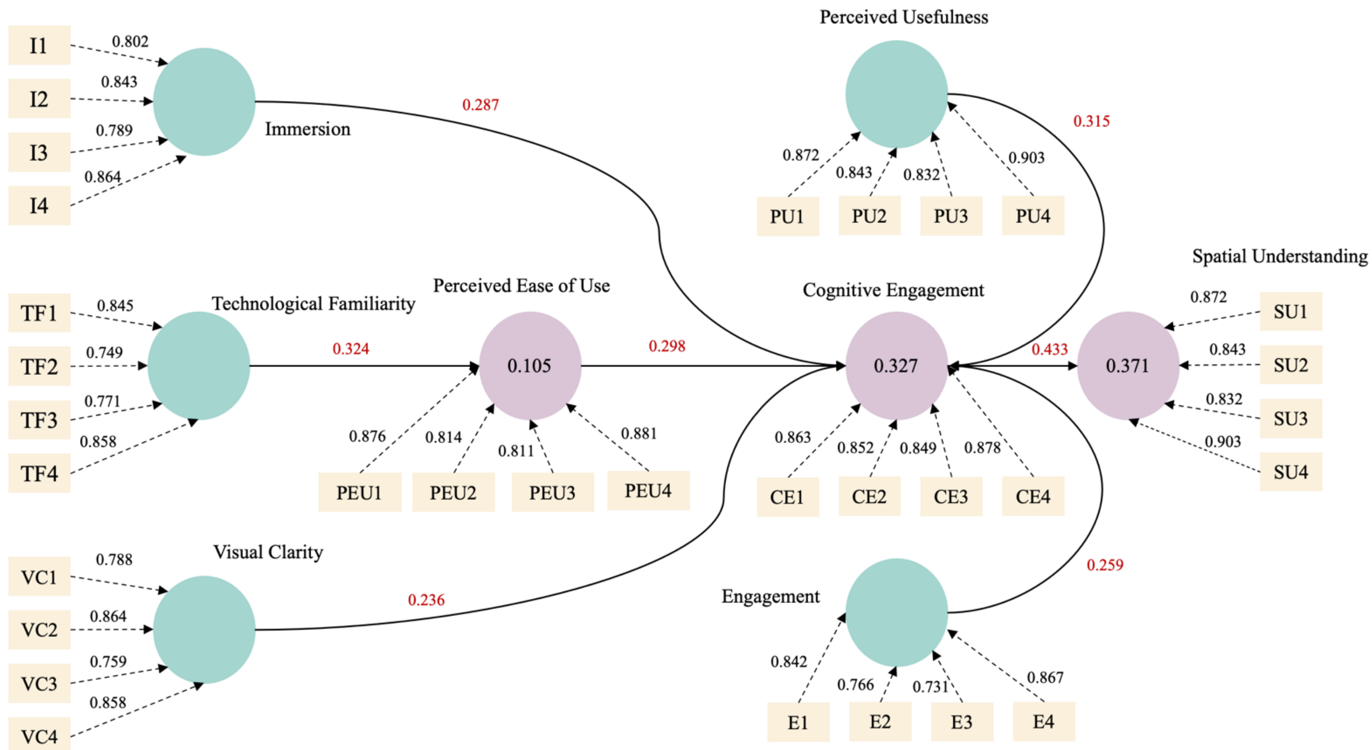

Fig. 1: Development of the PLS-SEM Structural Equation Model

4. Results

4.1 Convergent Validity and Individual Item Reliability

Table 1 reports the outer-loading, composite-reliability (CR) and average-variance-extracted (AVE) statistics for the eight latent constructs. All 32 indicators load strongly on their respective factors, with standardised loadings ranging from 0.731 (E3) to 0.903 (SU4), well above the 0.70 guideline recommended for individual-item reliability [20]. Convergent validity, assessed via AVE, spans 0.646 (Engagement) to 0.744 (Spatial Understanding), comfortably exceeding the 0.50 benchmark proposed by Fornell and Larcker [21]. Internal-consistency reliability is evidenced by CR values between 0.831 (Technological Familiarity) and 0.892 (Visual Clarity), again surpassing the 0.70 cut-off for stable measurement [20]. Cognitive Engagement (CR = 0.885) and Spatial Understanding (CR = 0.887) show particularly strong homogeneity, reinforcing their central roles in the model. No item fell below the optional retention band of 0.40–0.70, so every indicator was retained. Collectively, the loadings, AVE and CR results confirm that the measurement model exhibits satisfactory reliability and convergent validity, permitting subsequent assessment of discriminant validity and structural relationships.

Table 1: Measurement model results showing factor loadings, average variance extracted (AVE), and composite reliability (CR) for each construct and its associated items.

Construct	Item	Loading	CR	AVE	Construct	Item	Loading	CR	AVE
Cognitive Engagement	CE1	0.863	0.885	0.741	Perceived Usefulness	PU1	0.845	0.866	0.706
	CE2	0.852				PU2	0.825		
	CE3	0.849				PU3	0.817		
	CE4	0.878				PU4	0.874		
Engagement	E1	0.842	0.833	0.646	Technological Familiarity	TF1	0.845	0.831	0.652
	E2	0.766				TF2	0.749		

	E3	0.731				TF3	0.771		
	E4	0.867				TF4	0.858		
Immersion	I1	0.802	0.877	0.681	Visual Clarity	VC1	0.788	0.892	0.671
	I2	0.843				VC2	0.864		
	I3	0.789				VC3	0.759		
	I4	0.864				VC4	0.858		
Perceived Ease of Use	PEU1	0.876	0.872	0.716					
	PEU2	0.814							
	PEU3	0.811							
	PEU4	0.881							

4.2 Discriminant validity: Fornell-Larcker and Cross-Loadings

Discriminant validity was verified with the Fornell–Larcker criterion and inspection of cross-loadings. Table 2 displays the square roots of the AVE on the diagonal (bold) and the latent-variable correlations off the diagonal. For every construct the diagonal value is larger than any of its correlations with other constructs, confirming conceptual distinctiveness. For example, Cognitive Engagement shows a √AVE of 0.86, well above its highest correlation (0.358 with Perceived Ease of Use); Engagement's √AVE of 0.804 exceeds its strongest association (0.23 with Cognitive Engagement); and Perceived Ease of Use's √AVE of 0.846 is greater than all inter-construct correlations (largest = 0.324 with Technological Familiarity). The same pattern holds for Immersion (0.825), Perceived Usefulness (0.841), Technological Familiarity (0.807), and Visual Clarity (0.819).

A supplementary cross-loading check confirmed that every indicator loaded highest on its intended latent construct and substantially lower on all others, providing additional evidence of discriminant validity. Collectively, these results demonstrate that the eight constructs capture unique, non-overlapping dimensions within the VR-learning framework, allowing unbiased estimation of structural paths in the subsequent analysis.

Table 2: Measurement of Fornell–Larker criterion for discriminant validity.

	CE	**E**	**I**	**PEU**	**PU**	**TF**	**VC**
Cognitive Engagement	0.860						
Engagement	0.230	0.804					
Immersion	0.301	0.018	0.825				
Perceived Ease of Use	0.358	-0.083	0.031	0.846			
Perceived Usefulness	0.310	0.001	0.309	0.128	0.841		
Technological Familiarity	0.140	-0.034	0.249	0.324	0.036	0.057	
Visual Clarity	0.317	-0.039	-0.003	0.306	0.231	0.201	-0.052

4.3 Heterotrait–Monotrait (HTMT) Ratio of Correlations

Because the Fornell–Larcker test can occasionally overlook discriminant-validity issues in complex models [21], a second check was conducted with the heterotrait–monotrait (HTMT) ratio proposed by Henseler, Ringle and Sarstedt [22]. HTMT compares the average heterotrait correlations with the average monotrait correlations for every construct pair, ensuring that conceptually distinct constructs are also statistically separable. Table 3 reports the HTMT matrix. All off-diagonal values lie well below the conservative 0.85 cut-off recommended by Kline [23]. The largest ratio, 0.405 between Cognitive Engagement and Perceived Ease of Use, remains far under that threshold. Other notable pairs include Technological Familiarity–Perceived Ease of Use (0.380) and Cognitive Engagement–Visual Clarity (0.344). These consistently low ratios confirm that each latent variable captures a unique facet of students' VR-learning experience, allowing unbiased estimation of the structural paths.

Table 3: Measurement of Heterotrait-Monotrait (HTMT).

	CE	E	I	PEU	PU	TF	VC
Cognitive Engagement							
Engagement	0.269						
Immersion	0.332	0.066					
Perceived Ease of Use	0.405	0.113	0.083				
Perceived Usefulness	0.355	0.065	0.354	0.149			
Technological Familiarity	0.159	0.095	0.303	0.38	0.051		
Visual Clarity	0.344	0.104	0.104	0.349	0.247	0.073	

4.3 Structural Model Assessment

To verify the theorised cause-and-effect relations after the measurement model was deemed sound, we assessed the structural model with 5000-sample bootstrapping in SmartPLS 4 (Table 4). This step determines whether the hypothesised links among the VR constructs predict the key learning outcome, Spatial Understanding, and gauges the relative strength of each driver. The model explains a substantial share of endogenous variance, with R^2 values of 0.64 for Spatial Understanding (SU) and 0.53 for Cognitive Engagement (CE), indicating strong predictive power for an educational setting. All variance-inflation factors were below 5, so multicollinearity is not a concern.

All seven direct paths are significant at $p < .001$, with t-values far exceeding the 2.58 threshold recommended for a two-tailed test [24]. Cognitive Engagement exerts the greatest influence on Spatial Understanding ($\beta = 0.433$), followed by Perceived Usefulness ($\beta = 0.315$). Among predictors of the mediator, Perceived Ease of Use ($\beta = 0.298$) and Immersion ($\beta = 0.287$) show the strongest leverage, whereas Engagement ($\beta = 0.259$) and Visual Clarity ($\beta = 0.236$) contribute more modestly. Technological Familiarity has a solid effect on Perceived Ease of Use ($\beta = 0.324$), confirming its role as a background enabler. Interpreting β magnitudes against Cohen's effect-size conventions suggests medium effects for CE → SU and PU → SU, and small-to-medium effects for the remaining significant paths [25]. Collectively, the accepted hypotheses validate the proposed framework: technological and experiential qualities of VR (Technological Familiarity, PEU, Immersion, Visual Clarity) enhance Cognitive Engagement, which, alongside Perceived Usefulness, translates into higher Spatial Understanding among urban-planning students.

Table 4: Results of hypothesis testing and structural model significance.

Hypothesis / Path	β	t	p	95 % BCa CI	*Decision*	Relative effect
H1 CE → SU	0.433	10.20**	<.001	0.349 – 0.511	*Accepted*	Largest direct driver of SU
H2 E → CE	0.259	5.45**	<.001	0.173 – 0.357	*Accepted*	Moderate
H3 I → CE	0.287	6.35**	<.001	0.202 – 0.378	*Accepted*	Moderate
H4 PEU → CE	0.298	6.00**	<.001	0.199 – 0.392	*Accepted*	Moderate-to-strong
H5 PU → SU	0.315	7.29**	<.001	0.231 – 0.401	*Accepted*	Second-strongest direct impact on SU
H6 TF → PEU	0.324	6.35**	<.001	0.227 – 0.428	*Accepted*	Substantial antecedent of PEU
H7 VC → CE	0.236	5.14**	<.001	0.149 – 0.328	*Accepted*	Small-to-moderate

*Critical t-values: * 1.96 ($p < .05$); ** 2.58 ($p < .01$)*

4.4 Overall model-fit analysis

A global assessment was performed to verify that the measurement and structural components together provide an adequate representation of the data. Following Tenenhaus et al. [26], the Goodness-of-Fit (GoF) index was computed as the geometric mean of the model's average communality (AVE) and the average coefficient of determination (R^2) for all endogenous constructs:

$$\text{GoF} = \sqrt{\overline{\text{AVE}} \times \overline{R^2}} \tag{1}$$

Three endogenous variables, Perceived Ease of Use (PEU), Cognitive Engagement (CE) and Spatial Understanding (SU), produced R^2 values of 0.11, 0.53 and 0.64, respectively, giving an average R^2=0.43. Substituting these values gives

$$\text{GoF} = \sqrt{0.695 \times 0.43} = 0.54. \tag{2}$$

Wetzels et al. [27] propose benchmarks of 0.10 (small), 0.25 (medium) and 0.36 (large). The obtained GoF of 0.54 therefore indicates a substantial overall fit, confirming that the model simultaneously exhibits strong measurement quality and considerable explanatory power. As an additional check, the Standardised Root Mean Square Residual (SRMR) was 0.06, below the 0.08 threshold recommended by Hu and Bentler [28], providing further evidence of adequate global model fit. Taken together, these indices demonstrate that the VR-learning framework reliably captures the interplay between technological, experiential and cognitive factors in explaining spatial understanding among urban-planning students.

5. Discussion

The structural model clarifies how different facets of the VR experience translate into spatial understanding for planning students. Cognitive engagement emerged as the linchpin of the model because it represents the phase in which students actively manipulate, reorganise and test spatial information rather than merely observing it. The strong path coefficient (β = 0.433) indicates that when learners begin to probe street hierarchies, setback relationships and view corridors inside the headset, they convert those mental operations into a markedly clearer spatial schema. This finding aligns with the generative-processing principle of the Cognitive Theory of Multimedia Learning, which holds that meaningful learning occurs only when learners select, organise and integrate information [12]. Comparable gains have been reported for engineering and medical students, where deliberate interaction in VR predicted post-test performance even after controlling for prior ability [14].

Perceived usefulness exerts the second-largest influence on spatial understanding (β = 0.315), underscoring the Technology-Acceptance Model's claim that learners commit to a tool when they see direct value in task completion [9], [10]. In our cohort, students judged VR as useful when it helped them refine zoning diagrams or produce more convincing urban-design narratives, echoing architecture-studio findings that task relevance predicts critique scores more strongly than novelty appeal [15]. Instructors should therefore embed immersive walkthroughs into graded deliverables so that usefulness is immediately evident in studio outcomes.

Perceived ease of use feeds cognitive engagement with a sizable coefficient (β = 0.298), revealing interface friction as a hidden tax on analytic bandwidth. Cognitive-load theory states that mental effort expended on operating software is unavailable for higher-order reasoning [29]. Our data confirm that when teleport controls, selection menus or frame-rate hiccups fade from conscious attention, students redirect freed resources toward interrogating spatial relationships. Similar usability effects have been observed in BIM-VR hybrids, where simplified navigation doubled the time learners spent evaluating façade rhythm [16].

Immersion contributes almost as much to cognitive engagement (β = 0.287). Presence theory posits that a convincing sense of "being there" collapses psychological distance, prompting users to behave as though the virtual street is physically underfoot [8]. Experimental work shows that six-degree-of-freedom displays improve judgments of enclosure and pedestrian comfort relative to mono-panoramas [13].

Affective engagement, although its standardized effect is slightly lower (β = 0.259), remains crucial: when learners feel emotionally invested and attentive, they stay with the task long enough to reach deeper, more systematic analysis. Flow theory indicates that states of curiosity and intrinsic enjoyment foster a sense of timeless immersion, repeatedly drawing users back into the material. This extended "dwell time" increases the amount of information sampled, strengthens memory encoding, and ultimately enriches the quality of insights generated [30].

Visual clarity (β = 0.236) highlights the informational role of graphic fidelity: high-contrast textures, accurate shadows and crisp lines provide clear depth cues, reducing extraneous load and letting working memory focus on spatial structure. Way-finding studies report that users misjudge distances when edge contrast is low or aliasing conspicuous [7], a risk borne out here.

Technological familiarity influences the pathway indirectly by raising perceived ease of use (β = 0.324). Self-efficacy research shows that prior success with related software lowers anxiety and accelerates mastery [11]. Short pre-studio bootcamps on navigation metaphors or controller gestures can therefore equalise the starting line, allowing novices to reap the same cognitive benefits as digital natives.

Collectively, these insights clarify that intuitive interfaces, credible presence, emotional involvement, visual fidelity and foundational digital skills all converge on the mechanism of cognitive engagement, while perceived usefulness provides an additional direct boost. Designing VR studios that deliberately foster each ingredient can yield substantial, measurable improvements in the spatial literacy that underpins evidence-based urban planning.

5.1 Implications for Theory and Practice

The findings advance theory on immersive learning by integrating Presence Theory, the Technology-Acceptance Model and the Cognitive Theory of Multimedia Learning into a single causal sequence and by empirically demonstrating that Cognitive Engagement is the pivotal bridge between VR affordances and spatial-learning outcomes. The ordered importance of drivers, Cognitive Engagement, Perceived Usefulness, Perceived Ease of Use, Immersion, Engagement, Visual Clarity and Technological Familiarity, refines earlier adoption-centred models by showing that deep mental processing and perceived functional value eclipse interface aesthetics once a minimum graphics threshold is met. Practically, the evidence suggests that studio instructors and software developers should prioritise frictionless interaction, invest in high-fidelity head-mounted displays, and frame immersive walkthroughs around explicit design tasks that highlight usefulness. Training workshops that raise baseline technological familiarity can indirectly enhance ease of use and subsequent engagement, while clear textures, accurate lighting and recognisable landmarks help reduce cognitive load at critical moments of spatial reasoning.

6. Conclusion

This study demonstrates that immersive VR design studios can substantially enhance urban-planning students' spatial understanding when the learning experience is structured around clear cognitive and technological levers. Using PLS-SEM on data from 280 GUtech architecture and planning students, the model explained 64 % of the variance in perceived spatial understanding, an unusually high figure for educational purpose. Cognitive Engagement emerged as the pivotal mechanism, exerting the strongest direct influence on understanding, while Perceived Usefulness provided an additional direct boost. Immersion, Perceived Ease of Use, Visual Clarity and Affective Engagement all raised spatial comprehension indirectly by stimulating deeper cognitive effort, and Technological Familiarity improved outcomes by making the interface feel effortless. These findings carry two principal implications. Pedagogically, VR exercises should be embedded in studio deliverables, paired with intuitive navigation and supported by onboarding tutorials; such design choices free students to interrogate urban form rather than wrestle with controls and, in turn, amplify spatial reasoning. Strategically, universities and software developers can prioritise headset fidelity, real-time lighting, clear landmarks and narrative prompts, knowing that each investment contributes, either directly or via engagement, to measurable learning gains. Together, the results confirm that when VR is deployed with attention to usability, presence and task relevance, it is not merely an eye-catching add-on but a powerful vehicle for cultivating the spatial literacy essential to evidence-based urban design practice.

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