Effectiveness of Virtual Reality and 3D Modeling Technologies in Driving School Training: A Controlled Pedagogical Study

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Abstract: This article presents the development and evaluation of a virtual reality (VR) based driving school system utilizing 3D modeling technologies. The study aims to create an innovative approach to driver education where students practice driving in a safe virtual environment through the integration of VR and 3D modeling. Models developed using Autodesk 3ds Max and Unreal Engine 5 enabled students to consolidate theoretical knowledge with practical skills. The system architecture incorporates modular components including 3D Asset Pipeline, Simulation Engine, VR Interface Layer, and Assessment Module. The system achieves approximately 85 FPS on average (84–91 FPS) across all evaluated scenarios. A pedagogical experiment involving 250 students from Navoi region driving schools showed that the experimental group achieved 10.33% higher learning outcomes compared to the control group using traditional methods. Statistical analysis using Student's t-test confirmed the significance of these results ($p < 0.01$). The article explores the potential of VR and 3D modeling technologies in educational processes and proposes further expanding their application for creating effective learning environments.

1 INTRODUCTION

In recent years, virtual technologies have caused significant changes in the field of education. Digital learning platforms, particularly in driving school systems, provide students with modern and interactive learning opportunities. VR-based driving schools create a more effective, safe, and comfortable environment for teaching students to drive. Through the use of virtual technologies, students can practice in a simulated environment before driving a real car, significantly reducing risks and improving learning outcomes.

3D modeling technologies enable the creation of accurate models of cars, roads, and traffic environments. With the help of 3D models, various automotive systems and driving scenarios can be visually explained to students. However, while existing research has demonstrated the potential of VR in education [1], [2], there remains a gap in systematically evaluating the technical implementation and pedagogical effectiveness of integrated VR-3D modeling systems specifically designed for driving education [3].

The novel contribution of this work is threefold: (1) a modular system architecture combining 3ds Max modeling pipeline with Unreal Engine 5 simulation and OpenXR-compatible VR integration; (2) comprehensive performance optimization methodology with quantitative metrics across different hardware configurations; and (3) statistically validated pedagogical evaluation demonstrating learning outcome improvements compared to traditional instruction.

2 METHODS

2.1 System Architecture and Data Flow

The proposed VR-based driving school system follows a modular architecture consisting of four main components: 3D Asset Pipeline, Simulation Engine, VR Interface Layer, and Assessment Module. Figure 1 shows the data flow diagram of the proposed VR driving school system, illustrating the interaction between the 3D Asset Pipeline, Simulation Engine (Unreal Engine 5), VR Interface Layer (OpenXR), and the Assessment Module.

3D Asset Pipeline (3ds Max → Unreal Engine). The 3D modeling process begins in Autodesk 3ds Max, where high-resolution car models, environmental assets (roads, buildings, traffic signs), and interactive elements are created. The asset pipeline involves: modeling phase with low-poly base meshes and subdivision-ready topology; UV mapping and texturing using Substance Painter integration; export process in FBX format with embedded animation data (wheel rotation, steering column movement); and import to Unreal Engine with automatic LOD generation and material instance creation. The pipeline ensures all assets maintain physical scale (1:1 ratio) and pivot point alignment for accurate VR interaction.

Simulation Engine (Unreal Engine Core). Unreal Engine 5 serves as the central simulation platform, handling: real-time rendering using Nanite virtual geometry and Lumen global illumination; physics simulation through Chaos Physics for vehicle dynamics (suspension, tire friction, collision detection); environment management with dynamic weather system (rain, fog, night/day cycle) and traffic AI for NPC vehicles; and spatial audio for engine sounds, tire screeches, and environmental noise [4].

VR Runtime and Device Interface. The system supports OpenXR standard for cross-platform VR compatibility. The VR interface layer includes: device abstraction supporting Oculus Rift, HTC Vive, and Pico headsets through Unreal Engine VR templates; 6-DoF head and controller tracking with room-scale boundaries; custom input profiles mapping VR controllers to steering wheel, pedals, and gear shift; and performance optimization using fixed foveated rendering and Asynchronous Spacewarp for maintaining 90 FPS.

Assessment and Scoring Module. The system includes a comprehensive assessment module that logs user performance metrics as detailed in Table 1.

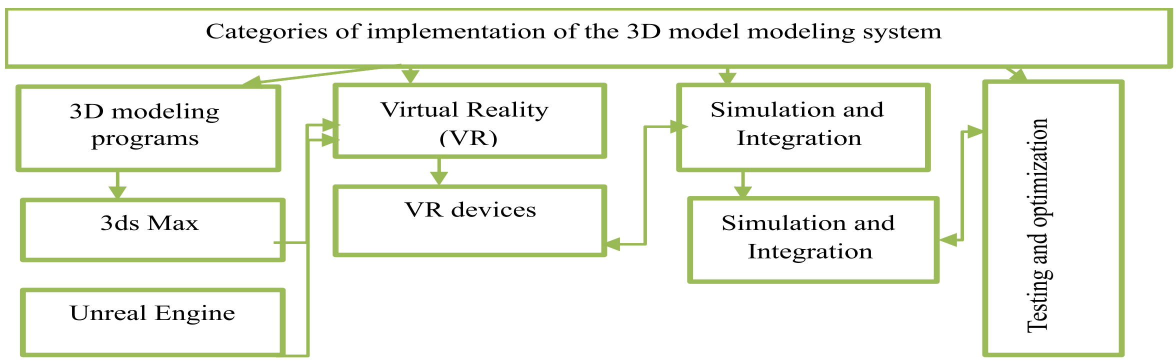

Figure 1: The data flow between these modules is organized as follows: the 3D Asset Pipeline (3ds Max) exports models to the Simulation Engine (Unreal Engine 5), which communicates bidirectionally with the VR Interface Layer (OpenXR devices) and sends performance data to the Assessment Module for logging and analysis. [2].

Table 1: Assessment module components and data collection.

Module Component	Function	Data Collected
Session Logger	Records all user actions	Timestamp, position, velocity, steering angle, pedal pressure
Event Detector	Identifies driving events	Speeding, lane departure, traffic violations, collisions
Scoring Engine	Calculates performance scores	Reaction time, smoothness, rule compliance (0-100 scale)
Progress Tracker	Monitors learning curve	Completion time, error reduction rate, skill mastery
Report Generator	Creates instructor reports	PDF/CSV export with visual analytics

2.2 3D Modeling Implementation

The technological process of creating three-dimensional car models in Autodesk 3ds Max includes several sequential stages. At the initial stage, the type of object to be modeled and its main technical parameters are determined, with corresponding reference blueprints placed on the stage planes. Metrological parameters of the working environment are then adjusted.

Model geometry formation begins with simple primitives (Box, Plane), on which the main body mass is created, with detail increased through conversion to 'Editable Poly' mode. Wheels are modeled using 'Cylinder' primitives with instances created; windows and optical instruments are treated as separate geometric objects as shown in Figure 2.

After completing model geometry, materials and texture maps reflecting physical properties of body, glass, and other structural elements are applied through the 'Material Editor' tool. In the final stage, lighting systems and cameras are positioned. After render settings selection, the finished 3D model is exported as an FBX file for Unreal Engine import [5], [6].

2.3 Performance Optimization

To ensure smooth VR experience, the system was optimized using multiple techniques and tested across different hardware configurations as shown in Tables 2, 3, and 4.

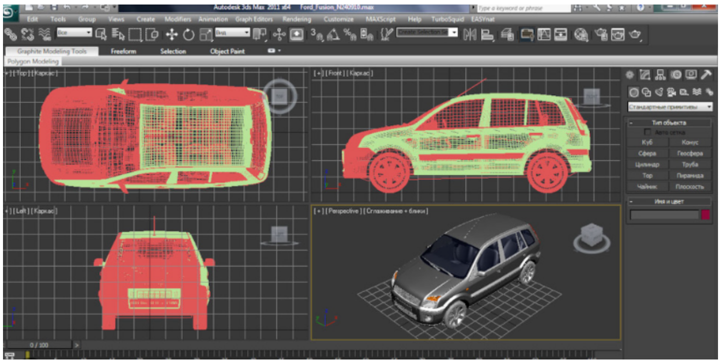

Figure 2: Car creation process in 3D max.

Table 2: Optimization methods and performance gains.

Optimization Technique	Implementation	Performance Gain
Level of Detail (LOD)	Auto-generated LODs (0-3) for all 3D assets	40% reduction in polygon count
Texture Compression	BC7 compression with mipmaps	60% VRAM usage reduction
Occlusion Culling	Hardware occlusion queries	25% fewer draw calls
Lighting Strategy	Baked lighting for static objects + dynamic for vehicles	30% faster render times
Shader Complexity	Optimized material graphs with instancing	20% GPU performance gain

Table 3: Hardware requirements and performance metrics.

Configuration	CPU	GPU	RAM	Target FPS	Measured FPS
Minimum	Intel i5-10400	NVIDIA GTX 1660	16GB	72	68-72
Recommended	Intel i7-12700K	NVIDIA RTX 3070	32GB	90	87-92
High-End	AMD Ryzen 9 5900X	NVIDIA RTX 4080	64GB	120	115-122

Table 4: Scenario-specific performance (recommended configuration).

Scenario	Polygon Count	Draw Calls	Avg FPS	GPU Utilization
Empty highway (day)	2.1M	3,450	91	78%
City traffic (day)	3.8M	5,200	88	85%
Night with rain	3.8M	5,800	86	89%
Dense fog + traffic	3.8M	6,100	84	92%

The system maintained stable VR performance on recommended hardware, achieving an average frame rate of approximately 85 FPS across all tested scenarios, with measured values ranging from 84 to 91 FPS.

2.4 Interactive Learning Environment

With the prepared 3D models and integrated VR system, students were presented with an interactive driving environment. Models created on the Unreal Engine platform allowed students to simulate driving, speed control, turning, and other actions in a virtual environment. This system helped students learn about various driving situations and became an effective tool for preparing them for actual driving.

Through the 3D environment, students had opportunities to perform actions such as driving, braking, and speed adjustment. With the VR system, students received realistic and dynamic training. Simulation of the prepared 3D models and their integration increased system interactivity, enabling students to learn about traffic control, braking systems, and automotive mechanics under various conditions (e.g., bad weather, night driving).

The appearance of car models, road conditions, lighting systems, and weather conditions were modeled close to reality, allowing students to experience realistic driving scenarios.

2.5 Pedagogical Evaluation Design

To evaluate the educational effectiveness of the proposed VR-based driver training system, a pedagogical experiment was conducted involving 250 students. The participants were randomly divided into two groups: an experimental group and a control group, each consisting of approximately equal numbers of students.

Before the beginning of the training process, a preliminary diagnostic assessment (pre-test) was conducted to determine the initial level of students' theoretical knowledge and practical understanding related to driver training concepts. The results of the pre-test showed that there were no statistically significant differences between the experimental and control groups, indicating that the groups were comparable at the initial stage of the study.

During the experiment, both groups received identical theoretical instruction following the standard curriculum. However, students in the experimental group additionally participated in 8 hours of practical training using the developed virtual reality (VR) driving simulation system. This VR-based training environment allowed students to practice driving scenarios in an interactive and immersive learning environment.

After completion of the training process, a final assessment (post-test) was conducted to measure learning outcomes in both groups. The obtained results were analyzed using statistical methods, including the independent samples t-test, in order to determine whether the differences between the groups were statistically significant. The analysis also included the calculation of effect size (Cohen's d) to evaluate the magnitude of the observed learning improvements.

The results of the statistical analysis demonstrated a measurable improvement in the performance of students in the experimental group compared to the control group, confirming the educational effectiveness of the proposed VR-based training approach.

3 RESULTS

3.1 Technical Performance Results

The system demonstrated stable performance across all tested scenarios as detailed in Table 4. On the recommended hardware configuration (Intel i7-12700K, NVIDIA RTX 3070, 32GB RAM), average frame rates ranged from 84 to 91 FPS across the evaluated scenarios, including the most demanding case of dense fog with traffic (84 FPS). GPU utilization ranged from 78% in simple highway scenarios to 92% in complex weather conditions, indicating effective resource utilization without major bottlenecks.

Rendering optimization techniques described in Table 2 collectively reduced polygon count by 40% and VRAM usage by 60% while maintaining visual fidelity. The combination of baked lighting for static environments and dynamic lighting for vehicles achieved 30% faster render times compared to fully dynamic lighting approaches.

User experience testing with 25 volunteer students indicated no reports of motion sickness or VR discomfort, which may be attributed to the stable frame-rate range of 84-91 FPS and the optimized rendering pipeline.

3.2 Pedagogical Evaluation Results

Table 5 presents the distribution of students who participated in the experiment and their performance indicators. Table 6 aggregates the total indicators for control and experimental groups. The variation series for statistical analysis is presented in Table 7. Figure 3 illustrates the dynamics of student assimilation comparing experimental and control groups [7], [8].

Table 5: Driving school student performance by group.

Driving School	Group	N	Excellent (5)	Good (4)	Satisfactory (3)	Unsatisfactory (2)
Navoi City	Experimental	65	24	26	13	2
Navoi City	Control	67	14	21	27	5
Karmana District	Experimental	62	19	27	14	2
Karmana District	Control	56	13	17	23	3

Table 6: Aggregate performance indicators.

Group	N	Excellent (5)	Good (4)	Satisfactory (3)	Unsatisfactory (2)
Experimental	127	43	53	27	4
Control	123	27	38	50	8

Table 7: Statistical distribution for experimental and control groups.

Selection 1 (Experimental)					
Score (X_i)	5	4	3	2	Total
Frequency (n_i)	43	53	27	4	n = 127
Selection 2 (Control)					
Score (Y_j)	5	4	3	2	Total
Frequency (m_j)	27	38	50	8	m = 123

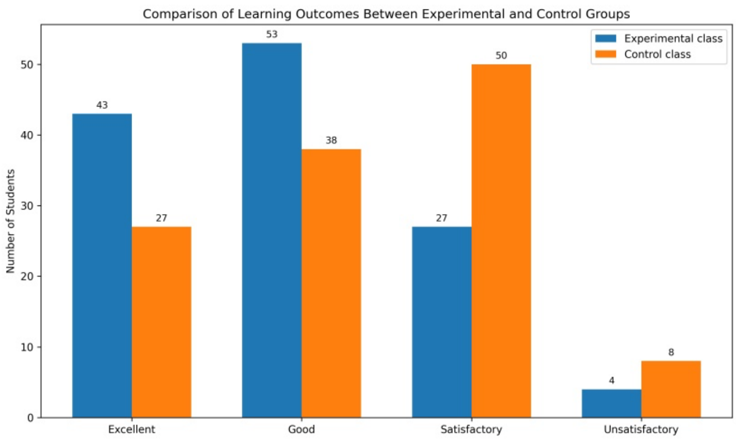

Figure 3: Dynamics of assimilation of students of driving schools.

3.3 Statistical Analysis

To determine the significance of differences between experimental and control groups, Student's t-test for independent samples was applied.

Step 1: Calculate means for each group.

For experimental group (scores converted to numerical values: 5, 4, 3, 2):

$\bar{X}_1$ = (43×5 + 53×4 + 27×3 + 4×2) / 127 = (215 + 212 + 81 + 8) / 127 = 516 / 127 = 4.06

For control group:

$\bar{X}_2$ = (27×5 + 38×4 + 50×3 + 8×2) / 123 = (135 + 152 + 150 + 16) / 123 = 453 / 123 = 3.68

Step 2: Calculate variances.

For experimental group:

S_1^2 = [43×(5-4.06)² + 53×(4-4.06)² + 27×(3-4.06)² + 4×(2-4.06)²] / (127-1)

= [43×0.8836 + 53×0.0036 + 27×1.1236 + 4×4.2436] / 126

= [38.0 + 0.19 + 30.34 + 16.97] / 126 = 85.5 / 126 = 0.68

For control group:

S_2^2 = [27×(5-3.68)² + 38×(4-3.68)² + 50×(3-3.68)² + 8×(2-3.68)²] / (123-1)

= [27×1.7424 + 38×0.1024 + 50×0.4624 + 8×2.8224] / 122

= [47.04 + 3.89 + 23.12 + 22.58] / 122 = 96.63 / 122 = 0.79

Step 3: Calculate t-statistic.

To determine whether the difference between the experimental and control groups is statistically significant, the independent samples t-test statistic was calculated using Equation (1):

$$d = \frac{\bar{X}_1 - \bar{X}_2}{S_p} \quad (1)$$

where:

$\bar{X}_1$ - mean score of the experimental group

$\bar{X}_2$ - mean score of the experimental group

S_1^2, S_2^2 - variances of the experimental and control groups

n_1, n_2 - sample sizes.

Substituting the obtained values:

$$t = \frac{4.06 - 3.68}{\sqrt{\frac{0.68}{127} + \frac{0.79}{123}}},$$

$$t = \frac{0.38}{\sqrt{0.00535 + 0.00642}},$$

$$t = \frac{0.38}{\sqrt{0.01177}},$$

$$t = \frac{0.38}{0.1085} \approx 3.50.$$

Thus, the calculated *t*-value equals t = 3.50.

Step 4: Determine degrees of freedom and critical value.

df = $n_1 + n_2 - 2 = 127 + 123 - 2 = 248$

For $\alpha = 0.05$ (two-tailed), critical t-value ≈ 1.97

For $\alpha = 0.01$ (two-tailed), critical t-value ≈ 2.60

Since calculated t = 3.50 > 2.60, the difference is statistically significant at $p < 0.01$.

Step 5: Calculate effect size (Cohen's d).

To evaluate the magnitude of the difference between the groups, the effect size was calculated using Cohen’s d. This value was determined using Equations (2) and (3).

$$d = \frac{\bar{X}_1 - \bar{X}_2}{S_p}, \quad (2)$$

where S_p is the pooled standard deviation:

$$S_p = \sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1+n_2-2}}. \quad (3)$$

Substituting the obtained values:

$$S_p = \sqrt{\frac{126 \times 0.68 + 122 \times 0.79}{248}},$$

$$S_p = \sqrt{\frac{85.68 + 96.38}{248}},$$

$$S_p = \sqrt{\frac{182.06}{248}},$$

$$S_p = \sqrt{0.734} \approx 0.857.$$

Now Cohen’s d:

$$d = \frac{4.06 - 3.68}{0.857},$$

$$d = \frac{0.38}{0.857} \approx 0.44.$$

Thus, the calculated effect size is Cohen’s d = 0.44, which corresponds to a medium effect size according to Cohen’s classification.

Step 6: Calculate learning improvement percentage.

Mean experimental score: 4.06 (converted to percentage: 4.06/5 × 100% = 81.2%)

Mean control score: 3.68 (converted to percentage: 3.68/5 × 100% = 73.6%)

Improvement: (81.2% - 73.6%) / 73.6% × 100% = 10.33%

From the above calculations, the experimental group demonstrated a 10.33% higher learning outcome compared to the control group, with the difference being statistically significant ($p < 0.01$) and representing a medium effect size (d = 0.44).

4 DISCUSSION

The results demonstrate that the integration of VR technologies and 3D modeling in driving school education yields significant pedagogical benefits. The 10.33% improvement in learning outcomes aligns with previous research on simulation-based training effectiveness [9], [10], while extending these findings to the specific domain of driver education.

Technical Contributions. The developed system addresses key technical challenges in VR-based education: maintaining stable real-time frame rates (84-91 FPS) to support comfortable VR interaction, optimizing 3D assets for real-time rendering, and creating realistic driving physics through Unreal Engine's Chaos Physics system. The modular architecture enables easy adaptation for different VR platforms and future enhancements.

Pedagogical Implications. Several factors likely contributed to the observed learning improvement: 1) safe environment for error-based learning without real-world consequences; 2) repetitive practice opportunities unavailable in traditional instruction;

3) realistic visualization of driving scenarios; 4) immediate feedback through the assessment module; and 5) increased student engagement through interactive VR experience.

Limitations. Despite positive results, several limitations should be acknowledged. First, the 3D modeling process remains time-consuming and resource-intensive, potentially limiting scalability. Second, VR hardware requirements may present accessibility challenges for some educational institutions: the cost of VR headsets (e.g., Oculus Rift, HTC Vive) may be prohibitive for some educational institutions, limiting scalability. Third, the study duration (one quarter) limits assessment of long-term knowledge retention and transfer to real driving situations. Fourth, while the system simulates various weather conditions, it cannot fully replicate all variables of real driving environments.

Comparison with Existing Work. Compared to previous VR driving simulators [11], [12], our system provides more comprehensive performance optimization data and includes a statistically validated pedagogical evaluation. The 10.33% improvement is comparable to findings by Chien and Wang [13] who reported 8-12% improvements in simulation-based training across different domains.

Future Improvements. Based on student feedback and system evaluation, several enhancements are planned: 1) addition of more complex scenarios including accident situations and emergency responses; 2) integration of eye-tracking for attention assessment; 3) development of adaptive difficulty based on individual progress; 4) optimization for standalone VR headsets to reduce hardware requirements; and 5) longitudinal studies to assess long-term retention and real-world driving performance.

5 CONCLUSIONS

This study demonstrated the effectiveness of integrating virtual reality technologies and 3D modeling in driving school education. The developed system, combining Autodesk 3ds Max for asset creation and Unreal Engine 5 for simulation, provided students with an interactive and realistic virtual driving environment.

The main advantages of the created system are:

- Interactive learning environment enabling realistic driving simulation.
- Optimized technical performance maintaining stable frame rates of 84-91 FPS across all scenarios.
- Comprehensive assessment through the modular scoring system.
- Statistically significant pedagogical improvement of 10.33% ($p < 0.01$).

Technical optimization techniques including LOD generation, texture compression, and occlusion culling successfully reduced resource requirements while maintaining visual quality. The system's modular architecture supports future enhancements and adaptation to different VR platforms.

The pedagogical experiment involving 250 students from two driving schools demonstrated that VR-based training significantly improves learning outcomes compared to traditional instruction alone. Statistical analysis using Student's t-test confirmed the significance of these findings, with medium effect size (Cohen's $d = 0.44$).

Future work will focus on expanding scenario complexity, reducing hardware requirements, and conducting longitudinal studies to assess long-term training transfer to real driving performance. The integration of VR and 3D modeling technologies represents a promising direction for modernizing driver education and improving road safety through better-prepared drivers.

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