

Impact of Sensor Technology and Virtual Production Equipment Integration on Film Model-making: Comparative Analysis of Traditional-craftsmanship-based and Virtual-reality-based Digital Workflows

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The effect of integrating sensor technologies into 3D modeling in virtual production was explored by comparing it with traditional-craftsmanship-based methods. Whereas physical model-making is widely used for production design and early-stage visual effects planning, traditional methods suffer from time-intensive iterations, limited real-time visualization, and high communication costs. To address such constraints, a sensor-integrated method that combines immersive previsualization, sensor-assisted spatial calibration, and iterative refinement through real-time feedback was developed in this study. The performance characteristics of the traditional and sensor-integrated methods were compared among 30 university students on 3D modeling tasks, and both objective and subjective measures were obtained from their experiments. Objective indicators to evaluate performance included task completion time, revision count, rework frequency, spatial deviation, and camera framing consistency. Subjective outcomes were assessed using the National Aeronautics and Space Administration Task Load Index for workload, the system usability scale for usability, and satisfaction ratings. The results showed that the sensor-integrated method significantly reduced task completion time, revisions, and rework while improving spatial accuracy and framing consistency. The participants reported lower workload, higher usability, and greater satisfaction. The results highlight the feasibility of extending virtual production concepts into physical model-making, offering a reproducible integration framework and quantitative evaluation approach for hybrid workflows that bridge tangible craftsmanship with real-time digital visualization. The proposed workflow further demonstrates the role of digital innovation and virtual prototyping in supporting more adaptive and efficient creative production workflows within contemporary film design environments.

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1. Introduction

In the rapid evolution of digital production pipelines for filmmaking, virtual production is regarded as a paradigm-shifting methodology that integrates sensor technologies with real-time rendering. In virtual production, sensor-based technologies are integrated into real-time rendering engines, enabling directors and production teams to visualize, evaluate, and refine cinematic scenes across pre-production, production, and post-production stages. By embedding real-time feedback from sensor systems into creative workflows in virtual production, production costs are considerably reduced, and image quality is significantly enhanced. Therefore, post-production-driven processes are revolutionized into iterative, sensor-assisted collaborative processes.⁽¹⁾

In virtual production, 3D modeling plays a vital role in production design and early-stage visual effects (VFX) planning. In 3D modeling, physical models are essential for providing tangible scale references, material feedback, and intuitive spatial validation, thereby supporting communication among directors, designers, and cinematographers. Traditional-craftsmanship-based workflows of 3D modeling must be conducted through trial-and-error iterations, largely relying on static 2D drawings and time-consuming camera testing. These limitations result in inefficiencies, cognitive discrepancies, and increased correction costs. The absence of real-time sensor feedback also restricts the validation of scale and composition in the 3D model design process.^(2,3)

To address these challenges, we developed a sensor-integrated virtual reality (VR) framework for 3D modeling. By pose tracking, position tracking, and depth sensing and using spatial information from the physical models, real-time rendering environments are constructed to capture and synchronize physical models. By establishing a physical–digital synchronization loop, the workflow enables continuous alignment between tangible models and virtual scenes. When combined with immersive VR previsualization, scale, composition, and lighting can be evaluated and adjusted from cinematic viewpoints during 3D modeling. The integration of sensor technology transforms a 3D modeling workflow from static verification into dynamic, sensor-driven iteration.⁽³⁾ The developed framework conducts real-time scale calibration through sensor-assisted positioning and VR references, the spatial synchronization of physical models with virtual production engines for accurate visual feedback, and iterative refinement for rapid decision-making and reduced communication costs. The developed sensor-integrated framework for virtual production was validated for its effectiveness through quantitative and human factors analysis, offering a reference model for the digital transformation of film production.^(4,5) The integration of sensor-assisted virtual production technologies reflects the growing importance of digital innovation and immersive visualization systems in transforming contemporary creative production practices.

2. Literature Review

Virtual production is carried out using real-time rendering engines such as Unreal Engine to integrate digital assets into live-action filmmaking.^(6,7) In virtual production, LED technology

replaces traditional green screens by rendering real-time, 3D environments behind the actors. An LED wall, i.e., a high-resolution, multi-panel display, is used as a digital backdrop, and an LED volume is also used to enclose a stage with a continuous curve of wall and ceiling panels. The LED technology, supported by sensor-driven camera tracking, enables the production of parallax effects and spatial coherence between virtual backgrounds and physical foregrounds.⁽⁸⁾ Compared with green-screen workflows, LED volumes reduce post-production burdens and enhance lighting realism for visual effects and production efficiency.

Immersive VR environments extend the capabilities of sensor-based virtual production by enabling directors and designers to evaluate scale, composition, and lighting directly from cinematic viewpoints during previsualization. For workflows, human factors research plays a critical role. The National Aeronautics and Space Administration (NASA) Task Load Index (NASA-TLX) is used to provide a multidimensional framework for assessing mental demand, temporal demand, effort, and frustration, thereby quantifying cognitive workload in complex production tasks.^(9,10) NASA-TLX is a widely used, multidimensional subjective rating scale designed to measure an individual's perceived workload while performing a task.^(11,12) NASA-TLX calculates an overall workload score based on a weighted average of ratings across six distinct subscales. The system usability scale (SUS) is used in parallel to offer a standardized and efficient measure of usability across diverse systems, making it particularly suitable for evaluating VR and sensor-integrated workflows.⁽¹⁰⁾ The tools are used to establish a rigorous foundation for assessing efficiency, usability, and user experience in sensor-driven cinematic environments.⁽⁴⁾

Traditional model-making continues to rely on manual craftsmanship and static visualization tools, limiting real-time collaboration and iterative refinement. This reliance on non-interactive methods results in inefficiencies and the delayed validation of scale and composition. Therefore, a sensor-integrated workflow is required for digital synchronization with physical models, optimizing production design workflows, and advancing virtual production methodologies.⁽⁵⁾

3. Methodology

In this study, the effect of sensor technologies in the 3D modeling of virtual production was validated by comparing a traditional-craftsmanship-based method with a VR–sensor-integrated digital method. For performance evaluation, we designed an experimental procedure under controlled conditions. To ensure comparability, both methods were used in an identical, structured 3D modeling task in the same space and camera frame.

In the traditional method, 3D model-making began with interpreting the production design brief and reviewing reference images or sketches. Scale and proportions were planned manually using conventional tools such as rulers and printed layout guides. Physical fabrication was then conducted, involving material cutting, component assembly, and surface detailing. Once the baseline structure was completed, camera framing was tested from preset viewpoints to determine whether the composition aligned with the plan. If discrepancies were identified, physical rework, repositioning, reshaping, or reassembling components was conducted. Iterative cycles were repeated until the final configuration met the design requirements. Despite the

reflection of established practices, the process was constrained by delayed visualization and repeated trial-and-error.

The sensor-integrated method incorporated immersive preview and sensor-driven spatial calibration to enable continuous validation during production. The design brief was imported into a VR environment, where virtual layouts and scale references were established. Sensor tracking was used to capture the pose and position of physical components or proxy objects, ensuring precise alignment between the physical workspace and the digital environment. Composition and camera framing were evaluated through immersive visualization, with real-time feedback guiding adjustments to spatial relationships and proportions. Discrepancies were resolved efficiently using VR calibration cues, minimizing unnecessary physical rework. Iteration remains possible, but verification occurs continuously rather than only after completion, resulting in improved accuracy, reduced revision frequency, and enhanced communication efficiency.

The performance of the two methods was assessed using indicators such as task completion time, revision count, rework frequency, spatial deviation, and camera framing consistency, alongside subjective measures including workload (NASA-TLX), usability (SUS), and overall satisfaction. The metrics were used to determine whether the sensor-integrated method can significantly improve efficiency and reliability compared with traditional methods.

3.1 Sensor-integrated system

The sensor-integrated system was developed to enable real-time spatial alignment, immersive preview, and iterative decision-making during model design and fabrication. In virtual production, real-time rendering environments synchronize with physical camera motion through tracking systems, allowing virtual imagery to respond immediately to real-world viewpoint changes. This principle is central to in-camera visual effects, where camera tracking, real-time rendering, and off-axis projection combine to achieve seamless integration between foreground subjects and virtual backgrounds. Such synchronization supports natural parallax, a critical visual cue for maintaining spatial consistency as the camera moves. The architecture adopts real-time tracking and visualization capabilities for 3D modeling, transforming the related workflow from a static build-and-verify process into a dynamic validate-while-building strategy. The architecture comprises four layers (Fig. 1).

- **Sensor layer:** Tracking devices, including outside-in optical tracking cameras, inside-out simultaneous localization and mapping (SLAM) cameras (Meta Quest 3), and fiducial reference markers, capture the position and orientation of physical model components. These inputs provide the spatial data necessary to establish correspondence between the physical and digital domains.
- **Data processing layer:** Raw tracking signals are synchronized and preprocessed to reduce drift, noise, and latency. Noise filtering, drift compensation, and coordinate transformation ensure that physical coordinates are reliably aligned with the virtual coordinate system, enabling low-latency feedback.

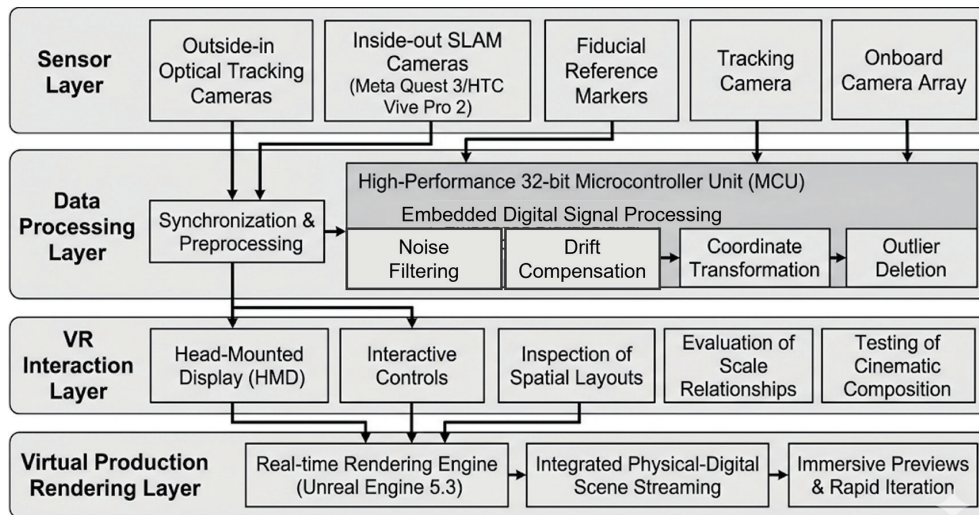


Fig. 1. Architecture of sensor-integrated 3D modeling system (created using AI).

- VR interaction layer: An immersive environment allows the inspection of spatial layouts, the evaluation of scale relationships, and the testing of cinematic composition from a first-person perspective. Through head-mounted displays and interactive controls, camera framing and spatial arrangement can be verified continuously during modeling.
- Virtual production rendering layer: The integrated physical–digital scene is streamed into a real-time rendering engine (Unreal Engine 5.3), producing previews of how physical model configurations translate into cinematic viewpoints. This supports rapid iteration, reduces unnecessary rework, and enhances communication efficiency.

This layered architecture demonstrates how sensor integration and real-time visualization can be adapted from virtual production into 3D modeling workflows, thereby improving efficiency, accuracy, and iterative refinement. To evaluate the effect of the sensor-integrated method, subjective workload was assessed using NASA-TLX,⁽¹³⁾ whereas system usability was measured using SUS.⁽¹⁴⁾ The NASA-TLX scores were obtained through a two-stage process: six-dimension intensity ratings (mental demand, physical demand, temporal demand, performance, effort, and frustration levels) followed by pairwise factor weighting to derive a composite workload score. SUS was calculated by summing the standardized scores of ten Likert-scale items and applying the conventional 2.5 multiplier to normalize the results to a 0–100 scale.

3.2 Data processing

The hardware and data synchronization framework was controlled by a high-performance 32-bit microcontroller unit. The sensor-integrated system incorporated two main optical sensor streams to capture precise spatial coordinates (Fig. 1).

- **Optical tracking system:** A tracking camera is positioned to capture high-frequency motion dynamics. The camera delivers raw spatial pose metrics to the processing pipeline on a stable wired bus interface.
- **Inside-out SLAM cameras:** The onboard camera array embedded within the VR HMD (Meta Quest 3 and HTC Vive Pro 2) was used for SLAM algorithms. This array calculates the user's position, orientation, and viewpoint relative to the physical workspace.

The 32-bit MCU functions as the central data aggregator. It receives high-frequency raw tracking signals from the sensor arrays and processes the incoming raw data through its dedicated embedded digital signal processing routines. Noise filtering was used to eliminate high-frequency jitter, whereas drift compensation was conducted to prevent accumulated tracking errors over time. Outliers, such as anomalous spatial readings, were deleted.

The preprocessed tracking data were subsequently processed through estimation algorithms to extract spatial and kinematic information. At this stage, absolute Cartesian positions were calculated together with rotational orientations, specifically pitch and roll, to establish the fundamental spatial framework. A secondary refinement loop was then applied to enhance positional accuracy and to generate complete six degrees of freedom data, encompassing roll, pitch, and yaw. Once the kinematic parameters were established, the coordinates underwent transformation and alignment procedures. This involved mapping the physical measurements into a unified world reference frame and synchronizing them with the corresponding virtual environment, ensuring that the scale and positioning of the physical workspace matched the digital coordinates precisely. To maintain responsiveness, the processed data were normalized and synchronized with system timestamps before transmission. A high-bandwidth wireless synchronization module broadcasted the spatial matrix directly to the rendering engine. By streaming this data into Unreal Engine 5.3, the system provided real-time visualization with minimal latency. This integration enabled physical movements and spatial adjustments instantly in the virtual environment, ensuring accurate alignment between physical and digital domains. The hardware and software configurations in the system are summarized in Table 1.

The Meta Quest 3 and HTC VIVE Pro 2 were employed as tracking sensors in the experiment, each utilizing distinct architectures for spatial localization. The Quest 3 integrates a proprietary inside-out SLAM system known as Oculus Insight, which fuses visual and inertial data to estimate position and orientation without external hardware. Multiple wide-angle visible-light and infrared cameras embedded on the front and sides of the headset capture environmental features such as edges and textures, whereas internal inertial measurement units (IMUs) that comprise high-frequency accelerometers and gyroscopes provide continuous motion data to bridge gaps between visual frames. In addition, the Quest 3 was used to incorporate an active depth sensor based on structured light projection, enabling the accurate mapping of room-scale geometry for mixed reality occlusion and safe boundary definition. The VIVE Pro 2 employs the SteamVR Lighthouse system, an outside-in tracking architecture. The headset surface is embedded with a constellation of infrared photosensors that detect sweeping laser planes emitted by external base stations. By calculating the timing of these laser hits, the headset determines its precise three-dimensional position and orientation. Internal IMUs complement this process by smoothing motion between laser sweeps, thereby ensuring low-latency stability in both

Table 1
Equipment and system configuration.

Category	Item	Specification	Purpose
VR HMD	Meta Quest 3 (Meta Platforms, Inc.)	Resolution: 2064 × 2208 per eye; Refresh rate: 72/90/120 Hz	Immersive previsualization and VR interaction
VR HMD	HTC VIVE Pro 2 (HTC corporation)	Resolution: 2448 × 2448 per eye; Refresh rate: 90/120 Hz	High-resolution PC-VR preview
Tracking sensors	Optical tracking (inside-out SLAM, integrated in HMDs)	Onboard cameras for HMD/controller tracking	Pose estimation for user motion
Tracking markers	Fiducial markers/proxy markers	Printed or physical markers attached to model components	Position reference for physical model elements
VP/real-time engine	Unreal Engine 5.3 (Epic Games, Inc.)	Released: September 6, 2023	Real-time visualization and VP rendering
Rendering module	Virtual camera and environment	Real-time preview scene with scale references	Cinematic framing validation
PC workstation	Windows PC (custom build)	CPU: Intel Core i7/AMD Ryzen 7 or higher; Graphics processing unit: NVIDIA RTX 3070 or higher; random access memory: ≥ 32 gigabytes	Stable real-time rendering and VR streaming
Data synchronization	Wi-Fi 6/USB Link/PCVR streaming	High-bandwidth, low-latency connection	Real-time interaction and update between VR HMD and PC
Measurement tool	Ruler, caliper, tape measure (Mitutoyo, Japan)	Millimeter-level measurement accuracy	Ground-truth spatial deviation measurement
Questionnaire tool	NASA-TLX (NASA Human Systems); SUS	NASA-TLX workload scales; System Usability Scale	Subjective evaluation of workload and usability

rotational and positional tracking. Whereas the Quest 3 relies entirely on onboard sensors, the VIVE Pro 2 depends on external base stations for spatial reference, offering high accuracy in large-scale tracking environments.

For tracking markers, fiducial markers (AprilTag) were used. AprilTag was developed by the University of Michigan, USA, and ArUco, which is included in the OpenCV library maintained by the OpenCV development team. AprilTag 3.4.5 was printed on high-contrast matte paper and affixed to proxy model components. This configuration ensured robust detection and enabled sub-millimeter pose estimation for accurate spatial alignment between physical and virtual environments.

3.3 Data collection and analysis

To evaluate the effectiveness of the sensor-integrated method, the performance of the system was compared with that in the case of the traditional 3D modeling method (Table 2). In the traditional method, design visualization was conducted using static 2D sketches or printed plans, with spatial calibration performed manually using rulers and scales. Camera framing verification was performed after the physical model was completed, often necessitating repeated cycles of cutting, reassembly, and physical adjustment. Communication is limited to static photographs

Table 2
Comparison of traditional and sensor-integrated methods.

Item	Traditional method	Sensor-integrated method
Design preview	2D sketches/printed plans	Immersive VR preview
Spatial calibration	Manual measurement (ruler, scale)	Sensor-assisted scale and alignment
Camera framing verification	After physical model completion	During iteration in VR
Revision method	Physical cutting/reassembly	Digital adjustment + guided physical revision
Communication mode	Static photos + verbal discussion	Real-time shared VR view
Output	Final physical model	Physical model + digital workflow record

and verbal discussion, and the final deliverable consists solely of the physical model. In contrast, the sensor-integrated method introduced immersive VR previews that allow the real-time visualization of scale, composition, and framing. Spatial calibration was conducted through sensor-assisted alignment, ensuring accurate correspondence between physical and digital environments. During modeling, the VR immersive camera composition technology was utilized continuously to verify the consistency between the physical model and the virtual scene, including spatial scale, object positioning, compositional accuracy, and consistency with cinematic shot imagery. This method effectively reduces the need for repeated disassembly and reconstruction of the model, thereby improving overall workflow efficiency. Revisions were performed through digital adjustments and calibration cues, enabling efficient refinement. Communication was enhanced through shared VR views, which provide stakeholders with synchronized perspectives of the evolving design. The output includes both the physical model and a digital workflow record, offering the traceability and reproducibility of design decisions.

Thirty students were recruited from a design program at Changchun College of Electronic Technology in China and randomly assigned to two groups using the traditional and sensor-integrated methods (Table 3). Random assignment was employed to minimize selection bias and to control for potential confounding factors related to prior 3D modeling or VR experience. Both groups performed the same standardized modeling tasks under controlled laboratory conditions, ensuring repeatability and comparability across workflows. The demographics of the participants showed a balanced gender distribution (53.3% male, 46.7% female) and a typical university demographic, with the majority of participants aged from 18 to 23 years old. Their grades ensured that novice and advanced students were included. Experience in 3D modeling varied: 40% reported basic exposure (≤ 1 year), 20% had intermediate experience (1–3 years), and 10% had advanced experience (≥ 3 years), while 30% had no prior experience. VR familiarity was similarly diverse, with 43.3% reporting no prior use, 36.7% occasional use, and 20% frequent use.

This demographic composition showed a sufficiently heterogeneous sample to capture performance differences across various levels of technical expertise and VR familiarity. By controlling assignment and standardizing task conditions, differences in efficiency, accuracy, and usability could be observed.

Before the experiment, the participants underwent a standardized training session to ensure familiarity with the assigned workflow and to mitigate potential learning-curve effects. Under

Table 3
Demographics and previous experience of participants in this study.

Variable	Category	<i>n</i>	Percentage (%)
Gender	Male	16	53.3
	Female	14	46.7
Age (years old)	18–20	12	40.0
	21–23	15	50.0
	24+	3	10.0
Grade	Freshman	8	26.7
	Sophomore	9	30.0
	Junior	7	23.3
	Senior	6	20.0
Experience in 3D modeling	None	9	30.0
	Basic (≤ 1 year)	12	40.0
	Intermediate (1–3 years)	6	20.0
	Advanced (≥ 3 years)	3	10.0
VR experience	Never used	13	43.3
	Occasional	11	36.7
	Frequent	6	20.0

the traditional condition, training emphasized physical measurement references and manual assembly procedures. Under the sensor-integrated condition, training content included the use of HMDs, navigation within the VR environment, and calibration steps for sensor-based alignment. To maintain parity in device proficiency across both conditions, a single 45-min familiarization session was conducted before the experiment. The training session was structured into three phases.

First, a system introduction was provided for 10 min to explain an overview of the equipment and basic navigation controls such as teleportation, object manipulation, and tool selection. Second, a guided practice was conducted for 20 min to enable the participants to perform a simplified, non-experimental 3D modeling. This exercise session focused on standard operations, including spatial alignment, component resizing, and camera framing adjustments, with step-by-step guidance provided through an instructional tutorial. Finally, in a validation session for 15 min, the participants completed a mock framing challenge. Through the task, the participants became familiar with the VR environment and performed calibration procedures without assistance to establish baseline usability proficiency.

In the experiment, performance indicators were continuously recorded to evaluate workflow efficiency and accuracy. The indicators included task completion time, revision count, rework frequency, spatial deviation, and camera framing consistency (Table 4). Task completion time represented the total duration required to complete the standardized model-making task, whereas revision count captured the number of major modifications performed after the initial build. Rework frequency represented the number of times disassembly and reconstruction were necessary, reflecting the stability of the workflow. Spatial deviation was measured by calculating the Euclidean distance between predefined reference points in the physical model and their corresponding target positions, thereby providing a precise metric of geometric accuracy.

Table 4
Performance indicators used in experiment.

Indicator	Definition	Unit	Data source
Task completion time	Total time required to complete the standardized model-making task	min	Stopwatch/log
Revision count	Number of major modifications performed after the initial build	count	Observation sheet
Rework frequency	Number of times disassembly and reconstruction were required	count	Observation sheet
Spatial deviation	Error between target and achieved spatial layout, calculated using Euclidean distance	mm/%	Measurement protocol
Camera framing consistency	Match score between target cinematic framing and achieved framing	score	Expert rating

Camera framing consistency was assessed by comparing the achieved composition against predefined cinematic framing references, with expert ratings used to determine the degree of alignment.

In addition to these objective measures, subjective assessments were collected immediately after task completion. Workload was evaluated using NASA-TLX,⁽⁹⁾ which provides a multidimensional measure of mental demand, temporal demand, effort, and frustration. Usability was assessed using SUS,⁽¹⁰⁾ a standardized instrument widely adopted for evaluating interactive systems. Finally, overall satisfaction ratings were obtained to capture user perceptions of workflow effectiveness and preference. Together, these objective and subjective measures provided a robust dataset for statistical analysis, enabling rigorous comparison between the traditional and sensor-integrated methods.

Statistical analyses were conducted for the collected data. Descriptive statistics were calculated to explore the tendency and variability of the data. The normality of continuous variables was examined using the Shapiro–Wilk test,⁽¹⁵⁾ and the proportion of variance in the dependent variable associated with an independent variable was assessed using Levene’s test.⁽¹⁶⁾ Between-group differences were evaluated using one-way analysis of variance,⁽¹⁷⁾ at a significance level of 0.05. When normality or homogeneity of variance was not assumed, the Mann–Whitney U test was used as a nonparametric alternative.⁽¹⁸⁾

4. Results

The participants’ performances with the two different models were analyzed across five indicators: task completion time, revision count, rework frequency, spatial deviation, and camera framing consistency. Table 5 shows the results with ANOVA and effect sizes.

The sensor-integrated method outperformed the traditional method in terms of performance. Task completion time was significantly shorter in the sensor-integrated method (30.29 ± 5.45 min) than in the traditional method (45.08 ± 7.95 min; $F = 35.31$, $p < 0.001$, $\eta^2 = 0.558$), indicating improved efficiency. Revision count and rework frequency were reduced with the sensor-integrated method (3.20 ± 1.61 and 5.40 ± 2.50 for revision count and 1.33 ± 1.18 and 3.20 ± 1.97 for rework frequency), reflecting fewer iterations and greater workflow stability. Spatial

Table 5
Performance indicators of two methods.

Indicator	Traditional method [<i>mean</i> ± standard deviation (<i>SD</i>)]	Sensor-integrated method (<i>mean</i> ± <i>SD</i>)	<i>F</i>	<i>p</i> -value	Proportion of variance (η^2)
Task completion time (min)	45.08 ± 7.95	30.29 ± 5.45	35.31	0.000002	0.558
Revision count (count)	5.40 ± 2.50	3.20 ± 1.61	8.2	0.007861	0.226
Rework frequency (count)	3.20 ± 1.97	1.33 ± 1.18	9.92	0.003861	0.262
Spatial deviation (mm)	19.79 ± 5.88	12.09 ± 4.88	15.25	0.000542	0.353
Camera framing consistency (score)	3.21 ± 0.70	4.20 ± 0.46	20.96	0.000088	0.428

accuracy was enhanced using the sensor-integrated method, with significantly lower spatial deviation (12.09 ± 4.88 mm), compared with that using the traditional method (19.79 ± 5.88 mm; $F = 15.25$, $p < 0.001$, $\eta^2 = 0.353$). Camera framing consistency was higher with the sensor-integrated method (4.20 ± 0.46) than with the traditional method (3.21 ± 0.70 ; $F = 20.96$, $p < 0.001$, $\eta^2 = 0.428$), demonstrating the effectiveness of sensor-assisted calibration and immersive preview in maintaining cinematic composition (Fig. 2).

Subjective measures were calculated using NASA-TLX (workload), SUS (usability), and satisfaction ratings. Table 6 shows the significant differences between the two methods.

The sensor-integrated method showed lower workload scores than the traditional method (42.0 ± 10.0 and 55.0 ± 12.0 ; $F = 7.32$, $p = 0.011$, $\eta^2 = 0.207$), indicating reduced cognitive and physical demand. Usability scores were higher with the sensor-integrated method than with the traditional method (75.0 ± 9.0 and 62.0 ± 10.0 ; $F = 13.62$, $p = 0.001$, $\eta^2 = 0.327$), reflecting improved system design and user interaction. Satisfaction ratings also favored Condition B (4.2 ± 0.6 vs 3.4 ± 0.8 ; $F = 9.21$, $p = 0.005$, $\eta^2 = 0.248$), suggesting greater acceptance and preference for the sensor-integrated method. The sensor-integrated method showed lower workload, higher usability, and greater satisfaction, with statistical significance indicated by annotation markers (Figs. 3 and 4).

The results showed that the sensor-integrated method significantly improved objective and subjective outcomes compared with the traditional method. Objective measures revealed faster task completion, fewer revisions and reworks, reduced spatial deviation, and higher framing consistency when using the sensor-integrated method. Subjective measures showed lower workload, higher usability, and greater satisfaction. The proportion of variance (η^2) across metrics indicated that workflow condition accounted for a substantial proportion of variance, providing strong empirical evidence that integrating VR previsualization with sensor tracking enhances efficiency, accuracy, and user experience in 3D modeling.

5. Discussion

We examined whether the sensor-integrated method enhances 3D modeling tasks compared with the traditional method. The results of this study showed that the sensor-integrated method

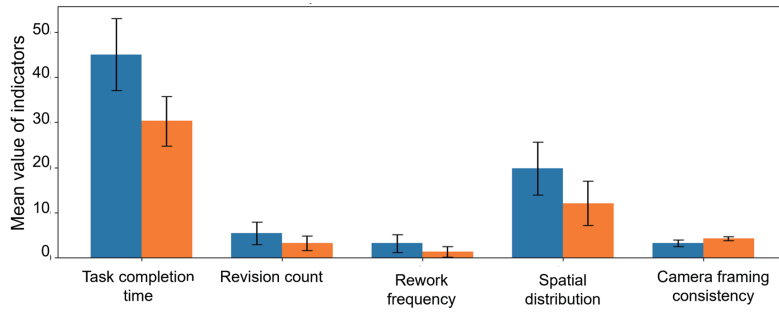


Fig. 2. (Color online) Performance indicators of traditional (orange bar) and sensor-integrated (blue bar) methods. Bars represent means and error bars indicate *SD*.

Table 6
Subjective measures (NASA-TLX, SUS, and satisfaction rating of two methods).

Indicator	Traditional method [<i>mean</i> ± standard deviation (<i>SD</i>)]	Sensor-integrated method (<i>mean</i> ± <i>SD</i>)	<i>F</i>	<i>p</i> -value	Proportion of variance (η^2)
NASA-TLX workload (score)	55.0 ± 12.0	42.0 ± 10.0	7.32	0.011	0.207
SUS usability (score)	62.0 ± 10.0	75.0 ± 9.0	13.62	0.001	0.327
Satisfaction rating (score)	3.4 ± 0.8	4.2 ± 0.6	9.21	0.005	0.248

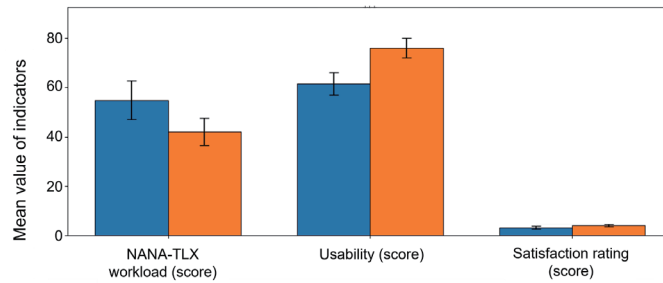


Fig. 3. (Color online) Subjective outcomes (NASA-TLX, SUS, and satisfaction ratings) of traditional (orange bar) and sensor-integrated (blue bar) methods. Bars represent group means and error bars indicate *SD* at a significance level of 0.001.

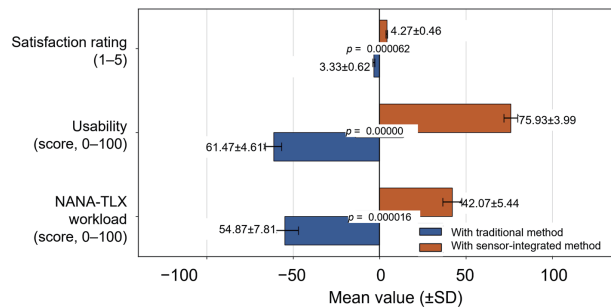


Fig. 4. (Color online) Subjective outcomes (*mean* ± *SD*) with proportion of variance and *p*-values. Negative axis values are used for visual comparison.

outperformed the traditional method for indicators and subjective measures, with statistically significant differences.

Task completion time was significantly reduced when using the sensor-integrated method, indicating a large practical improvement in efficiency. This reflects the advantages of immersive previsualization and real-time spatial feedback, which enabled the participants to detect scale mismatches earlier and avoid prolonged trial-and-error revisions. Similarly, revision count and rework frequency were significantly lower with the traditional method at $p < 0.01$, indicating improved process stability. These reductions were attributed to continuous validation during fabrication, where spatial relationships and camera framing could be iteratively verified rather than postponed until model completion. In professional 3D modeling, fewer revisions and reworks reduce labor costs, minimize schedule risks, and improve consistency between physical models and digital pipelines.

Spatial deviation was significantly lower with the sensor-integrated method, confirming that sensor-assisted calibration improved geometric accuracy. Traditional methods relying on manual measurement tools are prone to cumulative errors, whereas sensor tracking provides a stable external reference system that reduces drift and misalignment. Camera framing consistency was also significantly higher with the sensor-integrated method, demonstrating that immersive preview and real-time visualization enhanced composition control. The sensor-integrated method enabled iterative framing validation, supporting the natural exploration of virtual production. From a filmmaking perspective, this capability is critical, as framing consistency directly affects narrative coherence, scene mood, and communication with cinematography teams.

Our experimental results show benefits for production design and virtual production pipelines. First, the sensor-integrated method enhances efficiency and reduces rework, lowering time and labor costs in pre-production. Second, enhanced spatial accuracy and framing consistency support cross-department collaboration, as physical and virtual references remain aligned. Third, the sensor-integrated method generates a structured digital record of iterative processes, supporting documentation, design tracking, and training. In contemporary production environments where virtual production methods are increasingly adopted, sensor-driven spatial alignment offers a bridge between physical craftsmanship and real-time digital visualization, enabling hybrid workflows that combine tangible materials with interactive validation.

Despite the benefits, the limitations of the sensor-integrated method must be addressed. The participant pool consisted of university students, which might limit generalizability to professional model-makers with higher craftsmanship expertise. The experimental task was standardized for comparability, whereas real-world modeling often involves diverse materials, larger scales, and complex constraints. The efficient use of the sensor-integrated method depends on tracking stability, latency, calibration accuracy, and user familiarity with immersive interfaces; variations in sensor quality or VR comfort may affect outcomes. Since this study was conducted for short-term performance, long-term learning effects, fatigue, and scalability were not assessed across repeated production cycles, which need to be explored in future studies.

6. Conclusion

The present study results demonstrated that integrating sensors in the 3D modeling of virtual production significantly improves workflow efficiency compared with traditional manual methods. Across objective and subjective measures, the VR–sensor-integrated workflow yielded faster task completion, fewer revisions and reworks, reduced spatial deviation, and higher camera framing consistency. Subjective outcomes further confirmed lower workload, higher usability, and greater satisfaction, underscoring the practical and experiential benefits of immersive, sensor-driven design environments.

The results prove the feasibility of extending virtual production concepts into early-stage physical model-making, where iterative decision-making, spatial calibration, and framing verification are critical. By enabling continuous validation during fabrication, the sensor-integrated method helps transform model-making from a build-first, validate-later process into a dynamic, feedback-driven methodology. This shift has significant implications for production design, where efficiency gains, improved accuracy, and enhanced creative control can directly reduce costs, mitigate schedule risks, and strengthen cross-departmental collaboration. The proposed framework also demonstrates how sensor-assisted virtual production technologies can support sustainable innovation by reducing repetitive fabrication processes and enabling more intelligent real-time creative workflows.

Beyond immediate efficiency and accuracy improvements, the sensor-integrated method contributes to the hybridization of physical and digital practices. The ability to generate a structured digital record of iterative processes provides traceability, supports training, and facilitates integration with downstream digital pipelines. In modern filmmaking and design, where virtual production methods are increasingly adopted, sensor-integrated model-making serves as a bridge between tangible craftsmanship and real-time visualization, reinforcing continuity between physical prototypes and digital assets.

Further studies are necessary to expand external validity by involving professional production designers and model-makers and to assess performance under expert-level constraints. Technical enhancements such as multi-sensor fusion, higher-precision tracking, and adaptive calibration algorithms are necessary to enhance robustness in large-scale or complex environments. Collaborative VR scenarios must be explored to enable simultaneous review by directors, cinematographers, and art departments, enhancing real-time decision-making. Moreover, integrating AI-assisted tools for layout suggestion, automated framing evaluation, or anomaly detection reduces cognitive burden and accelerate iteration cycles.

The sensor-integrated method can be used in virtual production, digital environment reconstruction, asset management, and cinematic rendering. By strengthening the connection between physical design and real-time visualization, the method has the potential to reshape pre-production practices, streamline communication across creative teams, and contribute to the evolving landscape of hybrid physical–digital production pipelines.

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