
FACTORS INFLUENCING THE ADOPTION OF MIXED REALITY TECHNOLOGY FOR CONSTRUCTION PROJECTS COST ESTIMATION

Raphael Olarewaju^{1,*}, Olubunmi Comfort Ade-Ojo¹

¹Federal University of Technology Akure

Email: olumider28@gmail.com*, ade-ojoco@futa.edu.ng

*Corresponding author: Raphael Olarewaju

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ABSTRACT

Cost estimation issues including budget overruns, delays in project delivery, and loss of stakeholder confidence remain as persistent challenges in the Nigerian construction Industry. By integrating Augmented Reality (AR) and Virtual Reality (VR) to visualize design and cost data in an interactive and real-time manner, Mixed Reality (MR) technology promises to enhance estimation precision, teamwork, and decision-making efficiency. Despite increasing interest in MR adoption in the construction industry, it is still not well explored in the Nigerian context, especially among Quantity Surveyors (QSs) for construction cost estimation. This study has investigated the factors influencing the adoption of MR technology for construction cost estimation among QSs in Lagos State, Nigeria. Five (5) latent constructs namely, Organizational Factors (ORGF), Infrastructural Factors (INFF), Training-Related Factors (TRF), Financial Viability Factors (FVF), and Institutional Factors (INSTF) were measured using a structured questionnaire via census sampling, which got 87.85% response rate. Data from 94 respondents were analyzed using Confirmatory Factor Analysis (CFA) in JASP software. The CFA model showed good model fit ($CFI = 0.973$, $TLI = 0.968$, $RMSEA = 0.054$, and $SRMR = 0.053$), and the five constructs achieved convergent validity ($AVE \geq 0.50$), and high internal consistency (α and $\omega \geq 0.89$). The results validate that organizational support, digital infrastructure, professional training, financial readiness, and institutional frameworks are important influencing factors of MR technology adoption in construction cost estimation. The findings give practical guidance to construction companies, government authorities, and professional organizations for promoting the uptake of MR in the construction industry in Nigeria.

Keywords: Mixed Reality; Construction; Cost Estimation; Technology Adoption; Quantity Surveyors

1. INTRODUCTION

Digitalization in the construction industry has brought the industry a range of innovative technologies to meet rapidly evolving developmental demands (Abanda et al., 2017). Among these innovative technologies, Mixed Reality (MR) technology stands out as one that has visualization and interactive functionalities (Alizadehsalehi et al., 2020). MR is a combination of the real and digital worlds to an extent that it allows users to see and interact with the virtual in real-life settings using a blend of Augmented Reality (AR) and Virtual Reality (VR) (Speicher et al., 2019). In the construction industry, MR enables stakeholders to work with 3D models, overlaid on physical spaces, which brings in a new perspective to design review, site planning, and decision-making (Osorto Carrasco & Chen, 2021; Anwar & Azhar, 2024). A global trend involving the integration of MR into construction procedures has resulted in less rework, enhanced collaboration, and improved productivity (Maqsoom et al., 2023).

Different researchers have given attention to automation, Artificial Intelligence (AI), and Building Information Modeling (BIM) in their studies on the innovation of technologies in construction cost estimation. For instance, Ahmed (2019) cited BIM-enabled automation, especially the 5D modeling and built-in quantity takeoff, as one of the key factors in enhanced cost accuracy at the initial stages of design. On the same note, Nia et al. (2023) and Ibrahim and Elshwadfy (2021) investigated ways of enhancing reliability of pre-construction costs, such as predictive models using AI and automated quantity takeoffs. While these studies provide valuable insights into the application of various technologies in cost estimation, they leave room for further exploration of Mixed Reality (MR) technology, particularly its potential in interactive visualization and real-time team collaboration.

This study therefore examined the factors influencing the adoption of MR technology for construction projects' cost estimation among Qs in Lagos State, Nigeria. In practice, the findings are useful in shedding light on the barriers and enablers of MR adoption, which can be helpful to Qs, firms, policymakers, and other construction professionals. Academically, the study contributes to the literature on MR adoption in developing regions, addressing the calls for context-specific studies (Delgado et al., 2019).

2. LITERATURE REVIEW

2.1 Mixed Reality Technology in the Construction Industry

MR is the immersive technology that combines the visual power of AR with the interaction of VR. This technology is a gamechanger in the construction industry, with the potential of increasing project execution precision and efficiency. The benefits of MR technology, while significant, are complicated by costs and technical challenges, yet research and investment efforts continue to push forward with the promise of revolutionizing current methods (Delgado et al., 2020). The difference between AR and VR is that AR is able to overlay digital data on a physical environment, whereas VR is able to produce full-scale simulations (Getuli et al., 2020). These technologies enable the study and manipulation of design concepts, training scenarios and virtual walkthroughs, in addition to the use of human interaction with advanced technologies, such as artificial intelligence or networking (Sidani et al., 2021).

2.2 Factors Influencing the Adoption of MR Technology for Construction Cost Estimation

The integration of the MR technology into construction cost estimation is predetermined by the combination of organizational, technological and human-related factors that define the desire and capacity of the users to introduce new digital tools into their professional practice. A study of the advanced digital technologies used in construction indicated that the perceived benefits, ease of use, support of leadership, readiness of the organisation, infrastructure and technical competence of the users are important factors influencing the outcomes of the adoption of the advanced digital technologies used in the construction field (Liu et al., 2023; Oke et al., 2022). Additionally, there are several factors highlighted, especially in developing economies where the process of digital transformation is not uniform, such as resistance to change, and uncertainty about the implementation process (Adebowale & Agumba, 2024; Babatunde et al., 2021). Understanding these influencing factors is therefore essential for promoting effective uptake of MR technology for accurate and efficient cost estimation of construction projects.

2.2.1 Organizational Factors

According to Bamgbose et al. (2024), Organizational factors determine whether the adoption of technology will succeed or not. There are several theoretical frameworks, including the Technology-Organization-Environment (TOE) model developed by Tornatzky and Fleischer in 1990, that give more weight to the role of organizational input in determining technology adoption practices. Various studies present how proactive organizational leadership can help align the technological initiatives with organizational objectives. Leaders in an organization who promote innovation usually create a conducive culture within the organization, thereby facilitating change and combating resistance to change, as well as boosting employees' motivation to accept new technologies (Bendak et al., 2020). Top management endorsement is a primary factor in technology acceptance, and it is appropriately in line with extensions of the TAM and Unified Theory of Acceptance and Use of Technology (UTAUT), where perceived strategic alignment and resource commitment minimize uncertainty and indicates organizational priority (Hong & Yu, 2018; Venkatesh & Davis, 2000). Proactive leadership in the construction industry would lead to buy-in, through the promotion of MR to improve visualization, error detection, and collaborative decision-making, thereby alleviating resistance due to disruption of

existing workflow (Maqsoom et al., 2023; Delgado et al., 2020). In developing economies such as Nigeria, leadership support is more decisive in the face of scarcity of resources and risk aversion. It is found that the technological diffusion can be triggered by the presence of an innovative leader who establishes budgets, initiates MR applications and connects the MR process to strategic goals, while the presence of a passive and/or short-term management can have the opposite effect (Aliu et al., 2025; Oke et al., 2023; Idowu et al., 2023).

2.2.2 Infrastructural Factors

Another barrier largely linked to the adoption of MR technology is infrastructural constraints. Limited broadband connection, unreliable power availability, and old hardware are mentioned among the major challenges (Akinradewo et al., 2025; Oke & Arowoia, 2022). According to Noghabaei et al. (2020), most companies feel that MR is not possible mainly because of the absence of proper infrastructure to support it. The low level of acquisition and maintenance of MR hardware is usually aggravated by low local support and lack of equipment (Uwaegbulam, 2025). Additionally, each of the issues relating to inadequate infrastructure would make it impossible to connect with the existing enterprise systems, e.g., Building Information Modelling (BIM) system. Global research proves that the level of MR technology integration in the coordination of projects, the presentation to a client, and direct on-site cooperation is higher in countries with effective digital infrastructure (Adebowale & Agumba, 2024). Also, hardware limitations such as high prices, technical complexity, and compatibility with the on-site workflow are some of the issues that make integration difficult (Oke & Arowoia, 2022). Stable internet connectivity is also a necessity when it comes to the deployment of MR technology, particularly when applications entail cloud computing, real-time data synchronization, and shared digital platforms. Studies indicate that low reliability of the network constrains system performance, introduces delays in data transfer, and lowers user trust in the use of the digital tools (Adebowale & Agumba, 2024; Liu et al., 2023). A digital divide is apparent in developing economies where there is a lack of infrastructure leading to a lack of accessibility, making it difficult for smaller companies and consultants to keep up with the investments that larger companies can make (Aliu et al., 2025; Akinradewo et al., 2025).

2.2.3 Training-Related Factors

The introduction of MR requires professionals to acquire new competencies in software manipulation, digital modelling, and immersive interface navigation. However, most construction professionals, including QSSs, have limited exposure to such digital tools in their education or ongoing professional development (Oke & Arowoia, 2022). This mismatch creates a knowledge gap that hinders the perceived ease of use (PEOU). Regardless of the increasing interest in most parts of the world, especially about improving design visualization, quantity take-off, and cost estimation, the lack of training is one of the most serious obstacles, especially in developing nations (Akinradewo et al., 2025; Orihuela et al., 2019). Orihuela et al. (2019) observed that when properly trained, users demonstrated higher confidence in applying MR technology during real-world planning and construction phases. Specific job-related training programs are also instrumental in the application of MR technology for cost estimation of construction projects. By adjusting the content of training materials to reflect the practical role of cost specialists in the construction industry, it is possible to increase the relevance of a work and decrease the perceived complexity of the new digital tools. Knowledge sharing among peers is informal yet another effective way of fostering the spread of any novel technology. As early adopters of MR tools can demonstrate the successful cost estimation applications to other collaborators, trust is established and encourages more project teams to embrace it (Liu et al., 2023). Akinradewo et al. (2025) emphasize the fact that the ad-hoc types of learning are not effective when it comes to maintaining adoption, hence measures such as peer-to-peer knowledge sharing, guided onboarding, and partnerships with tech vendors should be leveraged to bridge gaps where formal education systems lag.

2.2.4 Financial Viability Factors

The initial purchase price is not the sole detail of the financial consideration; the operating cost of software upgrades, maintenance, licensing charges and special training also add to the overall cost

of ownership (Prabhakaran et al., 2022). Perceived return on investment (ROI) is hence a vital factor. When the advantages are evident, i.e. the increase in the quality of cost estimation, better visualization of construction processes, fewer errors and rework, and more efficient project monitoring, organizations are more willing to use the MR technologies (Apinayan et al., 2023; Delgado et al., 2020). Companies that have a stronger financial base or have access to external resources are in a better position to take these initial costs and achieve long-term efficiency and productivity benefits (Aliu et al., 2025; Maqsoom et al., 2023). Research has shown that strong initial investment needs are one of the initial limitations to the adoption of advanced technologies in developing economies (Maqsoom et al., 2023; Oke et al., 2022). MR software license is another major financial obstacle. MR applications can be platform-dependent and demand dedicated license for systems that use BIM models, real-time rendering, and collaboration features. High licensing costs, often in foreign currencies, are frequent in developing nations, which adds additional financial burdens amid economic volatility, import duties, and constrained budgets of SMEs (Uwaegbulam, 2025; Akinradewo et al., 2025).

2.2.5 Institutional Factors

The adoption of MR technologies may be supported or hindered by institutional pressures, such as regulatory frameworks, industry standards, professional guidelines, and the organizational policies (Aliu et al., 2025; Oke & Arowoia, 2022). Companies usually react to compulsive forces of state authorities or professional organizations that can force them to certain modern technologies or sustainable building concepts. Organizations located in jurisdictions that have favorable policies on the use of digital construction tools have higher chances of integrating MR into their work processes (Adebawale & Agumba, 2024; Prabhakaran et al., 2022). The perceived legitimacy of MR technologies is increased by institutional support, in the form of workshop programs, technical advice, and knowledge sharing platforms, which leads to increased adoption (Prabhakaran et al., 2022; Anireddy, 2020). Moreover, the cooperation among stakeholders would enable sharing of knowledge, collaborative research and development, curriculum design, and pilot projects (Kline & Ayer, 2023; Radianti et al., 2020). Also, public sector project requirements such as mandates, procurement specifications, or tender conditions are standing as factors capable of influencing the adoption of emerging technologies such as MR in construction. Government can hasten the diffusion of MR technology by controlling and purchasing innovative tools for government infrastructure through their high purchasing power and regulatory force (Maqsoom et al., 2023). Industry-wide advocacy in the form of professional associations, trade bodies, conferences, workshops, and thought-leadership campaigns is critical in increasing awareness, consensus, and normalization of the use of MR in construction. This advocacy generates momentum by spreading success stories, which offer evidence of the benefits of MR and refutes the perceptions of the technological immaturity or high risk (Maqsoom et al., 2023; Delgado et al., 2020).

3. METHODOLOGY

3.1 Research Design

For this research, an extensive review of literature was performed, after which a quantitative approach was employed to carefully evaluate the factors influencing the adoption of MR Technology for construction cost estimation. Quantitative research approach is a survey used to acquire information from subjects or study participants (sample) using self-report; objectively, the study population or participants respond to questions posed to them by the researcher (Leavy, 2017). This method enables systematic collection of data on individuals' attributes, behaviors, beliefs, and perceptions (Creswell & Creswell, 2018), thereby supporting the study's aim to explore observable patterns and relationships within a defined context (Saunders et al., 2019).

3.2 Research Population

The research population comprised Quantity Surveyors in registered consulting and construction firms in Lagos State, Nigeria. The reason for selecting Lagos State is because, as Nigeria's commercial hub with a high volume of construction projects, the state offers a rich environment to study new technologies such as MR for cost estimation. Its relative advanced technological adoption, strong

regulatory frameworks, and diverse construction landscape makes it an ideal case for broader national insights. A census sampling technique was applied, targeting all one hundred and seven (107) eligible QSSs. The consulting firms were identified through the QSRBN 2025 directory, while the construction firms were identified through Google Business 2025 directory. One (1) respondent from each firm was selected to participate in this study. Table 1 below presents the population distribution across the two firm types.

Table 1: Research Population

Firm Type	Number of Firms	No. of QSSs (Population)
Consulting Firms	53	53
Construction Firms	54	54

Source: QSRBN (2025); Author's Compilation (Google Business Directory, 2025)

3.3 Data Collection Instrument

A structured questionnaire was used as the data collection instrument for this study. The questionnaire was sectioned into two (2) parts: The first part was designed to obtain the demographic and background data of each respondent, which includes their qualifications, years of experience, type of firm, and areas of specialization. The second section focused on the factors influencing MR technology adoption for construction cost estimation. A 5-point Likert scale was used in rating the opinions, where 5 = very high, 4 = high, 3 = average, 2 = low, 1 = very low. The latent factors measured included Organizational Factors (ORGF), Infrastructural Factors (INFF), Training-Related Factors (TRF), Financial Viability Factors (FVF), and Institutional Factors (INSTF), each with four (4) observed indicators, totaling twenty (20) items.

3.4 Method of Data Analysis

Confirmatory Factor Analysis (CFA) was applied to examine the factors influencing MR adoption for construction cost estimation, to assess whether observed variables load appropriately on latent factors and whether the latent factors significantly predict the observed variables. An Exploratory Factor Analysis (EFA) was not conducted because the five latent constructs are drawn from established theoretical frameworks whose factor structure has been extensively validated (Venkatesh & Davis, 2000; Davis, 1989). The individual observed indicators, however, were newly developed for this study by adapting the broader TAM/UTAUT and TOE dimensions to the specific context of MR-based cost estimation (e.g., mobile support for MR applications, interoperability with BIM), since directly validated item sets for this technology-task combination were not available in prior literature. This is acknowledged as a limitation of the CFA-only approach, as the item-level structure had not been previously confirmed through exploratory analysis. CFA nonetheless remains appropriate for theory-driven constructs to confirm hypothesized measurement structures without prior exploratory analysis (Hair et al., 2019; Kline, 2016). The latent factors include ORGF, INFF, TRF, FVF, and INSTF, all measured using a 5-point Likert scale, with each latent factor having four (4) corresponding observed indicators, totaling twenty (20) observed indicators. The hypothesized CFA model specified that each latent factor is measured by its respective indicators. Each indicator was restricted to load on only one latent factor, and the latent factors were allowed to co-vary.

CFA requires the use of multiple indices to assess how well a proposed measurement model fits the data, as no single index is sufficient for evaluating model adequacy (Hair et al., 2019; Kline, 2016). Following best practice, this study used three major index families: Absolute Fit Indices (χ^2 , χ^2/df , RMSEA, SRMR), Incremental Fit Indices (CFI and TLI), and Construct Validity Indices (R^2 , standardized factor loadings, AVE, Cronbach's Alpha, and McDonald's Omega). Following the recommendations of Kline (2016), Byrne (2016), and Hair et al. (2019), acceptable thresholds of $\chi^2/\text{df} \leq 3$; CFI/TLI ≥ 0.90 ; RMSEA ≤ 0.08 ; SRMR ≤ 0.08 align with widely adopted CFA standards. Standardized factor loadings ≥ 0.50 (preferably above 0.70) were retained in accordance with Hair et al. (2019). Internal consistency was assessed using both Cronbach's Alpha (α) and McDonald's Omega

(ω), with reliability coefficients ≥ 0.70 deemed acceptable. Convergent validity was examined using AVE (≥ 0.50), following Fornell & Larcker (1981). Analysis was conducted using JASP software.

4. RESULTS AND DISCUSSION

4.1 Response Rate

Table 2 presents the breakdown of the return rate of the questionnaires sent out. Out of the One Hundred and Seven (107) questionnaires sent out to Quantity Surveyors in selected consulting and construction firms in Lagos State, Nigeria, a very high return rate was recorded (84.91% and 90.74% respectively) from each firm type. An overall return rate of 87.85% was recorded across both firm types.

Table 2: Response Rate of Respondents

Firms	Distributed	Retrieved	% Retrieved
Consulting Firms	53	45	84.91%
Construction Firms	54	49	90.74%
Total	107	94	87.85%

Author's survey (2025).

4.2 Respondents' Profile

Table 3 presents the demographic information of the Quantity Surveyors that were part of this research. The results show that 74.47% of respondents were Male and 25.53% Female. In the Academic Qualification category, most of the respondents possess only a First-degree certificate (B.Sc/B.Tech), with approximately 51.06% representing that group, followed by those who possess Master's degree (approximately 36.17%), and those with Higher National Diploma (HND) (approximately 12.77%). In the Years of Professional Experience category, the group with the highest percentage is 6–10 years (approximately 43.62%), followed by professionals with 11–15 years' working experience (approximately 30.85%), 1–5 years working experience (approximately 13.83%), and respondents with 16–20 years of professional working experience (approximately 11.70%). It is worth noting that most respondents fall into the group of professionals with less than 16 years' working experience, which establishes the non-redundancy of the sampled professionals to new technological trends. Lastly, in the primary area of specialization category, most of the respondents specialize in Infrastructural projects (approximately 48.94%), while approximately 24.47% specialize in Commercial projects, approximately 20.21% in Residential projects, and approximately 6.38% in Industrial projects.

Table 3: Respondents' Information

Variable		Classification	Frequency	Percentage (%)
Gender		Female	24	25.53
		Male	70	74.47
		Total	94	100.00
Highest Qualification	Academic	HND	12	12.77
		B.Tech / B.Sc	48	51.06
		M.Tech / M.Sc	34	36.17
		Total	94	100.00
Years of Experience		1–5	13	13.83
		6–10	41	43.62
		11–15	29	30.85
		16–20	11	11.70
		Total	94	100.00
Primary Specialization	Area of	Commercial	23	24.47
		Industrial Projects	6	6.38
		Infrastructure	46	48.94
		Residential	19	20.21
		Total	94	100.00

Author's survey (2025).

4.3 Model Fit Indices of the Factors Influencing the Adoption of MR Technology for Construction Cost Estimation

Table 4 shows the results of the model fit of the factors influencing MR adoption for construction cost estimation. The chi-square score ($\chi^2 = 204.017$, $df = 160$, $p < 0.05$) is statistically significant but the chi-square test is highly sensitive to sample size (Kline, 2016). In this case, the χ^2/df ratio is lower than the recommended value of 3 (Kline, 2016; Carmines & McIver, 1981), implying strong model fit with a moderate sample ($N = 94$). Additional model fit indices reflected in Table 4 show that the model fits the data well. The Comparative Fit Index ($CFI = 0.973$) and Tucker–Lewis Index ($TLI = 0.968$) are above the 0.95 cut-off, showing that it fits quite well. In addition, both the RMSEA (0.054) and SRMR (0.053) are below their respective thresholds of 0.06 and 0.08, which indicates that the covariance predicted by the model is in line with the observed variables. All in all, the measurement model can be deemed as acceptable.

Table 4: Model Fit Indices of the CFA for the Factors Influencing MR Adoption

Index	Value	Threshold
χ^2/df	1.28	≤ 3.0
Comparative Fit Index (CFI)	0.973	≥ 0.90
Tucker–Lewis Index (TLI)	0.968	≥ 0.90
Root Mean Square Error of Approximation (RMSEA)	0.054	≤ 0.08
Standardized Root Mean Square Residual (SRMR)	0.053	≤ 0.08

Note. $\chi^2 = 204.017$, $df = 160$, $p = .011$. $N = 94$.

4.4 R-Squared Values, Factor Loadings, AVE, and Reliability

The R^2 values presented in Table 5 are squared multiple correlations of the observed indicators, which denote the extent of variance in each indicator explained by its corresponding latent construct. The values fall between 0.469 and 0.844, which show moderate to strong measuring strength among the five constructs. According to Hair et al. (2019), R^2 values of 0.75, 0.50, and 0.25 may be described as strong, moderate, and weak, respectively. The Organizational factors represent strong indicator representation, specifically Management commitment ($R^2 = 0.784$) and Organizational willingness to invest in MR technology ($R^2 = 0.742$). The Infrastructural factors also exhibit high measurement strength with Availability of MR-capable hardware ($R^2 = 0.843$) and Mobile support of MR applications ($R^2 = 0.815$) showing the strongest explanatory power. The same can also be said about Training, Financial and Institutional factors that have R^2 values ranging between moderate and strong, suggesting that their indicators are sufficiently described by their latent constructs.

The factor loading values are all statistically significant at $p < .001$, which means that all the indicators have a significant contribution to their corresponding latent construct. The standardized factor loadings vary between about 0.68 and 0.92, all above the required minimum of 0.50 and the desirable level of 0.70 (Hair et al., 2019). The findings indicate excellent convergent validity of the model. The AVE values for all five constructs, ORGF (0.709), INFF (0.707), TRF (0.724), FVF (0.755), and INSTF (0.769), are greater than the recommended value of 0.50 (Fornell & Larcker, 1981), which confirms that over 50% of the variation in each set of observed indicators is attributed to its corresponding latent factor. This shows that the indicators are meaningfully convergent to measure their respective latent factor. The excellent internal consistency of all latent factors is also confirmed through the reliability results. The ORGF omega (ω) and alpha (α) coefficients of 0.905 each indicate that the indicators are quite consistent in their measurement of the same latent factor. INFF follows, with $\omega = 0.893$ and $\alpha = 0.902$. TRF is also highly consistent with $\omega = 0.911$ and $\alpha = 0.913$. FVF is even more reliable with $\omega = 0.924$ and $\alpha = 0.925$, while INSTF has the best construct-level reliability, with $\omega = 0.930$ and $\alpha = 0.928$. The constructs are highly reliable since all of them have coefficients that greatly exceed the widely recognized 0.70 threshold, and most of them exceed the 0.90 standard (Hair et al., 2019). The total scale reliability scores ($\omega = 0.990$ and $\alpha = 0.958$) further confirm that the overall measurement framework of the Influencing Factors is stable and internally consistent.

Table 5: R-Squared Values, Factor Loadings, AVE, and Reliability of the Influencing Factors

Factor	Indicator	R ²	AVE	α	ω
ORGF	Leadership support for MR technology adoption	0.656	0.709	0.905	0.905
	Innovation-friendly organizational culture	0.638			
	Management commitment	0.784			
	Organization's willingness to invest in MR technology	0.742			
INFF	Availability of MR-capable hardware and devices	0.843	0.707	0.902	0.893
	Mobile support for MR applications	0.815			
	Stable internet access	0.469			
	Interoperability with BIM	0.645			
TRF	Access to MR Technology training	0.721	0.724	0.913	0.911
	Training programs aligned with job roles	0.795			
	Peer knowledge sharing	0.767			
	Opportunities for hands-on practice using MR tools	0.632			
FVF	Affordability of MR hardware and related devices	0.841	0.755	0.925	0.924
	Availability of financing options for MR adoption	0.743			
	Perceived Return on Investment (ROI) of MR adoption	0.799			
	Affordability of MR software licenses	0.644			
INSTF	Collaboration with tertiary institutions and research bodies on MR standards	0.668	0.769	0.928	0.930
	Public sector project requirements pushing MR adoption	0.791			
	Regulatory frameworks supporting digital adoption in construction	0.770			
	Industry-wide advocacy for MR adoption	0.844			

4.5 Factor Covariances of the Factors Influencing MR Adoption

Table 6 presents the factor covariances, which indicate the strength and significance of the relationship among the five (5) latent factors. A positive and significant covariance means that an increase in one variable predicts an increase in the other variable, hence there is conceptual compatibility and interdependence between the variables. The covariances are all positive and statistically significant ($p < .001$) with estimates between 0.604 and 0.732. This shows that the variables have a moderate to a strong relationship, which proves that they are related concepts but not the same dimensions in the model. Particularly, ORGF demonstrates high positive covariances with all other latent factors; INFF (0.700), TRF (0.604), FVF (0.732) and INSTF (0.612). Additionally, INFF has significant correlation with TRF (0.672), FVF (0.668) and INSTF (0.684). On the same note, TRF has a substantial correlation with FVF (0.679) and INSTF (0.652). Lastly, FVF and INSTF also show positive and significant covariance (0.678). These findings imply that the five (5) latent factors are strongly associated, but each one of them is unique enough to reflect a different dimension of the model.

Table 6: Factor Covariances of the Influencing Factors

Covariance			Estimate	Std. Error	Z	p	95% CI
ORGF	↔	INFF	0.700	0.145	4.841	< .001	[0.417, 0.984]
ORGF	↔	TRF	0.604	0.122	4.942	< .001	[0.365, 0.844]
ORGF	↔	FVF	0.732	0.143	5.126	< .001	[0.452, 1.012]
ORGF	↔	INSTF	0.612	0.134	4.561	< .001	[0.349, 0.875]
INFF	↔	TRF	0.672	0.136	4.928	< .001	[0.405, 0.939]
INFF	↔	FVF	0.668	0.150	4.466	< .001	[0.375, 0.962]
INFF	↔	INSTF	0.684	0.152	4.516	< .001	[0.387, 0.981]
TRF	↔	FVF	0.679	0.132	5.125	< .001	[0.419, 0.939]
TRF	↔	INSTF	0.652	0.133	4.914	< .001	[0.392, 0.913]
FVF	↔	INSTF	0.678	0.146	4.649	< .001	[0.392, 0.963]

Note. CI = Confidence Interval. All covariances significant at $p < .001$.

4.6 Discussion of Findings

The adoption of MR technology for construction cost estimation is shaped by several factors. These factors are referred to as Influencing Factors (IF) in this study. These IF collectively determine organizational readiness and user acceptance. Findings from this study reveal that Organizational, Infrastructural, Training-Related, Financial Viability, and Institutional Factors are influencing factors to MR adoption for construction cost estimation.

4.6.1 Organizational Factors (ORGF)

There were four (4) observed indicators loaded on this latent factor, namely; Leadership support for MR technology adoption, Innovation-friendly organizational culture, Management commitment,

and Organization's willingness to invest in MR technology. All the four (4) indicators underscore the central role of organizational readiness in driving the adoption of emerging technologies such as MR for construction cost estimation. These indicators collectively reflect the degree to which an organization's internal environment enables or constrains technological innovation. This is a very important variable, because for technology to be fully embraced, organizational influence is huge. The high covariance between ORGF and other constructs, particularly FVF (0.732) and INFF (0.700), further confirms the interdependence of organizational capacity with financial and infrastructural readiness.

These findings align with Bamgbose et al. (2024), who reported that organizational leadership, culture, and resource commitment are primary determinants of technology adoption in the construction sector. The results also support the extended TAM proposition of Venkatesh and Davis (2000) and Hong and Yu (2018), where perceived strategic alignment and management endorsement reduce uncertainty and signal organizational priority. In the Nigerian context, where resource constraints and risk aversion are common, the role of organizational support in catalyzing MR adoption is even more decisive (Aliu et al., 2025; Oke et al., 2023).

4.6.2 Infrastructural Factors (INFF)

Four (4) observed indicators were also loaded on this latent factor. These indicators include Availability of MR-capable hardware and devices, Mobile support for MR applications, Stable internet access, and Interoperability with Building Information Modelling (BIM). All the four (4) indicators capture the fundamental role of technological infrastructure in shaping the feasibility and ease of using MR technology for construction cost estimation. Availability of MR-capable hardware and Mobile support for MR applications emerged as the strongest predictors within this construct, suggesting that access to specialized devices is the most immediate infrastructural barrier.

These findings are consistent with Akinradewo et al. (2025) and Oke and Arowoia (2022), who identified limited broadband connectivity, unreliable power supply, and old hardware as the major infrastructural challenges to AR/VR/MR adoption in Nigeria. Adebawale and Agumba (2024) similarly reported that the level of MR technology application is substantially higher in countries with effective digital infrastructure, suggesting that bridging the infrastructure gap is a precondition for accelerating MR adoption in Lagos State.

4.6.3 Training-Related Factors (TRF)

There were four (4) observed indicators loaded on this latent factor, namely; MR technology training, Training programs aligned with job roles, Peer knowledge sharing, and Opportunities for hands-on practice using MR tools. These four (4) indicators capture the Training and Expertise dimension influencing MR technology adoption. They highlight the indispensable role of human capacity development in facilitating the adoption of MR technology for construction cost estimation. Training programs aligned with job roles emerged as the strongest predictor within TRF, suggesting that role-specific training is more impactful than generic digital literacy programs.

These findings are consistent with Akinradewo et al. (2025), who emphasized that the ad-hoc types of learning are not effective when it comes to maintaining adoption, and that peer-to-peer knowledge sharing, guided onboarding, and partnerships with tech vendors should be leveraged to bridge gaps where formal education systems lag. In contexts like Nigeria, the absence of institutionalized training on MR technology in curricula or industry workshops has slowed down diffusion, as corroborated by Liu et al. (2023) who demonstrated that organizations investing in structured digital training achieve higher productivity benefits and improved user commitment.

4.6.4 Financial Viability Factors (FVF)

There were four (4) observed indicators loaded on this latent factor, namely; Affordability of MR hardware and related devices, Availability of financing options, Perceived return on investment (ROI), and Affordability of MR software licenses. These indicators show that the cost of technology remains a major influence on MR adoption for cost estimation. Contextually, this means financial viability determines whether MR adoption is viewed as possible or out of reach. Affordability of MR hardware and Perceived ROI are the dominant indicators within this construct.

These results are supported by Maqsoom et al. (2023), who identified high upfront investment costs, coupled with perceptions of low immediate ROI and limited demand, as factors that suppress adoption momentum. Uwaegbulam (2025) and Akinradewo et al. (2025) corroborate these findings in the Nigerian context, noting that high licensing costs, often denominated in foreign currencies, impose additional financial burdens amid economic volatility, import duties, and constrained budgets of SMEs. The strong AVE and reliability coefficients reported in Table 5 further confirm the construct's internal coherence and the centrality of financial considerations in adoption decisions.

4.6.5 Institutional Factors (INSTF)

Also, four (4) observed indicators were loaded on this latent factor, namely; Collaboration with tertiary institutions and research bodies on MR standards, Public sector project requirements pushing MR adoption, Regulatory frameworks supporting digital adoption in construction, and Industry-wide advocacy for MR adoption. All the four (4) indicators show how the institutional environment shapes the perceptions of organizations and professionals about adopting MR technology for cost estimation. Industry-wide advocacy for MR adoption emerged as the strongest predictor. INSTF also recorded the highest AVE and the highest reliability coefficients among all five constructs.

These findings align with Aliu et al. (2025) and Oke and Arowoiya (2022), who highlighted that institutional pressures, including regulatory frameworks, professional norms, and peer expectations, are important determinants of MR technology adoption decisions. The findings also corroborate Maqsoom et al. (2023) and Delgado et al. (2020), who emphasized that industry advocacy generates momentum by spreading success stories and refutes perceptions of technological immaturity or high risk. In developing economies where formal digital construction policy structures are still emerging, institutional support becomes an even more critical lever for normalizing MR adoption across the sector.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study examined the factors influencing the adoption of Mixed Reality (MR) technology for construction projects' cost estimation among Quantity Surveyors in Lagos State, Nigeria. Using Confirmatory Factor Analysis (CFA), the measurement model comprising five latent constructs, Organizational Factors (ORGF), Infrastructural Factors (INFF), Training-Related Factors (TRF), Financial Viability Factors (FVF), and Institutional Factors (INSTF), demonstrated excellent model fit (CFI = 0.973; TLI = 0.968; RMSEA = 0.054; SRMR = 0.053), high convergent validity (AVE values exceeding both the 0.50 minimum threshold and the 0.70 desirable benchmark), and outstanding internal consistency (α and $\omega \geq 0.89$) across all constructs. The following conclusions were drawn:

1. Adopting MR for construction cost estimation is not driven by technology alone; it requires the intentional alignment of organizational support, infrastructural readiness, training and capacity development, financial viability, and institutional frameworks. When these Influencing Factors are addressed together, they translate professionals' awareness of MR into concrete adoption action.
2. The financial viability and infrastructure constructs had the highest individual indicator predictive power, indicating that they are likely the closest and most visible barriers to MR adoption in the construction context in Lagos.
3. The study also found that MR technology provides the greatest benefits in areas that require visualization, collaboration, and real-time decision-making. These findings provide practical direction for firms, Qs, and technology developers seeking to align MR deployment with the highest-impact estimation tasks.
4. Influencing Factors (IF), comprising organizational, infrastructural, training, financial, and institutional factors, are the most influential antecedents of MR technology adoption for

construction cost estimation. These factors significantly show that adoption success depends heavily on external readiness and contextual support within the construction environment.

5.2 Limitations of the Study

This study is subject to two main limitations. Firstly, the sample size ($N = 94$) is modest, compared to the measurement model (20 observed indicators and 5 latent constructs). Larger samples are generally recommended for CFA to provide stable parameter estimates; this should be taken into consideration when assessing the quality of the reported fit indices. Secondly, the study is limited to Lagos state and despite Lagos being chosen due to the high technological adoption of the technology and the high construction activity in the state, the results and recommendations might not necessarily apply to other states in Nigeria with varying technological adoption levels and institutional support. Larger and multi-regional samples are recommended for future studies to increase the generalizability of the findings.

5.3 Recommendations

The following recommendations were made in lieu of the research findings:

1. Construction and consulting companies need to show greater leadership in their digital transformation efforts by incorporating MR technology into cost estimation and project management processes. Senior management should establish clear policies, allocate resources and establish innovation-friendly environments to support experiments with MR applications and other innovative technologies.
2. Strategic partnership of universities, professional and regulatory organisations (e.g. NIQS, COREN) and MR technology developers should be fostered. These partnerships will foster local research, the adaptation of MR solutions to the local context, and the development of platforms for knowledge exchange and continued innovation in construction cost management.
3. Government agencies and industry regulators should develop digital adoption policies to promote the use of MR technology in the construction industry. Tax reliefs, research grants or public-private partnerships could lower the cost burden on companies and encourage them to increase their innovation in the cost estimation process.
4. Due to high costs and uncertain return on investment, construction companies should consider new models for financing, including leasing, technology sharing consortia and innovation funds. Digital innovation loans with a low interest rate can also be distributed by financial institutions to enable MR acquisition and implementation.
5. Industry associations are encouraged to conduct demonstration projects, small-scale studies and open house exhibits of the cost-saving and other practical value of MR in cost estimation. By documenting and sharing success stories and best practices, confidence will build, resistance to change will diminish, and best practices will be adopted broadly throughout construction.

5.4 Contribution to the Body of Knowledge

This study has provided empirical and theoretical contributions to knowledge on the adoption of MR technology for construction projects' cost estimation. It has demonstrated that MR, through its immersive and visualization capabilities, has strong potential to enhance the precision, accuracy, and communication efficiency of cost estimation processes in construction. Through the application of CFA, the research established and validated five latent constructs, Organizational, Infrastructural, Training-Related, Financial Viability, and Institutional Factors, as significant influencing factors of MR adoption among Quantity Surveyors in Lagos State. The validated measurement model, with excellent fit indices, convergent validity, and internal consistency, offers a replicable framework that future studies can adapt for other contexts and emerging digital technologies. Finally, this study contributes to the limited pool of local academic research on advanced construction technologies in Nigeria, providing a contextual foundation for future studies and implementation of immersive technologies within the construction cost management discipline.

5.5 Areas of Further Studies

From the research, some of the findings provided possible directions for further studies in the following areas:

1. Given the strong covariance observed between Organizational and Financial Viability Factors in this study, future research could specifically investigate the relationship between organizational readiness and financial commitment to determine whether strengthening one factor accelerates improvement in the other.
2. Future work can conduct cost–benefit analyses to assess the financial viability and return on investment (ROI) of MR adoption in cost estimation processes within different firm sizes and project types.
3. Lastly, further research should investigate the roles of regulatory bodies, professional institutions, and government agencies in supporting MR adoption, especially in relation to policy design, incentives, and training programs.

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