A TISM and Fuzzy MICMAC Analysis of Barriers to Immersive Technology Adoption in Supply Chains: A Structural Modeling Study

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ABSTRACT:

Immersive technologies (virtual, augmented, and extended reality) are entering supply chain operations through warehouse order picking, assembly support, workforce training, and collaborative planning, yet adoption remains uneven because barriers interact in reinforcing ways rather than operating independently (Rejeb, Keogh, Wamba, et al., 2021; Jalo et al., 2022; Pote et al., 2025). This study structures ten adoption barriers through an interpretive structural modeling workflow: a graded fuzzy influence matrix summarized in a Structural Self-Interaction Matrix, fuzzy max-min transitive closure, thresholded level partitioning, link-level interpretation, and Fuzzy MICMAC classification. Although practitioner surveys rank high implementation cost among the leading obstacles to adoption, the model assigns it the highest dependence power and places it at the top of the hierarchy: a lagging manifestation of weak sponsorship, an undemonstrated business case, and infrastructure gaps rather than a root cause. Limited customer readiness forms the structural root; a six-barrier core containing all four linkage barriers transmits and amplifies influence; and data security risk and regulatory uncertainty join cost as dependent manifestations. No barrier classifies as autonomous, indicating a tightly coupled system. MICMAC classifications are threshold-invariant by construction, while the hierarchy depends on the binarization threshold, so a sensitivity analysis at 0.40, 0.50, and 0.60 is reported. The study is a methodological demonstration based on literature-informed judgments; complete matrices are published for replication, and a Delphi protocol for expert validation is specified.

Keywords: immersive technology adoption, supply chain management, total interpretive structural modeling, fuzzy MICMAC, technology adoption barriers.

1. Introduction

Immersive technologies are increasingly discussed as strategic enablers for design visualization, digital training, remote collaboration, customer experience management, and industrial simulation, particularly in firms

undergoing digital transformation (Jalo et al., 2022). Despite growing technological maturity, adoption remains constrained because organizations do not face isolated implementation problems; they face clusters of mutually reinforcing strategic, infrastructural, behavioral, financial, and regulatory barriers (Kamble et al., 2018). This makes immersive technology adoption an appropriate setting for interpretive structural modeling (ISM), a method introduced by Warfield (1974) to clarify contextual relationships among complex variables through hierarchical decomposition.

Within supply chain management (SCM), immersive technologies are no longer speculative. A systematic review by Rejeb, Keogh, Wamba, et al. (2021) identifies five supply chain value areas, warehousing, manufacturing, sales and outbound logistics, planning and design, and human resource management, while field studies document augmented reality (AR) pick-by-vision in order picking and warehouse navigation (Stoltz et al., 2017). Adoption nevertheless lags the technology: AR smart-glasses deployments in logistics confront clusters of technical, organizational, and ergonomic challenges (Rejeb, Keogh, Leong, et al., 2021), and a bibliometric assessment locates AR and virtual reality (VR) in operations and SCM at the introduction-to-growth phase of maturity rather than mainstream practice (Akbari et al., 2022). The barrier set in this study is therefore read through a supply chain lens: vendor interoperability concerns multi-vendor integration with warehouse management and enterprise systems across firm boundaries; the employee skill gap concerns frontline logistics operators as much as engineers; customer readiness concerns the downstream clients of market-facing immersive services; and regulatory uncertainty concerns data flows that cross organizational and national borders.

Recent work on immersive technologies in small and medium-sized enterprises (SMEs) reports that adoption remains limited even where potential benefits are recognized, because practical constraints such as weak standardization, organizational readiness gaps, and implementation uncertainty remain significant (Jalo et al., 2022). That pattern is consistent with the broader Industry 4.0 literature, where adoption is inhibited by managerial, infrastructural, financial, and strategic barriers that operate simultaneously rather than sequentially (Kamble et al., 2018). Structural methods are useful in such settings because they reveal not merely whether a barrier exists, but how it shapes other barriers in the adoption pathway (Jena et al., 2017). Methodologically, ISM captures pairwise directional judgments in an SSIM using V-A-X-O notation, converts them to a reachability representation, and partitions variables into hierarchical levels (Jena et al., 2017); total interpretive structural modeling (TISM) extends ISM by interpreting links as well as nodes (Sushil, 2012); and MICMAC classifies variables by driving and dependence power, with fuzzy variants building on fuzzy set theory (Zadeh, 1965) to admit graded relationship strengths (Ahmad, 2024).

This paper structures ten barriers to immersive technology adoption within one coherent workflow: graded fuzzy influence elicitation, SSIM summary, fuzzy max-min transitive closure, thresholded level partitioning, link-level interpretation, and Fuzzy MICMAC classification. The study is organized around one structural question: when market-facing constraints (customer readiness and regulatory uncertainty) are modeled alongside the internal barriers that dominate factory-centric Industry 4.0 studies, do they occupy structurally distinctive positions in the adoption hierarchy? The workflow follows the template established by Ben Ruben et al. (2023) for Industry 4.0 barriers but extends it in three ways. First, the barrier set incorporates the market-facing constraints named above, which factory-centric studies do not model, and these turn out to occupy structurally distinctive positions: one at the root of the hierarchy and two at its top. Second, the study reports a threshold sensitivity analysis rather than a single partition. Third, the complete input and closure matrices are published in appendices so that every reported quantity can be independently recomputed. The study is presented as a methodological demonstration whose relational judgments are literature-informed; a Delphi protocol for its empirical validation with supply chain domain experts is specified in the Conclusion.

2. Methodology

Design: The study adopts a qualitative conceptual-structural design rooted in interpretive structural modeling (Warfield, 1974). This design is suitable when the research problem contains many interrelated barriers, the causal ordering among them is not directly observable, and structured judgment must be converted into a systematic hierarchy (Jena et al., 2017). The workflow comprises variable selection, graded influence elicitation, SSIM derivation, transitive closure, level partitioning, link interpretation, and MICMAC classification.

Participants/Sample: The unit of analysis is the adoption barrier. The ten barriers were isolated through a structured narrative synthesis of two literature streams: empirical studies of immersive technology adoption in organizations, including SCM and logistics reviews (Jalo et al., 2022; Hoang et al., 2019; Stoltz et al., 2017; Rejeb, Keogh, Leong, et al., 2021), and structural barrier models of Industry 4.0 adoption (Kamble et al., 2018; Ben Ruben et al., 2023). A candidate barrier was retained when it (i) recurred in at least two independent sources spanning both streams, (ii) was conceptually distinct from already-retained constructs rather than a synonym, and (iii) mapped to the technology–organization–environment (TOE) structure so that the final set covers technical, organizational, and environmental constraints (TOE column of Table 1). Two near-miss candidates were excluded under criterion (ii): ergonomic and health concerns with head-worn devices, which at the level of the adoption system operate through workforce acceptance and are treated as subsumed within the employee skill gap and change resistance constructs (Rejeb, Keogh, Leong, et al., 2021), and the limited availability of proven use cases, which is absorbed into the unclear ROI and business case construct. The list was capped at ten to keep pairwise judgment tractable for TISM while preserving construct coverage (Table 1). This selection procedure is transparent but not exhaustive; a formal systematic review with documented search strings and screening counts is identified as future work. The contextual relationships among the barriers were specified from analytically plausible, literature-informed judgments recorded in a structured elicitation template rather than from a live expert panel; this scope condition is addressed in the Discussion and a validation protocol is given in the Conclusion.

Table 1. Barrier set for immersive technology adoption in supply chains

Code	Barrier	TOE	Rationale and supply chain reading
B1	High implementation cost	O	Financial burden constrains experimentation and scaling of pilots across sites and partners (Kamble et al., 2018).
B2	Lack of digital infrastructure	T	Digital readiness shapes integration with warehouse management and enterprise systems (Kamble et al., 2018; Stoltz et al., 2017).
B3	Data security and privacy risk	T	Immersive platforms capture operational and personal data across firm boundaries, intensifying governance concerns (Kulkarni et al., 2023).
B4	Employee skill gap	O	Frontline operator capability drives acceptance and safe use in warehouse and assembly tasks (Kamble et al., 2018; Rejeb, Keogh, Leong, et al., 2021).
B5	Resistance to organizational change	O	Behavioral resistance can block assimilation into standard operating procedures (Kamble et al., 2018).
B6	Lack of strategic leadership support	O	Leadership commitment acts as a root enabler or blocker of technology programs (Kamble et al., 2018).
B7	Unclear ROI and business case	O	Adoption slows when value cannot be demonstrated against operational baselines (Kamble et al., 2018).
B8	Vendor interoperability issues	T	Fragmented device and platform ecosystems raise multi-vendor integration complexity across the chain (Rejeb, Keogh, Leong, et al., 2021).
B9	Regulatory and compliance uncertainty	E	Governance uncertainty over cross-border data flows reduces confidence and scale (Jalo et al., 2022).
B10	Limited customer readiness	E	Downstream client acceptance shapes the feasibility of market-facing immersive services (Rejeb, Keogh, Wamba, et al., 2021).

Note. TOE = technology (T), organization (O), environment (E) dimension of the technology–organization–environment framework to which each barrier is mapped under selection criterion (iii).

Instruments: Relational judgments were captured as graded influence strengths: every ordered pair of barriers was assigned a value between 0 and 1, with an interpretive note recorded for the strongest links (Appendix C). Judgments were anchored on a five-point linguistic scale (very weak = 0.15, weak = 0.30, moderate = 0.45, strong = 0.60, very strong = 0.75) and adjusted by at most one 0.05 step where required to preserve the rank ordering of influences within a row; the 0.05 grid therefore carries ordinal rather than cardinal precision. The graded matrix (Appendix A) is the computational input for all subsequent steps. For presentation and for comparability with the ISM tradition (Jena et al., 2017), the SSIM in Table 2 is derived from the graded matrix at the 0.50 significance cut: a pair is coded X when both directions carry strength of at least 0.50, V when only the row-to-column direction does, A when only the column-to-row direction does, and O otherwise. The SSIM is therefore a categorical summary that is consistent with the computation by construction. Six pairs code as X (B2–B8, B3–B9, B4–B5, B4–B6, B5–B6, B6–B7), showing that mutual influence is a substantive feature of this system rather than an artefact of notation.

Table 2. Structural Self-Interaction Matrix (SSIM), derived from the graded influence matrix

i \ j	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	A	O	A	A	A	A	O	O	O
B2		V	V	O	A	O	X	O	O
B3			O	O	O	O	A	X	O
B4				X	X	O	O	O	O
B5					X	A	O	O	O
B6						X	O	O	O
B7							O	O	A
B8								O	O
B9									O

Note. V = row influences column; A = column influences row; X = mutual influence; O = no significant direct relation. Derived from Appendix A at the 0.50 cut, so the categorical and graded representations are consistent by construction.

Procedure: The graded matrix was processed through fuzzy max-min transitive closure (Zadeh, 1965; Ahmad, 2024), which updates each relation according to the rule $r_{ij}^{*} = \max_k \min(r_{ik}, r_{kj})$, iterated to a fixed point, so that indirect effects are propagated whenever mediated influence is stronger than the current direct value. The closure matrix is reported in Appendix B. Entries at or above the 0.50 threshold were set to 1 to form the binary reachability structure. Level partitioning then followed standard ISM logic (Jena et al., 2017): at each iteration, a barrier whose reachability set equals the intersection of its reachability and antecedent sets is assigned to the current level and removed. Levels are numbered from the top of the digraph downward: Level I contains the most dependent elements, which are partitioned first, and the final level contains the structural root. Link-level interpretations for all direct relations of strength at least 0.55 are provided in Appendix C, supplying the interpretive layer that distinguishes TISM from conventional ISM (Sushil, 2012).

Data Analysis: Driving power was computed as the row sum of the fuzzy closure matrix and dependence power as the corresponding column sum (Jena et al., 2017); both sums include the unit diagonal, which adds a constant 1.00 to every barrier's driving and dependence power and therefore does not affect relative comparisons. The MICMAC quadrant boundaries were set at the mean driving power and mean dependence power (both 5.91); a barrier counts as high on an axis when its value is greater than or equal to the mean. The mean was preferred to the

conventional midpoint of a binary reachability count because fuzzy closure sums are real-valued and concentrated well above the midpoint of their feasible range, which would otherwise classify every barrier as high on both axes. Because the closure matrix does not depend on the binarization threshold, MICMAC classifications are threshold-invariant by construction; the hierarchy, in contrast, depends on the threshold, so the level partitioning was repeated at thresholds of 0.40 and 0.60 as a sensitivity check. All computations were verified by independent recomputation from the input matrix in Appendix A.

3. Results

Table 3 reports the driving power, dependence power, hierarchy level, and MICMAC classification for each barrier. Driving power ranges narrowly from 5.05 (B1) to 6.50 (B6) and dependence power from 5.05 (B10) to 6.30 (B1), indicating a densely coupled system. Lack of strategic leadership support (B6) has the highest driving power; high implementation cost (B1) has the highest dependence power; limited customer readiness (B10) has the lowest dependence power.

Table 3. Barrier-level results: driving power, dependence power, hierarchy level, and MICMAC class

Code	Barrier	Driving power	Dependence power	Level	MICMAC class
B1	High implementation cost	5.05	6.30	I	Dependent
B2	Lack of digital infrastructure	6.30	5.70	II	Independent
B3	Data security and privacy risk	5.35	6.00	I	Dependent
B4	Employee skill gap	6.05	6.00	II	Linkage
B5	Resistance to organizational change	6.35	6.05	II	Linkage
B6	Lack of strategic leadership support	6.50	6.00	II	Linkage
B7	Unclear ROI and business case	6.10	6.20	II	Linkage
B8	Vendor interoperability issues	6.15	5.75	II	Independent
B9	Regulatory and compliance uncertainty	5.30	6.05	I	Dependent
B10	Limited customer readiness	5.95	5.05	III	Independent

Note. Quadrant boundaries at the mean of each axis (5.91); high = value ≥ mean. Levels: I = top (most dependent), III = root.

The level partitioning at the 0.50 threshold produced three levels (Table 4, Figure 1). Level I (top) contains high implementation cost, data security and privacy risk, and regulatory and compliance uncertainty. Level II contains six barriers: digital infrastructure, employee skill gap, change resistance, leadership support, ROI clarity, and vendor interoperability. Level III (root) contains limited customer readiness alone. In the binary reachability structure, no barrier reaches B10 at or above the threshold, while B10 reaches every other barrier; its only supra-threshold direct link is to unclear ROI and business case (strength 0.55). The six X-coded pairs in Table 2 all fall within Level I or Level II.

Table 4. TISM level partition at the 0.50 threshold

Level	Barriers
I (top)	High implementation cost; Data security and privacy risk; Regulatory and compliance uncertainty
II	Lack of digital infrastructure; Employee skill gap; Resistance to organizational change; Lack of strategic leadership support; Unclear ROI and business case; Vendor interoperability issues
III (root)	Limited customer readiness

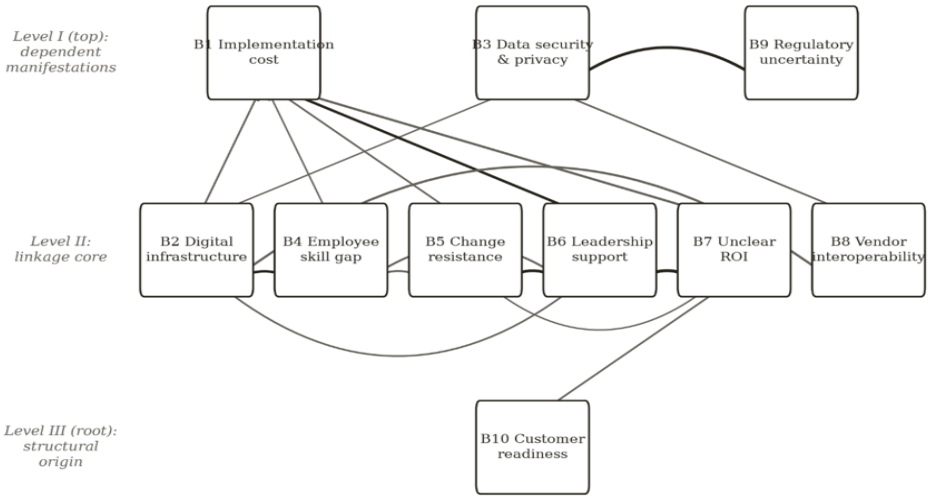

Figure 1. TISM digraph at the 0.50 threshold. Arrows show direct links of strength ≥ 0.50 from the input matrix; double-headed arrows mark mutual links; line weight is proportional to strength.

The Fuzzy MICMAC classification (Table 5, Figure 2) assigns four barriers to the linkage quadrant (employee skill gap, change resistance, leadership support, and ROI clarity), three to the independent quadrant (digital infrastructure, vendor interoperability, and customer readiness), and three to the dependent quadrant (implementation cost, data security risk, and regulatory uncertainty). No barrier is autonomous.

Table 5. Fuzzy MICMAC classification of barriers

MICMAC group	Barriers
Dependent	High implementation cost; Data security and privacy risk; Regulatory and compliance uncertainty
Linkage	Employee skill gap; Resistance to organizational change; Lack of strategic leadership support; Unclear ROI and business case
Independent	Lack of digital infrastructure; Vendor interoperability issues; Limited customer readiness
Autonomous	— (none)

Table 6 reports the sensitivity of the level partition to the binarization threshold. At 0.40 the structure collapses to a single level because nearly all closure entries exceed the threshold; at 0.60 a three-level structure persists but limited customer readiness moves into the top group because its 0.55-strength link to ROI clarity no longer survives, leaving it disconnected, while digital infrastructure and vendor interoperability form the root level. MICMAC classifications are unaffected by the threshold. The root position of customer readiness is therefore conditional on admitting moderate-strength (0.50–0.59) links, and the top-level position of cost, security, and regulatory uncertainty is stable across the 0.50 and 0.60 partitions.

Table 6. Threshold sensitivity of the level partition

Threshold	Levels	Partition (top → root)
0.40	1	All ten barriers in one level (structure collapses)
0.50	3	{B1, B3, B9} → {B2, B4, B5, B6, B7, B8} → {B10}
0.60	3	{B1, B3, B9, B10} → {B4, B5, B6, B7} → {B2, B8}

Note. MICMAC classes are computed from the closure matrix and are invariant to the threshold by construction. At 0.60, B10 is disconnected rather than dependent; isolated elements partition into the first level by construction.

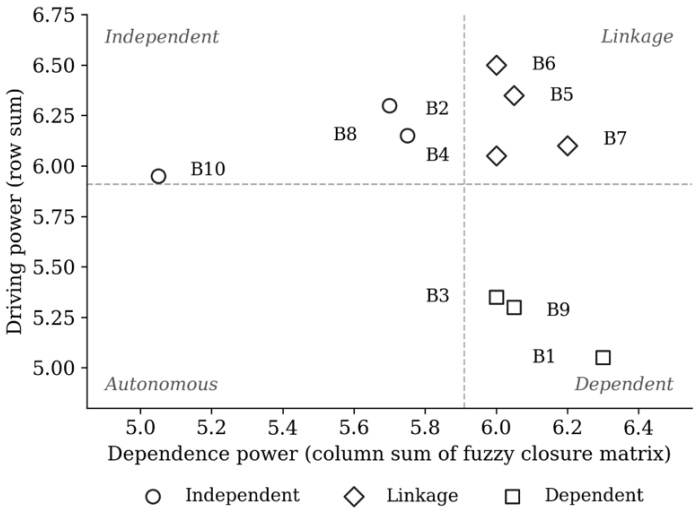

Figure 2. Fuzzy MICMAC driving–dependence map, with dependence power on the horizontal axis and driving power on the vertical axis. Dashed lines mark the quadrant boundaries at the axis means (5.91, 5.91).

4. Discussion

The most consistent message of the model is that immersive technology adoption behaves as a tightly coupled system. Driving and dependence powers are compressed into a narrow band, no barrier classifies as autonomous, and four of ten barriers are linkage variables, simultaneously influential and influenced. In MICMAC logic, linkage-heavy systems are unstable: an intervention on any core barrier propagates widely but also feeds back on itself (Jena et al., 2017; Kamble et al., 2018). Practically, this cautions supply chain decision-makers against treating any single obstacle in isolation.

The position of high implementation cost is the most counterintuitive result. Practitioner surveys routinely rank cost among the leading obstacles to immersive technology adoption (Jalo et al., 2022; Stoltz et al., 2017), and the barrier-set rationale in Table 1 reflects that framing. The structural model, however, places cost at the top of the hierarchy with the highest dependence power in the system: cost behaves as a manifestation of deeper conditions (weak sponsorship, an unclear business case, resistance, and infrastructure gaps all transmit into it) rather than as a root cause. The same holds for data security risk and regulatory uncertainty, which form a mutually reinforcing pair (strengths 0.75 and 0.70) at the top of the structure. For managers, these three barriers are better read as lagging indicators of adoption-system health than as primary intervention targets; treating the visible symptom while the underlying drivers remain untouched is unlikely to shift the system (Hoang et al., 2019).

The lagging-indicator reading is actionable because all three dependent barriers map onto performance metrics that supply chain organizations already track. Implementation cost manifests in the total-cost-of-ownership variance and budget-overrun percentage of technology programs and, downstream, in cost-to-serve movements at pilot sites. Data security risk manifests in security-incident and near-miss rates, audit non-conformities, and supplier security-assessment scores where devices and data cross firm boundaries. Regulatory uncertainty manifests in compliance-audit pass rates and in the lead time to attain compliance when new requirements bind. Monitoring these as adoption key performance indicators, rather than treating them as investment gates, aligns measurement with the model's causal reading: improvement in the dependent cluster should follow, not precede, interventions in the linkage core. These metric mappings are managerial inferences drawn from the model's causal ordering rather than results of the analysis itself.

The six-barrier middle level constitutes the operating core of the adoption problem. It contains all four linkage barriers. The strongest single directed link in the system runs from leadership support to ROI clarity (0.80, with a

reciprocal of 0.60), and the strongest mutual pair couples change resistance and leadership support (0.75 and 0.70): weak sponsorship limits strategic justification, an undemonstrated business case erodes sponsorship, and entrenched resistance discourages sponsorship in turn (Jalo et al., 2022). Leadership support carries the highest driving power in the system, so it remains the most potent lever, consistent with prior structural studies in which managerial commitment determines whether advanced technologies are piloted, funded, and scaled (Kamble et al., 2018). But its linkage classification qualifies the usual prescription: because leadership support is also highly dependent, one-off executive mandates will erode unless the feedback loops that sustain sponsorship (demonstrated value, visible capability, manageable resistance) are serviced at the same time. Case evidence from SME adopters of augmented and virtual reality similarly pairs top-management commitment with low employee resistance as joint preconditions (Pessot et al., 2025). The two independent barriers in this level, digital infrastructure and vendor interoperability, are the supplier-facing pair: they concern integration with warehouse management and enterprise systems and across multi-vendor device ecosystems, the same technical and organizational challenge clusters documented for AR smart glasses in logistics (Rejeb, Keogh, Leong, et al., 2021).

Limited customer readiness occupies the structural root at the 0.50 threshold: nothing in the system drives it above threshold, and it reaches the entire system through a single transmitting link into ROI clarity. This is a distinctively market-facing finding that differentiates the immersive technology context from factory-centric Industry 4.0 barrier models, where root positions are typically occupied by internal factors such as management support or financial constraints (Kamble et al., 2018; Ben Ruben et al., 2023). The sensitivity analysis, however, requires a conditional reading: the root position rests on a moderate-strength link (0.55) and dissolves at a 0.60 threshold. This fragility is informative rather than embarrassing, because it identifies the market conditions under which the structure should hold or flatten. The link should be strong where immersive offerings are market-facing and demand is unproven, consumer-facing retail chains piloting virtual try-on, or logistics service providers selling immersive training to clients, so that customer readiness governs whether a business case can be demonstrated at all. It should weaken where adoption is internally anchored, and benefits accrue regardless of customer perception, as in warehouse pick-by-vision, where the beneficiary of the technology is the firm's own operations (Stoltz et al., 2017; Rejeb, Keogh, Wamba, et al., 2021). External anchors, a dominant business customer mandating immersive collaboration, co-funded pilots with key accounts, maturing industry standards, would inject drive into customer readiness, raising its dependence and dissolving its root position. These are testable propositions for the expert panel specified in the Conclusion.

Two limitations bound these claims. First, the relational judgments are literature-informed rather than elicited from a domain expert panel, so the model demonstrates a method and proposes a structure; it does not yet establish one empirically. Second, the hierarchy is threshold-dependent, and the narrow dispersion of driving and dependence powers means that barriers near the quadrant boundaries could change class under modest revisions of the input judgments (Ahmad, 2024): employee skill gap sits at 6.05/6.00 against means of 5.91, and the independent classification of limited customer readiness rests on a driving power of 5.95, a margin of only 0.04 above the mean. The root position of customer readiness in the hierarchy is more robust than its quadrant assignment, because no closure entry into it exceeds 0.45, below every threshold considered. Sensitivity reporting mitigates but does not remove this fragility.

5. Conclusion

This study applied a graded fuzzy influence matrix, an SSIM summary, fuzzy max-min transitive closure, thresholded level partitioning, link-level interpretation, and Fuzzy MICMAC classification to ten barriers affecting immersive technology adoption in supply chains. The verified model yields a three-level structure in which limited customer readiness forms the structural root, a linkage-dense six-barrier core (infrastructure, skills, resistance, leadership, ROI clarity, interoperability) transmits and amplifies

influence, and implementation cost, data security risk, and regulatory uncertainty emerge as dependent manifestations. No barrier is autonomous. The practical reading is sequenced accordingly: anchor adoption in market readiness and business-case development, stabilize the leadership–ROI–capability core with feedback-aware governance, and monitor cost, security, and compliance as lagging indicators through the supply chain performance metrics discussed above.

The immediate next step is empirical validation. We specify a two- to three-round Delphi study with eight to fifteen supply chain domain experts spanning manufacturers, logistics service providers, and technology vendors. Each expert independently re-scores the 90 ordered barrier pairs on the published 0–1 scale with rationale notes for strong links; responses are aggregated by median, consensus is assessed by interquartile range and Kendall's W across rounds, and the published analysis pipeline regenerates the hierarchy, classification, and sensitivity results from the consensus matrix. Beyond validation, future work should compare sector-specific structures (for example, consumer-facing retail chains versus industrial business-to-business chains, where the customer-readiness root is predicted to behave differently) and integrate the framework with structural equation modeling (SEM), DEMATEL, the analytic hierarchy process (AHP), or fuzzy multi-criteria decision-making (MCDM) methods. The appendices provide the complete input and closure matrices so that all reported results can be independently recomputed and extended.

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Appendix A. Initial fuzzy influence matrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	1.00	0.40	0.35	0.45	0.30	0.20	0.25	0.30	0.20	0.15
B2	0.55	1.00	0.50	0.70	0.35	0.45	0.30	0.65	0.40	0.20
B3	0.40	0.35	1.00	0.30	0.25	0.30	0.35	0.45	0.75	0.15
B4	0.50	0.45	0.40	1.00	0.60	0.55	0.45	0.30	0.20	0.25
B5	0.55	0.30	0.25	0.50	1.00	0.70	0.45	0.20	0.15	0.35
B6	0.70	0.55	0.30	0.60	0.75	1.00	0.80	0.35	0.25	0.40
B7	0.65	0.35	0.30	0.40	0.50	0.60	1.00	0.25	0.25	0.45
B8	0.45	0.60	0.55	0.35	0.30	0.35	0.30	1.00	0.40	0.20
B9	0.30	0.25	0.70	0.20	0.15	0.20	0.25	0.35	1.00	0.10
B10	0.35	0.25	0.15	0.30	0.45	0.35	0.55	0.20	0.10	1.00

Note. Entry (i, j) is the graded direct influence of barrier i on barrier j on a 0–1 scale; diagonal entries are 1.00. Table 2 is derived from this matrix at the 0.50 cut.

Appendix B. Fuzzy max-min transitive closure matrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	1.00	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
B2	0.60	1.00	0.55	0.70	0.60	0.60	0.60	0.65	0.55	0.45
B3	0.45	0.45	1.00	0.45	0.45	0.45	0.45	0.45	0.75	0.45
B4	0.60	0.55	0.55	1.00	0.60	0.60	0.60	0.55	0.55	0.45
B5	0.70	0.55	0.55	0.60	1.00	0.70	0.70	0.55	0.55	0.45
B6	0.70	0.55	0.55	0.60	0.75	1.00	0.80	0.55	0.55	0.45
B7	0.65	0.55	0.55	0.60	0.60	0.60	1.00	0.55	0.55	0.45
B8	0.60	0.60	0.55	0.60	0.60	0.60	0.60	1.00	0.55	0.45
B9	0.45	0.45	0.70	0.45	0.45	0.45	0.45	0.45	1.00	0.45
B10	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	1.00

Note. Row sums give driving power; column sums give dependence power (both include the unit diagonal). Entries ≥ 0.50 define the binary reachability structure.

Appendix C. Interpretive matrix: direct links of strength ≥ 0.55

Link	Strength	Interpretation (why the influence operates)
B2 → B1	0.55	Poor infrastructure forces costly workarounds and rework during implementation.
B2 → B4	0.70	Inadequate digital infrastructure limits opportunities to build immersive-technology skills in daily work.

B2 → B8	0.65	Weak infrastructure amplifies integration difficulty across vendor platforms.
B3 → B9	0.75	Perceived security and privacy exposure heightens perceived regulatory and compliance uncertainty.
B4 → B5	0.60	Low workforce readiness strengthens resistance to organizational change.
B4 → B6	0.55	Visible capability gaps reduce executives' confidence in sponsoring adoption.
B5 → B1	0.55	Resistance slows rollouts and extends timelines, inflating implementation cost.
B5 → B6	0.70	Entrenched resistance discourages executives from sponsoring immersive initiatives.
B6 → B1	0.70	Weak sponsorship prevents pooled, planned investment, raising effective implementation cost.
B6 → B2	0.55	Without strategic sponsorship, infrastructure modernization is deferred.
B6 → B4	0.60	Without leadership commitment, capability-building programs are not funded.
B6 → B5	0.75	Absent leadership sponsorship legitimizes resistance to change.
B6 → B7	0.80	Weak sponsorship limits strategic justification of the business case.
B7 → B1	0.65	An unclear business case blocks coordinated budget approval, so implementation proceeds inefficiently.
B7 → B6	0.60	Inability to demonstrate return on investment erodes leadership support.
B8 → B2	0.60	Fragmented vendor ecosystems complicate infrastructure integration.
B8 → B3	0.55	Multi-vendor integration expands the attack surface and data-handling ambiguity.
B9 → B3	0.70	Unsettled regulation keeps data-governance requirements ambiguous, sustaining perceived security risk.
B10 → B7	0.55	Weak customer readiness makes market-side value difficult to demonstrate, keeping ROI unclear.

Note. The interpretive layer required by TISM (Sushil, 2012). Links below 0.55 are omitted for brevity; the full graded matrix is in Appendix A.