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OBJECT-LEVEL MULTI-DIMENSIONAL ANALYSIS OF LEVEL OF INFORMATION REQUIREMENTS ACROSS PROJECT LIFECYCLE

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Abstract

Optimizing multi-purpose specifications requires understanding information requirement overlap and burden distribution, yet systematic object-level analysis remains absent. This study introduces a hierarchical 12-KPI framework quantifying geometrical, alphanumerical information, and documentation requirements across 80 objects, 22 purposes, and five lifecycle phases using 5,048 specifications. The key contributions include: (1) a validated three-archetype hierarchy with distinct temporal signatures; (2) the identification of universal objects as multi-purpose integration points; (3) the quantification of purpose-specific uniqueness challenging consolidation assumptions; (4) an interactive dashboard enabling evidence-based Exchange Information Requirement optimization. This object-purpose-phase granularity advances systematic BIM specification from aggregate analysis to decision-support frameworks for practitioners.

Introduction

The adoption of the ISO 19650 series as international standards for information management using BIM creates expectations for standardised information delivery across project stakeholders (Abanda et al., 2025). This regulatory push, occurring alongside intensifying BIM mandates, creates substantial pressure for comprehensive, multi-purpose implementation serving diverse information needs throughout building lifecycles (Mitera-Kiełbasa & Zima, 2024). Each construction phase requires information in different forms, and what is required changes with the activities performed. Information models must simultaneously serve design coordination, regulatory compliance, energy analysis, cost estimation, construction planning, and facility management, each potentially requiring different information requirements as specified by stakeholders.

ISO 7817-1:2024 addresses this through the Level of Information Need (LOIN) framework, structuring requirements across three components: geometrical information (detail, dimensionality, location, appearance and parametric behaviour), alphanumerical information (properties and attributes), and documentation (deliverable files). Although "LOIN" is an acronym to be avoided in projects, it is used here for simplicity. The standard also introduces purposes, the specific reasons for information exchange, as the main organising principle for requirement specification. However, implementing LOIN requires decisions about which purposes to include, which building objects to specify for each, and how requirements evolve across phases from design through operation (Lindholm et al., 2025; Liu et al., 2023).

Despite extensive BIM research, systematic understanding of information requirements at object-purpose-phase granularity remains limited. Existing studies analyse requirements at aggregate levels, treating purposes as monolithic without examining variation across object types. Cavka et al. (2017) developed comprehensive owner requirement frameworks but did not differentiate by object. Krijnen and Tamke (2015) analysed implicit knowledge in models using machine learning yet focused on model-level patterns. Patacas et al. (2020) evaluated IFC and COBie for asset management but aggregated across objects. Phase-based studies investigate limited purpose sets or restricted object types (Noardo et al., 2020), and recent infrastructure work acknowledges substantial cross-discipline and cross-phase variation but lacks systematic object-level quantification.

More recent work has begun to operationalise LOIN. Malla et al. (2023) proposed a structured approach aligned with ISO 7817-1 yet remained at the purpose level without disaggregating by object. Lindholm et al. (2025) demonstrated LOIN-driven exchange connected to production planning, confirming applicability but limiting analysis to a single purpose context. EU-funded projects such as BIM4EEB and DigiChecks produced LOIN-based templates for energy retrofitting and regulatory compliance respectively, but address domain-specific purposes without cross-purpose comparison (Rathnasinghe et al., 2022). Quantitative or KPI-based assessment remains scarce: existing metrics focus on model maturity or compliance scoring rather than characterising the structure and distribution of requirements. To date, no comprehensive analysis examines how requirements for specific objects vary across multiple purposes and lifecycle phases.

This gap prevents evidence-based optimisation of multi-purpose specifications. Practitioners selecting purposes for Exchange Information Requirements (EIR) face unanswered questions: Do different purposes require fundamentally different information for the same objects, or do requirements largely overlap, enabling duplicity across models? Which objects accumulate the heaviest specification when multiple purposes converge? Can shared baseline specifications satisfy multiple purposes, or are requirements genuinely purpose-specific? How do these patterns evolve from preliminary design through facility operation? Without systematic object-level evidence, decisions rely on institutional experience, vendor recommendations, or conservative over-specification, none enabling sustainable data-driven optimisation balancing coverage against practical constraints, overcomplicating BIM implementation and reducing data management efficiencies.

This study addresses this gap through systematic multi-dimensional analysis at object-purpose-phase granularity. This paper examines standardized information delivery purpose specifications across building object types and project phases aligned with RIBA Plan of Work 2020 (PoW), quantifying geometrical, alphanumerical, and documentation requirements for discrete object-purpose-phase sequential combinations. This granular approach enables investigation of requirement variation patterns, multi-purpose object utilization, and consolidation potential not addressable through aggregate analysis. An interactive dashboard complements the analytical framework, supporting practitioners in exploring purpose combinations and assessing marginal contributions for project-specific specification decisions.

This analysis addresses five research questions:

RQ1: How do information requirements vary across purposes, phases, and object types?

RQ2: What is the distribution of geometrical, alphanumerical, and documentation requirements across information delivery purposes?

RQ3: Which building objects exhibit highest information specification burden across multiple purposes?

RQ4: To what extent do individual objects support multiple information delivery purposes across project phases?

RQ5: What is the uniqueness of purpose-specific requirements at object-phase granularity?

Methodology

Data Source

The analysis utilized all 22 standardized information delivery purposes from BIMids, an industry-academic collaboration platform that supports the implementation of ISO 19650 series and ISO 7817-1 standards in construction projects. BIMids is maintained through collaboration between industry practitioners and academic researchers, with specifications developed through expert consensus and aligned directly with ISO 7817-1 LOIN component structures. It represents the largest publicly available multi-purpose LOIN specification dataset, providing systematic coverage across building object types, project phases, and information delivery purposes, supporting its relevance as an empirical basis for cross-purpose analysis. Each purpose specifies information requirements for building object types across three LOIN components (geometrical, alphanumerical, and documentation) and five project phases mapped to RIBA PoW 2020: Phase 1-PD (RIBA 0-2: Strategic Definition through Concept Design), Phase 2-FD/AUT (RIBA 3-4: Spatial Coordination through Technical Design), Phase 3-FP/TEND (RIBA 4-5: Tender through Early Construction), Phase 4-EXE/ASB (RIBA 5: Construction), Phase 5-OPE (RIBA 6-7: Handover through Use).

The dataset encompasses 80 building object types spanning architectural (door, window, wall, etc.), structural (beam, column, slab, etc.), and MEP (duct, pipe, lift, etc.) disciplines. In the end, a dataset is created comprising 5,048 requirements: 2,443 geometrical, 1,866 alphanumerical, 739 documentation (distributed across 2,603 object-purpose-phase combinations).

Interactive Dashboard

To enable practical application, an interactive web dashboard was developed to enable data access and serve as a combinatory playground for practitioners. The tool embeds all 22 purposes with complete object-level data (5,048 requirements) enabling offline browser-based analysis. Implementation uses vanilla JavaScript and Chart.js for universal compatibility.

Users may select purposeful combinations, and the dashboard shows the variability in information requirements based on the delivery purposes. For unselected purposes, the dashboard displays a marginal score (new requirements added) and uniqueness percentage (proportion not already covered by selected purposes), ranking recommendations by contribution value. The intended workflow follows four steps: (1) select initial information delivery purposes reflecting project requirements; (2) review real-time KPI updates showing cumulative coverage, component distribution, and object-level burden for the selected set; (3) evaluate the marginal contribution panel, which ranks unselected purposes by new requirements added and uniqueness percentage; and (4) iterate by adding or removing purposes until the desired coverage-to-overhead balance is achieved.

The dashboard supports exploratory investigation of purpose combinations, helping practitioners make evidence-based decisions about EIR specifications while visualizing information overhead implications.

LOIN-based KPIs

To address the research questions systematically, a hierarchical framework of KPIs operating at three analytical levels is proposed: purpose level (characterizing overall information delivery needs), object level (identifying integration points where multiple purposes converge), and combination level (quantifying granular requirement patterns). This hierarchical structure enables investigation from macro-patterns (which purposes are geometry-dominant?), through meso-patterns (which objects serve most purposes?), to finally micropatterns (how much do purposes overlap for specific objects in specific phases?). Figure 1 illustrates this

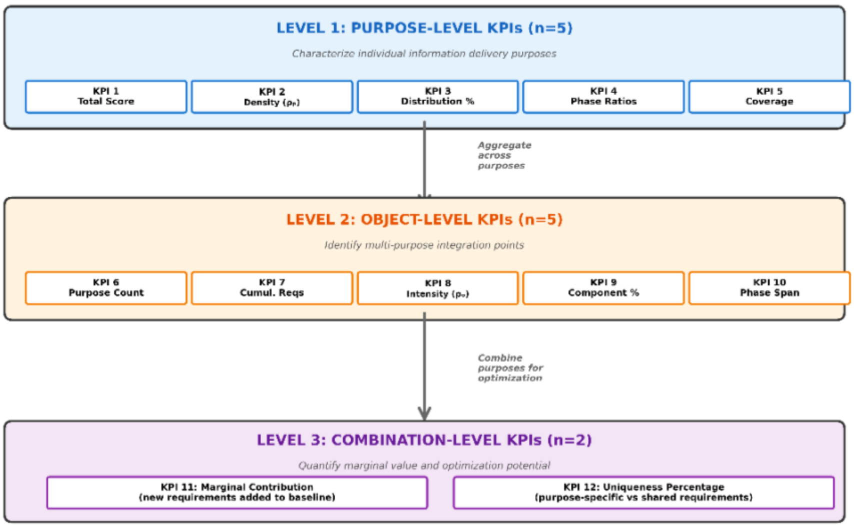

Figure 1. Hierarchical framework of LOIN Key Performance Indicators (KPIs).

hierarchical relationship and the specific LOIN KPIs proposed at each level.

Purpose-Level KPIs. For each purpose (p), five indicators characterizing its overall information requirements are defined.

Total Information Score: it quantifies information requirements burden.

$$S_p = \sum_{o \in O_p} (G_{p,o} w_G + A_{p,o} w_A + D_{p,o} w_D) \qquad (1)$$

where (O_p) is the set of objects specified by purpose (p), and ($G_{p,o}$), ($A_{p,o}$), ($D_{p,o}$) represent geometrical, alphanumerical, and documentation requirement counts for object (o) in purpose (p). (w) are weighing coefficients given to each type of information purpose to model different management burden – external file references versus embedded geometrical or alphanumerical data. The default weighting adopted in this study assigns equal weights to geometrical and alphanumerical components and a reduced half weight to documentation. This choice reflects two considerations. First, ISO 7817-1 treats geometrical and alphanumerical information as structurally parallel LOIN components, both requiring embedded model data authored and maintained within the BIM environment, whereas documentation requirements reference external deliverable files with lower authoring overhead per specification. Second, in the absence of empirical evidence quantifying differential management burden across component types, equal weighting represents the most neutral baseline assumption, avoiding a priori bias toward either spatial or property-based specifications. The sensitivity of results to alternative weighting schemes is discussed in Section 5.

Information Density: this is the normalised score by object count, revealing the specification intensity per object.

$$\rho_p = S_p / |O_p| \qquad (2)$$

High density purposes impose heavy specifications per object (intensive); low density purposes show broad but shallow coverage (extensive). This metric complements the Total Information Score as purposes can have high scores through either intensive specification of few objects or extensive specification of many objects.

Component Distribution Percentages: this KPI reveals information specialization for each purpose:

$$\%G_p = \frac{\sum_o G_{p,o}}{\sum_o (G_{p,o} + A_{p,o} + D_{p,o})} \qquad (3)$$

with analogous definitions for ($\%A_p$) and ($\%D_p$). This KPI enables deterministic approaches to understand how burden is distributed across purposes, i.e. there may be geometrical-dominant purposes if ($\%G_p$)>0.5.

Phase Allocation Ratios: this KPI indicates temporal distribution of each purpose's information requirements across project phases.

$$R_{p,\phi} = \frac{|C_{p,\phi}|}{|C_p|} \qquad (4)$$

where ($C_{p,\phi}$) is the set of requirements for purpose (p) in phase (ϕ), and (C_p) are the total requirements for purpose (p). This reveals whether purposes concentrate in design, construction, or operation phases.

Object Coverage: this KPI ($|O_p|$) simply counts the number of objects per purpose, indicating scope breadth versus narrow specialisation.

Object-Level KPIs. Purpose-level indicators aggregate requirements, but obscure which specific objects bear heaviest specification burdens. Object-level KPIs address this by aggregating across all purposes mentioning each object. For each object (o), it is defined:

Purpose Count: this KPI indicates multi-purpose utilization.

$$N_o = |\{p : o \in O_p\}| \qquad (5)$$

Objects with a large (N_o) identify critical multi-purpose integration points requiring coordinated information management.

Cumulative Requirements: this KPI sums specifications across all purposes. This reveals absolute specification burden accumulated when multiple purposes converge on single object.

$$R_o = \sum_{p:o\in O_p}(G_{p,o} + A_{p,o} + D_{p,o}) \quad (6)$$

Information Intensity: this KPI provides a symmetric metric to purpose-level density, normalizing cumulative requirements by purpose count.

$$\rho_o = R_o/N_o \quad (7)$$

This reveals average specification burden per purpose using the object. High intensity objects are heavily specified by each purpose, whereas low intensity objects are lightly specified despite appearing in many purposes. This symmetry with (ρ_p) enables comparative analysis: purposes with high density specify many requirements per object; objects with high intensity accumulate many requirements per purpose.

Component Intensity: this KPI analyses cumulative composition of object information, revealing whether object specifications emphasise over geometry (coordination), properties (performance), or documentation (compliance).

$$I_o^G = \frac{\sum_p G_{p,o}}{\sum_p(G_{p,o}+A_{p,o}+D_{p,o})} \quad (8)$$

with analogous definitions for (I_o^A) and (I_o^D).

Phase Coverage: this KPI identifies object lifecycle span.

$$\Phi_o = \left|\{\phi: \exists p, o \in O_p\}\right| \quad (9)$$

distinguishing objects serving only single phases from those persisting through project lifecycle.

Combination-Level KPIs. The most granular level examines individual object-purpose-phase triplets (o, p, ϕ), enabling investigation of requirement overlap and consolidation potential.

Uniqueness: this KPI quantifies purpose-specific requirements versus shared requirements.

$$U_{o,p,\phi} = \frac{1}{|O_p|\times|\Phi_p|}\sum_{o\in O_p,\phi\in\Phi_p}\frac{|R_{o,p,\phi}\setminus \cup_{p'\neq p} R_{o,p',\phi}|}{|R_{o,p,\phi}|} \quad (10)$$

where ($R_{o,p,\phi}$) is the set of requirements for each triplet of information, averaged across all object-phase combinations where requirements exist. High uniqueness indicates genuine purpose-specific needs requiring dedicated specifications; low uniqueness suggests consolidation opportunities through shared baseline definitions.

Marginal Contribution: this KPI measures the incremental value of each information set when adding a new purpose to a baseline set.

$$M_{p'} = \frac{\left|R_{p'}\setminus \cup_{p\in P_{base}} R_p\right|}{|R_{p'}|} \quad (11)$$

where (R_p) represents all the requirements for purpose (p). This efficiency metric enables evidence-based purpose prioritisation during EIR specification. Purposes with high (M_p) contribute substantial new information, while those with low (M_p) largely duplicate selected purpose information.

Analytical Framework

The analysis employs a progressive validation framework advancing from descriptive pattern identification through multivariate confirmation, structured in five complementary phases. Descriptive analytics will first establish empirical patterns through univariate distributions and bivariate relationships, identifying three purpose archetypes based on component composition (geometrical, alphanumerical, and documentation dominant), universal objects spanning multiple purposes, and temporal requirement concentration patterns. These descriptive findings generate hypotheses requiring statistical validation: whether archetype classifications represent natural groupings versus arbitrary thresholds, whether the proposed 12-KPI framework provides complementary versus redundant measurements, and whether patterns generalize across analytical dimensions.

Multivariate validation is then employed through four methods testing different framework aspects. Correlation analysis (Pearson r across the 12×12 KPI matrix) assesses indicator complementarity, where low-moderate within-level correlations confirm coherence without redundancy. Cronbach's alpha validates internal consistency at each level, where low alpha combined with weak cross-level correlations confirms a multidimensional complementary design rather than a unidimensional redundant scale. Principal component analysis then reveals dataset dimensionality, reducing the 12 KPIs to combined orthogonal components and demonstrating archetype clustering in multivariate space, empirically validating natural groupings. Finally, temporal profile analysis extends validation to the lifecycle dimension, revealing archetype-specific phase concentration patterns that transcend component and object composition differences.

Methodological triangulation across five analytical phases provides convergent validation unavailable through single-method approaches. Patterns identified descriptively (archetype classification, universal objects, phase concentration) receive confirmation through correlation structure, dimensional reduction, and temporal differentiation. This progressive framework—descriptive hypothesis generation followed by multivariate statistical validation—strengthens confidence that findings represent genuine data structure rather than analytical artifacts, supporting framework generalizability beyond the BIMids case study.

Reflecting on the research questions established, RQ1 (requirement variation) is addressed through purpose-level KPIs via descriptive analytics and temporal profiling. RQ2 (component distribution) is addressed through descriptive analytics and PCA archetype validation. RQ3 (object specification burden) is addressed through object-level KPIs via descriptive analytics and correlation analysis. RQ4 (multi-purpose object coverage) is addressed through correlation analysis and PCA. RQ5 (purpose-specific uniqueness) is addressed through combination-level KPIs via descriptive analytics and dashboard implementation.

Results

Descriptive Analysis

This section addresses RQ1–RQ4 through descriptive characterisation of purpose archetypes, object-level burden, and lifecycle patterns. Analysis of LOIN component distribution across 22 purposes reveals three distinct purpose archetypes (see Figure 2). Geometrical-dominant purposes (n=15, 68%) allocate majority requirements to spatial specifications: '2D documents' (100% geometrical, 374 requirements total) and 'Clash detection' (96.5% geometrical, 342 requirements) exemplify purposes where 3D spatial representation is paramount. Alphanumerical-dominant purposes (n=5, 23%) prioritize property data: 'Maintenance' (57.8% alphanumerical, 552 total requirements) focuses on operational parameters including schedules, warranties, and performance thresholds. Documentation-dominant purposes (n=1, 5%) emphasize deliverable files: 'Minimum requirements' (59.4% documentation, 1,130 total) establishes comprehensive baseline spanning all components but emphasizing document deliverables.

Total information requirements vary substantially: 'Minimum requirements' (1,130) and 'Maintenance' (552) impose heaviest specification loads, while specialized purposes like 'Programming' (5) and 'Access management' (43) target narrow scopes with low demand.

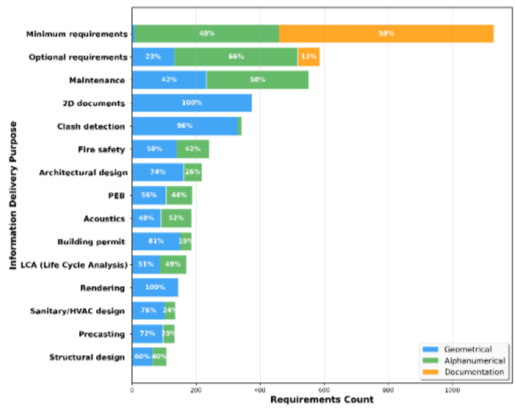

Figure 2. Top 15 component distribution by purpose.

Object-level aggregation identifies universal building elements supporting multiple purposes (see Figure 3). Core architectural objects accumulate highest cumulative requirements: door (172 requirements across 16 purposes), window (148, 16 purposes), ramp (133, 15 purposes), space (125, 17 purposes), slab (122, 14 purposes). These objects function as integration points because they serve multiple purpose archetypes: geometrical-dominant purposes require spatial properties for coordination, alphanumerical-dominant purposes specify performance attributes, and documentation-dominant purposes demand compliance deliverables.

Space achieves highest purpose count (17) spanning spatial programming through facility management; door and window support 16 purposes each. In contrast, specialized MEP equipment serves 1-4 purposes only. Analysis reveals 29 objects (36%) support 10+ purposes each, identifying critical targets for standardization and information quality management.

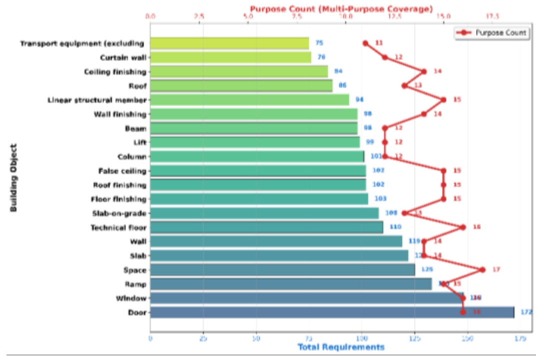

Figure 3. Top 20 object analysis by total requirements and multi-purpose coverage.

Requirement distribution across phases demonstrates progressive intensification (see Figure 4). Phase 1 specifies 660 requirements, escalating to 2486 in Phase 2 (+277%), 3784 in Phase 3 (+52%), peaking at 4750 in Phase 4 (+26%). Phase 5 surprisingly denotes fewer requirements at 3485 (-27%) for operation and use. Note that there is quite a balanced G-A-D distribution across project phases.

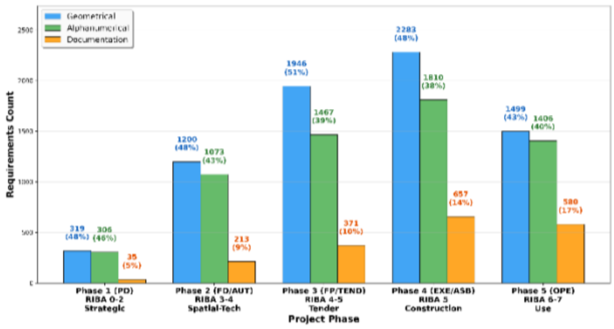

Figure 4. Lifecycle requirement intensification by component.

Correlation Analysis

This section validates KPI complementarity underpinning all five research questions, with relevance to RQ3 and RQ4 (object-level structural relationships). Correlation analysis across hierarchical levels reveals predominantly weak to moderate inter-correlations, supporting complementary nature of the proposed indicators (see Figure 5). However, some can be noted: 1) there is a significant positive correlation ($r > 0.9$) between (N_o) and (R_o) and (ρ_o) and (Φ_o) denoting structural relationships between KPIs (as expected based on their equations); 2) there is a moderate negative correlation ($r = -0.399$) between total information score and uniqueness demonstrating the cumulative nature of information requirements and duplicities existing in practice; and 3) there is a significant positive correlation ($r > 0.9$) also between ($R_{p,\phi}$) and (ρ_o), which may indicate a structural pattern in information requirement distribution across project lifecycle.

When looking at the cross-independence of the KPIs (purpose level vs. object level), there is a minimal correlation between them (median $|r| = 0.22$). This confirms that the bi-level KPI definition captures different dimensions of LOIN integration and validates the hierarchical approach.

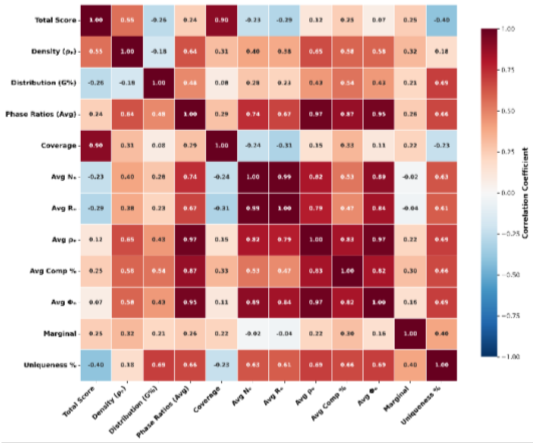

Figure 5. Correlation matrix for the 12 proposed LOIN KPIs.

The Cronbach's alpha results show internal consistency for purpose-level KPIs as they demonstrate low inter-item correlation (α=0.19), confirming multi-dimensional measurement where each indicator captures distinct information aspects. Object-level KPIs show moderate consistency (α=0.56), reflecting structural relationships (e.g., multi-purpose objects accumulate requirements) while maintaining conceptual distinctiveness. Low within-level alpha combined with weak cross-level correlations (median |r|=0.22) validates the framework's multi-dimensional design: indicators provide complementary rather than redundant information, justifying the 12-KPI structure.

Principal Component Analysis

Principal component analysis on all 12 KPIs reveals concentrated variance structure with first three components explaining 87.4% (PC1: 52.3%, PC2: 22.7%, PC3: 12.4%), demonstrating efficient framework dimensionality. PC1 presents existing object-level lifecycle complexity ($\overline{\Phi_o}$: 0.392, $\overline{\rho_o}$: 0.391), separating purposes with sustained cross-phase object engagement from phase-concentrated specifications. PC2 captures purpose scope (Total Score: 0.595, Coverage: 0.540), distinguishing comprehensive from specialized purposes. PC3 emphasizes component archetype (Geom %: 0.599), with purposes clustering in multivariate space according to archetype classifications (see Figure 6). This emergent clustering validates the three-archetype framework: purposes classified by component thresholds demonstrate multivariate similarity within groups and dissimilarity across groups, confirming natural rather than arbitrary categorization. High PC1 variance (52.3%) suggests object-level temporal patterns dominate purpose variation, informing optimization priorities. Framework efficiency—87.4% variance captured by three dimensions from 12 indicators—supports measurement adequacy without redundancy.

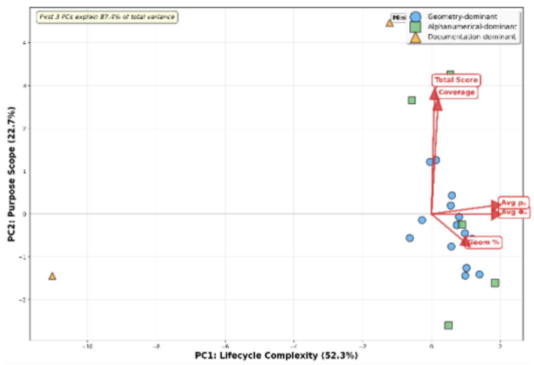

Figure 6. Principal component analysis biplot: purpose clustering and LOIN KPIs loadings.

Temporal Profile Analysis

Temporal profiling completes the validation of RQ1 by demonstrating archetype-specific lifecycle signatures. The temporal requirement profiling reveals that each archetype exhibits a distinct project lifecycle signature (see Figure 7). Geometrical-dominant purposes concentrate in Phase 3 (mean: 32.4%) and decline sharply in Phase 5 (mean: 12.6%). This reflects the spatial coordination emphasis during detailed design that diminishes after the construction stage. In contrast, alphanumerical-dominant purposes distribute more uniformly across phases (concentration coefficient: 0.33) and sustain strong operational presence (Phase 5: 22.5%). This reflects performance monitoring needs throughout the building lifecycle. Documentation-dominant purposes show gradual accumulation without dramatic peaks. Figure 7 left panel compares mean archetype profiles (solid lines) against the overall average (dotted lines). As seen, geometrical purposes peak earlier than average while alphanumerical purposes sustain beyond average into operation. Its right panel shows normalized stacked bars for all 21 individual purposes, revealing systematic clustering by archetype despite variation within groups. Purposes with similar component compositions exhibit similar temporal patterns, independent of their total burden. This temporal differentiation validates archetype classification through an independent dimension beyond component percentages, demonstrating that geometrical-dominant, alphanumerical-dominant, and documentation-dominant purposes differ fundamentally by which project phase requirements concentrate, not merely in what components dominate.

Discussion

The three-archetype classification, validated through PCA and temporal profiling, reveals fundamental differences in how information purposes operate across

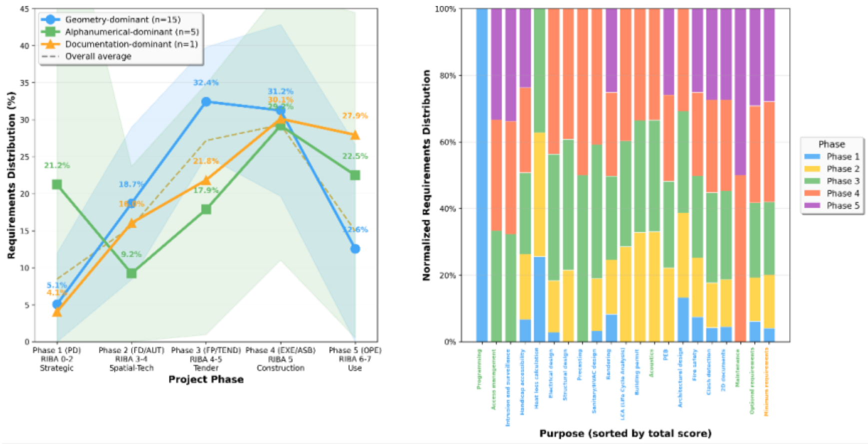

Figure 7. Temporal profiling analysis. Left: average temporal profile of the requirements distribution by project phase. Right: phase distribution per purpose.

building lifecycles. Geometrical-dominant purposes peak during detailed design coordination then declines post-construction, whereas alphanumerical-dominant purposes sustain operational relevance, reflecting performance monitoring needs. This suggests purpose selection should align with project delivery emphasis, consistent with established procurement patterns: design-build contracts typically emphasise early geometry coordination for clash detection, while long-term arrangements demonstrate value in lifecycle information exchange and operational performance monitoring (Ozcan-Deniz & Lokhandwala, 2023), indicating differential emphasis rather than exclusive requirements across procurement routes.

The identification of universal objects supporting 16-17 purposes confirms theoretical expectations from ISO 7817-1 about multi-purpose convergence on core architectural elements. However, the cumulative burden (e.g., door: 172 requirements) raises practical concerns about specification overload and duplicities. High uniqueness scores indicate however limited consolidation potential; available purposes genuinely require distinct information despite object overlap. This validates ISO 7817-1's purpose-driven approach but challenges assumptions about baseline specifications serving multiple purposes efficiently.

The interactive dashboard operationalises findings by quantifying marginal contribution and uniqueness for purpose combinations, letting practitioners identify high-value additions versus redundant purposes. For example, adding 'Maintenance' to geometrical-dominant baselines provides substantial alphanumerical information (57.8%) with moderate uniqueness, whereas adding 'Clash detection' to existing coordination purposes yields diminishing returns.

To illustrate, consider a practitioner preparing an EIR for a design-build project. They select 'Clash detection' and 'Energy analysis' as initial purposes, covering 58 and 41 objects respectively with predominantly geometrical requirements, giving cumulative coverage of 63 unique objects and 684 total requirements. The marginal contribution panel then ranks remaining purposes: 'Maintenance' contributes 552 new requirements (57.8% alphanumerical) with approximately 65% uniqueness, indicating substantial non-overlapping content. In contrast, 'Quantity take-off' contributes only 38% new requirements, largely duplicating geometrical specifications already covered by 'Clash detection'. The practitioner can therefore justify including 'Maintenance' as a high-value addition while deprioritising 'Quantity take-off', reducing overhead without sacrificing coverage.

The 12-KPI framework enables evidence-based EIR optimization, moving beyond institutional practice toward data-driven specification. Purpose-level indicators identify comprehensive versus specialized approaches; object-level metrics highlight multi-purpose integration points requiring quality management; combination-level metrics quantify consolidation feasibility. This hierarchical structure supports decisions at strategic (which purposes?), tactical (which objects?), and operational (which requirements?) levels.

The weighting assumption in Total Information Score treats geometrical and alphanumerical equally ($w_G = w_A = 1$) while assigning reduced weight to documentation ($w_D = 0.5$), potentially oversimplifying data acquisition and management differences between embedded model data and external file references. Preliminary sensitivity analysis varying the weighting ratio w_G:w_A:w_D across three alternative schemes, be that (2:1:0.5), (1:2:0.5), and (1:1:1), indicates that archetype classification remains stable: all 22 purposes retain their original archetype assignment, and the top-10 purpose ranking by Total Information Score changes by at most two positions. This suggests moderate robustness to weighting assumptions for the primary analytical findings. Nevertheless, further weighting scenarios (e.g., $w_D = 2$, reflecting high document management overhead in regulated projects) could alter downstream interpretations, and systematic sensitivity analysis across a wider parameter space, including weighting based on project role or stakeholder positioning, remains warranted.

The empirical findings reflect BIMids specification patterns and may not generalise directly to bespoke employer specifications, non-European regulatory contexts, or different infrastructure typologies (bridges, tunnels, process plants). Nevertheless, BIMids represents the largest publicly available multi-purpose LOIN specification dataset with expert-consensus development, providing the strongest available empirical basis for cross-purpose analysis. The 12-KPI framework itself is source-agnostic: its formulations depend only on object-purpose-phase triplets with geometrical, alphanumerical, and documentation components, and can be applied to any dataset structured according to ISO 7817-1. Future research should validate archetype classification and universal object patterns through comparative crosswalks against national LOIN implementations (e.g., Dutch, Finnish, or Austrian frameworks) and extend analysis to the remaining LOIN aspects in ISO 7817-1 (detail, dimensionality, parametric behaviour) not covered here.

Conclusions

This study systematically quantified information requirement patterns across object-purpose-phase dimensions using 5,048 specifications from 22 standardized BIM purposes. The hierarchical 12-KPI framework operating at purpose, object, and combination levels revealed three distinct archetypes validated through multivariate analysis: geometrical-dominant purposes (68%) concentrating in design coordination, alphanumerical-dominant purposes (23%) sustaining through operations, and documentation-dominant purposes (5%) establishing baseline deliverables. Universal objects accumulate heaviest specification burden across 16-17 purposes, identifying critical multi-purpose integration points.

Principal component analysis confirmed framework dimensionality (87.4% variance in three components) and archetype clustering, demonstrating natural rather than arbitrary categorization. Temporal profiling validated archetypes through independent lifecycle signatures, transcending component composition differences. Correlation analysis revealed complementary indicator structure (median cross-level r=0.22), supporting measurement adequacy without redundancy.

The interactive dashboard operationalizes findings for practitioners, enabling evidence-based EIR optimization through marginal contribution and uniqueness quantification. High uniqueness scores across purposes challenge consolidation assumptions, validating ISO 7817-1's purpose-specific approach while highlighting ISO 19650 specification overhead implications.

This granular analysis advances BIM research from aggregate requirement studies to object-level multi-dimensional characterization, providing empirical foundation for standardization efforts and practical decision support for project information management. Future research should validate findings across construction typologies, test alternative KPI weighting schemes, and extend temporal analysis beyond RIBA phase structures to international delivery models.

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