The Economic Paradox of Design and the integration of Artificial Intelligence (AI) within Building Information Modelling (BIM)

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Abstract –

The management of data in complex construction projects represents a significant challenge in the design and realization of infrastructure. This paper examines the implementation of an integrated Common Data Environment (CDE) to centralize graphical and non-graphical information, aiming to optimize coordination, improve quality, and increase productivity throughout the project lifecycle. The study advocates for shifting effort to the initial design phases where decisions have the maximum impact on performance and cost. It further explores the integration of Artificial Intelligence (AI) within Building Information Modelling (BIM) workflows, emphasizing that structured data collection is a prerequisite for advanced automation. The methodology aligns with Integrated Project Delivery (IPD) models and Concurrent Design principles to foster stakeholder collaboration. Results indicate that establishing a centralized data repository allows for the effective deployment of predictive AI models. The article concludes that the successful digital transformation of the construction sector requires a collective commitment to collaborative cultures and rigorous data centralization from the onset of conception.

Keywords –

Common Data Environment; Artificial Intelligence; Integrated Project Delivery; Information Management

1 Introduction

Data management has become a critical bottleneck in the digital transformation of infrastructure projects [1] [2]. As projects increase in scale, the fragmentation of information across disparate stakeholders frequently leads to inefficiencies, including cost overruns and schedule delays [3] [4]. This paper examines the implementation of an integrated CDE designed to centralize both graphical data—such as 3-dimensional geometric models—and non-graphical information, including specifications and maintenance records. Establishing such a repository is essential to optimize coordination and ensure data integrity throughout the project lifecycle.

Drawing on the principles associated with Concurrent Design [5] and IPD models [6], which foster interdisciplinary collaboration, this study advocates for a strategic shift of engineering effort to the initial design phases, where decision-making capabilities have the maximum influence on asset performance and cost. This approach aligns and reduces the prevalence of downstream rework and costs [7]. Furthermore, the research explores the integration of AI within BIM workflows. It is observed that rigorous, structured data collection within a CDE is a prerequisite for advanced automation and the effective deployment of predictive AI models. Consequently, this paper argues that the digital transformation of the sector requires a dual commitment to collaborative organizational cultures and the robust centralization of data from the onset of conception.

2 Theoretical Background

2.1 The Economic Paradox of Design

The Paulson curve (shown in Figure 1) serves as a foundational concept in construction project management, illustrating the relationship between the timing of design decisions and their subsequent economic impact. This theoretical model posits that the ability to influence project cost and functional performance is highest at the project's inception and diminishes rapidly as the project progresses [7]. Conversely, the cost associated with design changes is low during the initial phases but increases significantly during the documentation and construction stages [7]. Consequently, literature indicates that preventing pathologies or resource inefficiencies during the design phase incurs minimal costs, whereas rectifying these issues during implementation or operation involves substantially higher expenditures [5] [2]. Therefore, rigorous planning during the initial stages—specifically conceptual design—is essential to ensure a coherent and efficient workflow throughout the asset lifecycle.

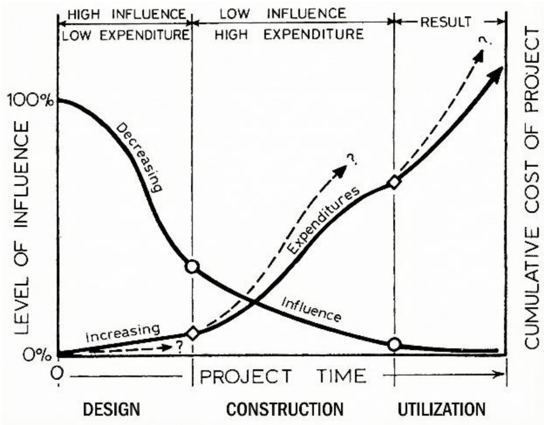

Figure 1. Level of Influence on Project Costs. (The Paulson curve) [7]

However, a critical analysis of the sector reveals a fundamental contradiction regarding the application of this concept. Although the Paulson curve is widely recognized within the Architecture, Engineering, and Construction (AEC) industry to justify the front-loading of design efforts, practical application often reflects a systemic lack of investment during these decisive preliminary stages [4]. This divergence creates an "economic paradox" where the industry acknowledges the necessity of early intervention yet systematically neglects the initial conceptual phases. This negligence tends to compromise overall project efficiency and frequently necessitates costly modifications at advanced stages of the project.

Furthermore, the context of Industry 4.0 introduces additional complexities to this paradox. The original Paulson model may not fully account for the exponential increase in data volume and complexity inherent in modern digital construction. The ability to "influence" a project early is increasingly contingent upon the availability of high-fidelity, interoperable data, which traditional workflows often struggle to provide [1]. Empirical data suggests that while the importance of structured management tools, such as BIM Execution Plans (BEPs), is recognized, their integration into the early stages of the project lifecycle remains inconsistent [9] [10]. To resolve this paradox and shift the industry from a reactive to a predictive state, it is necessary to prioritize the establishment of automated data pipelines and robust information management strategies at the very onset of the project.

2.2 IPD and Collaboration

To address the inefficiencies inherent in fragmented construction processes, the industry has increasingly turned toward collaborative frameworks such as IPD. As defined by the American Institute of Architects [6], IPD is a project delivery approach that integrates people, systems, business structures, and practices into a process that collaboratively harnesses the talents and insights of all participants to optimize project results, increase value to the owner, reduce waste, and maximize efficiency through all phases of design, fabrication, and construction. Central to this approach is the early involvement of key stakeholders—including clients, engineers, and specialized consultants (e.g., HVAC, acoustics, fire safety)—during the conceptualization phase. This early coordination allows for a more rigorous management of constraints and facilitates a holistic vision of the project, thereby mitigating the risk of costly modifications during the execution phase [11] [12].

Closely aligned with the objectives of IPD is the concept of "Concurrent Design" [5]. Theorized as a model for integrated product development, Concurrent Design emphasizes the parallel execution of design tasks and the cross-functional integration of knowledge [5]. In the context of building construction, this method necessitates a shift away from linear, isolated workflows toward a model where multidisciplinary teams interact simultaneously from the project's inception. It is through this simultaneity that potential conflicts are identified and resolved before they manifest on the construction site.

It is critical to recognize that the adoption of IPD and Concurrent Design constitutes more than a mere administrative change or a revision of contractual procurement routes. Literature suggests that while IPD serves as the contractual formalization of collaborative principles, its successful implementation represents a fundamental shift in project methodology [2]. It provides the necessary foundation for coherent project development by institutionalizing the exchange of information and ensuring that the high volume of data generated in the early phases is managed effectively [13]. Without this foundational shift toward genuine stakeholder integration, the technological tools available to the industry—such as BIM and CDEs—may remain limited in their capacity to enhance project performance. Consequently, establishing these collaborative frameworks is a prerequisite for resolving the "economic paradox" of design and shifting the industry from a reactive to a predictive state [14] [15].

2.3 Process Management and BPMN in AEC

The digital transformation of the AEC sector transcends mere technological adoption, representing a profound organizational evolution that necessitates the systematic revision of institutional workflows [16]. Recent literature emphasizes that successful BIM implementation is predicated on procedural integration and institutional restructuring, effectively overcoming barriers related to management maturity and organizational readiness [16]. Within this context, Business Process Model and Notation (BPMN) has emerged as the global standard for capturing "as-is" workflows—documenting current operational states—and designing "to-be" processes optimized for a digitized environment [16, 17].

According to the formal OMG specification [17], BPMN serves as a "standardized bridge" between business process design and technical implementation. In the AEC industry, this capacity is vital for visualizing complex multidisciplinary interactions through collaboration and choreography diagrams, which delineate tasks and message exchanges between distinct entities (Pools) and stakeholders (Lanes). Raj et al. [16] argue that detailed mapping with BPMN enables organizations to identify latent inefficiencies, redundancies, and coordination bottlenecks that, under traditional methods, frequently result in design errors and unforeseen cost overruns.

Furthermore, process modeling provides the foundational architecture for information management as prescribed by standards such as ISO 19650. It facilitates the precise definition of roles and responsibilities—such as the CDE Manager and the BIM Coordinator—by linking specific tasks to professional profiles at a level of granularity that conventional textual documentation cannot achieve [16]. This clarity in the chronology of instructions ensures that data-driven decisions are rooted in a logical, transparent, and auditable framework.

In the scope of this research, BPMN is not merely a documentation tool but a fundamental prerequisite for "AI-readiness." By structuring validation gates and analysis protocols within a BPMN model, the necessary context is provided for artificial intelligence models to determine when and where to intervene for compliance checking or predictive analysis. Ultimately, this transformation shifts the CDE from a passive repository into an active engine for project management and decision-making.

2.4 The Role of CDEs in AI Readiness

The centralization of project data within a CDE is increasingly recognized as a determinant of project success, yet it remains subject to significant implementation difficulties [4]. In a fundamental study regarding the application of these environments, Sevis [3] demonstrated the critical importance of data centralization, identifying 54 distinct benefits and 15 associated challenges. Among these challenges, it is frequently observed that the most critical failure lies in the methodological approach itself: the omission of CDE planning during the initial phases of the project. This lack of early integration suggests a substantial lost potential, as the opportunity to structure data effectively is often missed during the conceptual stages where it could have the greatest impact.

Consequently, addressing this planning deficit is essential not only for immediate project coordination but also for future technological integration. The implementation of AI technologies is currently hindered by obstacles that require a preliminary evolution in data management strategies. Dzhusupova et al. [15] emphasize that AI cannot function effectively without a rigorous foundation. They identify several essential conditions for the successful deployment of AI systems, including the constitution of a sufficiently large and accessible data corpus, followed by a rigorous process of analysis, cleaning, and validation to ensure data quality.

Furthermore, the training of models based on this data, combined with systematic performance evaluation and continuous retroactive improvement, constitutes a mandatory workflow for AI readiness. The generation and centralization of data through a properly planned CDE constitute the indispensable foundation for this evolution [1] [8]. Therefore, the implementation of a CDE at the onset of a project initiates the structured collection of data, which naturally paves the way for the subsequent stages of analysis and validation required for advanced AI applications [8] [9].

Building upon these theoretical foundations, the present study proposes a specific technological solution designed to operationalize these concepts within the conceptual design phase. While the literature establishes the necessity of a CDE for data centralization, the framework developed in this research aims to go beyond passive storage by implementing a dynamic platform capable of synchronizing both graphic and non-graphic information. This solution addresses the planning deficit identified by Seyis [3] by instituting a rigorous data validation protocol from the project's inception, thereby satisfying the data quality prerequisites for AI adoption outlined by Dzhusupova et al. [15]. By structuring the information flow to support early stakeholder collaboration and automated compliance checking, the proposed methodology seeks to transform the CDE into an active engine for predictive analysis, ultimately resolving the economic paradox of design by ensuring that high-fidelity data is available when it has the maximum capacity to influence project outcomes.

It is important to emphasize that the primary innovation of this proposed framework does not reside in defining an exhaustive inventory of specific project deliverables—which remains a massive and variable undertaking depending on project scope. Instead, it focuses on establishing a rigorous and universal

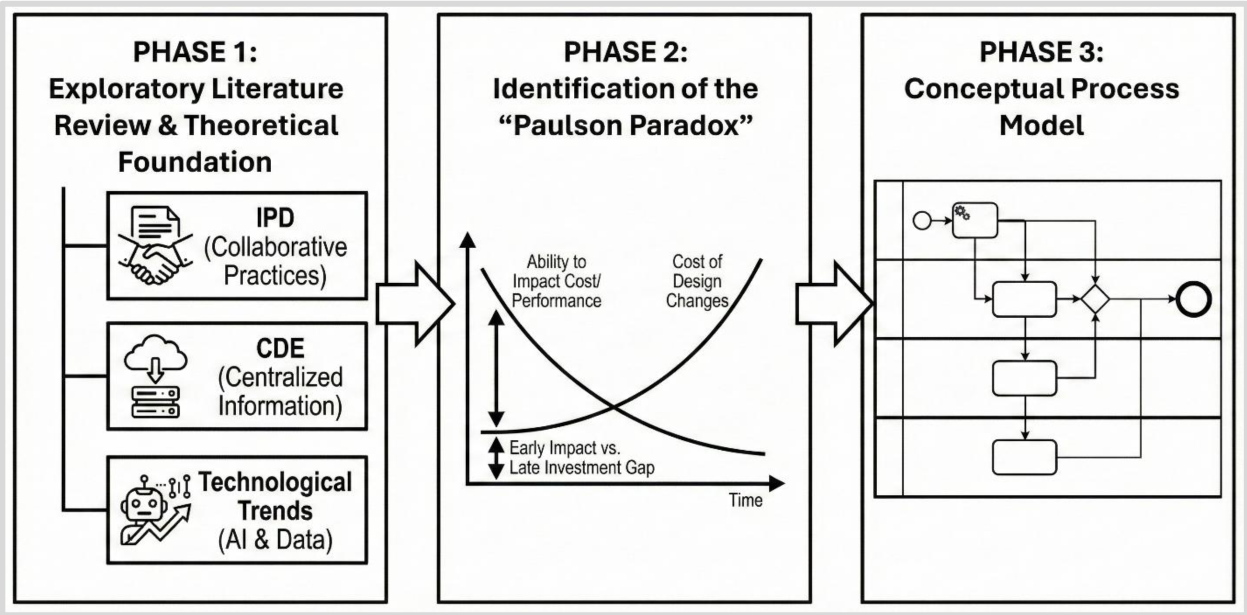

Figure 2. Schematic representation of the research phases, integrating IPD, CDE, and technological trends.

mechanism for information management. By institutionalizing 'Validation Gates' and 'Data Hygiene' protocols, the framework provides a structured architecture to ensure the creation of a reliable data corpus for AI implementation, regardless of the specific nature of the data being collected.

3 Methodology

The methodology of this study follows a qualitative and exploratory approach, structured into 3 main phases: an integrative literature review, the identification of industry paradoxes, and the proposal of a conceptual process model (Figure 2).

3.1 Phase 1: Exploratory Literature Review and Theoretical Foundation

The first stage involved a systematic search for literature regarding the management of data and equipment in complex infrastructure projects. The review focused on 3 core pillars:

IPD: Analyzing collaborative practices and early involvement of stakeholders as defined by the AIA [6] and the principles of concurrent design.

CDE: Investigating the benefits and challenges of centralizing information to improve coordination and productivity.

Technological Trends: Exploring the integration of AI for predictive project management and the requirements for high-quality data corpuses.

3.2 Phase 2: Identification of the "Paulson Paradox"

A critical analysis was conducted using the Paulson Curve [7] to identify a fundamental contradiction in the construction industry. This phase involved mapping how the ability to impact cost and performance is highest during the preliminary design phase, yet industry practices often neglect investment at these early stages. This analysis served as the justification for the proposed process workflow, which emphasizes clear roles and essential tool usage from the project's inception.

3.3 Phase 3: Conceptual Process Model

The final stage (Figure 3) consisted of developing a structured workflow for data transformation and validation during the design phase. The modeling process followed these technical criteria and steps:

Maturity Level: The model was developed at "Level 2" (Level 2 modeling functions as an operational bridge, detailing the specific sub-processes and exception-handling mechanisms that allow for the structured application of tools and roles defined at the project's outset), representing an intermediate approach with defined roles and a clear chronology of instructions.

Data Centralization: The flow was designed to feed into a centralized platform (CDE), ensuring that structured data is available for future AI implementation, as conceptualized in literature.

1. **Innovation & Data Framework**: The initial phase focused on developing validation gates

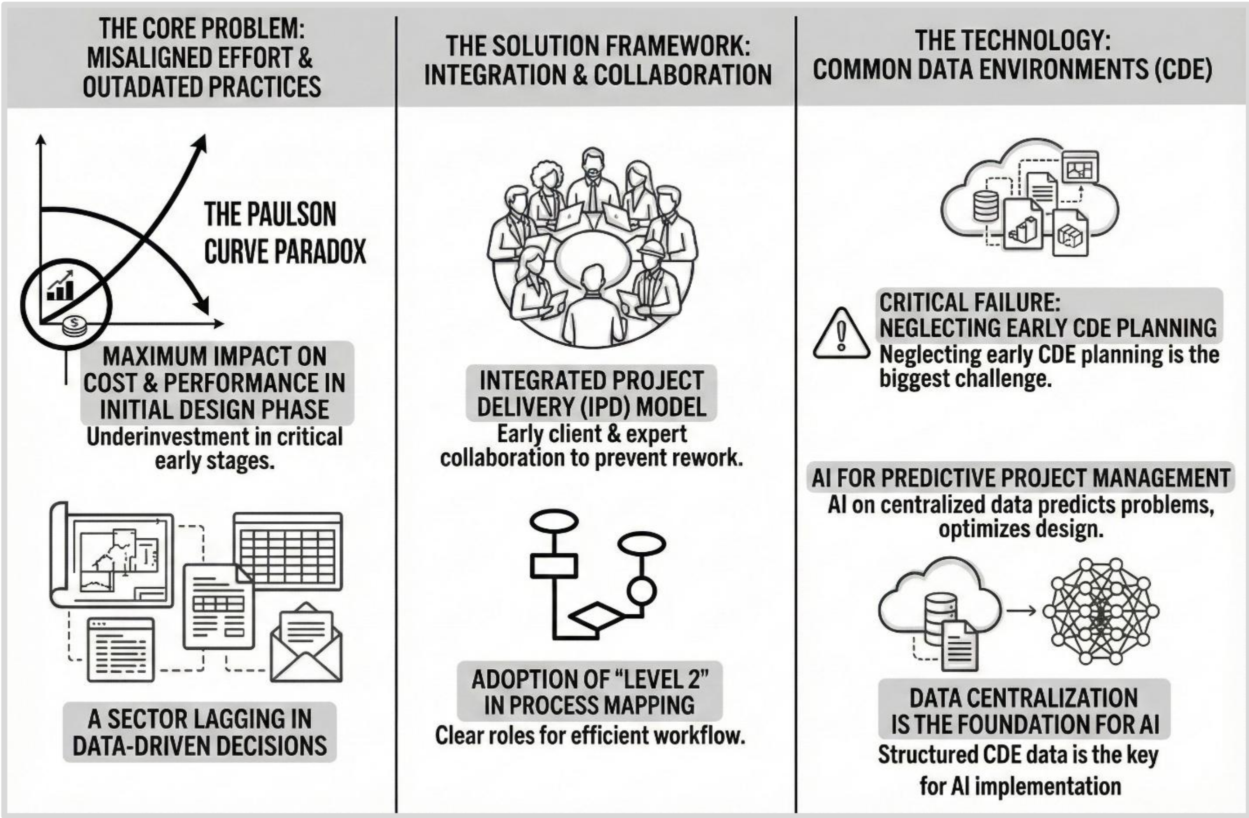

Figure 3. Core pillars of the proposed model: misaligned practices, collaborative solutions, and data-driven technology.

(for quality assurance) and protocols for data structuring and analysis. These stages represent the core innovation of this research, synthesizing existing literature into a practical solution designed for implementation within a CDE.

2. **Process Mapping**: The authors conducted a detailed mapping of the dataflow in the conceptual design phase, using a small Toronto-based architecture firm (5–10 employees) specializing in small-scale single and multi-family residential buildings as a case study (Figure 4). Although modeled after a specific firm, the workflow reflects the researchers' experience with industry-standard practices common across similar architectural offices.
3. **Integration & Practical Application**: In the final stage, the innovations from step 1 were integrated into the workflow mapped in step 2.

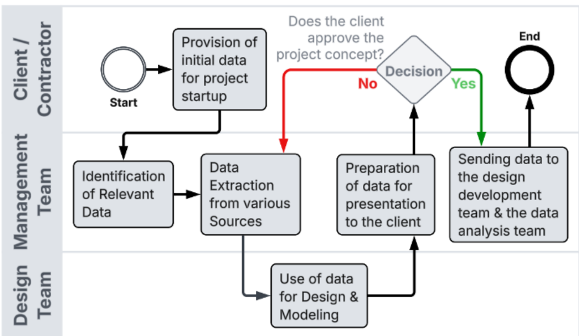

Figure 4: Existing dataflow of the conceptual design phase

4 Results

Based on the theoretical review, these proposed steps constitute the core innovation of this research. As illustrated, the proposed modules are divided into two **primary functions (Figure 5):**

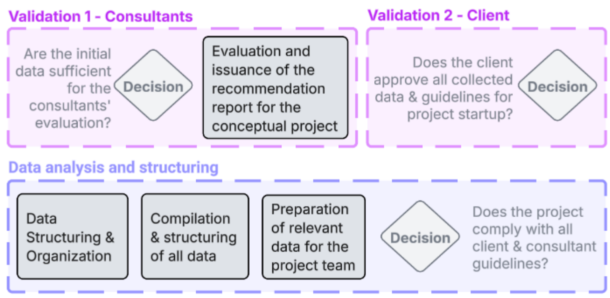

Figure 5: Proposed data structuring and validation gates.

1. **Data Analysis and Structuring:** A sequence designed to organize, compile, and prepare relevant data prior to any modeling efforts, ensuring compliance with client and consultant guidelines.
2. **Validation Gates:** Decision nodes that require explicit approval from technical consultants (Validation 1) and the client (Validation 2) before the project can proceed to the next phase.

These gates/steps represent the synthesis of how collaborative IPD principles and CDE data management can be practically applied to initial project stages. Implementing these specific modules within a CDE establishes a reliable "single source of truth," thereby opening future pathways for the utilization of AI in the design process.

Integrating these gates (Figure 5) into the firm's existing dataflow (Figure 4) illustrates how the proposed modules can be implemented in a real-world scenario (Figure 6). The developed workflow integrates practices inspired by the IPD model. It necessitates the active involvement of the client in decision-making and the early participation of technical experts—such as HVAC specialists, acousticians, and fire safety consultants—prior to the development of complex geometry. This early coordination allows for the management of constraints and the development of a holistic project vision, thereby avoiding costly downstream modifications.

4.1 Data Transformation and Validation

The mapped process relies heavily on a technological centralization strategy. The review of literature cited in this paper confirms that a centralized platform—specifically a CDE—is required to valorize the varied nature of collected data and facilitate access for all stakeholders.

The proposed framework addresses this lacuna by mandating the integration of centralization solutions at the very onset of conception. By synchronizing graphical (BIM) and non-graphical information, the strategy optimizes coordination between actors and increases productivity throughout the project lifecycle.

4.2 Centralization Strategy

The implementation of this structured framework serves as a foundational step for the integration of AI in construction. While AI offers promising capabilities for predicting issues and identifying recurrent patterns in complex infrastructure, its current deployment is hindered by the lack of structured data.

This framework specifically addresses:

- **Constitution of a Data Corpus**: The workflow ensures the creation of a sufficiently large and accessible data corpus.
- **Data Hygiene**: The "Structuring and Organization" phase implements a rigorous process of analysis, cleaning, and validation to guarantee data quality.
- **Systematic Training**: By standardizing the input data, the framework allows for the methodical training of predictive models.

Therefore, the implementation of this technological solution initiates the structured collection of data, which is the indispensable foundation for the future evolution of AI in project management.

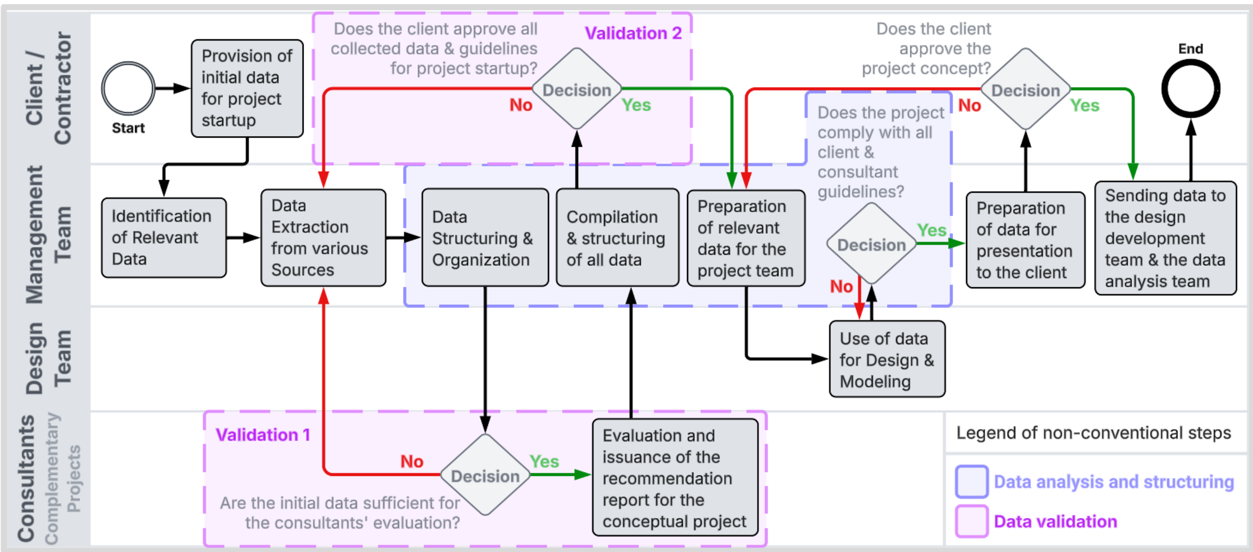

Figure 6. Early-stage Data-Driven Design Process Workflow

4.3 Expected Impact and Measurable Performances

Because the proposed solution is currently a conceptual framework, its practical deployment must be monitored to validate its efficacy. For future applications in real-world CDE environments, the expected impacts of adopting this integrated workflow include a substantial reduction in late-stage rework and the creation of a reliable database for machine learning models.

To quantify these impacts, future implementations should track specific Key Performance Indicators (KPIs) and measurable performances:

- **Deliverable Adherence Rate**: Measuring the percentage of deliverables that meet the exact specifications outlined in the MIDP (Master Information Delivery Plan) and TIDP (Task Information Delivery Plan) during the conceptual phase.
- **Reduction in RFI (Request for Information) Volume**: Tracking the decrease in technical queries during the detailed design and construction phases, which would indicate that constraints were successfully resolved during the early validation gates.
- **Data Completeness and Quality Score:** Utilizing automated CDE auditing tools to measure the percentage of structured, standardized data available at the end of the conceptual phase, which serves as a metric for "AI-readiness."
- **Cost Predictability:** Comparing the estimated conceptual budget against the final construction cost to measure the economic impact of early data validation.

5 Conclusion & Limitations

‘The development of this framework highlights a fundamental contradiction in the industry, the "Paulson Paradox." Although the Paulson curve is widely cited to justify front-loading design efforts, practical application reveals a systemic lack of investment in these decisive preliminary stages. This negligence compromises overall project efficiency and necessitates costly modifications during advanced stages.

Nevertheless, the proposed flowchart is currently conceptual and has not yet been validated. Therefore, while logic aligns with established literature on IPD and BIM, empirical validation through case studies is necessary to measure the framework's impact on actual project KPIs.

The construction sector remains surprisingly delayed in data-driven decision-making compared to other industries that rely on rigorous historical data analysis. The absence of centralized, accessible data repositories constitutes a major handicap that explains the persistence of empirical methods and chronic inefficiency.

Success in modern construction projects relies on two complementary pillars: a structured approach and harmonious collaboration. However, technological tools (such as CDEs and BIM) remain limited in their capacity to enhance performance if the underlying information flows are not carefully mapped and validated. The proposed framework argues that the progressive implementation of a centralized, reliable database—starting from the conceptual phase—is the necessary lever to shift the industry from a reactive to a predictive state.

Furthermore, the application of this flowchart represents only an initial step toward the evolution of the AEC sector into a truly data-driven industry. Given the massive volume of data generated in modern infrastructure and the fluid dynamics of the sector—characterized by constant changes in project scope and design processes—manual data management remains insufficient. In this context, the integration of Artificial Intelligence for data treatment, adaptation, and analysis becomes imperative. AI is required not only to predict outcomes but to manage the "exponential increase in data complexity" that traditional workflows struggle to handle. As the project environment evolves, AI models can provide the necessary agility to analyze and clean data corpuses in real-time, allowing the centralized database to remain a reliable "single source of truth" even amidst shifting constraints. Ultimately, shifting the industry from a reactive to a predictive state requires this synergy between structured human processes and automated machine intelligence.

In conclusion, the successful digital transformation of the construction sector depends on more than technological adoption; it requires a collective commitment to a collaborative organizational culture. Prioritizing the systematic registration and centralization of data from the earliest stages of design is essential to move beyond empirical methods and achieve a more efficient, integrated, and data-driven future for complex infrastructure projects.

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