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A NOVEL FRAMEWORK FOR STRUCTURING AND AUTOMATING SCHEDULE-READY DATA FROM BIM FOR ADVANCED CONSTRUCTION SCHEDULING

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SUMMARY*: Construction scheduling still relies on fragmented manual preparation of activity, location, and labor data, even when BIM models are available. This paper addresses the challenge of systematically structuring and automatically extracting enriched BIM data to enable schedule-ready inputs for advanced construction scheduling. The paper develops an Enhanced Planning and Scheduling (EPS) based framework and applies it through BIM enrichment, spatial decomposition, classification mapping, labor-hour calculation, and Dynamo-based data extraction in a building case. The framework generates a reusable dataset that links model elements to zones, floors, workspaces, activity categories, labor hours, and EPS priority IDs for downstream scheduling. The paper's contribution lies in providing a structured EPS-based framework that transforms enriched BIM data into reusable schedule-ready inputs linking locations, activity categories, labor hours, and priority logic for downstream scheduling. Further research is needed to validate the framework across various project types and scheduling workflows, and to examine dynamic model–schedule updating and AI-assisted scheduling integration.*

KEYWORDS*: construction scheduling, building information modeling (BIM), automation, BIM data, schedule-ready data.*

REFERENCE*: Amarkhil, Q., & Elwakil, E. (2026). A novel framework for structuring and automating schedule-ready data from BIM for advanced construction scheduling. Journal of Information Technology in Construction (ITcon), 31, 651-673. https://doi.org/10.36680/j.itcon.2026.029*

1. INTRODUCTION

Effective and reliable scheduling in construction management is critical for the timely and cost-effective completion of projects. Traditionally, construction scheduling has relied heavily on manual planning methods such as the Critical Path Method (CPM) and linear scheduling. Traditional scheduling methods in construction, characterized by their rigidity and lack of collaboration, lead to inefficiencies and delays (Ballard & Tommelein, 2021; Hall et al., 2022; Parsamehr et al.,2023). Traditional methods increasingly show limitations in integrating modern construction management approaches and advanced technologies (Ballard & Tommelein, 2021; Soman & Molina-Solana, 2022).

This has prompted the adoption of collaborative and adaptive management strategies and methods, such as Lean, Agile, and 5S methodologies, providing flexibility and continuous improvement to overcome traditional methods limitations (Ribeiro et al., 2010; Shaqour, 2022; Sheikhkhoshkar et al., 2023). However, these methods present challenges for fully automating and optimizing project timelines, work sequences, and resource allocation, as they emphasize iterative human input and experiential decision-making often limits systematic data integration, scalability, and predictability.

This gap highlights the need for a structured and technology-enabled scheduling approach that retains flexibility while enabling greater automation and consistency. To address this, Amarkhil and Elwakil (2024) proposed the Enhanced Planning and Scheduling (EPS) method, which introduces structured activity categorization, spatial decomposition of project work, and quantified labor-based planning metrics to support consistent schedule development, improve reliability, and reduce manual planning effort. To support structured scheduling methods, such as EPS, and enhance construction scheduling automation, it is essential to streamline the process by automating the capture of scheduling data directly from the project's BIM or other digital models with the important details in a standardized structure.

Furthermore, literature shows that advanced technologies remain underutilized in construction planning and control practice despite their potential (Amer et al., 2021; Singh et al., 2023). The development of BIM and automation technologies offers a promising solution to the scheduling challenges. Researchers have identified the potential of automated scheduling systems to enhance the efficiency and reliability of construction planning (Parsamehr et al., 2023).

Faghihi et al. (2015) and Amer et al. (2021) assert that integrating BIM data with optimization techniques significantly advances construction management, streamlining project planning, reducing manual errors, and enhancing overall project efficiency. Recent studies further highlight BIM's role as a dynamic and reusable source of construction information for downstream automation and coordination (Disney et al., 2023; Kone & Mahesh, 2025; Alves et al., 2025), which can support more accurate and interactive scheduling at the site level. However, the practical integration of BIM-based automation with existing construction planning and scheduling methods remains challenging because schedule-relevant data are often fragmented and lack a standardized, structured format suitable for advanced scheduling applications. One critical barrier to this integration is the fragmented nature of data preparation processes and the lack of standardized, structured BIM data extraction methods (Torres-Calderón et al., 2019; Tallgren et al., 2020; Pishdad & Onungwa, 2024). To support structured scheduling methods, such as the Enhanced Planning and Scheduling (EPS) approach, it is essential to streamline the process by automating the extraction of schedule-relevant information directly from BIM or other digital models into a standardized, structured format suitable for scheduling automation.

Therefore, this paper proposes to address a practical gap in current scheduling workflows, where schedule-ready activity, location, and labor data still depend heavily on manual preparation even when BIM models are available. The developed framework addresses the challenge of fragmented scheduling processes caused by multi-layered manual data entry and reliance on planner experience. This approach addresses the need for compatible and innovative scheduling strategies utilizing the full potential of advanced technologies and optimization techniques, minimizing the need for manual and experience-based inputs. This paper aims to develop a structured framework that automates the extraction of schedule-relevant data from enriched BIM models to advance scheduling automation, feasibility, and reliability, which can be effectively integrated with current planning methods and optimization techniques. This problem is particularly relevant to contractors, planners, and BIM managers, especially on projects characterized by densely modeled elements and multiple sections and buildings. In such contexts, manual structuring of BIM data becomes time-consuming, inconsistent, and difficult to reuse.

The research question addressed in this paper is: How can BIM data be enriched for scheduling purposes and systematically structured and automatically extracted to generate schedule-ready inputs for advanced construction scheduling?

1.1 Background and Technological Foundation for BIM-Based Scheduling Automation

Integrating advanced technologies such as computer-aided modeling and BIM has significantly driven the development of automated scheduling in construction. Early efforts demonstrated improved schedule reliability by combining 3D models with scheduling processes (McKinney & Fischer, 1998). This advancement has been expanded by incorporating BIM in construction planning and scheduling, according to a study conducted by Park and Cai (2015). They developed a framework to auto-generate construction schedules using BIM models, and Jeong et al. (2016) integrated BIM into simulation processes for better productivity prediction.

BIM has been recognized as a transformative tool in construction (Merschbrock & Munkvold, 2014; Martins et al., 2022; Awe et al., 2025). BIM enhances project scheduling and planning by allowing stakeholders to visualize construction project information in 3D, 4D, and 5D. Integrating BIM with various rule and logic-based techniques and algorithms has led to significant advancements, including AI and machine learning, enabling predictive analysis and more accurate scheduling (Pan & Zhang, 2023; Heidari et al., 2023). This integration has also led to semi-automated schedule generation (Fazeli et al., 2022; Le et al., 2023). In this paper, semi-automated scheduling refers to workflows in which part of the structured data extraction and the mapping of BIM elements to work areas, activity categories, and productivity information is automated. Planners still define essential assumptions, such as constraints and productivity rates. Automated scheduling often requires integrating BIM with construction methods using BIM tools, scheduling algorithms, and computational methods. Wu and Ma (2023) integrated BIM with a genetic algorithm (GA) and ontology constraint rules to generate construction schedules automatically. Open-source tools such as Revit Dynamo have enhanced BIM's functionality by allowing for custom scripting and automation, which is essential for improved planning and control (Ahmed, 2019; Mazars & Francis, 2020; Yang et al., 2022). While prior studies have already explored BIM-based automation and schedule generation (Park and Cai, 2015; Wu and Ma, 2023), this paper focuses on the structured preparation of schedule-ready inputs through enriched BIM data and EPS logic.

Moreover, the need for combining automation and optimization (Amer et al., 2021) has led to using optimization techniques, machine learning algorithms, constraint programming, and priority rules in automating and enhancing construction project planning and scheduling. These techniques automate and optimize the process to improve productivity and create more reliable work plans. Hua et al. (2022) utilized genetic algorithms to optimize resource-constrained schedules, showing the effectiveness of algorithmic approaches in scheduling. Camacho et al. (2018) applied constraint programming for its computational efficiency to enhance scheduling. Tang et al. (2014) utilized linear scheduling and constraint programming techniques to solve schedule control problems. These studies highlight the increasing use of advanced technologies and techniques in construction project planning and scheduling. While these methods often enhance efficiency and reliability, their effectiveness can be influenced by the extent of automation, the need for manual data inputs and data structure required, and the planner's expertise in identifying activity dependencies and attributes.

Although there is potential to enhance further automating and optimizing construction scheduling with technology, there are still challenges to achieving this. Optimization and logic-based planning and scheduling often rely on manual input, where human experts manually define activity, dependencies, characteristics, and process templates (Amer et al., 2021). BIM-based scheduling tasks like estimating activity durations and identifying successors and predecessors heavily depend on the planner's experience (Parsamehr et al., 2023). Despite technological advancements, the essential role of professional expertise and judgment in the scheduling process persists. This dependency on manual data entry and the absence of a structured approach for defining activities and their spatial attributes limit the automation potential of these methods. The prevalent manual input methods in scheduling systems restrict their ability to fully leverage advanced technologies (Amer et al., 2021). This gap highlights the need for a data entry approach that can automate and optimize planning and scheduling tasks more effectively. Recent research further emphasizes the importance of standardized and structured extraction of BIM data for enhancing scheduling effectiveness (Tallgren et al., 2020; Pishdad & Onungwa, 2024). Advances in BIM and tools that provide programmable access through APIs and custom scripts, such as Revit Dynamo, facilitate automated handling of scheduling data from BIM models, enabling more efficient and accurate schedule creation and management. Effective scheduling automation also depends on how well BIM data can be accessed, extracted, and structured. Table 1 summarizes common BIM data-handling methods relevant to schedule-related information extraction and to position the proposed framework and Revit Dynamo application within this broader context.

Table 1: Common Methods and Tools for Data Handling in BIM.

Method	Tools
Direct Export/Import	IFC, DWG, DXF (Import/Export functions in BIM software)
APIs and Custom Scripts	Python, Macro, C# scripts using BIM software APIs
Data Exchange Formats	COBie (Construction-Operations Building Information Exchange)
BIM Collaboration Formats	BCF (BIM Collaboration Format)
Plugins and Extensions	BIM software plugins and extensions (e.g., Revit add-ins)
Database Queries	SQL and other database query tools

Dynamo, an open-source programming tool, can represent Revit API, custom scripts, plugins, and extension categories as it automates and extends BIM capabilities through its interface and integration with BIM software APIs. However, despite this advancement, there are still challenges to developing and practical validation of BIM-based automated scheduling due to a lack of an enhanced data automation framework and a compatible scheduling strategy (Tauscher et al., 2014; Torres-Calderón et al., 2019; Kolarić et al., 2022). The developed framework in this paper integrates BIM with the Enhanced Planning and Scheduling (EPS) method and demonstrates the critical role of structured data extraction in addressing these challenges. Location-based planning and location-based management system (LBMS) provide an important reference point for this paper because they structure production by workspace and workflow rather than by activities alone and help address well-known CPM limitations related to flow continuity and continuous resource use (Olivieri et al., 2018). In parallel, openBIM interoperability extends beyond file transfer alone, and IFC and BCF are better understood within the broader buildingSMART-aligned ecosystem of structured information exchange and coordination workflows (Khorchi & Boton, 2024; Kone & Mahesh, 2025). Compared with downstream 4D coordination and schedule-generation or LBMS studies, this paper focuses on the upstream structuring and extraction of schedule-ready BIM data.

1.2 Structuring Activities and Work Areas Using EPS Logic

The Enhanced Planning and Scheduling (EPS) method supports structured scheduling and resource analysis by employing a combinatorial optimization concept with a systematic breakdown of project work and work areas, using labor hours as a base unit for work planning to streamline the scheduling process and improve automation readiness and activity sequencing (Amarkhil & Elwakil, 2024).

A labor hour is a unit of measure representing one hour of work a laborer performs to complete the assigned task. Alternatively, the same planning logic can be extended to resource hours for machines, equipment, or robotic systems when non-labor resources are considered. Labor hours are used as a metric in the Enhanced Planning and Scheduling (EPS) approach for construction projects because they provide a precise and quantitative measure for estimating the time and resources required to complete tasks. Focusing on labor hours allows for standardizing planning input and enabling progress and target-driven scheduling. It addresses potential issues related to estimating activity duration and enables dynamic planning. Using labor hours facilitates a standard unit for scheduling. It helps plan and measure work progress more dynamically by determining daily or weekly labor hours to be completed in delivering the project.

Furthermore, the EPS approach categorizes project work activities into Project Critical, Site Critical, Site General, Site Finishing for building structures, Floor Production, Space Production, Connecting Activities, and Finishing Activities, enabling enhanced planning and control, realizing the project's complexity, and determining the optimal work sequence. Figure 1 shows the breakdown of the project activities based on the EPS approach.

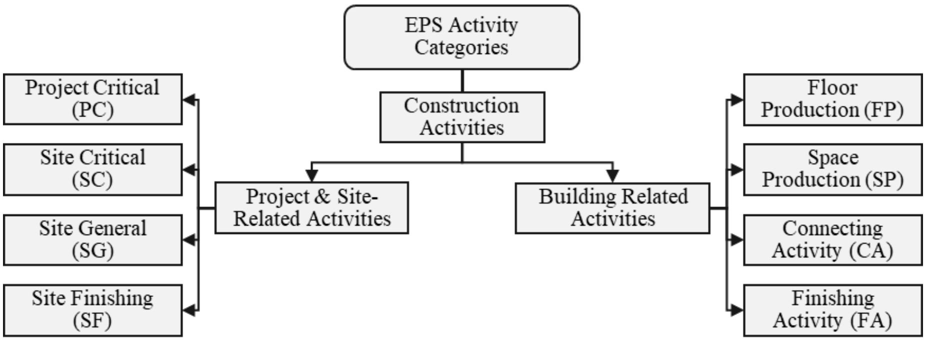

Figure 1: Construction Work Activity Categories Based on the EPS Approach.

Project site-level activities:

- Project Critical (PC): Activities and tasks needed before production work begins, like site access and temporary offices.
- Site Critical (SC): Underground and other activities and tasks dependent on different zones, such as drainage and MEP systems.
- Site General (SG): Activities and tasks not dependent on other zones' work, like subgrade work and equipment installation.
- Site Finishing (SF): Final activities and tasks on and above the surface, like landscaping and lighting.

Vertical structures and buildings level activities:

- Floor Production (FP): Activities and tasks needed to build the structure of floors and levels, such as building foundations, columns, and slabs.
- Space Production (SP): Activities and tasks dividing floors into spaces, like walls and frames.
- Connecting Activities (CA): Activities and tasks extended from one floor or zone to another, like MEPF rough-in.
- Finishing Activities (FA): Construction activities and tasks not included in the other categories, like tiling, painting, and roofing.

Alongside this categorization, EPS methodically breaks down project work areas into work zone, work floor, and workspace, considering task interdependency and sequence. This facilitates the planned work at its location for easy sequencing and resource allocation. Figure 2 shows the breakdown of the EPS-based project work area.

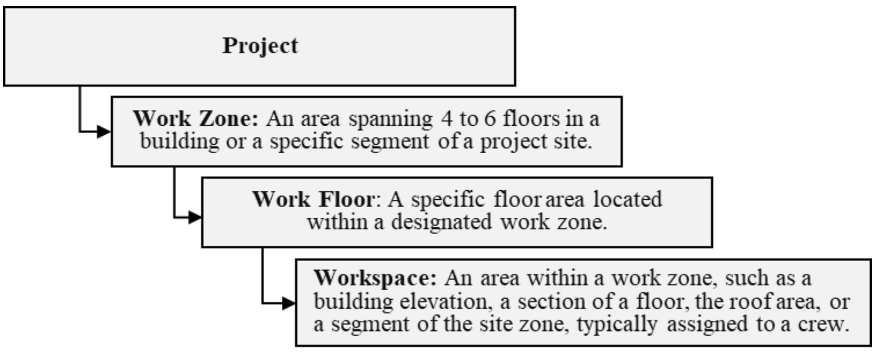

Figure 2: Project Work Areas Breakdown.

The purpose behind categorizing construction activities into groups and breaking down their work areas in the EPS methodology is to facilitate more standardized planning and efficient project management. This categorization and focus on labor hours enhance the ability to effectively plan and control project work, offering insights into resource allocation, dynamic scheduling, and progress tracking. It aligns with the goals of enhanced automation in construction by providing a structured yet adaptable framework to handle the complexities of construction projects (Amarkhil & Elwakil, 2024).

These features make EPS compatible for integration with BIM and automation tools since the input data for the schedule is captured from the project BIM model in a structured format with comprehensive attributes, and project activities are linked to their actual location. In addition, EPS uses labor hours (LH) or resource hours to make the schedule instead of manually estimating each activity duration and determining their dependencies using traditional methods. It helps overcome the challenge of construction project schedule automation and standardization. In this paper, labor hours are calculated using material quantities extracted from the BIM model and crew productivity rates assigned externally to the corresponding work items, which are used as the foundational unit for generating scheduled tasks automatically. To further enable structured and logic-based scheduling, each activity in EPS is assigned a unique Priority ID, which encodes information about its type, location (zone, floor, workspace), and execution order. These IDs help automate activity sequencing and reduce reliance on manually defined relationships (Table 2).

Table 2: Activity Sequencing and Priority Assignment.

Activity Priority ID			
Activity	Workspace	Floor	Work zone
Activity rank within the assigned workspace	Workspace rank within the designated floor or site	Floor rank within the assigned work zone	Work zone rank within the overall project

1.3 Gaps in the Current Literature

BIM has been widely adopted for design coordination, visualization, and quantity takeoff. However, its application in generating structured data that is compatible with automated or logic-based construction scheduling remains limited. Despite decades of research, a standardized and widely adopted framework for preparing BIM data suitable for advanced scheduling systems has yet to emerge.

Amer et al. (2021) conducted a comprehensive review of three decades of construction planning research and found that most projects still rely on manual workflows. They emphasized that scaling automation remains difficult due to rigid data structures and a lack of systematized planning methods. Similarly, Doukari et al. (2022) observed that, although it is technically possible to automate the links between construction schedules and BIM models, in reality, the process still requires significant manual effort and technical expertise.

Tallgren et al. (2020) reported that available 4D BIM scheduling tools are primarily targeted toward expert users familiar with specialized planning and authoring software, making them impractical for broader adoption in multidisciplinary project teams. Malacarne et al. (2018), examining small and medium-sized enterprises (SMEs), confirmed that due to the absence of standardized scheduling practices, these firms often resort to developing their procedures, limiting BIM's utility for consistent scheduling.

These findings underscore a persistent gap: while BIM contains rich project data, its transformation into structured, automation-ready scheduling inputs remains fragmented, inconsistent, and heavily reliant on manual, project-specific workflows. The absence of standardized methods further limits consistency, benchmarking, and reuse. Addressing this issue is essential for enabling scalable, logic-compatible scheduling and broader integration with optimization and decision-support tools. Therefore, this paper proposes a structured framework, based on the EPS methodology, to extract schedule-ready data from BIM models automatically using spatial breakdown, labor-hour planning metrics, and activity classification, thereby reducing manual input and supporting logic-based scheduling.

2. METHODOLOGY

This paper presents a structured and automation-compatible framework that addresses the challenge of transforming enriched BIM data into schedule-ready inputs for advanced construction scheduling. This section details the design, integration, and application of the proposed framework, highlighting its components and operational logic. The proposed approach integrates the EPS approach with BIM, aligning with the complex and dynamic nature of construction projects. Figure 3 illustrates the flowchart of the study methodology.

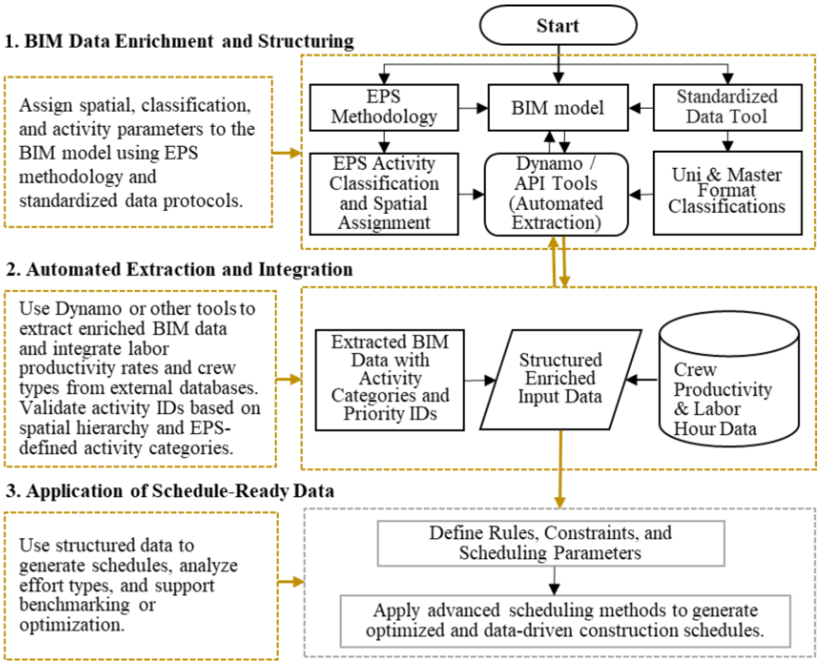

Figure 3: Workflow for BIM-based scheduling data preparation and application using EPS methodology.

The methodology operationalizes the BIM-EPS integration through three main stages:

- enrichment and structuring of BIM data using spatial, functional, and activity attributes,
- automated extraction and integration of structured scheduling inputs and
- utilization of schedule-ready data for advanced scheduling, optimization, and project effort analysis.

Figure 4 illustrates how the BIM and EPS components work together to auto-extract enriched BIM data for scheduling purposes.

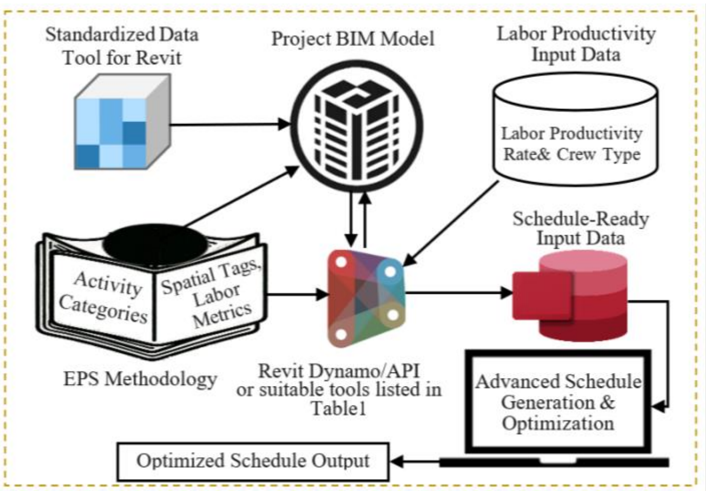

Figure 4: Framework for BIM Data Enrichment and Automation for Construction Scheduling.

The output of this process is a logic-compatible, schedule-ready dataset that can be used with various scheduling and optimization methods. It also supports deeper project analysis by categorizing activity types, estimating total required effort, and enabling benchmarking across project components and schedules.

2.1 Enrichment and structuring of BIM data

Building Information Modeling (BIM) provides comprehensive multidimensional datasets that can be leveraged for detailed project planning, visualization, and schedule preparation. Before extraction, the BIM model should be prepared and enriched with spatial, classification, and activity-related attributes so that the relevant elements can be associated with work areas and scheduling categories. The proposed framework enhances the BIM model by assigning spatial attributes (zone, floor, workspace), construction classifications (MasterFormat, UniFormat), and activity categories based on the EPS methodology. This enrichment process ensures that each model element contains the necessary parameters for downstream scheduling logic and resource planning.

The spatial structuring of project work areas follows the EPS breakdown shown in Figure 2. These work areas are critical for organizing and sequencing activities according to location and type. Once assigned, classification codes and activity categories are used to define work types and their associated productivity requirements. Standardized classification systems, such as MasterFormat and UniFormat, support the consistent organization of model elements and facilitate the automated structuring of scheduling input data. In this framework, MasterFormat codes are used to associate model components with standard work items, enabling the lookup and assignment of relevant crew types and productivity rates. UniFormat, which classifies elements by their functional roles in the building, supports logical grouping for activity categorization. Together, these systems enable the automated allocation of labor effort and enhance the structure and consistency of scheduling inputs.

As shown in Figure 5, a UML class diagram defines the relationships between BIM elements and their spatial and functional assignments. While BIM tools within MEP systems can define spaces and zones, these features are not typically structured or utilized for construction scheduling. The UML-based structure introduced in this framework enables the explicit modeling of zone, floor, and workspace relationships required for EPS-based scheduling and data extraction.

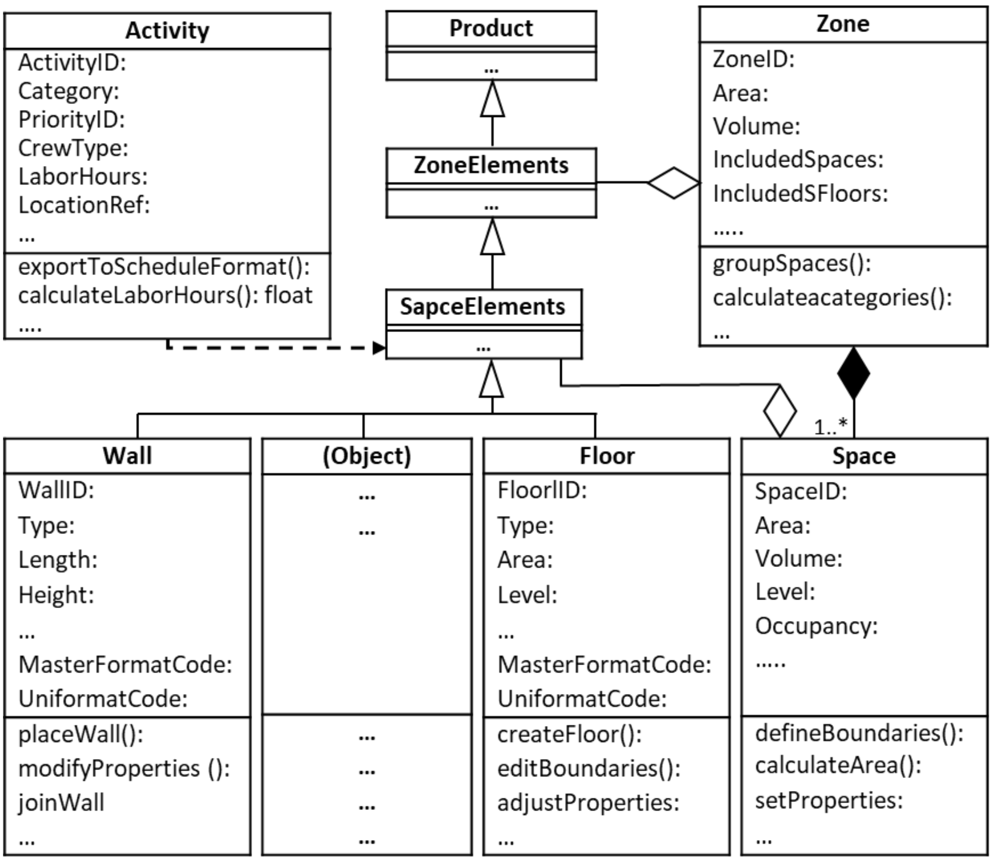

Figure 5: UML Class Diagram Representing BIM Element Structuring and Activity Generation for Automated Construction Scheduling.

Once enriched, the model data is extracted using visual scripting tools such as Revit Dynamo or other BIM data handling tools listed in Table 1. These tools enable automated extraction of both geometric and non-geometric parameters, including element ID, quantity, type, classification codes, and spatial location.

The resulting dataset includes labor productivity rates, assigned crew types, and total labor hours per activity, forming a comprehensive scheduling input that reduces reliance on manual planning and expert judgment.

2.2 Automated Extraction and Integration of Structured Scheduling Inputs

Building upon the enrichment and classification of BIM elements presented in Section 2.1, the second phase focuses on the systematic and automation-compatible extraction of structured data and its subsequent integration with labor productivity metrics. This process transforms semantically enriched BIM content into quantifiable, logic-ready scheduling inputs that form the backbone of the proposed EPS framework.

To extract the required data from the enriched BIM environment, this paper employed Revit Dynamo, a visual scripting interface that interacts directly with Revit's API. Dynamo enables the automated retrieval of both geometric parameters (e.g., area, volume, perimeter) and non-geometric metadata (e.g., element IDs, material definitions, classification codes, and spatial tags). These attributes are essential for organizing construction tasks by type and location and for associating them with the scheduling hierarchy defined during the enrichment phase. The developed Dynamo script, based on the data handling approaches summarized in Table 1, functions as a reusable template for systematically extracting schedule-relevant data from BIM models across different projects.

Before data extraction, spatial structuring was implemented using Revit's zone and space tools, which were repurposed beyond their conventional use in MEP modeling to establish a construction-specific zoning framework. However, Figure 5 presents a UML-based schema that extends this concept by formally modeling the relationships required for construction-oriented BIM structuring. This approach addresses the lack of built-in support in current BIM authoring tools for assigning hierarchical spatial attributes aligned with scheduling logic. Each model element was annotated with defined parameters denoting its associated workspace, floor, and zone. This structured spatial breakdown is visualized in Figure 6, which illustrates how classification metadata and locational attributes were embedded within the BIM model, a parking garage and office building project, to support downstream extraction and scheduling.

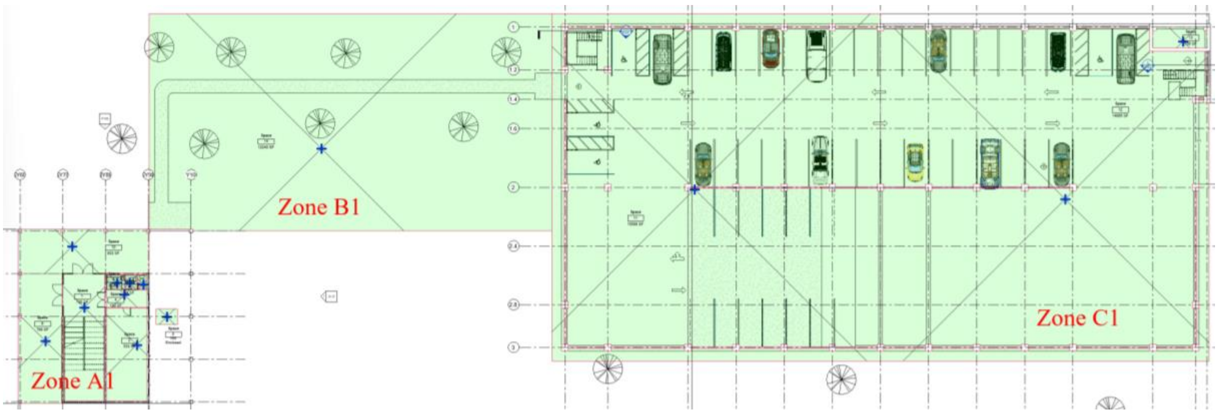

Figure 6: Project identified workspaces in three work zones.

Figure 7 further illustrates how spatial workspaces and zone identifiers were assigned within the selected BIM model, alongside the classification of elements using standardized UniFormat and MasterFormat codes.

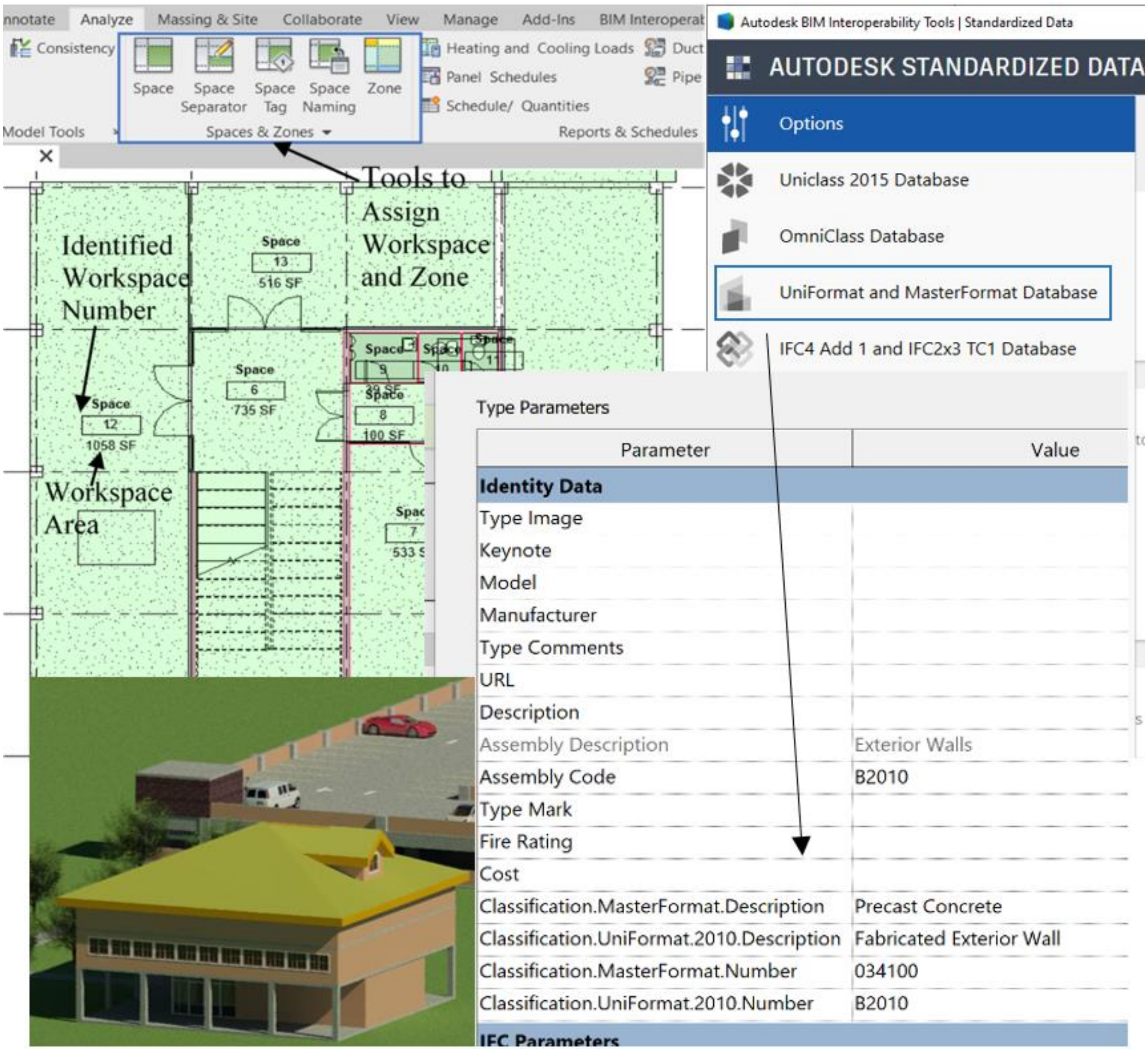

Figure 7: Assignment of workspace numbers, zone identifiers, and standardized classification codes (UniFormat and MasterFormat) within the BIM model.

Once the spatial and classification attributes were embedded in the model, a custom Dynamo script was developed to automate the extraction of structured element-level data. As illustrated in Figure 8, the script captures a comprehensive set of parameters, including element ID, element name, material quantities, perimeter, standardized MasterFormat and UniFormat classification codes, and the associated spatial designations (workspace, floor, and zone). The script is designed to be modular and extensible, allowing adaptation to extract additional project-specific attributes as needed. The resulting dataset, a subset of which is presented in Table 3, includes extracted wall elements annotated with their unique element IDs and corresponding workspaces. This structured output forms the basis for calculating labor requirements by linking element quantities to productivity rates and mapping each component to its assigned workspace, floor, and zone within the BIM model.

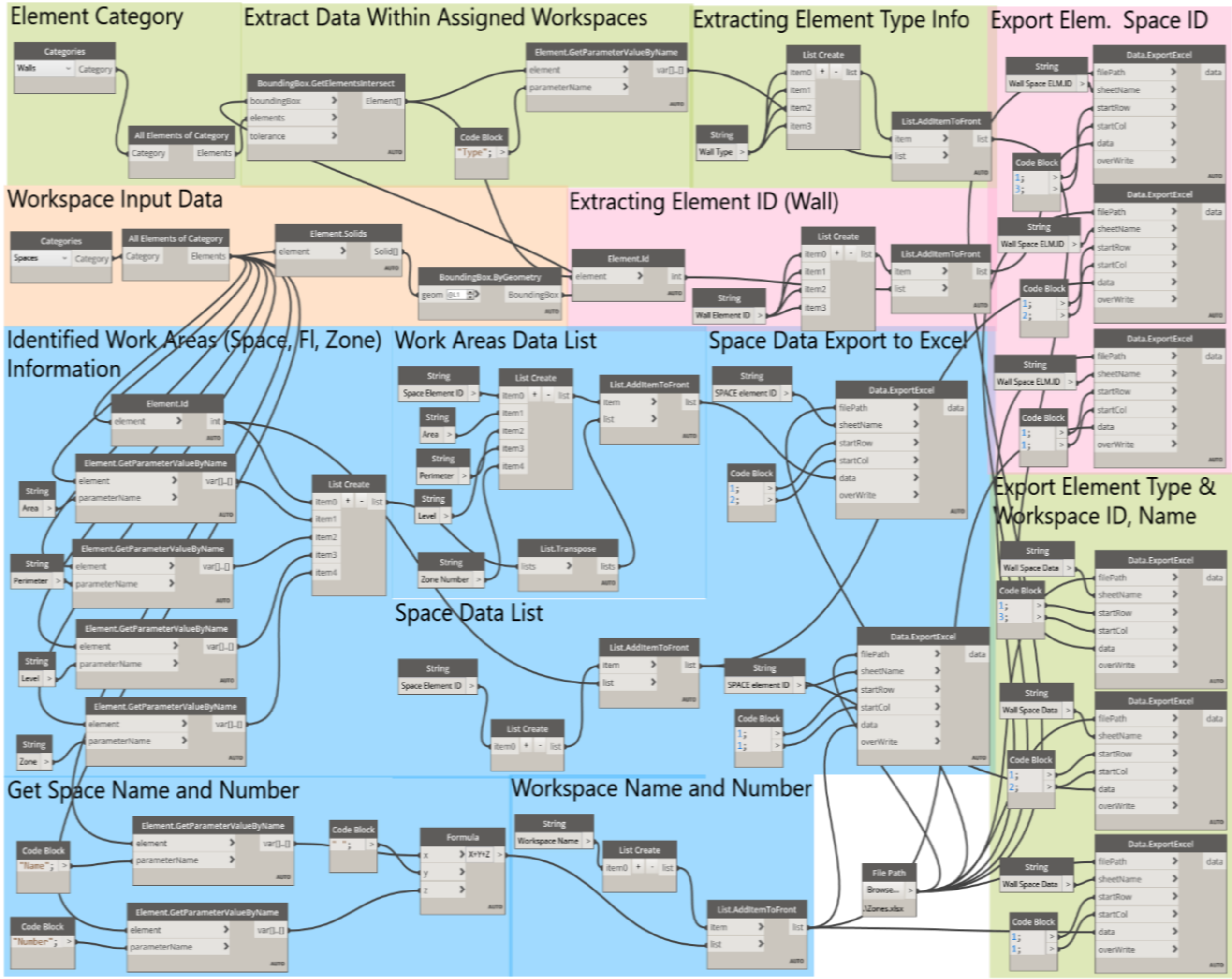

Figure 8: Dynamo script used to extract element-level quantities, classification data, and spatial assignments from the BIM model.

Table 3: Extracted wall elements with associated workspace and spatial assignment data.

Workspace Name	Space Elem.ID	Area (SFT)	Perimeter (FT)	Level	Zone Number	Wall Element ID	Wall Element ID	Wall Element ID	Wall Element ID
Space 1	685178	735	127	1FL_RB	A1	685178	642177	642178	642180
Space 2	685180	533	100	1FL_RB	A1	685180	642178	642179	642181
Space 3	685182	0	0	1FL_RB	A1	685182	642179	642180	642181
Space 4	685775	100	44	1FL_RB	A1	685775	642179	642181	667401
Space 5	685777	39	25	1FL_RB	A1	685777	642180	642181	669754
Space 6	685779	24	20	1FL_RB	A1	685779	642180	669754	669943
Space 7	685781	21	19	1FL_RB	A1	685781	642179	642180	669943
Space 8	686247	1050	170	1FL_RB	A1	686247	642178	642179	-
Space 9	686295	795	136	1FL_RB	A1	686295	642177	642544	642577
Space 10	686297	703	137	1FL_RB	A1	686297	642179	642180	642181
Space 11	686351	10179	1414	1FL_PG	B1	686351	363837	364519	412733
Space 12	686353	9601	1067	1FL_PG	B1	686353	364200	364230	364519
Space 13	686357	256	56	1FL_PG	B1	686357	391739	391778	391863
Space 14	686436	12240	464	ST1	C1	686436	-	-	-
Space 15	686768	502	95	2FL_RB	A1	686768	642182	642185	642188
Space 16	686771	497	95	2FL_RB	A1	686771	642182	642183	642188
Space 17	686773	522	95	2FL_RB	A1	686773	642183	642184	642187
Space 18	686775	498	95	2FL_RB	A1	686775	642184	642186	642187
Space 19	686777	498	95	2FL_RB	A1	686777	642182	642185	642186
Space 20	686779	1492	158	2FL_RB	A1	686779	642182	642183	642184
Space 21	686781	124	48	2FL_PG	B1	686781	391739	391863	391910
Space 22	687095	8502	428	2FL_PG	B1	687095	365452	390206	390283
Space 23	687097	5671	358	2FL_PG	B1	687097	365015	365180	365452
Space 24	687099	8538	437	2FL_PG	B1	687099	365015	390206	390283
Space 25	687101	5070	335	2FL_PG	B1	687101	363039	365015	365452
Space 26	687128	242	63	2FL_PG	B1	687128	363039	414932	-
Space 27	687134	4092	256	RF_RB	A1	687134	642218	642219	642220

Following this spatial and element identification, additional geometric and classification-related attributes were extracted to support activity definition and labor integration. Using the extended Dynamo script shown in Figure 8, the model was queried for each element's material description, dimensional properties (area, length, height), and associated MasterFormat and UniFormat classification data. These parameters are critical for matching building components to their respective construction tasks and productivity benchmarks. The resulting information is summarized in Table 4, which presents the quantified material data and classification codes for wall elements. This dataset enables the next step of assigning crew types and calculating total labor hours for each activity.

Table 4: Extracted element quantities, dimensions, and MasterFormat/UniFormat classification data.

Element ID	Element Material Description	Area (sf)	Length (ft)	Height (ft)	Master Format. Description	Master Num.	Uni-Format Description	Uni-Num.	Floor
642185	Generic - 8"	517.3	64.7	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	PG2
642186	Generic - 8"	517.2	64.7	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	PG2
642187	Generic - 8"	517.3	64.7	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	PG2
642188	Generic - 8"	517.2	64.7	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	PG2
642219	Generic - 8"	517.2	64.7	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	PG2
642220	Generic - 8"	517.2	64.7	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	PG2
642221	Generic - 8"	517.2	64.7	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	PG2
642544	Storefront2 Lab2	192.0	16.0	12.0	Glazed Curtain Wall	08 44 13.1	Fabricated Exterior	B2010.40	PG2
642577	Storefront	129.7	16.2	8.0	Glazed Curtain Wall	08 44 13	Fabricated Exterior	B2010.40	Roof
657220	Generic - 8"	84.0	10.5	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	Roof
657411	Generic - 8"	84.0	10.5	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	Roof
657489	Generic - 8"	80.0	10.0	8.0	Precast Concrete	03 40 00	Exterior Horizontal	B30	PG2
667401	Interior - 3 1/8" Partition (1)	186.6	15.6	12.0	Gypsum Board Area Separation	09 21 16.3	Interior Partition	C1010	2FL
668753	Interior - 3 1/8" Partition (1)	122.7	15.3	8.0	Gypsum Board Area Separation	09 21 16.3	Interior Partition	C1010	2FL
668887	Interior - 3 1/8" Partition (1)	122.7	15.3	8.0	Gypsum Board Area Separation	09 21 16.3	Interior Partition	C1010	2FL
668957	Interior - 3 1/8" Partition (1)	122.7	15.3	8.0	Gypsum Board Area Separation	09 21 16.3	Interior Partition	C1010	2FL
669071	Interior - 3 1/8" Partition (1)	122.7	15.3	8.0	Gypsum Board Area Separation	09 21 16.3	Interior Partition	C1010	1FL
669754	Soffit - 1/2" GWB & Metal	72.0	6.0	12.0	Partitions	10 22 00	Interior Partition	C1010	1FL
669943	Soffit - 1/2" GWB & Metal	72.0	6.0	12.0	Partitions	10 22 00	Interior Partition	C1010	1FL
673388	Soffit - 1/2" GWB & Metal	148.2	12.3	12.0	Partitions	10 22 00	Interior Partition	C1010	1FL
673756	Soffit - 1/2" GWB & Metal	28.1	2.3	12.0	Partitions	10 22 00	Interior Partition	C1010	1FL

To accommodate composite elements such as multi-layered walls or slab assemblies, an auxiliary Dynamo workflow was developed, as shown in Figure 9. This extended script extracts nested layer data from Revit element structures, capturing the material name, functional type, and thickness of each layer. These attributes are essential for accurate quantity takeoff and for assessing the construction complexity associated with multi-material assemblies, thereby supporting more precise labor estimation and planning.

The data extracted using the Dynamo script in Figure 9 is presented in Table 5, which details the internal composition of composite wall and slab elements. For each component, the table lists the element ID, wall type, layered material composition, individual layer thicknesses, and the functional role of each layer (e.g., finish, structure, insulation). This layered representation enables a deeper understanding of material buildup and supports activity-level labor assignment based on material functions and construction difficulty.

By capturing this information directly from the BIM model, the method reduces the need for manual decomposition of complex elements. It facilitates more accurate labor-hour calculations grounded in material-specific effort.

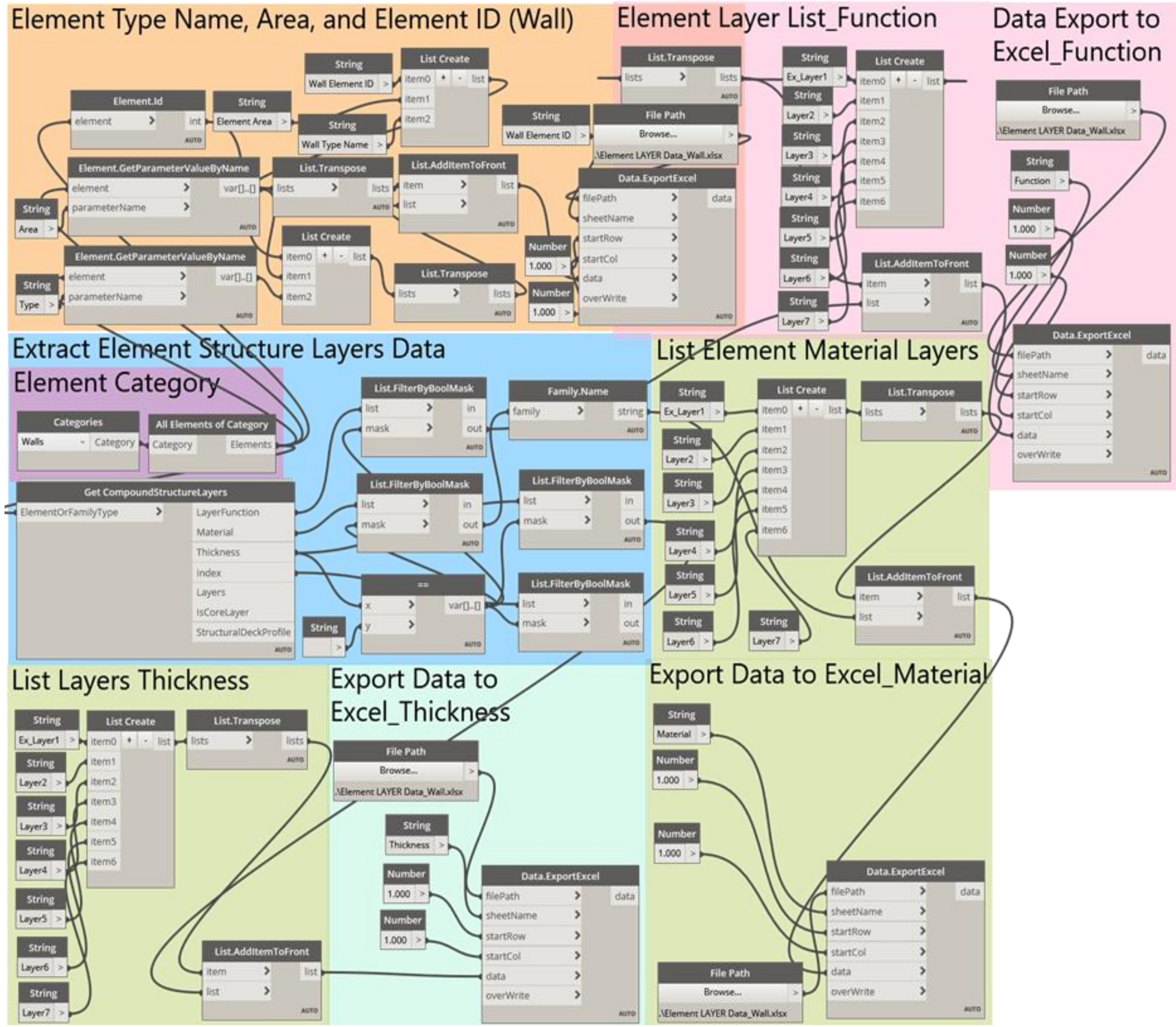

Figure 9: Dynamo workflow for extracting composite element layer data, including material, thickness, and functional role.

Table 5: Extracted composite element layer data with material type, thickness, and functional role.

Element Description			Composite Element Layers by Material Type			Layer Thickness (ft)			Layer Function		
Wall ID	Area(ft2)	Type Name	Exterior Layer1	Layer 2	Layer 3	Exterior Layer1	Layer 2	Layer 3	Exterior Layer1	Layer 2	Layer 3
362916	163.4	Exterior Brick on CMU	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
363039	152.3	Exterior Brick on CMU	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
363837	57.2	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
364200	208.8	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
364230	17.1	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
364519	764.417	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
364877	360.8	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
365015	826	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
365180	324.3	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
365317	21.14	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
365452	707.4	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
384565	145.6	Exterior Brick on CMU MJF	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
390206	211.2	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
390283	504	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
391739	462.6	Exterior Brick on CMU MJF	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
391778	184.7	Exterior Brick on CMU MJF	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
391863	437.2	Exterior Brick on CMU MJF	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
391910	159.3	Exterior Brick on CMU MJF	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
392712	85.8	Exterior Brick on CMU MJF	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
393041	138.6	Exterior Brick on CMU MJF	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
393669	127.5	Exterior Brick on CMU	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
393777	54.1	Exterior Brick on CMU MJF	Brick, Common	Air	Rigid insulation	0.25	0.04	0.21	Finish1	Insulation	Insulation
412733	823.6	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2
414809	40.7	Generic - 8"	Paint Sienna	Concrete, Precast	Paint Sienna	0.01	0.67	0.01	Finish1	Structure	Finish2

The classification metadata and geometric quantities summarized in Tables 3–6 form the basis for linking model components to standardized productivity benchmarks and labor resource requirements. This integration was achieved through a semi-automated hybrid workflow that combines Excel-based functions and a Python script to ensure scalability, flexibility, and consistency across varying project datasets. The integration process involves mapping each element's MasterFormat classification number (e.g., as listed in Table 4) to a curated RSMeans 2011 reference table, which includes corresponding crew types, unit productivity rates, and standardized activity descriptions. Using this mapping, extracted BIM quantities are divided by their respective productivity rates (e.g., SF/day, CY/day) to compute the total labor hours (LBH) for each task. These LBH values are then re-associated with the spatial context (workspace, floor, zone) of the elements, maintaining alignment with the structured breakdown shown earlier in Figures 6 and 7.

This calculation is executed using a dual-mode integration approach:

- Excel logic (e.g., VLOOKUP, INDEX-MATCH) is used for early-stage analysis and model iterations requiring manual review.
- A Python script automates batch calculations for larger BIM models, enabling efficient lookups, aggregation, and LBH generation across hundreds of elements.

Although the initial mapping of RSMeans codes required a one-time manual setup, the overall process is structured as a modular and reusable template, similar to Dynamo scripts, allowing for easy adaptation and repeated use across different BIM models or project types.

The computed labor inputs for first-floor structure or floor production (FP) activities are presented in Table 6, which details the tasks, crew types, productivity units, and spatial allocations. Each task is directly traceable to a BIM element, with the assigned zone, floor, and workspace clearly defined. This table provides a structured basis for evaluating labor demand by location and task type.

Table 6: First-floor FP tasks with crew types and estimated labor hours.

Element ID	Tasks Description	QTY	Activity Category	Unit	Crew	Daily Output	Total LBH	Space Number	Floor	Zone
642729	Column Installation	12	FP	L.F.	C11	0.6	7	8	1	A1
642630	Slab on Grade Formwork	1461	FP	L.F.	C1	175	268	1-10	1	A1
642630	Floor Slab Steel Work	34	FP	Ton	4Rodm	2.1	520	1-10	1	A1
642630	Floor Slab Concrete Pouring	315	FP	C.Y	C20	160	126	1-10	1	A1
410251	Beams Installation Type2_36"x36"	1	FP	Ea.	C11	22	4	14	1	C1
410084	Beams Installation Type2_16"x32"	1	FP	Ea.	C11	22	4	14	1	C1

To support downstream scheduling automation, each task was assigned a unique Activity Priority ID following the EPS hierarchy logic introduced in Section 1.2 and Table 2. These IDs encode information about task location, sequence, and category, enabling automated sequencing without reliance on manually defined dependencies. This enhanced dataset, integrating element IDs, quantities, crew assignments, and scheduling metadata, is presented in Table 7. It reflects the selected schedule-ready activity set for the first-floor FP activities, organized by zone, floor, space number, activity type, and labor attributes. Each row represents a discrete task, now embedded with a priority structure that supports algorithmic scheduling, optimization, and resource allocation.

Table 7: Schedule-ready activity dataset with priority IDs and labor productivity data.

Element ID	Activity Unique ID	Tasks Description	QTY	Activity Category	Unit	Crew	Daily Output	Total LBH	Space Number	Floor	Zone	Priority ID
642729	FP_A1_1028	Column Installation	12	FP	L.F.	C11	0.6	7	8	1	A1	5.2.1.1
642630	FP_A1_1033	Slab on Grade Formwork	1461	FP	L.F.	C1	175	268	1-10	1	A1	2.1.1.1
642630	FP_A1_1034	Floor Slab Steel Work	34	FP	Ton	4Rodm	2.1	520	1-10	1	A1	3.1.1.1
642630	FP_A1_1035	Floor Slab Concrete Pouring	315	FP	C.Y	C20	160	126	1-10	1	A1	4.1.1.1
410251	FP_A1_1042	Beams Installation Type2_36"x36"	1	FP	Ea.	C11	22	4	14	1	C1	7.1.1.3
410084	FP_A1_1044	Beams Installation Type2_16"x32"	1	FP	Ea.	C11	22	4	14	1	C1	8.1.1.3

Together, Tables 6 and 7 represent the culmination of the data enrichment, extraction, and integration process. They provide the foundational inputs required for logic-based and AI-supported scheduling. An instance of the application is discussed in Section 2.3, bridging the gap between digital modeling and automated planning systems.

2.3 Utilization of Schedule-Ready Data for Advanced Scheduling and Optimization

The following example illustrates how the extracted schedule-ready dataset can support downstream scheduling; the primary contribution of this paper remains its structured and automated preparation from BIM. The structured dataset generated through the proposed framework is not only suitable for advanced scheduling but also supports broader project effort analysis due to the granularity and structure of the data it provides. Specifically, the dataset includes multi-level spatial attributes (workspace, floor, zone), standardized classification codes (MasterFormat and UniFormat), task categories, element IDs, material quantities, and calculated labor hours. Each activity record is enriched with these values, allowing for precise filtering, sequencing, and resource evaluation. This structure enables activities to be grouped, prioritized, and analyzed across various dimensions of the project, eliminating the need for manual reprocessing or reclassification.

This section demonstrates how such structured BIM-derived data can be applied for logic-compatible scheduling and optimization. While not representing a full implementation of the entire project work, the scheduling use case presented here is based directly on the enriched dataset from the selected project application described in Section 2.2 and detailed in Tables 6 and 7. The structured input supports the application of logic-based and combinatorial scheduling techniques to explore feasible planning scenarios. As described earlier, the BIM model was divided into three independent work zones, with the structured dataset representing only the first floor. Leveraging the spatial assignments, activity categories, and estimated labor metrics, the analysis first applied combinatorial optimization techniques to evaluate alternative groupings and execution orders of work zones. Once a preferred zone configuration was identified, activity sequencing was carried out accordingly to reflect logical task dependencies and spatial constraints within each zone.

In this paper, combinatorial optimization refers to the process of selecting the most suitable option from a finite set of alternatives. In this context, it supports evaluating alternative zone execution plans against specific objectives, such as optimizing duration and balancing resource use. The dataset's structure enables this analysis by encoding each activity's zone, estimated labor hours, classification type, and spatial context. The maximum number of possible zone groupings, when order is not considered, is determined using Equation (1):

$$|\mathrm{P(A)}|=2^{n} \tag{1}$$

Where n is the number of independent work zones. For three zones identified as A, B, and C, Equation (1) provides the combinatorial basis for identifying possible zone groupings. Table 8 summarizes the grouping and sequencing scenarios considered in this paper.

In scenarios requiring defined sequencing among zones, such as those with lead-lag relationships or site-specific constraints, that is, when order matters, the number of possible ordered arrangements can be determined as follows:

$$\mathrm{P(n)} = \mathrm{n!} \tag{2}$$

For a subset of zones:

$$P(\mathrm{n,k})= \frac{n!}{(\mathrm{n}-k)!} \tag{3}$$

This formula calculates the number of ordered arrangements of k items (zones) selected from a total of n items (zones), as shown in Table 8.

Based on the dataset and combinatorial optimization analysis, Zone A was selected for the first stage, followed by Zone C and then Zone B. This order was determined by evaluating multiple structured parameters, including total labor hours, activity category types, and the ratio of finishing tasks to total labor hours. Zone A had the highest share of finishing activities, the greatest task-to-labor-hour ratio, and the highest labor intensity per unit area. These factors, combined with the assigned resource availability and minimal inter-zone dependencies, made Zone A the most efficient starting point in terms of resource utilization. However, alternative zone orders could be selected depending on available resources or project-specific preferences. This selected zone sequence served as the foundation for applying constraint-based activity scheduling in subsequent phases.

Once the zone execution order was determined, the next step involved translating this result into a constraint-based scheduling model. At the activity level, constraints such as task precedence, minimum crew sizes, workspace availability, and spatial access limitations were defined using the structured dataset. Each activity, already tagged with a unique Priority ID and spatial assignment, was sequenced accordingly. These constraints ensured that tasks were both logically and spatially feasible, taking into account interdependencies within and across zones. To simulate realistic scheduling outcomes, a constraint solver (e.g., constraint programming) was applied. The solver utilized the activity-level data outlined in Tables 6 and 7 to generate a logic-compliant schedule. Figure 10 presents the resulting Gantt chart, which visualizes the schedule derived from this process and highlights the sequence of activities across the prioritized zones. The schedule durations are based on an eight-hour working day, assigned crew sizes, crew daily output rates, Priority ID sequencing, spatial constraints, and permitted parallel work where crew and workspace conflicts do not occur. Based on the defined constraints and available resources, the resulting schedule produced a total project duration of 23 working days, sequencing only structure or floor production (FP) activities, as shown in Figure 10.

Table 8: Work zone combinations and sequences considered using combinatorial analysis and zone-level scheduling criteria.

Zone Grouping Scenario	EPS-Based Zone Combination and Lead/Lag Sequence	Description of Zone Execution Sequence	Ordered Sequence ID
1	{A}→{B}→{C}	Activities start in Zone A, proceed to Zone B, then proceed to Zone C.	1
	{A}→{C}→{B}	Activities start in Zone A, proceed to Zone C, then proceed to Zone B.	2
	{B}→{A}→{C}	Activities start in Zone B, proceed to Zone A, then proceed to Zone C.	3
	{B}→{C}→{A}	Activities start in Zone B, proceed to Zone C, then proceed to Zone A.	4
	{C}→{A}→{B}	Activities start in Zone C, proceed to Zone A, then proceed to Zone B.	5
	{C}→{B}→{A}	Activities start in Zone C, proceed to Zone B, then proceed to Zone A.	6
2	{A}→ {B, C}	Activities start in Zone A, then proceed to Zones B and C.	7
	{A}→ {C, B}	Activities start in Zone A, then proceed to Zones C and B.	8
3	{B}→ {A, C}	Activities start in Zone B, then proceed to Zones A and C.	9
	{B}→ {C, A}	Activities start in Zone B, then proceed to Zones C and A.	10
4	{C}→ {A, B}	Activities start in Zone C, proceed to Zone A, and Zone B.	11
	{C}→ {B, A}	Activities start in Zone C, proceed to Zone B, and Zone A.	12
5	{A, B} →{C}	Activities start in Zones A and B, then proceed to Zone C.	13
	{B, A} →{C}	Activities start in Zones B and A, then proceed to Zone C.	14
6	{A, C} →{B}	Activities start in Zones A and C, then proceed to Zone B.	15
	{C, A} →{B}	Activities start in Zones C and A, then proceed to Zone B.	16
7	{B, C} →{A}	Activities start in Zones B and C, then proceed to Zone A.	17
	{C, B} →{A}	Activities start in Zones C and B, then proceed to Zone A.	18
8	{A, B, C}	Activities start in Zones A, B, and C.	19
	{A, C, B}	Activities start in Zones A, C, and B.	20
	{B, A, C}	Activities start in Zones B, A, and C.	21
	{B, C, A}	Activities start in Zones B, C, and A.	22
	{C, B, A}	Activities start in Zones C, B, and A.	23
	{C, A, B}	Activities start in Zones C, A, and B.	24

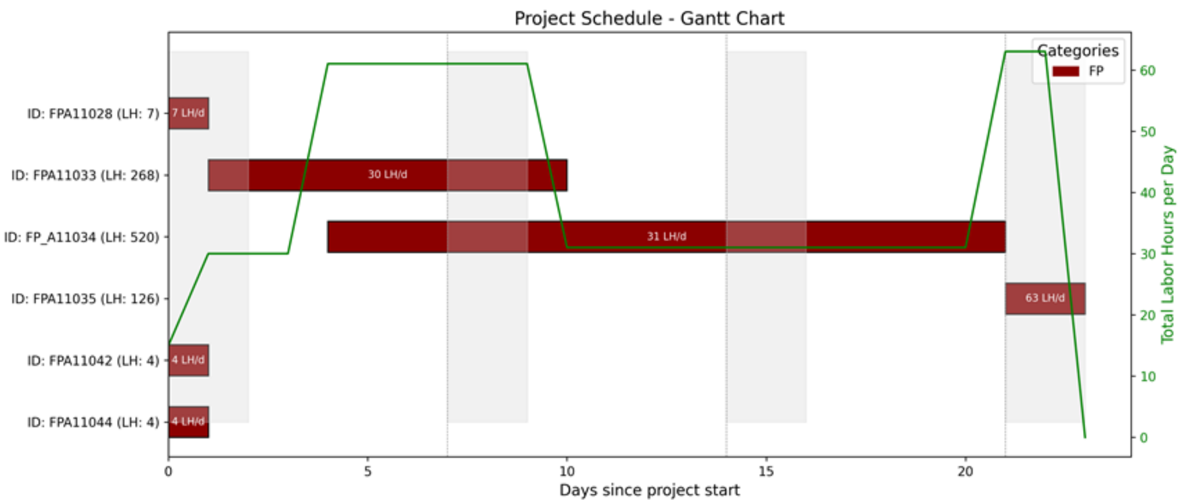

Figure 10: Constraint-based schedule with activity sequencing and 23-day project duration.

In the schedule shown in Figure 10, activities were sequenced based on their spatial assignments, logical dependencies, and available resources, allowing for parallel execution where feasible to minimize the overall project duration.

To enhance consistency in resource utilization, the same dataset was used to minimize fluctuations in daily labor demand. The following objective function (Equation 4) was applied to reduce the variance between planned and ideal (target) daily labor hours:

$$\min \sum_{t\in T}\left(\sum_{i\in A} LH_{i,t} - LH_t^{ideal}\right)^2 \qquad (4)$$

$\sum_{i\in A} LH_{i,t}$ = total planned labor hours in time period t
LH_t^{ideal}= ideal (target) labor hours for time period t
A = set of all activities
T = set of all time periods

Using this formulation, the scheduling model redistributed tasks to smooth labor demand across periods while still adhering to spatial and logical constraints. The result, illustrated in Figure 11, is a revised schedule with a total duration of 29 days. Although this scenario requires a longer execution period compared to Figure 10, it significantly reduces fluctuations in daily labor usage, leading to improved workforce stability.

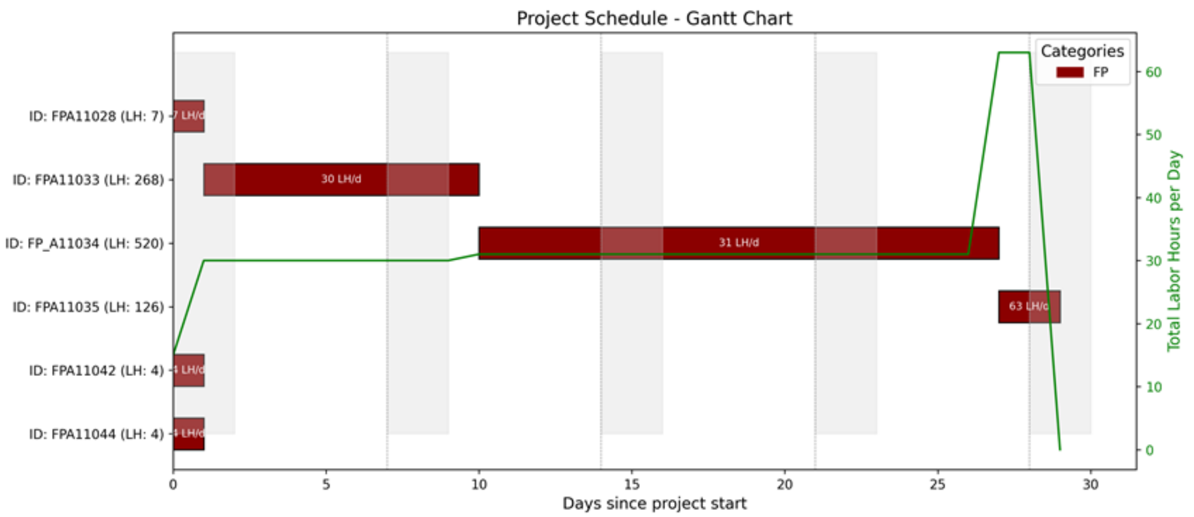

Figure 11: Schedule scenario minimizing labor fluctuations (29 days).

This application demonstrates how structured, schedule-ready BIM data can support downstream logic-based sequencing and related scheduling analyses. The same data structure can facilitate a range of additional planning methods that depend on organized and machine-readable inputs, including rule-based systems, AI-assisted scheduling, resource-constrained planning, and scenario-based analysis. It contributes to the broader goal of developing reusable, automation-compatible data templates.

3. DISCUSSION

The results of this paper demonstrate how structured scheduling data, extracted explicitly from BIM, including spatial location, activity categorization, and labor-hour planning metrics, can serve beyond sequence generation. These attributes enable detailed analyses that support alternative scenario analysis, schedule creation, and performance benchmarking. For example, cumulative labor hours across a project, the ratio of finishing to structural activities, or zone-specific productivity levels can all be derived and used for evaluating planning efficiency, labor intensity, or space-time allocation patterns.

More importantly, this structured dataset enables comparative analysis between projects. When the same attributes are captured across projects, such as labor hours per square foot or meter or labor allocation per task type, scheduling performance can be benchmarked, allowing for the calibration of expectations, refinement of targets, and informed future planning. The consistent structure enables the creation of reusable templates that can be redeployed across similar project types, significantly reducing the need for manual effort or rule redefinition.

Despite these capabilities, a significant limitation remains the lack of BIM modeling practices and tools aligned with such advanced scheduling requirements. The proposed UML schema, as part of the framework, addresses this by establishing modeling expectations for activity decomposition, classification tagging, and resource assignment, supporting richer, machine-readable models tailored for logic-based and AI-assisted scheduling systems.

The potential of this framework extends beyond 4D visualization. By transforming BIM into a data-rich planning asset, it supports combinatorial analysis of alternative zone sequences, delays analysis, feasibility assessment, and rule-based or AI-driven sequencing. The structured dataset provides the inputs needed for exploring multiple viable schedule alternatives and selecting one that optimizes performance against resource or productivity targets. While past research has focused heavily on scheduling algorithms and automation strategies, less attention has been given to how data should be structured, enriched, and extracted for such advanced uses. This paper addresses that gap by establishing a practical foundation. It highlights that construction activities should not be defined solely by quantities or durations but also by their functional role, spatial context, and effort intensity. Such a structure enables dynamic, goal-driven planning, where labor targets or productivity benchmarks guide the generation of schedules rather than rigid task orders alone. The proposed framework was developed and applied using a BIM model that was prepared and enriched for scheduling purposes. Its implementation, therefore, assumes consistent spatial assignments, classification information, and productivity-rate inputs for the model elements considered. Where such inputs are incomplete or revised or where model information changes, additional preparation and verification may be required before the extracted data are used for scheduling. The present case is intended to demonstrate the application of the framework in the selected project context and to illustrate its use for preparing schedule-ready data from BIM.

4. CONCLUSION

This paper proposed and applied a structured framework for transforming BIM design data into schedule-ready inputs for subsequent logic-based and optimization-driven scheduling applications. By embedding spatial decomposition, activity classification, and labor-hour or resource-hour estimation into each task, the framework supports the preparation of schedule-ready inputs for downstream scheduling, benchmarking, and resource analysis. The framework facilitates not only the preparation of schedule-ready inputs for feasible construction schedules but also the reuse of structured templates across projects. Its consistent data model supports the comparison of planning performance and AI-assisted or rule-based decision-making. Moreover, the framework shows how rich BIM content can be used not only for 4D visualization but also for scheduling grounded in logic, constraints, and effort-based planning. For contractors, planners, and BIM managers, the framework provides a structured approach for preparing schedule-ready data from BIM and minimizing repetitive manual input in scheduling workflows. For researchers, it provides a basis for further work on structured and automation-compatible scheduling data.

This paper demonstrates the framework through a single-case application in the selected project context. Future research may further examine the framework in additional project contexts, explore dynamic model–schedule updating, and investigate integration with AI-assisted scheduling methods.

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Data Availability Statement
The data supporting the findings of this paper are available within the article.

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