From Geometry to Semantics: Elevating Building Model Semantics with Geometric Intelligence

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Abstract

Traditional 3D modeling in the AECO industry often emphasizes geometric data over semantic details, leading to potential inconsistencies. This paper introduces an innovative approach to enhancing Building Information Models using geometric intelligence. The core idea of this geometric intelligence is that an object's geometric features and semantic properties are intrinsically linked. Our method uses artificial intelligence to analyze 3D models, extracting implicit semantic insights from high-quality geometric data through feature extraction and AI-based semantic classification. By creating a framework incorporating this 'Geometric Intelligence,' we reduce the dependency on manually entered data and identify inconsistencies between geometric and semantic information. This research highlights geometric data's potential to enrich semantic content, promoting safer and more sustainable building practices.

1. Introduction

The modern Architecture, Engineering, Construction, and Operation (AECO) industry increasingly relies on model-based processes where geometric and semantic information are critical. The implementation of Building Information Modeling (BIM) has heightened the need for high-quality development in terms of Level of Geometry (LoG) and Level of Information (LoI). While combining these elements in digital models is essential, it presents significant challenges (Borrmann et al., 2018).

While geometric errors are typically visible and quickly corrected, defects in semantic modeling often go unnoticed and unresolved. This discrepancy underscores the need for better integration and management of semantic information in digital models. The AECO industry faces significant challenges with data interoperability, particularly when integrating geometric and semantic data. The lack of standardized practices for semantic information often leads to inconsistencies and errors. Misalignment between geometric and semantic data can propagate errors throughout the project lifecycle, affecting everything from design to construction and operation. This can increase costs and delays and reduce efficiency (Dinis et al., 2022). Despite the critical role of semantics in digital modeling, it remains elusive for many stakeholders in the construction industry. The secure and quality-assured handling of semantic information has yet to become widespread, and the qualitative standards for this information have yet to be applied across the board. In contrast, models' geometry benefits from well-established practices and expertise, often receiving preferential treatment. Adopting open semantic standards has been crucial in addressing these issues, but the industry still struggles with fully integrating these standards into everyday practices (Zhang et al., 2020).

Integrating semantics is crucial for ensuring modern structures' efficiency, safety, and durability. Moreover, without holistic semantic consideration, the benefits of digital models in planning, such as accurate model validation and quantity estimation, cannot be fully realized, further compromising the project's success.

This research's primary question is whether the imbalance between geometry and semantics can be leveraged to improve semantic information quality without adding more data to the model. The goal is to explore whether insights can be derived solely from geometry, which is typically more reliable and of higher quality than semantics. This approach aims to enhance digital building models by reducing the dependence on manually entered semantic data, prone to errors and inconsistencies. The main contributions of this paper are:

- Proposing a novel method for extracting valuable semantic insights solely from geometric features of single components and their context to neighboring components.
- Developing a comprehensive framework that leverages *Geometric Intelligence* by applying advanced artificial intelligence techniques to establish precise correlations between geometric features and semantic attributes, thereby significantly enhancing digital building models' semantic depth, accuracy, and reliability. This approach integrates machine learning algorithms for feature extraction, classification, and semantic enrichment, ensuring that the geometric data is effectively translated into meaningful, context-aware information within the digital building environment.
- Demonstrating the potential of this approach to improve the accuracy and quality of construction planning and execution by utilizing AI-driven correlations between geometric and semantic features.

2. Background and Related Research

Semantic enrichment enhances data with additional information to make its meaning and context more comprehensible (Bloch, 2022). Semantic enrichment in the context of BIM involves integrating metadata, context information, and external knowledge sources into the geometric data. There are numerous approaches to semantic enrichment, each attempting to tackle the challenge in various ways (Jiang et al., 2023). Some focus on ontology-based methods, leveraging structured knowledge representations, while others use machine learning techniques to infer semantic information from geometric data. This diversity of methods highlights the richness of the field and the potential for innovative solutions to improve the semantic quality of BIM models. Most methods focus on enriching geometry obtained from existing structures (e.g., TLS, photogrammetry) without a corresponding BIM model.

The recognition and classification of semantic objects based on geometry or images in 2D and 3D data is a significant aspect of these methods. Object classification involves the recognition and grouping of objects for specific purposes, consisting of two main steps: feature extraction and feature-based classification (Ullman, 2007). This approach has been used in civil engineering to detect various elements such as construction equipment, activities, and structural defects (Spencer Jr et al., 2019) – 3D object classification benefits from additional spatial information. Wang and Cho (2014) proposed a method for building component recognition and reconstruction from LIDAR data, and Sacks et al. (2017) relied on similar data for classification and consecutive enrichment.

In contrast, other approaches rely on manufactured models created during planning. While such models are often classified during modeling, an automated classification may improve the results by eliminating errors. Wu and Zhang (2019) developed a sequential algorithm to classify IFC-based BIM models while Li et al. (2023) focused on invariant signatures of AEC objects. Koo et al. (2021), on the other hand, combined images, point clouds, and geometric features of objects in a deep learning approach to classify wall and door BIM elements. However, these approaches usually rely on meta-information of the particular data schema (e.g., IFC) besides the pure geometric information.
Our approach addresses the limitations of these existing methods by focusing solely on the raw geometric characteristics of models created during the digital planning process. Unlike methods that depend on meta-information, which can introduce errors and inconsistencies, we propose a neutral set of geometric features derived purely from the components' shapes within a model. We explicitly do not rely on external metadata, which may be incomplete or inaccurate, ensuring that the classification process is based on universally applicable geometric data. By leveraging engineering knowledge to consider the shape characteristics of common building elements, our method enhances the semantic richness of BIM models more reliably and flexibly. Ultimately, this will lead to more precise and consistent semantic information.

3. Methodology

The geometric complexity of 3D models may not appear immediately meaningful at first glance, but it holds immense potential. The high attention paid to geometry during the design process harbors a largely unexploited wealth of valuable insights. Just as humans can classify components based exclusively on geometric features or infer the materials used, this ability can also be harnessed for machine processing in the construction industry.
The core of this concept lies in identifying and analyzing simple geometric features tailored explicitly for components typically found and used in the AECO industry. This ability to infer semantic properties from geometric properties, such as shapes, patterns, spatial relationships, dimensions, and proportions, can be referred to as *Geometric Intelligence*. This suggests that each component within a building model possesses an inherent understanding embedded within its geometric features. When extracted, these features can be used as input for a neural network to provide valuable insights into the component's function, relationships to other components, and semantic information.
This approach takes advantage of the high quality of geometric data in digital building models and aims to enhance their semantic richness. Unlike traditional methods that rely on the human capacity to learn features from 2D images, Geometric Intelligence focuses on a novel selection of three-dimensional properties of components derived from their 3D representation. By leveraging machine learning methods, we can identify correlations between geometric features and semantic attributes, making it possible to deduce properties such as the type of object or the likely materials used.
Applying AI and large datasets enables us to extract and utilize these correlations effectively. This methodology aims to improve the accuracy and quality of construction planning and execution by applying these insights to individual building components. Geometric Intelligence, through the in-depth understanding and analysis of shapes, patterns, spatial relationships, and proportions, opens up significant opportunities in the construction industry and provides a novel perspective in understanding and analyzing building components at a deeper, more intrinsic level.
Figure 1 shows our proposed procedure in simplified form. The individual steps are explained in detail in the following sections.

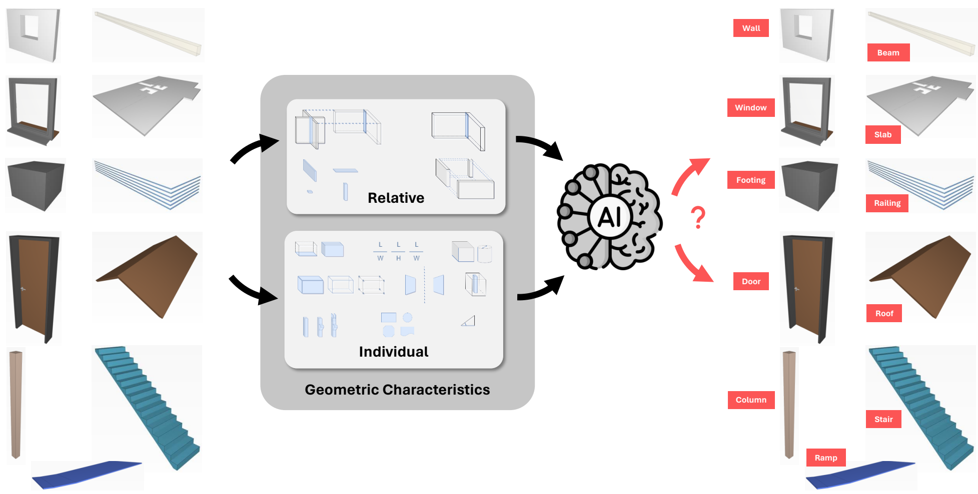


Figure 1: Procedure for deriving semantic features from the geometric features

Our primary objective is identifying geometric features that can effectively predict a selected semantic characteristic or property. The first step is to develop a catalog of geometric characteristics that can be universally identified for components and construction elements, regardless of their specific geometric representation or data format. These features must be consistently derivable from any representation type, ensuring the broad applicability of our methodology.

First, we focus on the component type corresponding to the entity in the IFC data schema. This choice is informed by the understanding that classifying component types is fundamental to understanding and utilizing digital building models. Besides, this decision is based on the premise that specific geometric characteristics, which humans typically use to differentiate between component types, can similarly be used by AI models to distinguish semantic properties effectively.

Our approach is flexible and designed to be adaptable, allowing for future extensions to other semantic properties, such as material type, load-bearing characteristics, or fire resistance classification. We hypothesize that specific geometric features will effectively distinguish component types.

We focus on informative, easily derivable, and meaningful aspects across different geometric representations and data models to identify initial geometric features. This ensures that our approach remains independent of specific data formats and is broadly applicable. The selected features include dimensions, shapes, spatial relationships, and other measurable aspects that can provide valuable information about the semantic properties of components. The first set of geometric features we identified as meaningful can be found in Table 1 with a description of which properties these features describe.

It is essential to emphasize that the geometric features' development and identification process is iterative and takes construction specific domain Knowledge into account. The catalog of geometric features is not static; it needs to evolve and expand as we collect more data and refine our methods. Initially, we focus on the most promising geometric features based on existing knowledge and preliminary analysis. As we gather more data, we will continuously refine and expand the catalog, improving the accuracy and reliability of the resulting AI models in predicting semantic properties.

The collected geometric features, sourced from models with accurately classified component types, are used to train AI models, enabling them to predict unknown components based on their geometric features. This process begins by extracting the identified geometric features from existing models. These features serve as the input data for both training and testing the AI models. The specific steps involved are as follows:

1. **Feature Extraction:** Extract geometric features from components within accurately classified models. This ensures the training data is reliable and representative of the component types.
2. **Model Training and Testing:** Use the extracted features to train AI models, enabling the AI to learn to predict a component's class or purpose based on specific shapes, dimensions, and other geometric properties. The training process involves splitting the data into training, validation, and test sets. During training, 80% of the data is used, with an additional 10% of this training data set aside for validation to monitor the model's performance and prevent overfitting. Subsequently, the trained models use the 20% test set to evaluate their performance, assessing how well the AI can predict component types from geometric features not encountered during training.
3. **Validation:** Apply the trained models to new, unfamiliar data to validate their effectiveness. This step involves evaluating the accuracy of the AI's predictions and ensuring they align with the actual properties and functions of the components.

4. Implementation

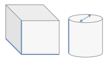
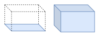
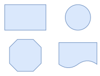
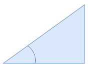
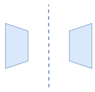
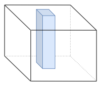
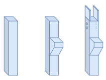
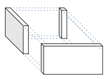
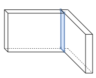
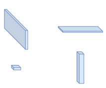
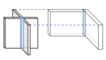
Our initial implementation focuses on IFC models due to their extensive, manufacturer-neutral database. This database allows us to utilize classified elements from various authoring tools as test data, providing a robust foundation for our model training and testing processes. However, it is essential to emphasize that IFC is only one possible data source. The geometric features we concentrate on can also be derived from other data models and formats, e.g., OBJ, STL, and CityGML.

Our approach involves a Python-based demonstrator, building on the methodology previously outlined. The implementation leverages several tools and libraries to achieve our objectives. We use public open-source libraries such as IfcOpenShell, NumPy, Trimesh, and OpenCASCADE to extract geometric features from IFC files. These tools allow us to interpret the IFC files and extract geometric data from building components.

The extraction process focuses on compiling a dataset with key spatial metrics for each building element, ensuring these metrics are consistently derivable from any geometric representation. Once the geometric features are extracted, we utilize a Multi-Layer Perceptron (MLP) neural network model implemented using TensorFlow's Keras API. The MLP consists of six dense layers and employs dropout techniques to prevent overfitting, enhancing the model's generalization capability. The training phase involves feeding the extracted features into the MLP, enabling the AI to learn to predict a component's class or purpose based on specific shapes, dimensions, and other geometric properties.

After training, we test the models using a separate dataset to evaluate their performance. This testing phase assesses how accurately the AI can predict component types from geometric features not encountered during training. The final step is to validate the trained models on new, unfamiliar data, ensuring their predictions align with the actual properties and functions of the components. The predictions are stored in an updated version of the test data IFC file, with the predicted class added to a dedicated property for each element. While the predicted component type can be reused in various ways, this method simplifies validation by comparing the actual component's class and the newly added property.

Table 1: Selection of geometric features for semantic classification

Individual Component		**Dimensions** Length, width, height, or diameter.
		**Ratio of dimensions** Length/width, length/height, height/width.
		**Surface area and volume** Calculation of surface area and volume.
		**Geometric representation type** Explicit (BREP, Advanced BREP) or implicit representation (CSG, Procedural, etc.).
		**Shape and contour** Recognition of specific shapes, such as rectangles, circles, and polygons, as well as more intricate shapes like free-form surfaces.
		**Angle and slope** Measurement of angles and slopes, crucial for structural integrity and design.
		**Symmetry and pattern recognition** Identification of symmetries and recurring patterns within the building structure.
		**Perforations and cavities** Recognition of holes, recesses, or voids within components.
		**Degree of complexity** Assessment of the geometric complexity of components, with implications for manufacturing and assembly processes.
Neighboring Components		**Position and alignment** Determination of spatial positioning and alignment of components relative to each other.
		**Connection and intersection points** Detection of points where components meet or intersect.
		**Proportions and ratios** Analysis of proportionality between different components.
		**Distance, contact, and overlap measurements** Determination of distances, contact areas, and overlaps between components.

The AI-Demonstrator was applied to various IFC models, yielding robust results. We focused on identifying essential properties that could enhance the AI model's ability to accurately predict the classes of architectural elements according to the identified characteristics shown in Table 1. The finalized feature set, crucial for our AI-based prediction model, is shown in Figure 2 and includes:

- **Sum of Length and Width Squared:** This metric helps distinguish between different component sizes and shapes (Figure 2 - b)
- **Areas:** The element's footprint and top surface areas provide insight into its spatial footprint and coverage (Figure 2 - c)
- **Coordinate Counts:** The number of distinct minimal and maximal x, y, and z coordinates in the element's footprint, aiding in understanding the element's spatial boundaries (Figure 2 - d)
- **Mesh Quantity:** The number of meshes present within the element's footprint, indicating the complexity of its geometry (Figure 2 - e)
- **Vertices and Faces Count:** The total number of vertices and faces of the element is crucial for understanding the element's geometric complexity (Figure 2 - f)
- **Volume Measurements:** Including the axis-aligned bounding box volume, the actual object volume, and the convex hull volume, these metrics are essential for assessing the element's overall size and shape (Figure 2 - a, g)
- **Ratio Calculations:** Such as length-to-width ratio, object-to-convex hull volume ratio, object volume-to-height ratio, convex hull volume-to-height ratio, and footprint area-to-height ratio. These ratios help in understanding the proportional relationships of the elements (Figure 2 - a, b, g)
- **Euler Characteristic:** Provides insight into the shape's topology, which is essential for distinguishing different types of components (Poincaré, 1895) (Figure 2 - h)

5. Test Cases and Discussion

To evaluate the accuracy of our prediction system, we derived features according to our presented methodology and verified the model with data previously unseen by the AI. Table 2 summarizes the AI prediction results for various IFC element types across six test models.

We selected different buildings, primarily from the field of building construction, including small-sized models, such as single-family houses from solid and timber construction, and larger models, like high-rise buildings and office complexes.

The results indicate high success rates for *IfcColumn*, *IfcDoor*, *IfcSlab*, *IfcWall*, and *IfcWindow*. These elements have distinctive geometric features that facilitate accurate predictions. For example, *IfcSlabs* often have large footprint areas, while *IfcDoors* and *IfcWindows* typically exhibit high vertex and face counts. *IfcWalls* are characterized by high length-to-width ratios combined with low vertex and face counts.

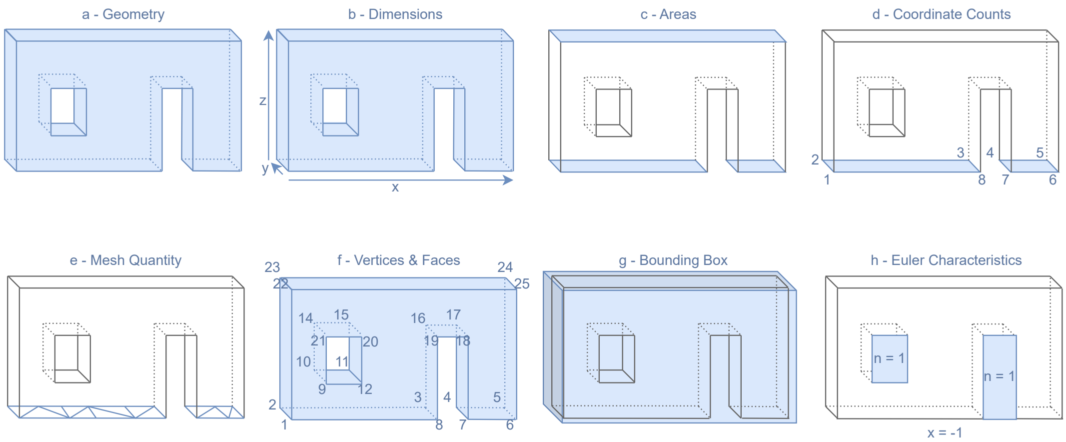


Figure 2: Geometric features used for the implementation of the demonstrator

Table 2: Results of the test cases with a set of IFC models

IFC Entity	# of Components	Correct Predictions	Average Confidence
IfcBeam	67	62.69%	66.99%
IfcColumn	36	93.36%	66.91%
IfcDoor	377	98.94%	99.13%
IfcFooting	62	69.35%	79.44%
IfcRailing	49	73.47%	85.80%
IfcSlab	65	97.10%	87.72%
IfcStair	17	76.47%	93.10%
IfcWall	1301	89.82%	83.11%
IfcWindow	398	97.82%	84.20%

Components with lower success rates, such as *IfcBeam*, *IfcFooting*, *IfcRailing*, and *IfcStair*, suggest potential areas for improvement. Figure 3 illustrates three common variations of railings, which differ significantly in geometry, such as volume, dimension ratios, and vertex and face counts. One strategy is to increase the training dataset size. A more extensive training dataset can help the model learn how these elements can be represented.

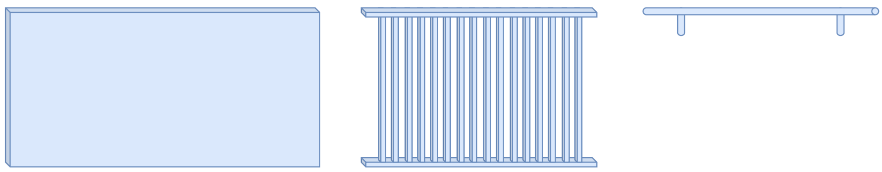


Figure 3: Common variations of IFC railings.

Improving predictions for *IfcBeam* and *IfcFooting* may require additional strategies due to classification thresholds. For instance, the distinction between a beam and a deep beam or wall depends on the ratio of the span to the overall section depth, with a ratio of ≥ 3 indicating a deep beam or wall. Figure 4 illustrates this threshold, showing elements that change from beam to deep beam or wall as the span-to-depth ratio exceeds 3 (Code, 2005).

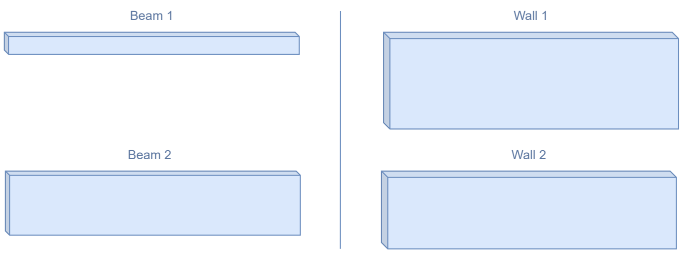


Figure 4: Transition threshold from IFC beam to IFC wall based on span-to-depth ratio.

In modeling software, while a wall with a low overall height ($\frac{l}{h} < 3$) can be modeled, it will not change automatically from *IfcWall* to *IfcBeam* and thus can be misclassified.
In our tests, the AI performed well across all models with comparatively uniform and geometrically less complex components, such as *IfcColumn* or *IfcSlab* elements, achieving high accuracy and confidence in predictions. However, persistent issues with less uniform and increasingly geometrically complex, such as *IfcRailing* or *IfcStairFlight* elements, indicate the need for further improvements in the AI model or the training data to

achieve better results for these elements. Additionally, the average confidence in predictions only sometimes correlates with accuracy; for example, predictions for *IfcColumn* have a low confidence of 66,91% but an accuracy of 93.36%. Variations in accuracy and confidence across different test models may be due to varying model complexities, insufficient training data for specific elements, or the AI model's inherent limitations.
Overall, the data indicates that our models' predictive performance is solid, with specific areas needing improvement. Further investigation should review the training datasets and the AI model to address area-specific weaknesses and achieve higher accuracy and reliability. Despite the promising results, several limitations need to be addressed:
First, the effectiveness of our approach depends on identifying the correct geometric features for each semantic characteristic. This iterative process requires continuous refinement to ensure the most relevant features are used.
Second, during our implementation and validation, we observed that a completely automated validation process is not feasible. The AI model sometimes predicts component types that, while different from their original classification in the IFC model, are not necessarily incorrect. For instance, a subcomponent of a curtain wall might be predicted as a support structure. Although this differs from its original classification as part of a curtain wall, it could still be valid. Therefore, human verification is required to determine whether the AI's predictions are sensible and accurate. This necessity for manual review makes fully automated validation impractical and time-consuming.
Second, during our implementation and validation phases, we observed that a completely automated validation process is not feasible. The AI model can predict component types that, while different from their original classification in the IFC model, are not necessarily incorrect. For instance, a subcomponent of a curtain wall might be predicted as a support structure, which could be a valid classification. Therefore, human verification is necessary to determine the correctness of the AI's predictions. This manual review process is time-consuming and indicates that fully automated validation is impractical. Third, developing geometric features and the AI model is an ongoing process. Initial results are promising, but significant time, effort, and resources are needed to continuously improve predictions' accuracy and reliability. This involves expanding the dataset and refining the feature extraction and model training processes. Lastly, the current implementation performs well for relatively standardized components that do not exhibit unusual behavior. However, the system's reliability decreases with more complex or less common components. Relying entirely on this system for all classifications may not be practical, but using it as a decision support tool could be beneficial.

6. Conclusions

The introduction of *Geometric Intelligence* offers a promising way to enhance the quality and interoperability of digital models in the construction industry. By using AI to extract and utilize *Geometric Intelligence*, we can improve the semantic richness of these models, leading to more efficient and accurate design, construction, and maintenance processes. However, this approach's success relies on several crucial factors: maintaining data quality and diversity, ensuring precise definitions of geometric features, and achieving consistent AI model performance. Our initial definition of geometric features is a first step, and we invite the community to develop this catalog further. As it stabilizes and gains broader recognition, this engineering approach will be especially useful for applying to other semantic attributes beyond component types.
Future research should apply this methodology to essential semantic attributes like load-bearing characteristics. One practical application could be integrating the AI model into authoring tools for real-time feedback, warning users of potential misclassifications. An-

other application uses the AI model as a decision support system during the design phase to help modelers correctly classify components and reduce errors.

While the initial implementation shows promise, especially for standardized components, significant areas for improvement remain. The iterative nature of the process and the need for human validation highlight the importance of continuous development and refinement. Future work should expand the methodology to other semantic properties and integrate it into practical applications to enhance its effectiveness.

Data availability statement

The data supporting this study's findings are available at https://gitlab.lrz.de/cpreidel/gibamo, ensuring that they are Findable, Accessible, Interoperable, and Reusable (FAIR).

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References

Bloch, T. (2022). Connecting research on semantic enrichment of BIM-review of approaches, methods and possible applications. *J. Inf. Technol. Constr.*, *27*, 416–440.

Borrmann, A., König, M., Koch, C., & Beetz, J. (2018). *Building information modeling: Technology foundations and industry practice*. Springer Cham, Switzerland.

Code, P. (2005). Eurocode 2: Design of concrete structures-part 1–1: General rules and rules for buildings. *British Standard Institution, London*, *668*, 659–668.

Dinis, F. M., Martins, J. P., Guimarães, A. S., et al. (2022). Bim and semantic enrichment methods and applications: A review of recent developments. *Archives of Computational Methods in Engineering*, *29*, 879–895. https://doi.org/10.1007/s11831-021-09595-6

Jiang, S., Feng, X., Zhang, B., & Shi, J. (2023). Semantic enrichment for BIM: Enabling technologies and applications. *Advanced Engineering Informatics*, *56*.

Koo, B., Jung, R., & Yu, Y. (2021). Automatic classification of wall and door BIM element subtypes using 3D geometric deep neural networks. *ADVEI*, *47*, 101200.

Li, H., Zhang, J., Chang, S., & Sparkling, A. (2023). BIM-based object mapping using invariant signatures of AEC objects. *Automation in Construction*, *145*.

Poincaré, H. (1895). *Analysis situs*. Gauthier-Villars Paris, France.

Sacks, R., Ma, L., Yosef, R., Borrmann, A., Daum, S., & Kattel, U. (2017). Semantic enrichment for building information modeling: Procedure for compiling inference rules and operators for complex geometry. *J. of Comp. in Civil Eng.*, *31*(6).

Spencer Jr, B. F., Hoskere, V., & Narazaki, Y. (2019). Advances in computer vision-based civil infrastructure inspection and monitoring. *Engineering*, *5*(2), 199–222.

Ullman, S. (2007). Object recognition and segmentation by a fragment-based hierarchy. *Trends in cognitive sciences*, *11*(2), 58–64.

Wang, C., & Cho, Y. K. (2014). Automatic as-is 3D building models creation from unorganized point clouds. *Construction Research Congress 2014: Construction in a Global Network*, 917–924.

Wu, J., & Zhang, J. (2019). New automated bim object classification method to support BIM interoperability. *Journal of Computing in Civil Engineering*, *33*(5), 04019033.

Zhang, J., Beetz, J., & Weise, M. (2020). Semantic enrichment for building information modeling: A review of developments and future directions. *Automation in Construction*, *119*, 103336.