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BIM and procurement data integration in industrialized construction using artificial intelligence

Integración de BIM y datos de aprovisionamiento en la construcción industrializada mediante inteligencia artificial

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Abstract

Industrialized construction (IC) has experienced significant achievements in the development of innovative construction methods in response to the demands of the construction industry. In this context, building information modeling (BIM) integrates and manages data throughout prefabrication phases (design, bid, and procurement) within an IC project. However, manual tasks such as data transfer between BIM models and enterprise resource planning (ERP) systems result in delays and errors due to the constant change of versions and large data flow between the involved parties. This research proposes the implementation of a novel method based on artificial intelligence (AI) to integrate the required information contained in elements in the BIM model with construction materials databases normally managed by ERP systems to procure and purchase materials in IC enterprises. Using a case study approach, this research presents a workflow with the proposed method whereas the results show that 81.57% of the elements were successfully identified, leading to a 63.47% reduction in the time compared to the manual assignment approach. Despite classifying a considerable percentage of the elements, it was identified that the implemented workflow depends on manual-dependent tasks during the design phase, such as modeling methodologies. This research contributes by providing new methods to improve IC projects and is expected to contribute to future research related to AI-based.

Keywords: Industrialized Construction; Natural Language Processing; Artificial Intelligence; Building information modeling; Lean construction; ERP.

Resumen

La construcción industrializada (CI) ha experimentado logros significativos en el desarrollo de métodos de construcción innovadores en respuesta a las demandas de la industria de la construcción. En este contexto, building information modeling (BIM) integra y gestiona los datos a lo largo de las fases de prefabricación (diseño, licitación y adquisición) dentro de un proyecto de CI. Sin embargo, las tareas manuales, como la transferencia de datos entre los modelos BIM y los sistemas de planificación de recursos empresariales (ERP), resultan en retrasos y errores debido al cambio constante de versiones y al gran flujo de datos entre las partes involucradas. Esta investigación propone la implementación de un nuevo método basado en inteligencia artificial (IA) para integrar la información requerida contenida en los elementos del modelo BIM con las bases de datos de materiales de construcción que normalmente son gestionadas por los sistemas ERP para la adquisición y compra de materiales en empresas de CI. Utilizando este enfoque en el caso de estudio, esta investigación presenta un flujo de trabajo con el método propuesto, cuyos resultados muestran que el 81,57% de los elementos fueron identificados con éxito, lo que llevó a una reducción del 63,47% en el tiempo en comparación con el enfoque manual de asignación. A pesar de clasificar un porcentaje considerable de los elementos, se identificó que el flujo de trabajo implementado depende de tareas manuales durante la fase de diseño, como las metodologías de modelado. Esta investigación contribuye al proporcionar nuevos métodos para mejorar los proyectos de CI y se espera que contribuya a futuras investigaciones relacionadas con la inteligencia artificial.

Keywords: Construcción industrializada; Procesamiento natural del lenguaje, Inteligencia Artificial; IA; BIM; ERP; Construcción Lean.

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1. Introduction

The construction industry has experienced significant transformations through the integration of new building methods and technological advancements in recent years. Despite these innovations, the industry`s productivity has only grown 1% annually over the past two decades, compared to 2.8% for the global economy (McKinsey Global Institute, 2017), which represents a continuous challenge for this sector. In this context, industrialized construction (IC) involves the off-site manufacture of building components using standardized and modular processes, similar to those used in serial production (Minvu, 2023), offering innovative solutions and achieving significant enhancements in project performance (as costs, waste, safety and time) at various stages (Durdyev and Ismail, 2019).

Based on these advancements, building information modeling (BIM) has been integrated into the industry achieving significant improvement in project and data management (Bryde et al., 2013), allowing users to access information efficiently and maintain a smooth workflow among all participants (PlanBIM, 2019). Within this approach, BIM is implemented in the IC context to develop projects and facilitate the digital coordination and management of information during the project's lifecycle, connecting data (e.g., quantity takeoffs, element's geometries, cost, etc.), especially during prefabrication phases (design, procurement, and bidding). This approach includes the necessary information provided by the element's geometry (such as area, volume, length, etc.) and the information related to its components to support processes associated with each project (Eastman et al., 2011).

However, data exchange between BIM models and other information systems, such as enterprise resource planning (ERP), is usually carried out manually, resulting in high execution times in the design phase and a large amount of information prone to errors, leading to additional costs, which calls for a standardized structure for the implementation of BIM and its information management (Manssori et al., 2023). Indeed, (Oyarhosseinm, 2021) mentions that the dispersion of large amounts of information and the lack of management practices to monitor data makes the implementation of BIM difficult and does not harness the full potential of BIM in the construction industry. Consequently, it is necessary to reduce user intervention to optimize the design workflow of IC projects, aiming to improve the efficiency of each associated process during the prefabrication phases (Barkokebas et al., 2021). Additionally, methods to manage company-related data are needed to ensure the successful implementation of ERP and the integration of its processes (Isikdag et al., 2013).

To identify patterns and manage large amounts of information in databases, a novel approach is proposed using artificial intelligence algorithms to search and classify elements in the BIM model, simplifying data access and manipulation. More specifically, Natural Language Processing (NLP) is a branch of artificial intelligence that allows computers to understand human language by analyzing the grammar, structure, and lexicon of the language (Eisenstein, 2019). Rule-based NLP focuses on a language component (lexicon and grammar) and a strategic processing and generation component based on an operation algorithm (Shaalan, 2010). These techniques enable computers to translate human language into information that can later be analyzed (Sun et al., 2017). Nevertheless, NLP still has limitations in understanding language. Indeed, despite having rules for identifying patterns in language processing, these rules fail to cover exceptions often performed by human-made mistakes such as mannerisms and metaphors in how data is entered into information systems. (Kang et al.,2020).

Therefore, this article proposes and evaluates the impact of the NLP-based method in IC premanufacturing phases, by applying rule-based NLP techniques to manage data (e.g., construction materials descriptions) contained in the BIM model elements and connect ERP systems to recognize its codes for procurement automatically. As mentioned above, this method takes advantage of the language compression process and facilitates the detection and extraction of information from ERP and BIM models. The objective of the proposed method is to minimize user intervention based on an automated workflow to reduce time during prefabrication phases and related processes. In this regard, a rule-based NLP method is developed to effectively identify elements based on the information available in their parameters, where the properties are stored in the BIM model. This research relies on the hypothesis that the application of AI-based methods will reduce IC project development times during premanufacturing phases while increasing the accuracy of data managed. In this context, the article provides a comprehensive literature review concerning this research's methods and information technologies. Within this workflow, the methodology and case study based on the scope of this research are introduced to establish the structure of the measure, design, and implementation processes in this research. Finally, the results and their discussion are presented, followed by conclusions from implementing the proposed solution and the long-term perspective considered for future research.

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2. Literature review

The construction industry has previously studied the impact of BIM on project performance (costs, design improvements, time, waste) and its improvements in different project phases and processes. Indeed, (Zheng et al., 2021) analyzed the impact of BIM-based digitalization methods on construction projects to reduce project costs and time, where new BIM methodologies improved performance during the research. Additionally, (Carvalho et al., 2019) proposed the integration of sustainability-related data in BIM models to reduce the environmental impact of construction industry projects by adopting sustainable criteria that contribute to more sustainable project development.

Regarding the automation of BIM processes, (Yin et al., 2020) developed an automatic interpretation system for digital 2D layers to develop a BIM facade model, achieving automation of a large portion of the plan components and avoiding manual data input from views. Similarly, (Sheikhkhoshkar et al., 2019) analyzed 4D projects by applying a combination of different methods based on BIM models, automated spreadsheets, and programming routines to offer an automated process to find patterns for concrete pouring, resulting in cost-effective and more accurate methodologies related to these types of issues. Additionally, (Wu and Zhang, 2019) propose an automated classification algorithm to identify elements in BIM models and to improve its interoperability considering Industry Foundation Classes (IFC), obtaining more than 80% effectiveness.

Considering the application of AI and NLP in the industry, its applicability has been limited across different stages of a construction project. Regarding the use of AI, (Senouci, 2008) proposes an optimization algorithm for scheduling linear construction projects to minimize times and costs related to project durations based on data processing, algorithms, and artificial intelligence. This process resulted in a model that allows to identification of the optimal option for resource allocation in activities during planning. Additionally, (Namcheol and Ghang, 2019) applied NLP methods based on search parameters and a support vector machine (SVM) to identify BIM projects through specific classification criteria, achieving a real approach to detecting BIM projects and reducing manual intervention related to the research. Similarly, (Lee et al., 2019) used NLP to identify relevant contract clauses for risk management in documents, obtaining high accuracy rates compared to manual review methodologies and allowing the development of a preventive model for studying such deliverables.

Related to industrialized construction, frameworks based on digitalization, standardization, and automatization methods are being used to improve performance considering specific requirements at IC projects. Indeed, (Yin et al., 2019) mentioned that the use of BIM could contribute to reducing costs and waste generated during IC projects. In this context, (Barkokebas et al., 2023) proposed and developed a workflow to connect project-related information (material specifications, list of materials, etc.) from BIM models to cost-based tools while achieving significant reductions in processing times and higher accuracy in the information being transferred. Likewise, (Gbadamosi et al., 2019) developed a BIM-based system to optimize recourses based on design and project requirements, contributing to reducing waste and improving performance in assembly phases.

Regarding automation in IC projects, these methods could contribute to reducing rework and time, allowing users to make accurate decisions at manufacturing stages (Chi et al., 2015). Indeed, (Kim et al., 2016) proposed an automated inspection process for precast concrete using BIM models and laser technology to improve its quality, obtaining an accurate method based on the dimensions of the elements. Particularly, (Tang et al., 2022) used NLP algorithms to identify and extract information related to automatizing construction-oriented quantity take-off (QTO), achieving an effective method to obtain information to estimate it.

Based on the information gathered, (Table 1) summarizes recent frameworks and methods applied to improve performance at different life cycle construction industry projects mentioned in this paper. In this context, a considerable amount of research in this review has been dedicated to automating processes in the design and manufacturing phases, with a particular emphasis in some cases on integrating artificial intelligence into key operations and stages of a life cycle project. Additionally, there is a clear trend toward utilizing BIM, considering it as both a methodology and a crucial tool in the development of new frameworks in industrialized construction (IC) projects. Upon reviewing the existing literature, it becomes evident that while significant research has been conducted on the application of BIM in IC, the integration of BIM models and other information systems has been largely overlooked in recent years. Furthermore, despite the growing use of NLP in many construction-related processes, its application within IC projects remains limited. Despite significant research in BIM and the application of NLP in construction, two research gaps are identified: (1) little use of NLP-based workflows to identify language patterns in IC, and (2) a lack of approaches combining BIM and NLP to improve processes in IC. Hence, this research proposes a novel method to automatically assign codes of construction materials contained in ERP systems by applying NLP algorithms to identify patterns in language extracted from BIM models and ERP systems, considering gaps previously acknowledged in the existing literature.

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Table 1. Summary of methods and frameworks to manage information between design features and information systems in the construction industry.

Author(s)	Description	Principles Applied					Project phase		
		BIM	AI	DG	ES	AT	PR	MN	EX
Barkokebas et al. (2021)	Digitalization plan to Premanufacturing processes	X		X			X		
Barkokebas et al. (2023)	Digitalization framework to improve performance at premanufacturing phases	X		X	X	X	X		
Mengtian et al. (2020)	Automated layer identification to BIM model generation	X				X	X		
Sheikhkhoshkar et al. (2019)	Automated methods for 4D projects to concrete pouring	X				X	X		X
Senouci (2008)	AI-based framework for Scheduling linear construction projects		X			X	X		
Lee et al. (2019)	AI NLP automated identification of clauses in contracts		X				X		
Gbadamosi et.al. (2019)	Bim-based optimizer for assembly using DFMA	X					X		
Kim et al. (2016)	Automated inspection of precast concrete	X				X	X	X	
Chi et. al, 2015	Framework using automated methods to improve fabrication quality	X				X	X	X	
Wu and Zhang (2019)	Automated classification of BIM elements to improve interoperability using IFC	X				X	X		
Tang et al. (2022)	NLP to Construction-oriented quantity take-off (QTO)		X				X		

DG=digitalization, ES= standarization. AT= automatization. PR= design/Premanufacturing. MN= manufacturing, EX=execution

3. Methods

This study employs a case study approach to evaluate, design, and determine the effectiveness of the proposed solution. The research methods are based on the framework developed by (Barkokebas et al., 2021) to create specific digitalization plans for industrialized construction. In this context, (Figure 1) shows the stages and methods of the research to improve prefabrication phases through automation methods.

In the first stage, referred to as the measure stage, the current workflow will be identified and mapped through interactions between developers and professionals from the design department. This includes identifying the problem and possible solutions, collecting relevant data, and determining the current workflow of the case study. To identify the actual durations of the workflow, information will be collected from the professionals who participated in the case study, along with a review of the literature on similar case studies to validate this information. This review will integrate recent methodologies in design, planning, and management, including Lean principles based on recent IC research. The measurement process will also include evaluating the performance of the current workflow, particularly the code assignment processes, and identifying any waste in the workflow. This approach allows determine the duration of the code assignment process and measure the workflow's waste.

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In the design stage, the categories regarding the scope of the research will be identified. Additionally, the necessary information to recognize elements in the BIM model (such as diameters, area, type, and material) within the project parameters will be selected based on the case study. Subsequently, design patterns in the BIM model and the code assignment process from the ERP database will be detected to determine the structure of the information for the development of search algorithms. The classification algorithms based on NLP will be developed within a dynamo extension in Revit software. Dynamo will be employed through its visual programming language and Python tools, where algorithms are integrated to automate the information assignment process. This NLP-based approach focused on grammatical structure and word types relevant to the case study, which algorithms are expected to identify for automated assignment. From the automated identification process, a workflow focused on the use of each algorithm separately will be proposed, aiming to evaluate the performance of both routines in the subsequent stage.

Finally, the proposed workflow and the measurement of the assignment process based on the developed algorithms will be evaluated to identify the execution times and accuracy of the routine. This validation stage will focus on testing the algorithms through the proposed workflow, to identify any areas for improvement. Particularly, the estimated time for code assignment and the automated workflow will be mapped, in addition to determining the accuracy of the results obtained from the proposed algorithms. Furthermore, a comparison will be made using the execution times of the real workflow and the proposed workflow to recognize and validate the improvement in the workflow and the algorithm that presents the best performance in element detection. Finally, opportunities for improvement in code assignment and execution time will be identified.

4. Case study

This study will be developed and executed in the design department of one of the largest IC companies in Brazil. In this context, a model of an industrialized bathroom project developed in Autodesk Revit and a spreadsheet with material and product information extracted from the ERP database are available. For this research, the workflow will focus on the elements corresponding to piping, pipes, pipe fittings, and their accessories. To improve efficiency in the prefabrication phases and in the assignment process, an automated information assignment to BIM elements is proposed using a case study approach using rule-based NLP algorithms. (Figure 2) presents the representative case study model for piping systems.

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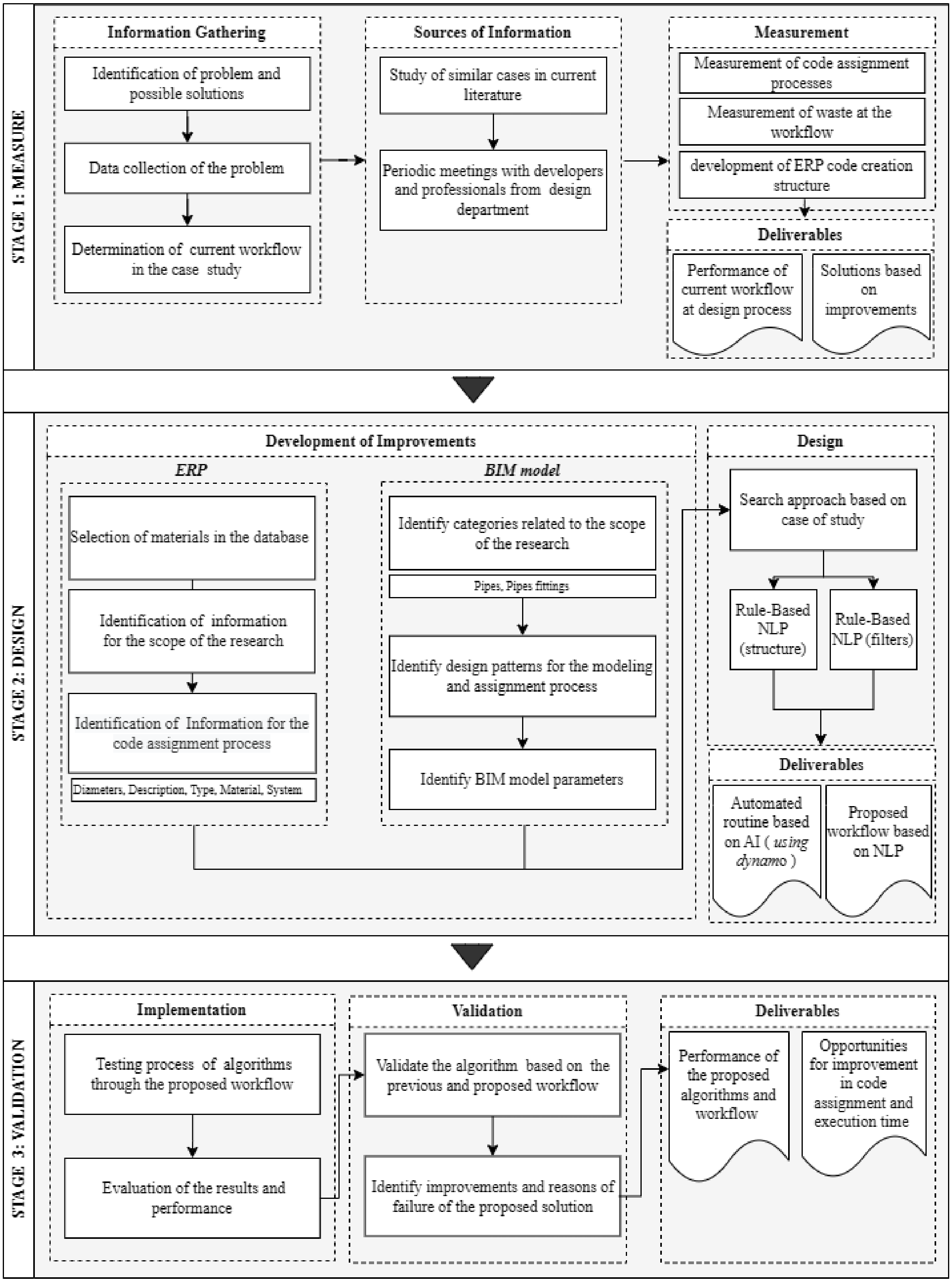

Figure 1. Research steps for the proposed research.

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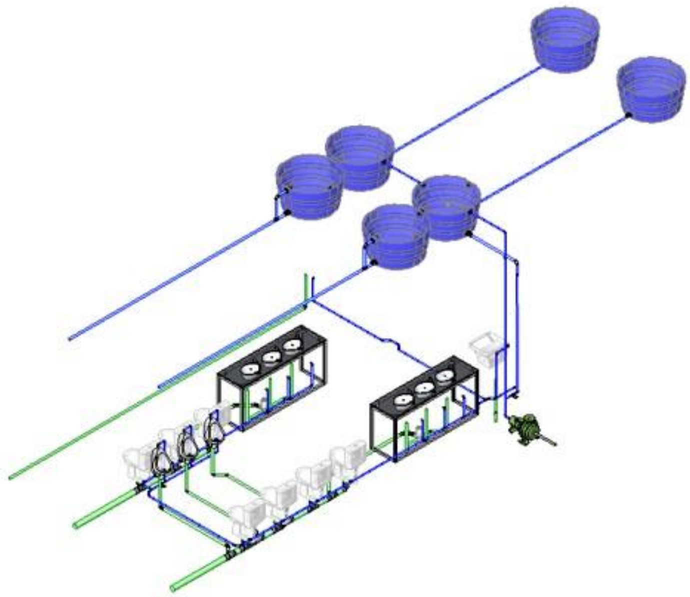

Figure 2. Sample of BIM model used in this research.

The current study is limited in its application to the design of sanitary installations within the BIM model and ERP system. However, this system was chosen due to its inclusion of diverse element types, each requiring specific information for accurate identification. Although these limitations may affect the generalizability of the proposed workflow, it is anticipated that by applying these algorithms to generalized construction systems, the required information could be adjusted to meet search requirements based on previously collected data.

5. Results and discussion

This section is based on the methodology developed by (Barkokebas et al., 2021) and presented as follows: (1) the measure stage identifies current processes in the case study, (2) the design stage shows the development of the proposed workflow based on results from previous stage and literature review, while (3) the propose and evaluate stage demonstrates the early implementation results.

5.1 Measure

The mapping and durations of each task performed by the design team are extracted from a previously validated time study performed in the same design team performed by (Barkokebas et al., 2021) and demonstrated in (Table 1). In this previous study, (Barkokebas et al., 2021) evaluated tasks performed by the design team considering a lean perspective (i.e., whether the tasks add value to the overall process or not) and the inherited uncertainty of design tasks. Considering the lean perspective, tasks are identified as value-added, necessary waste, and pure waste, where the latter two types are to be reduced. Considering the inherited uncertainty of design tasks, the duration of the tasks is determined by three possible scenarios: optimistic (O), pessimistic (P), and realistic (R). During the present study, interviews with participants in the design team were performed to confirm design practices and durations demonstrated in (Table 2) are still valid for the present study. Based on interviews and results in (Table 2), the proposed workflow will focus on reducing tasks 1 and 2, considered necessary work, which amounts between 9% to 30% of the total duration spent per project depending on each scenario.

Table 2. Mapped tasks according to their durations and types (adapted from (Barkokebas et al., 2021).

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ID	Task	P	R	O	Type
1	Special items and quantity take off	8	4	2	NW
2	Special items to ERP	7	7	7	NW
3	Electrical design	1.3	1.3	1.3	VA
4	Plumbing design	1	1	1	VA
5	Electrical design rework	2.5	2.5	2.5	PW
6	Plumbing design rework	2	2	2	VA
7	Opening and partition design	2	5	9	NW
8	Revised quantity take-off	10	20	40	NW
9	Registry to ERP system	20	20	40	NW
	TOTAL	**53.8**	**62.8**	**104.8**	

VA: Value-added, NW: Necessary waste, PW: Pure waste, P: Pessimistic scenario, R: Realistic scenario, O: Optimistic scenario

(Figure 3) presents the current workflow executed during the premanufacturing phases regarding code assignment according to the information provided by the design department of the studied company. After the project is awarded, the design department, in addition to being responsible for design for manufacturing and assembly during pre-manufacturing stages, must perform code assignments (i.e., assign each material designed in the BIM model to be procured and purchased by other departments) and quantity take-offs for each of the materials and labor based on the codes that identify each material existing in the ERP (assembly codes). Currently, the company manually assigns each ERP code to each respective element in the BIM model based on the description in both systems (BIM and ERP) including new materials in the database (i.e., special cases). Special cases in this research are referred to new materials proposed in the BIM model that still do not exist in the ERP system. The process consists of searching for elements with specific characteristics based on their description in the ERP database and matching them with the information contained in the BIM model. Based on the performed interviews with the design team, this practice leads to mistakes in quantity and assignment of wrong materials for the production line such as plumbing connections of different types (sewage and water supply) and different diameters. Finally, the model is delivered with this information required for fabrication in the production line.

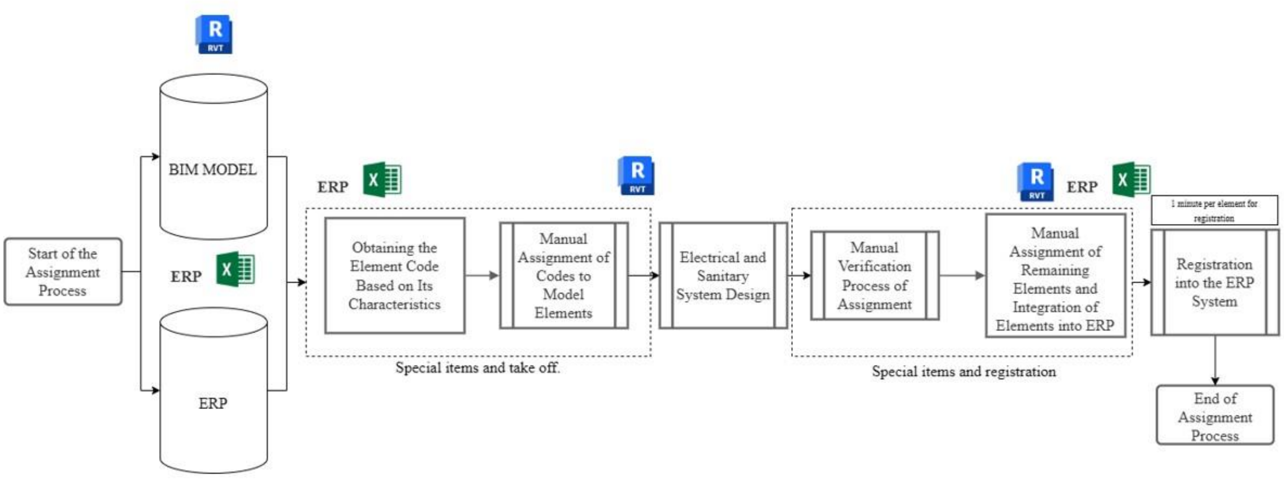

Figure 3. Current mapped workflow.

5.2 Design

Based on results from the previous stage, an AI-based method is developed to assign codes of construction materials automatically between the ERP system and BIM models. Particularly, an NLP-based workflow is proposed due to the significant volume of materials found in the ERP system (more than 4 thousand) coupled with the dynamic environment of design practices found in the design team in which new construction materials are needed to be registered in the ERP system after each project. Considering the scope of this study, the research team decided to develop the

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proposed workflow to be tested in plumbing discipline (sewerage, rainwater, and water supply) components due to its high number of pieces and connections. To assign ERP codes to each element of the BIM model, the necessary information was matched with data found in the parameters of the elements contained in the BIM model, corresponding to the properties of the elements in the information model. In this context, parameters contain information on the materials designed in the BIM elements and will allow information collection through the proposed method. This information enables algorithms to compare both codes and obtain a matching percentage based on comparative metrics and NLP rules. (Table 3) presents the source of information and type in the BIM model used to identify the initial characteristics in the model and the grammatical component that determines the information.

Table 3. Available Information according to parameters found in BIM models.

Source of information in the BIM model	Type	Information available
Family	Family	Element family name, additional information
Type	Type of Family	Element type name, additional information
Materials	Type Parameter	Materials (PVC, copper, aluminum, etc.)
Dimensions	Type Parameter	Diameters
System	Instance Parameter	Associated System (hot water, cold water, sanitary, etc.)

According to the mapped workflow, modeling practices, and available information in the ERP system, (Figure 4) shows the proposed workflow where NLP algorithms will be applied to automatically assign codes from the ERP system to elements in the BIM model based on its descriptions and characteristics. This workflow is implemented through the development of specialized plugins using Autodesk Dynamo, to improve the integration of automated processes in BIM models and data management from ERP systems contained in comma-separated-values (CSV) files and spreadsheets.

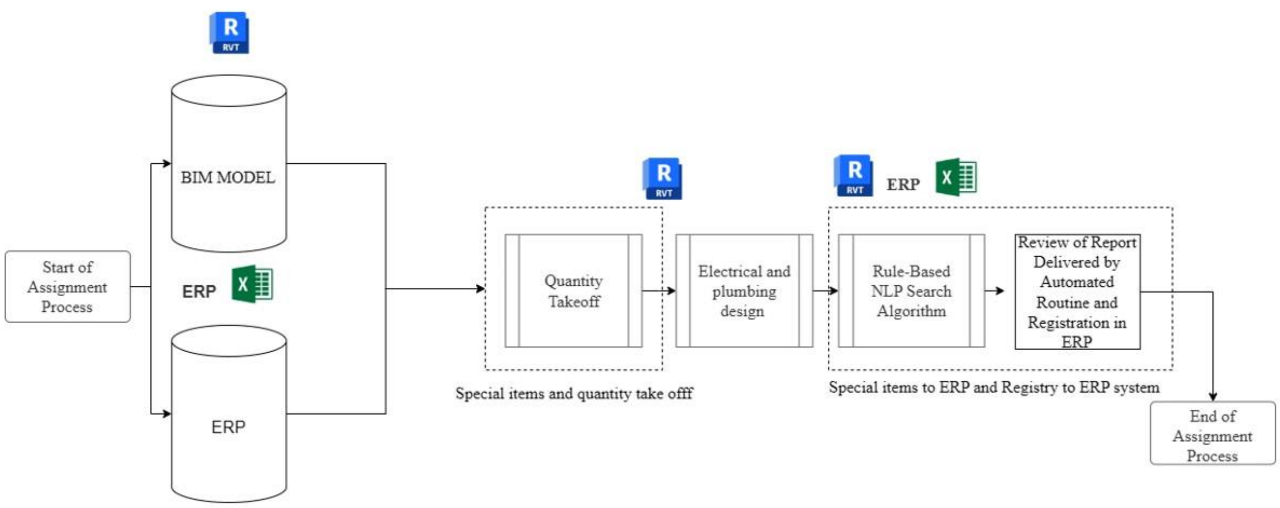

Figure 4. Proposed workflow for the case study.

For the development of the proposed workflow, two approaches are tested: (1) NLP-based approach using text matching particularly based on the general structure of the available information, and (2) NLP-based approach using filters on the available information for the general case study. (Figure 5) shows the applied logic in both approaches.

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Regarding the first approach, comparative metrics are developed based on the general structure detected in the description of the materials found in the database regarding both the structure and the type of information. In this sense, a methodology based only on the preliminary content of the predefined coding in the previous section is developed. The second approach applies two filters to further increase the accuracy of the first approach. Firstly, the type of connection of each element (e.g., plumbing elbow, union, etc.) is identified. Then it is classified according to the element's radius (radius of connections and pipes). Suppose no match is found in terms of the diameter. In that case, the algorithm is reprocessed to verify if there is another element of the same type in the database and determine if the elements were correctly detected. The algorithm stores all elements that can potentially be the correct code and filters based on a predetermined percentage of the match for each of them, considering the content and the type of text of the element. Finally, the algorithm saves the element with the highest percentage of match and assigns the code to the element in a type parameter. It is also reported in a spreadsheet to verify the correct assignment.

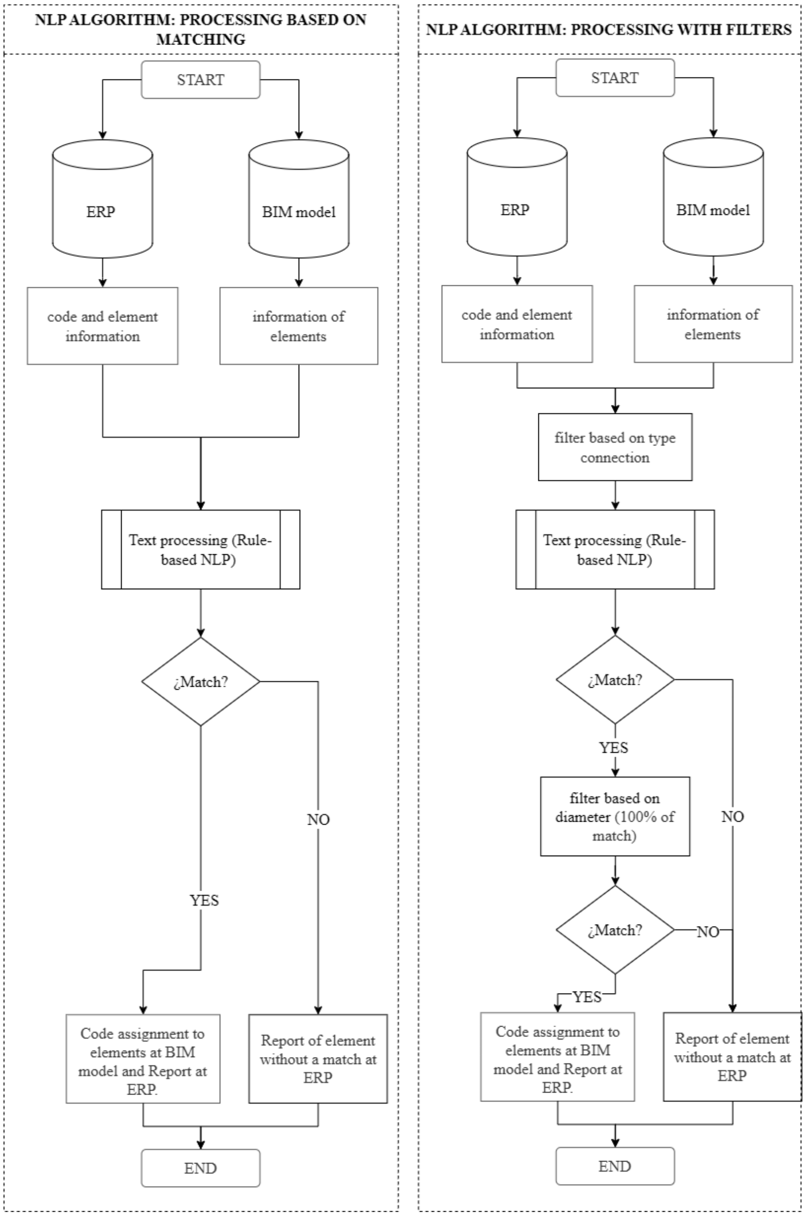

Figure 5. Proposed NLP-based approaches implemented in the proposed workflow.

6. Propose and evaluate

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Based on the proposed approaches, (Tables 4) and (Table 5) present the results of the classification and assignment processes carried out by the proposed automated routines. From the above, it can be observed that approach 2 is considerably more effective than approach 1. Additionally, it is noted that a large portion of the accessories regarding approach 1 were not correctly identified by the search algorithm based solely on the matching criteria of the coding pattern within the database. On the other hand, it can be observed that approach 2, a total of 80.78%, was correctly detected and assigned, where 57.25% was correctly assigned according to the matching algorithm, and 23.52% did not have an ERP code in the provided data. In this context, it was found that the execution time between activities compared to the values previously presented is reduced by 63.47% based on the estimated duration of the manually performed activity, considering only the elements in the previously mentioned target category. Furthermore, regarding the target time, it can be identified that based on the values obtained from approach 2, it is possible to reduce the estimated execution time by 35.8%, equivalent to a fraction of the 47 target hours.

However, it was observed that despite developing approach 2 specialized in identifying text strings for pipe and plumbing connection elements, a significant portion of the sample was not adequately assigned to a code, resulting in an 18.04% error in code assignment and user verification. Among the sources of error associated with code assignment are the sensitivity of the routine to design and drawing methodologies derived from each element's parameters, as well as how the user develops the model and ERP coding. It was observed that the absence of standardized modeling and coding practices significantly affects the assignment process, as there is dispersion in the methods of structuring the proposed coding in the ERP system. Elements showed a high error rate when they have specific characteristics, such as unique types of products, leading to a particular situation in the BIM model. Similarly to (Tang et al., 2022), the NLP algorithm could be limited based on the amount of data and information type that is processed. In this sense related to the proposed algorithm, technical limitations of the codes assignment process associated with this variable were identified, as well as a potential source of error based on the modeling methodology of other potential case studies.

These advancements highlight the importance of a unified framework for managing BIM information, as non-standardized methods could lead to significant errors in element identification (Massori et al., 2022). Additionally, as (Barkokebas et al., 2023) noted, results may differ depending on the digitalized methods implemented to meet each company's needs. Therefore, to enhance the effectiveness of the study methods applied in this research, increasing the information associated with the elements that the algorithm can detect is essential to reduce user intervention during quantification processes. It is also necessary to consider a standardized information management method related to the data from the model and its design.

Table 4. Estimated time reduction based on Approach 2.

	Correctly detected *	Without an ERP code	Correctly assignment	No assigned	Routine Executed time	Estimated time Reduction**	Objective Reduction Time
Amount	206	60	146	46	15	146	-
Percentage	80.78%	23.52%	57.25%	18.39%		63.47%	35.54%

*The element that exists or does not exist in the ERP database and matches 90% with the algorithm routine is considered "correctly detected." If it does not exist, it is verified that its best match is not assigned in the model.

** Considering 230 minutes of manual code assignment and only a reduction in time for elements in the "correctly assigned" category that are automatically assigned in the model. (146 minutes less, considering 1 minute per element).

To effectively integrate the automated method and proposed workflows, professionals should adopt a gradual implementation process, beginning with standardizing their BIM design methodologies. This approach should include validating the results and progressively expanding the implementation as confidence in the system's accuracy and reliability grows.

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Table 5. Summary of results obtained from both NLP-based approaches according to types of elements in BIM models.

	Total, correctly identified (%)	Element type correctly identified (%)	elements with code in ERP correctly identified (%)	elements identified without code in ERP (%)	elements incorrectly assigned and not identified (%)
Approach 1	30.98	51	9.01	21.960	68.62
Plumbing accessories	18	46.5	18.4	0.0	81.60
Pipes and plumbing	43.4	70.0	2.000	43.41	100.0
Approach 2	80.78	98.3	57.26	23.5	18.04
Plumbing accessories	69.84	93.8	66.67	3.18	30.16
Pipes and plumbing	94.57	99.0	48.06	46.51	6.20

7. Conclusions

This research presented an AI-based method to automate processes in pre-manufacturing phases in IC projects using two NLP rule-based approaches. The objective of this method is to integrate and identify the elements and their information in the BIM model into ERP data, achieving greater accuracy in its assignment and reduced processing times during data exchange and project development. Considering the proposed method in the current workflow, the performance of the new proposed activities was measured and compared with the performance values previously obtained by the design office. Based on this approach, the case study was applied to BIM models of sanitary systems on an IC project.

In this regard, the implementation of an automated routine based on NLP has effectively identified a large portion of the codes for elements from the BIM model and in the ERP while also reducing the duration of activities through the implementation of new automated workflows. However, even though access to automated methodologies could be effectively implemented, there are still limitations in the early implementation of the NLP routine in ERP databases. This is because such workflows still depend on more complex search patterns and algorithms that allow for the internalization and standardization of design methodologies for various types of products and projects. These complexities result in challenges considering the process of recognizing the human language and the process of its information to structured data. These limitations of NLP understanding of human language and patterns in the codification process at ERP suggest that it is necessary to develop specific rules that could contribute to improving the performance of NLP rule-based algorithms.

To improve the results obtained in this research, it is suggested to integrate more information (such as construction systems, different types of projects, and BIM models) to test possible issues associated with the accuracy of the algorithm. Also, it is necessary to apply this method to another case study, considering the variability that may exist in each of them concerning their design process. Alternatively, the NLP-based method could be integrated with neural network mechanisms to facilitate an automated learning process to supply the gaps identified in this study, promoting AI integration from a more complex perspective. In this regard, it is hoped that this document will provide an approach to more efficient assignment methodologies based on the development of automated workflows related to using artificial intelligence in the construction industry.

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9. Declaration of AI-Assisted Tools in Manuscript Preparation

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