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NLP-BASED SYSTEM FOR AUTOMATIC PROCESSING OF QUALITY DEMANDS IN ITALIAN PUBLIC PROCEDURE: A SYSTEM ENGINEERING FORMALIZATION

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Abstract

Natural Language Processing (NLP) is widely used to solve several tasks in different construction fields. However, there are no applications related to the pre-design phase. Analysing the Italian public design call for tender procedure, possible information criticalities can be identified. The study proposes a formalization, from a System Engineering (SE) perspective, of the implementation of an NLP-based system in the pre-design phase of an Italian public procedure. SE focuses on the formalization of main stakeholders, system values and functions via IDEF0, Analytical Hierarchy Process (AHP), and Quality Function Deployment (QFD).

Introduction

Natural language in pre-design phase

Pre-design is the initial phase of an architectural design and construction process and it has a significant impact on the project's value (Senescu et al., 2014). The main purpose of this phase is to define project goals and objectives which must satisfy stakeholders' needs and demands reaching a consensus between the stakeholders' needs and design teams' proposals. Thus, an effective communication and understanding of the expressed requirements and demands is crucial for the project success (Taleb et al., 2017). Effective communication means that the intended messages and information have been properly understood and processed by the actors involved (Norouzi et al., 2015). Typically, during pre-design phase, communication is mainly based on natural language: verbal expressions, written or spoken, are collected in text documents (Di Giuda et al., 2020). Natural language is pervasive and one of the richest forms of knowledge representation and communication. However, natural language is also prone to ambiguity due to its complex form and can lead to misinterpretations (Sun and Li, 2022).

Italian public design call for tender: actors, information flow and criticalities

The procedure of a public design call for tender, in the Italian context, involves mandatory steps and participation of several actors:

- Public actor (appointing party): it defines needs, objectives, and requirements to be reach by the project, and it shares and communicate this information via a text document called Documento di Indirizzo alla Progettazione (DIP) in the Italian context.
- Design teams: design groups participating to the call for tender. They aim to produce a design proposal to meet the public actor's demands and, by means of that, win the tender.
- External committee: appointed by the public actor, it evaluates the bids to identify the best design project, namely the most compliant with the declared demands.

From this point of view, the DIP document is the instrument for the public actor to share the expectations regarding the design and construction of the building. The DIP is divided into two main sections: I) a quantitative section about the state of the premises, technical requirements, restrains, and regulations which can be defined via alpha-numerical parameters; II) a qualitative section which describes quality objectives and expectations like e.g., flexibility of spaces, perceptual or visual comfort. All these characteristics are defined and shared via verbal and natural language expressions. Analysing a public design call for tender procedure in the Italian context, some criticalities in the information flow among the involved actors can be identified, as illustrated in Figure 1.

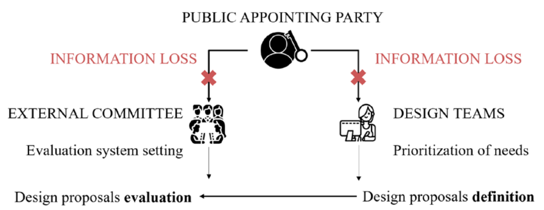

Figure 1: Document-based information flow criticalities.

The first criticality occurs when the design teams must identify the quality objectives and demands in the DIP and translate the natural language expressions into a list of prioritized goals to be pursued and met by the design proposals. The same criticality comes up for the external committee in charge of the evaluation, which must identify and translate the public actor expressions into a numerical evaluation system to compare the design proposals and find the most compliant one. During the whole process, the public actor has no control on the translation procedure, which is manually implemented and strongly subjective, being based on the actors' ability and experience to interpret the hierarchy of quality needs and demands.

A misinterpretation or an error during the identification and translation task, made by the design teams or/and by the external committee, can lead to an undetectable and unmeasurable quality gap (Locatelli, Seghezzi and Di Giuda, 2021). In the Italian public procedure context, the application of NLP to translate quality expressions to support the definition of an evaluation system can avoid, or at least, reduce the mentioned quality gap.

State of the art

Natural Language Processing

As explained above, all the quality-related information is expressed relying on human natural language, via written text documents, which is considered an unstructured data form and can be digitally managed via a specific technique called Natural Language Processing (NLP). In a broader view, NLP aims to allow computers to process human natural language and generate knowledge (Montgomery, 1969, Pacak and Pratt, 1971, Barnett et al., 1990, Lenci et al., 2005, Young et al., 2018).

Natural Language Processing in AECO sector

An analysis of the NLP applications in the Architecture, Engineering, Construction and Operation (AECO) field is provided to frame existing applications and studies and detect possible deficiencies and research gaps. NLP systems seem to be already applied in several AECO sector fields (Wu et al., 2022). Procurement, Safety, Project, and Construction risk management are the fields where NLP is most widely used. Articles about NLP applications in AECO are listed and gathered according to field and scope/task performed:

- Procurement management: Classification of legal clauses (Hassan and Le, 2020, 2021); Automated detection of risky clauses in contract documents (Mahfouz et al., 2018, Lee et al., 2019, 2020); Automated detection of contract changes (Khalef and El-adaway, 2021); Facilitate disputes resolution (Fan and Li, 2013).
- Safety management: Safety risks prediction (Ajayi et al., 2020, Zhong et al., 2020); Accidents analysis (Zhang et al., 2019); Safety incompatibilities prediction (Tixier et al., 2017); Accidents and injuries prediction (Tixier et al., 2016a, 2016b, Baker et al., 2020).
- Project and construction risk management (different from safety and legal risks): Automated detection of requirements defects (Ferrari et al., 2018); Estimation of the risk of non-compliance with time, cost, and project quality levels (Lee and Yi, 2017, Siu et al., 2018, Bilal and Oyedele, 2020, Faraji et al., 2021); Support project and construction risk management (Zou et al., 2017); Support or automate compliance checking (Zhang and El-Gohary, 2017, 2019).

No articles seem to be related to the pre-design or preliminary phases, representing a possible research area not covered by the Academia as of now (Locatelli, Seghezzi, Pellegrini, et al., 2021). Seen the potentiality and the existing applications, NLP techniques can be applied to automatically identify and translate the quality objectives and needs expressed via a DIP document into a numerical and machine-computable form (Locatelli, Seghezzi and Di Giuda, 2021). The paper proposes a formalization and the conceptual modeling, based on System Engineering techniques, of an NLP-based system to automatically process and translate needs and quality objectives into hierarchized objectives and the integration in a public tender procedure in the Italian AECO context. The NLP-based system aims to optimize communication among the actors and consequently minimize the demand/offer quality gap.

Methodology

System Engineering approach: reasons and scope

Being the research object a multi-stakeholder and complex system a System Engineering approach is applied to depict a clear view of the theorized system supporting the identification and definition of I) Main stakeholders, II) System contents, boundaries, and relationships, and III) Target values (decision criteria) and mission (functions). In fact, Systems Engineering (SE) is defined as a transdisciplinary and integrative approach, embracing systems principles and concepts, as well as, technological and managerial approaches. (Silitto et al., 2019). SE allows to balance technical and social needs of system stakeholders, including clients, end-users, and interested third parties. The goal of the approach is the formalization of the "whole system" and its relationships, not just the engineered artifacts. The steps of the manuscript are here summarized:

- Purpose, boundaries and a first description of the system are defined via an IDEF0 context diagram.
- System values are defined and then prioritized according to the stakeholders' interests using the Analytic Hierarchy Process (AHP).
- Technical functions are identified and via Quality Function Deployment (QFD) approach are hierarchized according to the AHP priority results.
- Then the IDEF0 context diagram is decomposed in sub functions via an IDEF0 child diagram providing a functional description of the whole system.

Conceptual modeling: IDEF0 context diagram

IDEF0 (Integration Definition for Process Modelling) diagram is used to conceptualize the system scope and boundaries, main stakeholders, and main function. IDEF0 is a diagramming technique for modelling representations of functions involved in complex systems allowing to categorize the functional context, main function and flows and state system's purpose and viewpoints (Manenti et al., 2019). The IDEF0 method uses the ICOM scheme (Inputs, Controls, Outputs, and Mechanisms/Resources): the main function, which receives inputs and controls, uses mechanism, or resources, and provides outputs are the five components of the IDEF0 diagram (Figure 2).

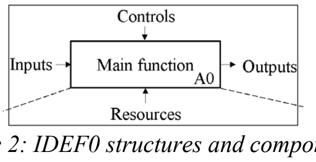

Figure 2: IDEF0 structures and components.

Conceptual modeling: AHP technique

In order to identify system values (decision criteria) and their relative priorities the system is analysed via an Analytic Hierarchy Process (AHP). AHP is considered a Multiple Attribute Decision Making technique and it has been applied in several fields (Vaidya and Kumar, 2006). The AHP allows to decompose a decision-making problem into different hierarchical structures according to the analysis goal (Saaty, 1987), as shown in Figure 3.

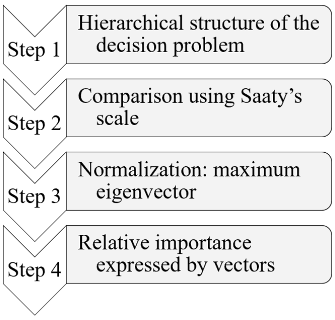

Figure 3: steps of AHP technique.

A series of pairwise judgments from domain experts or decision-makers allows the assignment of the relative importance between criteria, sub criteria, or alternatives solving the eigenvectors of a matrix to find the priority of each factor (Sun et al., 2019). The relative importance between two criteria/values is measured according to the Saaty scale (1 equal importance - 9 absolute importance) (Saaty, 1980).

The approach enables to reduce complex decisions to simple rankings of criteria, sub criteria, and/or alternatives which would help the expert or the decision maker classifying the best decision accordingly to his/her own interests, while perceiving a clear rationale of the decisions (Chin et al., 1999).

Conceptual modeling: AHP and QFD combination

Quality Function Deployment (QFD) was developed as a customer-oriented approach for product innovation, gathering and transforming the customer requirements throughout the design process, from product concept to manufacturing operations (Chan and Wu, 2002). Generalizing the QFD method in a Systems Engineering approach, two elements must be identified and evaluated at the beginning:

- Key functions.
- Values used to judge the importance of the functions.

Key functions of the system are identified as the first step of the approach. Then the QFD technique includes the evaluation of the defined functions according to the effect/impact/satisfaction of each function respect to the values/criteria. The effect/impact between each function and each criterion is measured according to the Likert scale: (1 weak – 5 maximum effect, impact, or satisfaction) (Likert, 1932). The results of the function-value evaluation are weighted multiplying them with the AHP relative importance results.

The QFD method is applied to find the technical functions required to the system, whereas AHP is used to measure the priority of each function accordingly to stakeholders' expectations. Decision support procedures based on the combined adoption of AHP and QFD can be considered useful methods to implement the engineering of a system based on the values identified as of highest importance (Vaidya and Kumar, 2006). The main goal of an AHP and QFD combined approach is to support a rational understanding and description of the interests expressed by different target stakeholders so that the system will have the capacity to provide the functions for achieving the stakeholders' desired values (De Felice and Petrillo, 2010).

Conceptual modelling: IDEF0 child diagram

IDEF0 boundary diagram used to identify the functional context, the main function, and state purpose and viewpoints is decomposed in an IDEF0 child diagram to describe function and flows with a higher degree of definition (Figure 4).

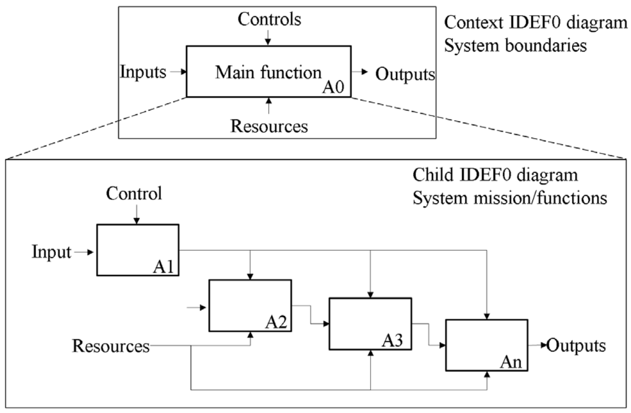

Figure 4: IDEF0 parent/child diagram structure.

Results and Discussion

IDEF0 context diagram: system conceptualization

A conceptualization of the system scope and boundaries, main stakeholders, and function via an IDEF0 diagram is provided in Figure 5.

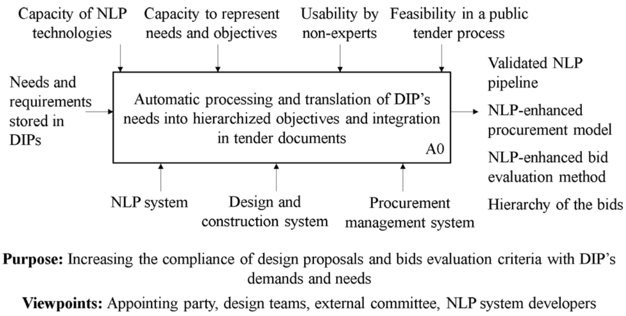

Figure 5: IDEF0 context diagram.

The main function of the system is the "Automatic processing and translation of DIP's needs into hierarchized objectives and integration in tender documents" with the purpose of increasing the compliance of design proposals and bids evaluation criteria with DIP's needs. The inputs of the system are the Client's needs stored in the DIP. The outputs are I) Validated NLP pipeline, II) NLP-enhanced procurement model, III) NLP-enhanced bid evaluation method, and IV) Hierarchy of the bids.

AHP: system values/criteria

The decision-making problem is divided into different hierarchical structures according to the AHP method to identify system values (decision criteria) and their relative priorities. Figure 6 shows the identification and categorization of the system values.

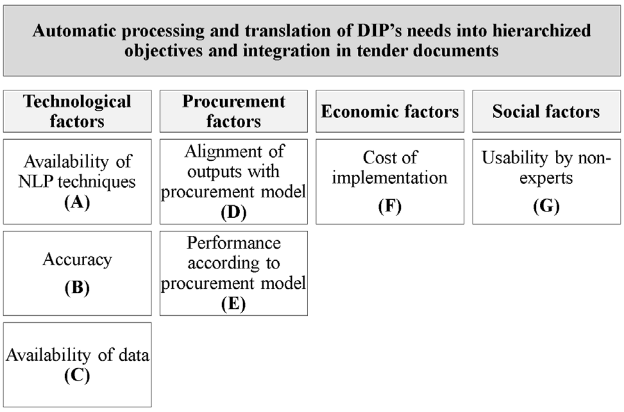

Figure 6: AHP values decomposition three.

A) Availability of NLP techniques: existence and suitability of NLP techniques for the purposes and their applicability to the available data sample.

B) Accuracy: capability of the NLP pipeline to properly translate and hierarchize quality needs.

C) Availability of a data sample: availability of a sufficient number of similar DIPs (in terms of building typology and budget) to properly train and validate the NLP pipeline.

D) Alignment of outputs with procurement model: feasibility of the outputs of the NLP pipeline to be integrated in the tender documents without any more processing (in terms of type of outputs).

E) Performance according to procurement model: impact of the NLP pipeline outputs in terms of improvement of the tender process according to the different procurement models.

F) Cost of implementation: costs of setting and implementing the NLP system.

G) Usability by non-experts: possibility to understand and use the outputs of the NLP pipeline and the NLP-enhanced tender documents by non-NLP experts.

The AHP involves the pairwise comparison of the identified 7 factors considering the system from the point of view of all stakeholders: public appointing party, design teams, external committee, and NLP system developers. Each stakeholder has different priorities, expectations, and values. The relative importance between two factors is measured according to the Saaty scale (1 equal importance - 9 absolute importance). An example of the comparison matrix for the appointing party stakeholder is provided in Table 1.

Table 1: AHP values comparison matrix.

Values	A	B	C	D	E	F	G	Norm
A	1	1/5	1/4	1/7	1/7	1/5	1/7	0.03
B	5	1	5	1	3	3	2	0.25
C	4	1/5	1	1/5	1/3	2	1/5	0.06
D	7	1	5	1	3	5	3	0.28
E	7	1/3	3	1/3	1	5	2	0.16
F	5	1/3	1/2	1/5	1/5	1	1/5	0.06
G	7	1/2	5	1/3	1/2	5	1	0.16

The AHP comparison has been conducted by 3 experts for each domain, with a solid background in the fields related to all the stakeholders (i.e., NLP experts, construction and design technicians, and procurement experts) allowing to identify the most important values for the whole system (normalized weight > 0.2; mean between max: 0.35 and min: 0.05), Figure 7. Most important values for each stakeholder:

- Accuracy (B) and alignment of outputs (D) for the appointing party (Public client).
- Accuracy (B), alignment of outputs (D), and usability by non-experts (G) for the design teams.
- Accuracy (B) and usability by non-experts (G) for the external committee.
- Availability of NLP techniques (A) for the NLP system developers.

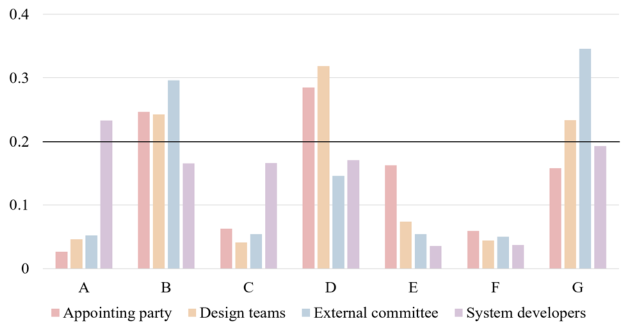

Figure 7: Most important values listed per stakeholders.

In general, the most important factors/values considering all the stakeholders, as shown in Figure 8, are:

B) Accuracy

D) Alignment of outputs

G) Usability by non-experts

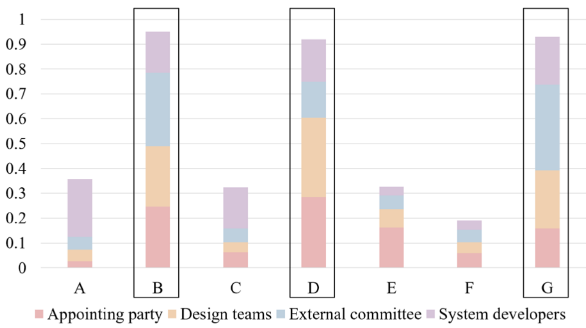

Figure 8: Most important values for all stakeholders.

Based on the AHP analysis, accuracy (a technological factor) and alignment of outputs (a procurement factor) rank as the two most important values, followed by usability (a social factor).

QFD and AHP combination: functions prioritization

The integration between the AHP results with a QFD analysis allows to identify the mission (main functions of the system) and define the values impacted by the importance of functions allowing to make a prioritization of the critical functions. The description of the system functions is here provided:

A1) Data collection and analysis: collection and analysis of data regarding quality needs and demands by analysing the selected DIPs.

A2) NLP technique selection: analysis of available NLP techniques to identify the most suitable for the system, considering the characteristic of the data sample.

A3) NLP pipeline setting: setting and training of the NLP pipeline to automatically and accurately translate quality needs and demands expressions into hierarchized objectives/evaluation criteria.

A4) NLP application and validation: DIP processing to digitalize quality needs and objectives expression stored in the DIP and subsequent output validation by the appointing party.

A5) Integration in procurement process: integration of the NLP pipeline outputs in the tender process and documents shared with the design teams and the external committee.

A6) Evaluation of bids: evaluation of the bids according to the hierarchized objectives/criteria used as an evaluation scoring system.

As stated, the QFD includes the evaluation of the functions according to the effect/impact/satisfaction of each function respect to the values/criteria previously identified in the AHP. The effect/impact between each function and each criterion is measured according to the Likert scale (1 Weak - 5 Maximum effect/impact/satisfaction). A functions-criteria/values relationship matrix is performed for each stakeholder. An example of the QFD and AHP matrix for the appointing party stakeholder is provided in Table 2.

Table 2: QFD and AHP combined values-functions matrix.

QFD	A	B	C	D	E	F	G
A1)	4	5	5	1	1	2	1
A2)	5	5	5	3	1	2	1
A3)	5	5	5	1	1	5	1
A4)	5	5	3	4	3	2	5
A5)	1	1	1	5	5	2	4
A6)	1	4	1	4	5	2	3
Weight	**0.03**	**0.25**	**0.06**	**0.28**	**0.16**	**0.06**	**0.16**
A1)	0.11	1.23	0.31	0.28	0.16	0.12	0.16
A2)	0.13	1.23	0.31	0.85	0.16	0.12	0.16
A3)	0.13	1.23	0.31	0.28	0.16	0.30	0.16
A4)	0.13	1.23	0.19	1.14	0.49	0.12	0.79
A5)	0.03	0.25	0.06	1.42	0.81	0.12	0.63
A6)	0.03	0.99	0.06	1.14	0.81	0.12	0.47

The values obtained for each function are then summed defining a priority scale:

A1) Data collection and analysis: 2.38

A2) NLP technique selection: 2.97

A3) NLP pipeline setting: 2.58

A4) NLP application and validation: 4.09

A5) Integration in procurement process: 3.32

A6) Evaluation of bids: 3.62

Figure 9 shows per each stakeholder the results of the QFD and AHP combined analysis. The two functions A4) NLP application and validation and A6) Evaluation of bids are identified as the most important; A2) NLP technique selection is also identified as a fundamental function for all the stakeholders.

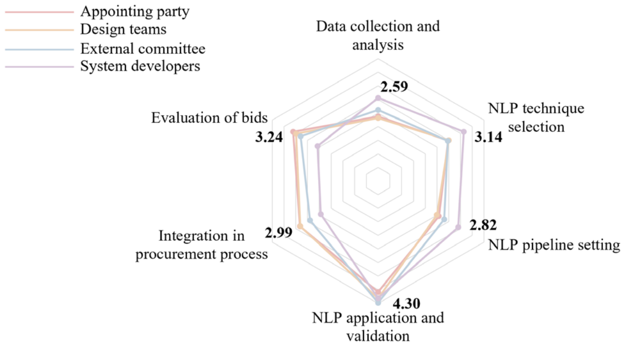

Figure 9: Radar chart of the effect/impact/satisfaction of each functions respect to the stakeholders' values/criteria.

IDEF0 child diagram: functional decomposition

An IDEF0 child diagram (Figure 10) to formalize the systems sub-functions is provided. Inputs, Controls, Outputs, and Mechanisms/Resources of the IDEF0 context diagram (Figure 2) are decomposed with a higher degree of definition according to the scheme shown in Figure 4 (IDEF0 parent/child diagram structure). Controls and Mechanisms/Resources decomposition list is provided.

Mechanisms/Resources decomposition:

- NLP system: NLP experts, NLP approaches, NLP libraries and algorithms.
- Design and construction system: Design and construction experts.
- Procurement management system: Procurement experts, External committee.

Controls decomposition:

- Capacity of NLP technology: Typology of NLP approach, NLP algorithm performances, NLP coding constraints.
- Capacity of the model to represent needs and objectives: Representative sample, Representativeness capacity.

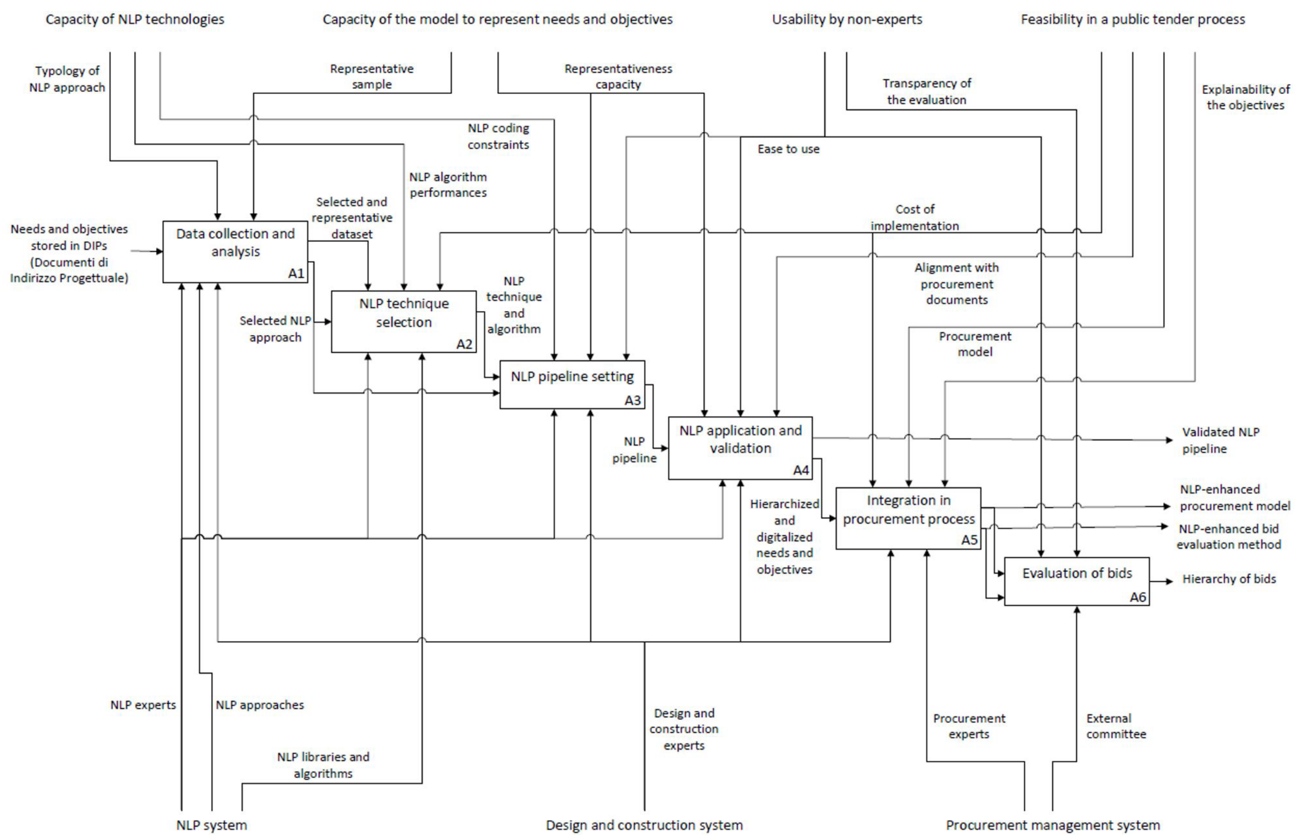

Figure 10: Overview of the functional decomposition from the Context Diagram – IDEF0 child diagram.

- Usability by non-expert: Transparency of the evaluation, Ease to use.
- Feasibility in a public tender process: Cost of implementation, Alignment with procurement documents, Procurement model, Explainability of the objectives.

The sub-functions identified are linked via mutual inputs and outputs. As stated, the IDEF0 diagram provides a broader description of the system from a functional point of view.

Conclusions

In this paper, the theorized NLP-based system is formalized and conceptually modelled using System Engineering techniques.

The IDEF0 context diagram highlights the system main function: "The automatic processing and translation of DIP's needs into hierarchized objectives and integration in tender documents".

The purpose of the whole system is to increase the compliance of design proposals and bids evaluation criteria with DIP's demands, improving effective communication among the actors involved in a public design call for tender procedure in the Italian AECO context. The higher level of communication and compliance aims to decrease the criticalities in the information flow among the main actors involved (i.e., appointing party, design teams, and the external committee in charge of the evaluation). Reducing possible misinterpretation during the quality objectives and demands identification and translation task, consequently minimizing the quality gap between quality demand and design offer.

The inputs of the system are also identified, namely the public appointing party's needs stored in the DIP, as well as the outputs of the system: I) Validated NLP pipeline, II) NLP-enhanced procurement model, III) NLP-enhanced bid evaluation method, and IV) Hierarchy of the bids.

Competencies and skills in NLP system developing, design and construction, and procurement management fields are identified as resources/mechanism necessary to develop the system. Modern NLP technologies capacity to model needs and quality demands, usability by non-expert, and feasibility in a public tender procedure are identified as main controls that rule the system.

The AHP analysis shows that the most important values, considering all the stakeholders, are B) Accuracy (a technological factor), D) Alignment of outputs (a procurement factor), and G) usability by non-experts (a social factor). The most important values belong to 3 out of the 4 general categories.

The AHP and QFD combined analysis identifies that function A4) NLP application and validation, and A6) Evaluation of bids are the most important for the whole system, likely because their outputs are the hierarchized objectives list which is fundamental to properly identify the winning bid. Function A2) NLP technique selection is also identified as fundamental since it is the starting point for the definition of the NLP pipeline leading the subsequent choice of the NLP algorithm.

In conclusion, formalizing the system through Systems Engineering allowed highlighting and balancing the technical and social needs of the stakeholders by modelling the entire system and its relationships, focusing not exclusively on engineered artifacts.

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