Generative AI for Business Model Generation (GAI4BM): from Textual Description to Business Process Model

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10th International Food Operations & Processing Simulation Workshop, 013
21th International Multidisciplinary Modeling & Simulation Multiconference

2724-0355 © 2024 The Authors.
doi: 10.46354/i3m.2024.foodops.013

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Abstract

Currently, companies are increasingly turning to process modeling as a tool to comprehend and enhance their internal operations, thereby boosting efficiency. However, executing these processes effectively poses a significant challenge for organizations. While process modeling serves as a pivotal step toward formal models that facilitate verification or simulation, the initial description of processes often relies on natural language. Transitioning from this textual description to a more formal BPMN (Business Process Model and Notation) representation remains a time-consuming and difficult task for experts. This article proposes exploring the use of Generative Artificial Intelligence and especially Large Model Language Models (LLM) such as GPT (Generative Pre-trained Transformer) to generate BPMN business process models from textual descriptions. This process includes various steps, including natural language understanding, extraction of pertinent information, and translation of this data into structured BPMN elements. By employing generative artificial intelligence, the objective is to automate and streamline this process, offering a more efficient approach to business process modeling.

Keywords: Business process model, BPMN standard, Generative Artificial Intelligence, natural language, transformation.

1. Introduction

In a competitive business environment, organizations are constantly trying to streamline operations and optimize performance. To this purpose business models - including business Process model - are a powerful tool for achieving these goals, enabling businesses to visualize, analyze, and improve their activities (Aguilar-Savèn, 2004). In this way, process modeling has become an important step to better understand the actions and activities involved in companies (Shafer *et al.*, 2005). Traditionally, process modeling involves manually converting textual descriptions (coming from documents or else interviews) of processes into formal models, such as BPMN (Business Process Model and Notation) (BPMN, 2021) (Chinosi *et al.*, 2012). This task remains time-consuming, error-prone, and requires specialized expertise, hindering the widespread adoption of process modeling (Alotaibi, 2016). In addition, this research work is being developed as part of the Smallders Project, the objective of which is to enable smallholders to master their process in order to optimize their KPIs in terms of cost, time and resources. In this case, Generative Artificial Intelligence (Generative AI) and its last development (such Chat GPT, Gemini or else Mistral AI) can be a good candidate to support business users in their modeling task.

Generative Artificial Intelligence is a field of AI focused on creating new content, like text, images, sounds, music, and even 3D models (Anantrasirichai *et al.*, 2022). It works by learning the patterns and relationships in a large dataset of existing content to create something new and original. Thus, the use of Generative AI would therefore be an innovative approach to translate a text description into a business process model. In fact, by automating the conversion of natural language process descriptions into BPMN models, Generative AI can significantly reduce the time and effort required for process modeling, making it more accessible and efficient for non-expert business users.

This paper presents the foundation of a novel approach to transforming text into business process model (such as BPMN) using Generative AI. The approach proposed here is exploratory and makes it possible to initiate research work around the use of Generative AI to allow automatic process modeling from text description.

The paper is organized as follows. After this brief introduction, Section 2 describes a state of the art about existing transformation from text to BPMN and Generative Artificial Intelligence. Section 3 introduces the proposed approach for automatic process modelling using the Generative IA. To illustrate the proposed method, examples of the first results are given in section 4. Section 5 presents discussion related to the limits of this research work. Finally, section 6 presents a conclusion and some perspectives for this research work.

2. State of the art

2.1. Text 2 Process Model

Transforming a text into a model is often facing several issues due to the inherent complexity of the Natural Language (NL). In that sense, the process of transformation must consider (Friedrich *et al.*, 2011):

- **Structural Ambiguity in NL:** Natural language is often ambiguous (ex. *"Mary walks the dog with a cap"*, is it Mary with the cap or the dog?), which can make it difficult to determine the exact meaning of a given text expression. This can lead to errors in the translation of text into models.
- **Lexical Ambiguity in NL:** There are many ways to express a business process in natural language. This can make it difficult for a text-to-BPMN translation system to learn the correct mapping between natural language expressions and BPMN elements ("*I take my breakfast and I read the newspaper*" the *and* leads to sequential activities or parallel activities?).
- **Incompleteness of NL (under-description):** Natural language descriptions of model are often incomplete, which can make it difficult to identify an object of the model (ex. an activity from process model)
- **Over completeness of NL (over-description/noise):** Natural language description of the model includes more and/or not useful information leading to identify objects that are not supposed to be in the final model.

Considering these challenges, two main approaches are usually implemented: the Natural Language Processing - NLP (ex. parsing) or the use of Domain Specific Language – DSL (ex: Controlled Natural Language) (Goncalves *et al.*, 2011), (Ivanchikj *et al.*, 2020). The first one can be limited by the complexity of some words and sentences (in term of semantic and syntax) not considered in the parsing rules. The second limits the user by using a specific grammar and may not allow the modeling of complex models. In the limited frame transformation of text to BPMN (Sholiq *et al.*, 2022) introduces different studies relying on NLP and CNL.

2.2. Generative Artificial Intelligence

In recent years, Generative Artificial Intelligence (GAI) has rapidly evolved and grown with the potential to revolutionize many aspects of our lives. Generative AI systems are able to create new content, such as images, music, and text, that is more and more impossible (or very difficult) to differentiate from human-created content. This makes Generative AI a powerful tool for a wide range of applications, including (Mandapuram *et al.*, 2018):

- **Art and Design** to create new and innovative artwork, such as paintings, sculptures, and music.
- **Scientific Discovery** to generate new hypotheses and theories in science.
- **Education** to create personalized learning experiences for students.
- **Business** to develop new products and services, and to improve marketing and customer service.

GAI are a type of artificial intelligence allowing to generate new content from already existing data. Algorithms are often based on probability distributions and on large databases to successfully create new data, which can be text (like Chat-GPT) (Singh *et al.*, 2023), images (like Mid-Journey) (Tanugraha, 2023) or even audio or video files. We can thus decompose the GAI into different subcategories:

- **Generative Adversarial Network (GAN)** represents a set of two networks of neurons working together. To put it simply, the first network's mission is to create the new data and the second is used to compare the created data with real data from a known database. As long as the second is able to do the difference between the "real" and the "created", he reviews the information in the first so that he begins his work again. The iterations are done until the second network of neurons are no longer capable of differentiating "real" from "created". This type of GAI is generally used for images. (Aggarwal et al., 2021).

- **Variational AutoEncoder (VAE)** makes it possible to reduce the base size of data. To do this, a neural network will encode the database into a dimension lower than the first dimension and AI intervenes in a second step: thanks to a probabilistic approach, the data will be decoded to return to the original dimension closest to the starting base (Pinheiro Cinelli *et al.*, 2021).
- **Transformers** are neural networks used to detect Data dependencies that may be very remote (Liu et al., 2021).
- **Generative Pre-Trained Transformers** (GPT) are Transformers that have been trained beforehand, that is to say to which multiple data have been provided allowing to optimize transformer calculation times (understanding of NL, spoken language, etc.). A very good example of GPT is simply Chat OpenAI (or Chat-GPT). This technology can also be found under the name LLM (Chavez et al., 2023).

Generative AI is still a young field, but it has already made significant progress only in few years. In the coming years, we can expect to see even more powerful and sophisticated Generative AI systems that will have a profound impact on our world and daily life (*e.g.*, GAI has already an impact on the way to work in business sector such as research).

In the frame of the model generation from text based on Artificial Intelligence is a growing discipline and we are starting to find some tools that allow us to obtain diagrams from text sources. In the more restricted framework of process model generation, we begin to find different tools - more or less accessible and among the few we can cite (Linkon *et al.*, 2024):

- **Figma**[1] which is a graphic design tool, it has an AI functionality which allows to generate organization charts, mind maps, Gantt charts, Timeslines...
- **Edraw**[2] which is an all-in-one diagramming software and also has a AI tool allowing you to generate a diagram via a description.
- **LucidChart**[3] diagramming software

These tools do not allow to create BPMN as target by this research but allows to obtain satisfying models especially for very simple process.

3. Text to BPMN: Proposed approach

Business process modeling notation (BPMN) is a visual representation of business processes that is widely used in organizations of all sizes (BPMN, 2021) (Chinosi *et al.*, 2012). It is a standardized notation that makes it easy to understand and communicate business processes to stakeholders. While BPMN offers expressive graphical elements like timer events, the learning and the expertise of both the individual symbol meanings (semantics) and the overall language structure (syntax) can be time-consuming. Additionally, the complexity of business activities, including internal activities as well as collaborative activities with external partners, makes longer to get a process models (time to model and validate). To address these challenges of learning the language and acquiring a model, tools exist to assist modelers by integrating syntax rules to correct model on the fly and offer also suggestions for refining modeling objects (ex. camunda, bpmn.io, bpmn2 modeler...) (Tiwari *et al.*, 2022). However, and despite these initiatives, performing a model still requires more expertise both in terms of knowledge about the language objects and the ability to model complex situations. This study proposes to develop a method to generate a process model from the very beginning of the collection of information (ex. interview of stakeholders) to the modeling of the process and relying on the use of GAI. Even if the ideal final result is a complete automation of the modelling process, i.e., without the intervention of any expert between the textual description of the process and its corresponding model, current developments require the involvement of an expert at various stages mainly to perform control. **Figure 1** describes the general transformation process.

3.1. Textual generation process

The initial process involves transforming speech from a stakeholder interview into a textual description of the process. The objective is to obtain a raw text description that can be further refined and implemented in the Generative AI (GAI) system. While this step is part of our proposed approach, it is not the primary focus since there are already various tools available for converting speech to text. Notable examples include Google Speech-to-Text, Microsoft Azure Speech Service, and others.

3.2. Process model generation

The process model generation involves converting the textual description into a visual model of the process. Two strategies can be adopted and tested for this conversion.

[1] https://www.figma.com/

[2] https://www.edrawsoft.com/

[3] https://www.langchain.com

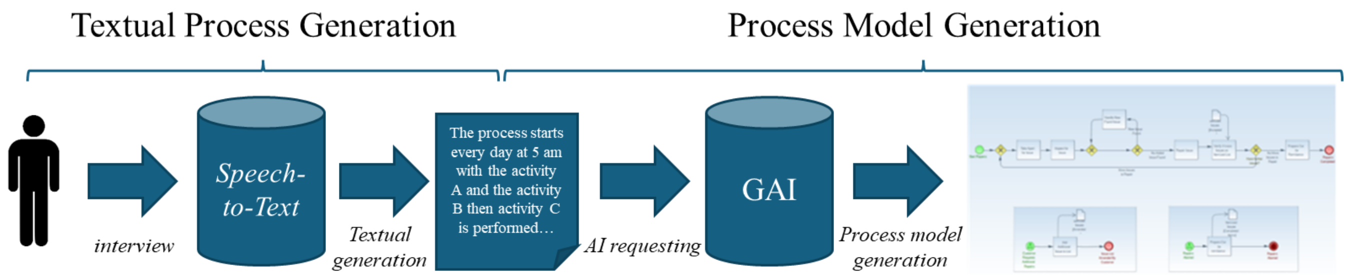

Figure 1. Proposed Approach: Generation of Business Process Model from Text using GAI.

It is to note that all the tests described below were conducted using ChatGPT version 4[4]. This choice was made due to the powerful capabilities and accessibility of OpenAI's architecture, making it an ideal tool for evaluating the relevance of the proposed approach. Similar tests were performed under identical conditions using the Gemini[5] and Copilot[6] architectures. However, the results from these tests are not presented or compared in this paper, as the focus is on showcasing the overall approach based on Generative Artificial Intelligence.

The first strategy is to directly prompt the text and request the corresponding process in various formats: as a textual description in terms of objects (e.g., activities), as a simple graphical representation, or as a BPMN file (e.g., *.bpmn using XML). For a straightforward example (**Figure 2**), the result is quite accurate and can be easily transcribed manually into a BPMN model with knowledge of the language.

This approach can be useful for simple processes and stakeholders who have knowledge of BPMN. However, The more the complexity of the process increases in its objects and its structure (e.g., involving sub-processes, loops, complex object such events etc.), the less satisfactory the results are. In such cases, there is a greater need for BPMN expertise to correct and accurately model the process. In this context, we encounter several issues:

- **Over-modeling:** Activities (the most common case) or other objects that do not exist are identified and proposed in the model.
- **Under-modeling:** Activities or other objects mentioned in the description are omitted.
- **Lack of BPMN objects:** Some elements are identified but not properly modeled. For instance, in the previous example, the citizen and administration are identified but not as two separate participants exchanging message flows, as required in BPMN.

Give me the bpmn process of this description:
« *The citizen fills in a form to apply for a ID card and sends it to the administration. The administration checks the application. If the application is complete, the administration issues the ID card and informs the citizen that he can collect the document. If the application is incomplete, the administration informs the citizen to reapply.*"

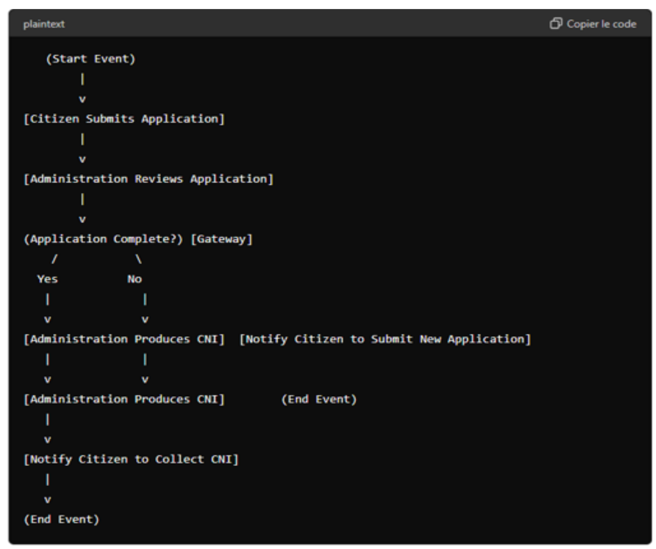
```
plaintext                                   Copier le code
   (Start Event)
        |
        v
[Citizen Submits Application]
        |
        v
[Administration Reviews Application]
        |
        v
(Application Complete?) [Gateway]
    /           \
  Yes            No
   |              |
   v              v
[Administration Produces CNI]  [Notify Citizen to Submit New Application]
   |              |
   v              v
[Administration Produces CNI]        (End Event)
   |
   v
[Notify Citizen to Collect CNI]
   |
   v
(End Event)
```

Figure 2. Result of direct prompting on a simple example

The second strategy involves "pre-processing" the text. This approach first identifies the objects involved in the process, then determines the sequence of activities, and lastly generates the process model. Relying onto GAI, the goal is to parametrize and use prompt engineering good practices to implement the approach. Prompt engineering is the practice of designing and refining the inputs (prompts) given to Generative AI models in order to achieve desired outcomes. It involves elaborating and formulating the text or instructions in a way that maximizes the effectiveness and relevance of the model's responses.

[4] https://chatgpt.com/
[5] https://gemini.google.com/app
[6] https://copilot.microsoft.com/

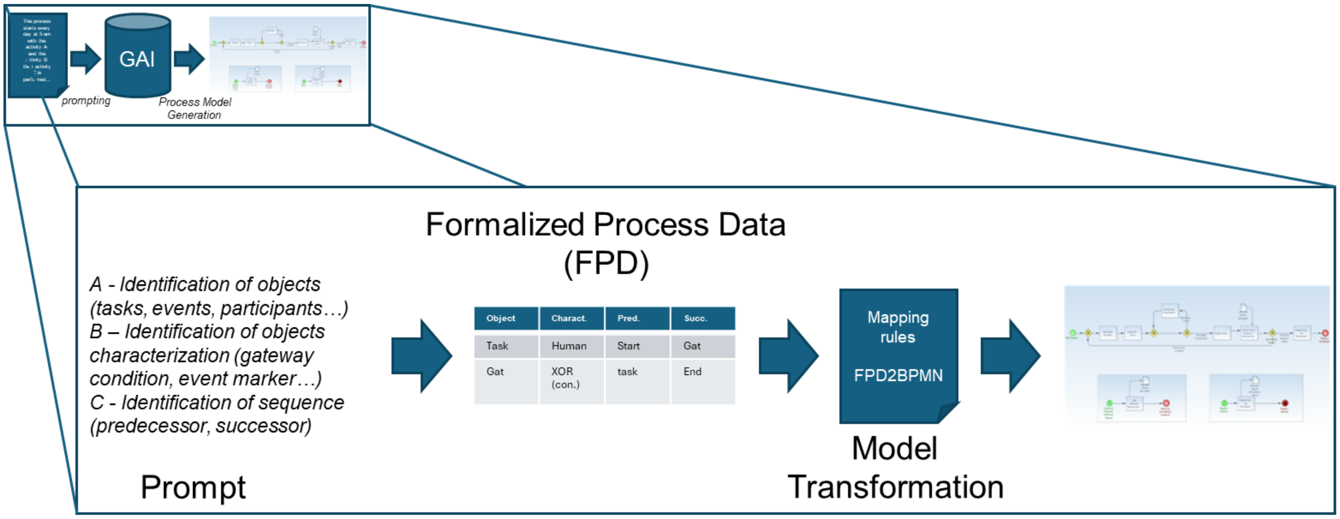

Figure 3. Generation of Formalized Process Data (FPD) from Text using GAI.

From the basic side of prompting, we can find rules and good practices such as reset AI memory before each new prompt, define inputs and outputs clearly, provide a context that will define the framework of the task to be accomplished by the AI, provide a clear, concise and error-free prompt to avoid AI interpretation errors, iterate and refine.

From a more advanced perspective of prompting, we can find automation through programming so that tasks can be optimized by generative AI, by combining this with code we can create applications that carry out very specific tasks, for example by creating chat-bots. In that case some prompt engineering methods can be deployed. We can mention several advanced techniques used in prompt engineering (Polat *et al.*, 2024):

- **Chain of Thought (CoT):** This technique provides the model with a sequence of detailed instructions describing the steps required to complete the task, enhancing the clarity and accuracy of the response.
- **Generate Knowledge (GK):** This method helps the model generate more precise and correct answers by encouraging it to think through the question and provide well-reasoned responses.
- **Retrieval Augmented Generation (RAG):** This approach involves retrieving relevant information from a set of documents and concatenating it into the prompt context, improving the model's ability to provide accurate and contextually rich answers.

The process from prompting to generating the process model is illustrated in the **Figure 3**. The current prompt aims to identify the objects types and characteristics (A and B) and the sequence of evolution of the process (C). Identifying the objects involves first categorizing them into different families according to BPMN standards, such as participants (containers Pools/Lanes), activities (Human, sub-process, loop...), events (start, end, boundary, in-flow), and gateways (XOR/AND/OR/Event-Based...). Each object is then characterized by specific attributes, for instance activities might be labeled as "*human*", events might be marked as "*timer*", and gateways might have conditions such as "*exclusive gateway*". Additionally, the participants involved in each object are determined.

To build the links between objects, both sequence flows and message flows need to be identified. This involves extracting the predecessor and successor of each object to define the sequence of activities (*e.g.*, a start event cannot have sequence flow as input). Establishing these connections between objects ensures that the sequence and message flows are accurately represented in the process model. This structured approach facilitates the generation of a precise BPMN model, ensuring all elements of the process are correctly identified and connected.

The expected result of this identification is a Formalized Process Data (FPD) table that presents all elements of the process along with their accurate characteristics (**Figure 4**).

Element	Type/marker	Name	Predecessor	Successor	Condition	Participants
Task	Human	T1	T0	T3	--	Pool1

Figure 4. Formalized Process Data template

If we take the previous example and made a very simple request for a FPD into ChatGPT 4, we get the following result (**Figure 5**). We can observe that information requested to produce a BPMN model are present and relevant with the initial description. Both participants are identified, and objects are positioned inside, except for the start event and the end event. It means that even if two participants are identified it seems that only one process is described (only one start event and one end event are extracted). The sequence is correctly determined from the begin to the end.

Give me a table of the bpmn objects including object, type, name, predecessor, successor, condition and participant for the following process description: *The citizen fills in a form to apply for a ID card and sends it to the administration. The administration checks the application. If the application is complete, the administration issues the ID card and informs the citizen that he can collect the document. If the application is incomplete, the administration informs the citizen to reapply*

Object	Type	Name	Predecessor	Successor	Condition	Participant
Start Event	Event	Start	None	Fill in Form	None	None
Task 1	Activity	Fill in Form	Start Event	Send to Administration	None	Citizen
Task 2	Activity	Send to Administration	Fill in Form	Check Application	None	Citizen
Task 3	Activity	Check Application	Send to Administration	Complete?	None	Administration
Gateway 1	Gateway	Complete?	Check Application	Issue ID Card, Inform to Reapply	Application complete?, Application incomplete?	Administration
Task 4	Activity	Issue ID Card	Complete?	Inform to Collect	Application complete?	Administration
Task 5	Activity	Inform to Collect	Issue ID Card	End Event	None	Administration
Task 6	Activity	Inform to Reapply	Complete?	End Event	Application incomplete?	Administration
End Event	Event	End	Inform to Collect, Inform to Reapply	None	None	None

Figure 5. Result of a simple prompting requesting a FPD on a simple example.

The resulting BPMN model is sufficient for use but would gain in accuracy if participants were identified separately and the exchanges between them were detailed (**Figure 6**). However, it is important to keep in mind that this example, along with the prompt used to obtain the various objects in a structured manner, is very simple. Trials on more complex examples do not yield such conclusive results (e.g., use of sub-processes). Despite these limitations, the prompt engineering approach for obtaining structured data remains the most effective method for the automatic generation of process models within the scope of this work.

Using the Formalized Process Data (FPD), we aim to transform it into a final process model. To achieve this, we propose building on the work by (Mallek- Daclin et al., 2023), who developed methods for converting structured data, such as Gantt diagrams, into BPMN models. Our objective is to establish transformation rules that convert FPD into the corresponding XML format used in BPMN models.

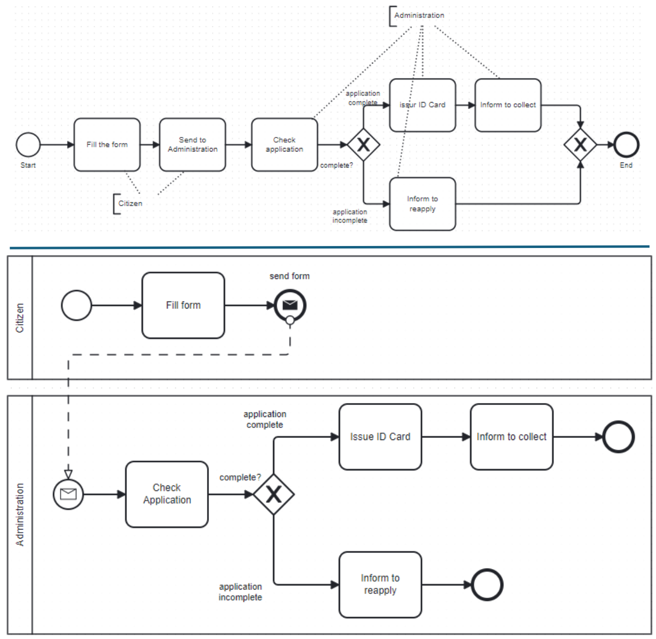

Figure 6. Process model from the FPD (upper model) vs. expected process model (lower model)

4. Discussion and further works

The initial results using a combined approach of prompt engineering and structured data within the framework of Generative AI (GAI) to obtain process models appear promising. However, these tests were conducted on very simple examples. As the complexity of the process increases, the prompts need to be more finely tuned as well as the expected FPD. Thus, this research continues to explore this approach, addressing the following research issues:

- The identification of missing information (ex. omission of a described object) and adding of information (ex. addition of a none described object)
- The identification of specific objects and constructs (ex. boundary event, loop, sub-process)
- A textual description of a process can lead to the use of different modeling objects depending on factors such as the degree of expertise of the modeler or the need for a more or less expressive model. For example, an exchange between processes can be modeled using a send task, which is very expressive and suitable for beginners, or a send event, which is less expressive and more suited to experts. The goal, in this case, is to allow the business users to define their degree of expertise and present a corresponding model tailored to their level.
- Train the GAI to improve the process model generation over time.

While the ultimate goal is to produce process models that can be directly implemented without requiring validation, we recognize that this is often unrealistic, particularly in complex fields such as healthcare or crisis management. Nonetheless, our aim is to minimize the need for extensive validation. This will enable business users who are not modeling specialists to effectively use various existing BPM tools, including those for modeling, automation /orchestration, and simulation.

5. Conclusion

This article proposes a GAI-based approach to generate a BPMN process model from textual description. It highlights potential benefits of this approach, such as reducing the time required for process modeling, improving accuracy through advanced semantic analysis, and the possibility of involving non-technical stakeholders in the modeling process.

However, considerations related to the quality of generated models, the complexity of business processes, and the nuances of natural language must be considered. In summary, the use of generative artificial intelligence to generate BPMN business process models from text (English in this research) represents an innovative approach aimed at simplifying and expediting the modeling process (even not providing directly an exploitable BPMN model), while offering potential advantages in terms of efficiency and stakeholder participation.

Future work will be concerned with the simulation of its models with the aim of offering a decision support tool to users such as smallholders (Smallders Project) in order to control KPIs (Velimirovića *et al.,* 2011) such as cost, time and resources thanks to simulation approach (El Kassis *et al.,* 2023), (BPSim, 2013). Work has already been initiated in this direction with the use of GAI for simulation (Alshareef *et al.,* 2023).

Acknowledgements

This research is supported by the research project entitled “Smart Models for Agrifood Local vaLue chain based on Digital technologies for Enabling covid-19 Resilience and Sustain- ability” (SMALLDERS), co-funded by the PRIMA Program - Section 2 Call multi-topics 2021, through the following National Authorities: Ministry of Universities and Research (MUR, Italy), State Research Agency (AEI, Spain), Agence Nationale de la Recherche (ANR, France), Ministry of Higher Education and Scientific Research (Tunisia). The authors acknowledge the grant P CI2022132924 funded by MCIN/AEI/ 10.13039/501100011033 and by the “European Union NextGenerationEU/PRTR”

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