MULTI-ASPECTUAL KNOWLEDGE ELICITATION FOR PROCUREMENT OPTIMIZATION IN A WAREHOUSE COMPANY

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ABSTRACT: *Efficient optimization of business processes required a profound understanding of expertise provided by domain specialists. However, extracting such insights can indeed be a laborious and time-consuming endeavour. This paper introduces the Multi-Aspectual Knowledge Elicitation framework (MAKE4ML) — a novel approach designed to effortlessly and effectively extract valuable information from domain experts. This framework inherently facilitates the development of machine-learning models capable of optimizing business processes, thereby diminishing reliance on experts. The framework's application within a food warehouse company is showcased, specifically targeting the enhancement of the procurement process. The employed methodology revolves around conducting comprehensive interviews with procurement experts, thereby enabling a meticulous exploration of diverse facets inherent to a business process. Subsequently, the gathered insights are employed to conceive and calibrate a machine learning model (time series forecasting). This model effectively emulates the domain experts' proficiency, offering invaluable decision-oriented insights. The outcomes of this study show that our framework allows efficient knowledge elicitation, which is a pivotal factor in formulating and deploying a bespoke machine-learning model. The proposed approach can be extended into various other business processes, thereby paving the way for operational refinement, cost reduction, and amplified efficiency.*

Keywords*: domain experts, knowledge elicitation, multi-aspects, machine learning, procurement optimization, warehouse, technology acceptance.*

1. INTRODUCTION

The growing demand for digitalization and process optimization has led to the integration of machine learning (ML) models across industries. This integration often requires insights from domain experts, necessitating the extraction of pertinent information to design tailored ML models. Researchers and ML engineers have employed various techniques, such as feature selection and knowledge elicitation, to enhance model accuracy while ensuring successful technology adoption. Studies have highlighted the challenges of knowledge elicitation, which significantly affect ML performance across disciplines. Researchers are increasingly exploring human involvement in ML workflows (D'Angelo & Palmieri, 2020; Park et al., 2023; Sundin et al., 2022; Wang et al., 2021), combining expert knowledge with data from diverse sources (Ademujimi & Prabhu, 2021; Ben Brahim et al., 2022; Hu et al., 2019; Huang et al., 2019; Lee et al., 2020; Seymoens et al., 2019), and innovative ways to extract insights (Afrabandpey et al., 2019; Campos et al., 2018; Cheung et al., 2011; Crerie et al., 2009; El-Assady et al., 2020; El-Assady et al., 2019; Mantik et al., 2022; Možina et al., 2018; Park et al., 2021; Yazici et al., 2022; Young et al., 2022).

First, human involvement in ML workflows referred to as "Human-in-the-loop", aims to create cost-effective prediction models by incorporating human knowledge during data preparation and refinement stages. Secondly, the integration of expert-derived knowledge with data from sources like sensors refines training objectives and contextual alignment, as standard sensor data might lack external factors' consideration. Finally, Intuitive techniques (e.g., decision-mining, process mining) bridge gaps between ML engineers and multi-disciplinary experts, translating meaningful insights into ML model specifications.

The central research question is: "How can we extract meaningful knowledge from domain experts for designing ML models while ensuring user acceptance?" To address this, a comprehensive framework is proposed, involving multi-aspectual knowledge extraction, translation into ML specifications, visualizing business workflows, and capturing decision-making rules and constraints. Key contributions include a multi-disciplinary knowledge extraction framework, translating knowledge into ML and software specifications, and visualizing business workflows and decision rules. The framework's efficacy is demonstrated in a warehouse setting, focusing on procurement. Experimental results reveal the successful extraction of diverse expert knowledge.

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2. RELATED WORK

2.1. Human Involvement in Machine Learning Workflow

In recent years, there has been a growing interest in human involvement in the machine-learning workflow. The use of human-in-the-loop techniques has been proposed to improve the performance and reliability of machine learning models. Several studies have investigated how human expertise can be used to improve the performance of machine learning models.

In the field of data science, (Wang et al., 2021) introduced AutoDS, an automated machine learning system that aims to support data science projects by automating tasks such as data exploration, model training, and model selection. This system proposes suggestions (ML configuration, pre-process data, etc.) to the users via a web-based graphical interface where they can interact and make amendments. They showed that the proposed system improved the productivity of ML workflow while delivering better models.

In the field of aerospace systems, (D'Angelo & Palmieri, 2020) proposed the use of genetic programming to extract knowledge from aerospace structural defects by providing a mathematical model of the defects, which can be used for recognizing other similar ones. They found that their approach was effective in building reliable models of the defects and can be considered a successful option for building the knowledge needed by tools for controlling the quality of critical aerospace systems.

(Sundin et al., 2022) proposed a principled approach to use human-in-the-loop machine learning to help chemists adapt the multi-parameter optimization (MPO) scoring function to better match their goal. They proposed a method that uses a probabilistic model that captures the user's idea and uncertainty about the scoring function and uses active learning to interact with the user. They showed the effectiveness of their approach in two simulated examples achieving significant improvement in less than 200 feedback queries.

Overall, these studies demonstrate the potential of a human involved in the ML workflow to improve the performance and reliability of machine learning models. However, further research is needed to understand the best ways to incorporate human expertise into the machine-learning process, and how to effectively balance the trade-offs between automation and human involvement.

2.2. Fusion-driven learning

The fusion-driven learning consists of the fusion of knowledge experts with data collected from other sources to improve the performance of machine learning models. Indeed, several works have been introduced to leverage the strengths of both human expertise and data-driven methods to create more accurate and reliable models. The most representative works are discussed hereafter (Ademujimi & Prabhu, 2021; Ben Brahim et al., 2022; Hu et al., 2019; Huang et al., 2019; Lee et al., 2020; Seymoens et al., 2019).

(Huang et al., 2019) propose a hybrid approach for identifying the structure of the Bayesian network (BN) for the threat assessment of mass protests. They demonstrate that traditional methods for discovering BN structure from data or experts were inadequate, and instead proposed a hybrid approach (ISM-K2) which enhanced the BN structure learning methods via a knowledge elicitation method called ISM (Interpretive Structural Model).

(Ademujimi & Prabhu, 2021) introduced a method for fusion-learning of Bayesian network (BN) models for fault diagnostics. They proposed an approach for expert knowledge elicitation of the BN structure aided by logged natural language data and sensor data. They found that the resulting fused BN model improved diagnostics as it had a wider fault coverage than the individual BNs.

(Hu et al., 2019) developed a methodology that combines sensor data with domain expert knowledge to improve energy fault detection. The proposed methodology includes an engagement process with experts in the energy system field to identify relevant data, an integration of domain knowledge with sensor data, an automatic selection of potential input data, and the use of machine learning to automatically build a data-driven fault detection model.

(Lee et al., 2020) presented an interactive machine-learning approach to improve the assessment of rehabilitation exercises by integrating a data-driven model with expert knowledge. This approach uses reinforcement learning to identify the most salient features of the exercise motions and generates a user-specific analysis to elicit feature relevance from a therapist for a personalized rehabilitation assessment. This study improves the performance of predicting assessment and demonstrates how machine-learning models can improve with expert knowledge for personalized rehabilitation assessment.

Overall, these studies demonstrate the potential of fusing knowledge from experts with data collected from other sources to improve the performance of machine learning models. However, further studies are needed to find techniques and methods to easily and efficiently fuse data used to train ML models while achieving the best performance.

2.3. Knowledge Elicitation Methods

There have been several studies in the past that have aimed to improve the efficiency and effectiveness of machine learning models through the incorporation of expert knowledge. These studies (Afrabandpey et al., 2019; Campos et al., 2018; Cheung et al., 2011; Crerie et al., 2009; El-Assady et al., 2020; El-Assady et al., 2019; Mantik et al., 2022; Možina et al., 2018; Park et al., 2021; Yazici et al., 2022; Young et al., 2022) have proposed various methods for extracting and utilizing expert knowledge: active learning, process mining and decision mining, and human-in-the-loop approaches.

One widely used approach is active learning, where a model is trained on a small initial labelled dataset and then iteratively queries the expert for labels on the most uncertain samples. (Možina et al., 2018) propose a data-driven tool for the semi-automatic identification of typical approaches and errors in student solutions for a programming course. They used the argument-based machine learning (ABML) method, which interactively exchanges arguments with an expert until the model is good enough. Similarly, (El-Assady et al., 2019) present a framework that integrates speculative execution, allowing users to preview the potential consequences of their actions with the model and make more efficient decisions.

Another approach uses process mining and decision mining to identify operational processes, viz., business rules. Indeed, (Campos et al., 2018) applies a decision-mining technique in an event log of a real company to discover tacit decisions that could be translated as business rules. In the same way, (Crerie et al., 2009) relies on process mining and data mining techniques to extract two sub-types of business rules: condition action assertions and authorization action assertions. Likewise, (Alkofahi et al., 2022) introduces a method to elicit business rules from real-world web applications; these rules are defined as one-to-one and one-to-many implicit dependency relations, thus minimizing the negative effect of substitute relations in decision-making.

A third approach relies on the concept of human-in-the-loop, (Afrabandpey et al., 2019; El-Assady et al., 2020; Park et al., 2021) whereby human experts are added into machine learning pipelines, allowing them to provide feedback or guidance at various stages of the model development process. For instance, (Park et al., 2021) describe a framework called “Ziva” that guides domain experts in sharing their knowledge with data scientists for building natural language processing (NLP) models. (Afrabandpey et al., 2019) introduce a method to elicit expert knowledge about pairwise feature similarities and use sequential decision-making techniques to minimize the effort of the expert while improving the prediction performance on a small dataset. (El-Assady et al., 2020) has developed a framework allowing users to provide semantics of their knowledge, which will contribute to topic model refinement.

Finally, (Yazici et al., 2022) performs knowledge prioritization after the elicitation from domain experts. The authors use knowledge elicitation and feature selection techniques to identify the most prevalent tacit knowledge variables, which are then prioritized using machine learning methods and the fuzzy Analytic Hierarchy Process (AHP).

Overall, various studies have proposed methods that allow the intuitive extraction of knowledge from experts and train optimized machine learning models. Although these methods allow knowledge elicitation, there are several areas and aspects that have not been (or have been poorly) considered so far. In this work, we aim to introduce a framework that considers the multi-aspect of concepts defining the context, their interdependence and translation into tailored specifications.

3. METHODOLOGY

3.1. Multi-aspectual Knowledge Elicitation (MAKE)

MAKE, multi-aspectual knowledge elicitation, developed by Winfield (Winfield, 2000) for planning and building knowledge-intensive systems, is based on Dooyeweerd's aspects (Table 1). By guiding and stimulating the participants to identify aspects that are important to their situation and opening up their constituents, MAKE begins with the most obvious aspects and gradually uncovers the relevance of each. As Winfield (Winfield, 2000) found, MAKE stimulated the participants to consider broader issues, lay participants were able to grasp the meaning of aspects and work with them during analysis, and some tacit knowledge was explicated through MAKE.

(Winfield, 2000) developed two visual tools to help multi-aspectual analysis. One employs a flexible mind map to build up an understanding of inter-aspectual relationships. The second method employs the Christmas Tree, designed to provide an overall picture of areas of concern that emerge during discussions. Any significant positive or negative repercussion that emerges can be 'hung on' the tree at the aspect in which it is meaningful, with the positive on one side and the negative on the other. As the picture develops, patterns emerge showing areas of significant benefit or problems, which can be clarified and tackled during the design and development process.

3.2. Proposed Framework

The framework in (*Fig. 1*) relies on the 15 aspects of Dooyeweerd (Basden, 2011) (*Table 1*) used in MAKE (Winfield, 2000) to elicit knowledge from domain experts through interactions, which allows an understanding of what is meaningful to them. Indeed, it uncovers the elements that are often not immediately apparent but contribute significantly to overall technology acceptance and success while avoiding unintended consequences. Our proposed framework consists of five key steps.

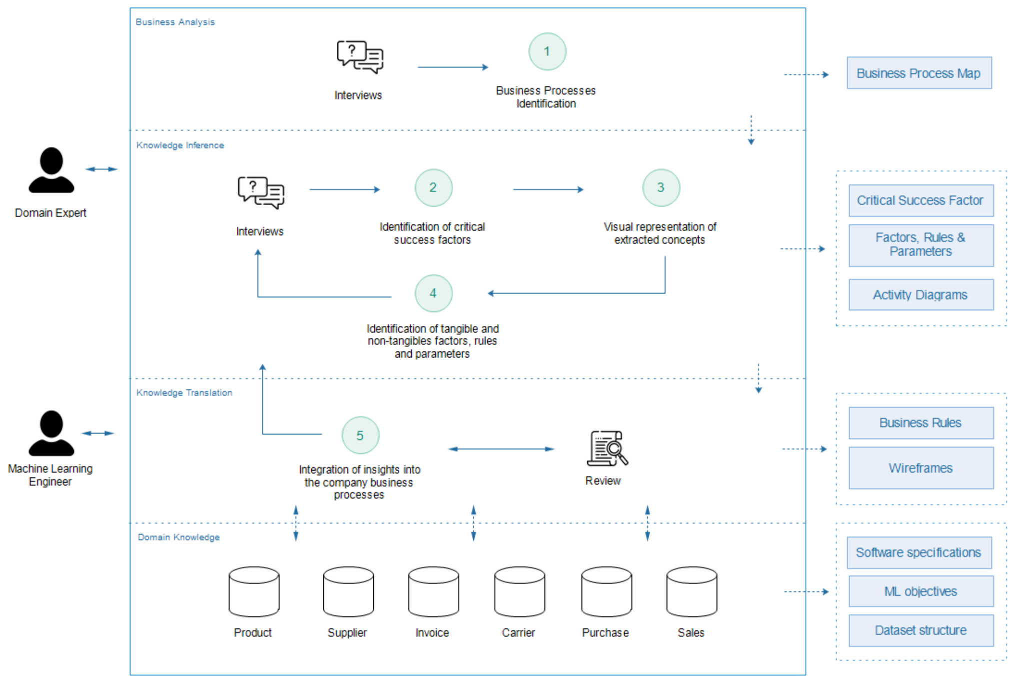

Fig. 1: Overview of the proposed Multi-Aspectual Knowledge Elicitation framework.

Table 1: fifteen aspects of Dooyeweerd (Basden, 2011) and their meaning

Aspect	Meaning
Quantitative	Discrete amount
Spatial	Continuous space
Kinematic	Movement
Physical	Energy + mass, forces
Biotic/Organic	Life functions + organisms

Sensitive/Psychic	Sense, feeling, emotion
Analytical	Distinction, conceptualization
Formative	Achievement, construction, history, technology
Lingual	Meaning carried by symbols
Social	'We': relationships, roles, convention
Economic	Frugal management of resources
Aesthetic	Harmony, play, enjoyment
Juridical	Due: responsibilities + rights
Ethical/Attitudinal	Self-giving love, generosity
Pistic/Faith	Vision, aspiration, commitment, belief

(1) Identification of business processes: analyse the company's internal/external processes to identify multiple cross-functional processes, data points, systems, and non-value-added operations. This step is essential to the identification of key data feeds (internal/external) favourable to the collection of intelligence to guide decision-making.

(2) Identification of critical success factors: gather insight from senior members and staff users of the company to understand the business and contextual issues. This step relies on a series of interviews where the discussion could turn around topics like system usefulness, job security, the impact of the technology on users and their work, user's attitudes to technology, skill levels and other factors that are meaningful to users.

(3) Visual representation of extracted concepts: take concepts from step (2) and map them against Dooyeweerd's aspects (e.g., technical, social, economic, ethical, etc.) to identify any gap or missing concept that will require further investigations (or interviews). The visual representation of extracted concepts highlights any laws, axioms, data, definitions and constraints that apply to the domain of the project.

(4) Identification of tangible and non-tangible factors, extra meta-level rules and parameters: provide a domain conceptualisation and presentation to an expert including different aspectual views to select the aspectual view(s) in which experts see their domain expertise lying. This step goes through the loop of detailed knowledge acquisition to identify business process workflows and decisions making scenarios.

(5) Integration of insights into the company business processes: propose a specification and design of the software solution to be integrated in the company information system to improve and overcome the existing limitations or challenges.

3.3. Knowledge Elicitation: application

The proposed framework relies on a series of interviews with domain experts or managers who have strong knowledge and understand the business processes. The application of this framework to a business starts with "Tutorial" interviews (Winfield, 2000), where the expert is asked to prepare a talk outlining the whole domain. , This helps provide an orientation to a domain and the identification of relevant concepts. The interviews are carried out with senior managers or team leaders who can explain the daily activities to a non-expert interviewer. As a result of these interviews, the interviewer should come up with internal/external processes which can impact the company's objectives.

The next step of the framework aims to identify critical factors which contribute to the success of the business processes. To achieve this, a "Focused" interview (Winfield, 2000) is carried out between an interviewer (ML Engineer) and domain experts to extract more detailed knowledge. This interview consists of three parts. First, there is an introduction where goals are explained to encourage the expert to take part in the discussion. Secondly, a set of topics is carefully chosen regarding previously identified concepts. These topics guide the interviewer to identify what is meaningful for experts (future users). Finally, the interviewer needs to evaluate and summarise the elicited knowledge before the interview ends.

The concepts, collected during the Tutorial interviews and Focused interviews, are mapped against the fifteen aspects of Dooyeweerd (Basden, 2011). Indeed, it consists of the analysis of each concept to determine if it can be defined or interpreted by these aspects. A set of keywords can be considered as references when analysing each concept. A keyword can represent an entity, a process, a task, or a system. As a result, the elicited knowledge can be visually illustrated and structured with the following parameters: laws, axioms, data, definitions, and constraints.

After the extraction of knowledge, the latter needs to be conceptualised to the domain and presented to an expert for validation. This step helps narrow down the knowledge and identify tangible & non-tangible factors, rules and constraints involved in the decision-making process. If the validation failed, the ML engineer needs to organize new interviews to clarify the misalignment or collect what is missing from the expert's knowledge.

Finally, the ML engineer relies on elicited knowledge to propose an ML design: dataset structure (features and observations) and the training objectives. Indeed, it helps in the creation of a multi-variant dataset that was used to train a time series model for stock forecasting purposes. Moreover, the collected knowledge guides the definitions of specifications for the software development part of the project. Indeed, it shaped the definition of models, database tables, workflows and wireframes (UX/UI).

4. RESULTS & EVALUATION

4.1. Case study

In this study, we worked with a wholesale company specializing in food export and distribution across the North UK. It operates in a multi-disciplinary environment, where teams from different disciplines work together to achieve the company's objectives. The company has several business processes, such as sales, procurement, logistics, accounting, warehouse, e-commerce, etc. that guide its daily activities and contribute to its success.

In a warehouse context, a procurement is a business process that involves identifying and selecting suppliers, negotiating contracts, and managing the purchase of food items to maintain inventory levels, meet customer demand and optimize costs. We applied our proposed method to the procurement business process, where we extracted knowledge from the team members and design machine learning models. The data and knowledge collected from the company's operations were used to train ML models, which were then deployed to support the procurement process.

Moreover, the company owns a bespoke resource management platform that supports various operations such as raising and amending purchase orders, stock management, goods-ins and quality control. The trained ML models were integrated into this platform to support the procurement process while offering a technology acceptance by the staff and final users.

4.2. Procurement: Elicited Knowledge

(1) Identification of business processes: the company's business model involves several processes, from ordering to delivery, which aims to meet the supply-demand needs. Interviews have been conducted with the company staff to better understand the existing processes and come up with a supply chain map (Fig. 2).

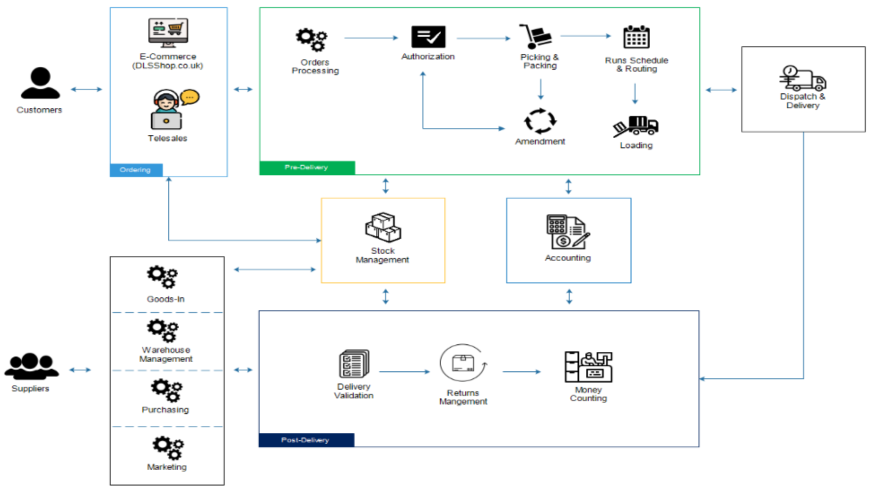

Fig. 2: Supply Chain Map

(2) Identification of critical success factors: we selected the characteristics/factors that will contribute to the technology acceptance of the new artificial intelligence (AI) platform with regards to the procurement business process.

(3) Visual representation of extracted concepts: several concepts have been identified during the interviews with the domain experts. From the procurement concept, we investigated and captured knowledge in terms of laws, axioms, data, definitions, and constraints. The following keywords have been selected as reference for our investigation: product, supplier, purchase manager, carrier, reference for quotation (RFQ), purchase order, manufacturing, delivery, return, and credit note. Table 2 illustrates the knowledge elicited from the entity "Product" and mapped against the 15 aspects of Dooyeweerd.

(4) Identification of tangible and non-tangible factors, extra meta-level rules and parameters: following the mapping of the key business processes against the Dooyeweerd's aspects, we identified data attributes and workflows required to design a ML solution. Indeed, the work sessions with experts from the procurement domain allow us to come up with tacit knowledge that is illustrated in an activity diagram (Fig. 3)

(5) Integration of insights into the company business processes: the knowledge elicited from previous steps allowed us to gather all specifications required to properly design databases of micro-services that will be part of a new software architecture in the company. Moreover, the extracted knowledge allows us to create interface insights (wireframes) illustrating each activity of the business process. Indeed, these wireframes (Figure 4) allows us to quickly validate our understanding of the business processes and ensure the technology acceptance of the future users.

Table 2: Multi-aspectual knowledge elicited from an entity "Product"

Laws	Axioms	Data	Definitions	Constraints	Aspects
Weights and Measures Act 1985	A product must have a measurable quantity	Product quantity, size, weight, cost price, sales price, online price, online offer price, collection price	A product has properties which can take a discrete amount: quantity, size, weight, price	A product should fit with the warehouse shelves dimensions/capacity	(1) Quantitative
Food Safety Act 1990 (Food Safety Act 1990)	A product must have a physical presence in a specific location	Product dimensions, location	A product has a shape, position,		(2) Spatial
Organic Products Regulations 2009 (*The Organic Products Regulations 2009*), Food Safety Act 1990 (Food Safety Act 1990)	A product must be kept in a suitable environment with respect of the shelf life	Product expiration date + Shelf life	A product has a life function	A product needs to be sold before the expiration date. A product expiration date needs to fit with the shelf life	(5) Biotic/Organic
General Food Law Regulation	A product must be stored and transported under conditions that	Product temperature, humidity and light	Product can be touched, smelled & tasted		(6) Sensitive/ Psychic

(EC) No 178/2002	maintain its sensory quality				
Food Safety Act 1990 (Food Safety Act 1990)	A product must be analysed and evaluated for its chemical and physical properties	pH, nutritional content, shelf life	Product can be distinguished	A product must have a set of chemical and physical properties	(7) Analytical
Food Standards Act 1999	A product must be capable of undergoing processing or transformation	Product Package	Some product packages are designed to meet customer expectations	Product rebranding designing should fit with each market segment	(8) Formative
Food Safety Act 1990 (Food Safety Act 1990)	A product must meet industry standards and regulatory requirements for labelling	Product name, description, code	Product labelling using symbols	Product name & code need to follow standards (length, symbols, languages)	(9) Lingual
Sale of Goods Act 1979 (Food Safety Act 1990)	A product must be priced in a manner that reflects its value	Product margin benefits, profitability and growth	Product has a limited value	Product has to be managed with frugality	(11) Economic
Food Standards Act 1999	A product must be consistent with customer preferences	Customers reviews, feedbacks	Product has to bring joy, fun, and harmony to customers	A product needs to satisfy the customers so that they get values for what they pay for	(12) Aesthetic
Food Safety Act 1990	A product must comply with relevant laws	Product reward, recompense	Product has to bring justice	A product needs to be sold in a fair ways	(13) Juridical
Food Safety Act 1990	A product must be produced and marketed with respect of ethical principles	Product advantages, benefits	Product can be beyond the imperatives	A product can be delivered earlier, discounted	(14) Ethical/Attitudinal
Food Safety Act 1990	A product must be produced and distributed with respect of spiritual and cultural beliefs	Dietary restrictions, consumer preferences	A product follows a commitment and trust	A product needs to be trustworthy	(15) Pistic/Faith

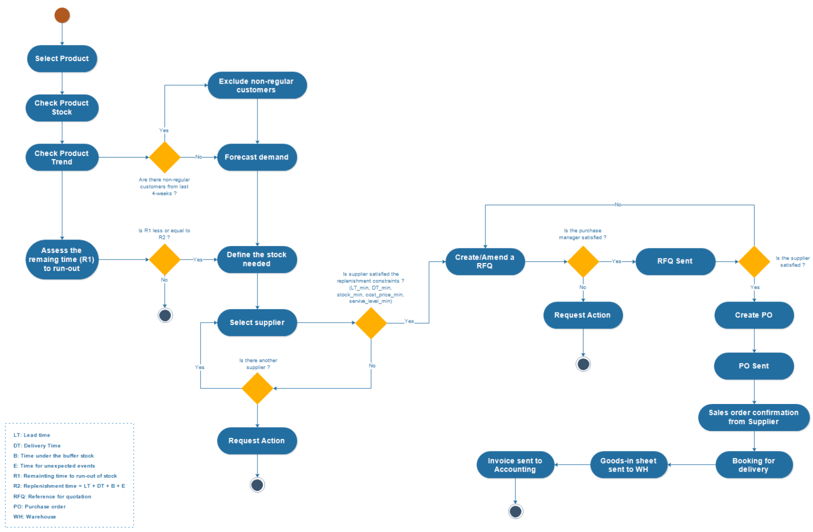

Fig. 3: Activity Diagram – Make a purchase order

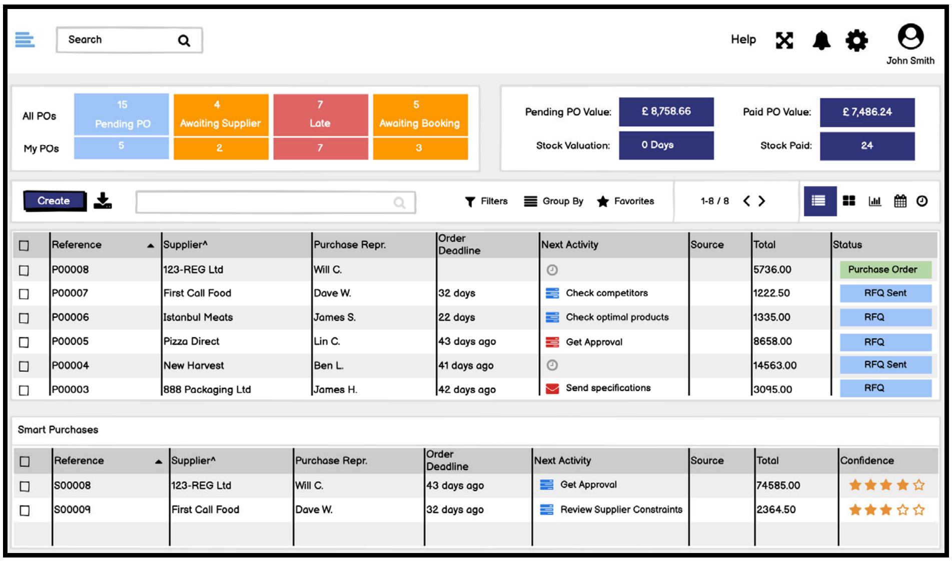

Fig 4: Procurement (Purchasing) module: this wireframe shows a quick representation of the overview page.

4.3. Evaluation of the results

The proposed framework was evaluated in a real-life warehouse environment where knowledge have been extracted from procurement experts and used to build historical sales datasets. These datasets were used to train time series forecasting models that optimize the procurement business process. We conducted the evaluation in two ways: a quantitative analysis and a qualitative analysis.

Quantitative analysis: to quantify the performance of the proposed method, we conducted a series of experiments which consists of training stock forecasting models using the datasets generated from historical sales data. These datasets were also enriched with knowledge elicited from procurement experts using our framework. These methods helped to identify the learning objectives and the representation of the dataset (features, observations, etc). We used two time series forecasting methods like ARIMA (Harvey, 1990) & TFT (Lim et al., 2020) from the literature to illustrate how our framework contribute in improving the performance of the models. To evaluate the performance of our models we used the following metric: Quantile loss (Wen et al., 2018). Table 3 shows the performance of the models trained on a dataset without elicited data (D1) and a dataset with elicited data (D2).

Table 3: Comparison of models trained on two datasets, without (D1) and with elicited features (D2), w.r.t a 0.5 percentile quantile loss (p50 loss) and 0.9 percentile quantile loss (p90 loss)

Datasets	Elicited Features	Model	p50 loss	P90 loss
D1	-	ARIMA	1.9929	1.9451
D1	-	TFT	0.6138	0.4266
D2	**Yes**	**TFT**	**0.5825**	**0.3780**

Each dataset has the following settings: 513484 time points (about 2 years of sales data), 30 days' horizon, and the stock quantity as the target feature.

Moreover, we did a comparison of models trained on datasets, which involved features extracted with knowledge elicitation techniques considered as baselines (ABML, IHTM, Ziva). We used the same time series-forecasting model (TFT) to ensure a fair comparison (Table 4).

Table 4: Comparison models trained on datasets generated with our proposed knowledge elicitation framework against baselines.

Datasets	Elicited Methods	Model	p50 loss	P90 loss
D2	IHTM	TFT	0.6827	0.4702
D2	Ziva	TFT	0.6764	0.4629
D2	**Ours**	**TFT**	**0.5825**	**0.3780**

Qualitative analysis: In order to evaluate the technology acceptance of solutions developed using our knowledge elicitation framework, we selected seven participants. This group included three individuals without prior knowledge in procurement and four members of the procurement team. The main objective was to determine whether the trained models effectively optimized business processes while considering the needs of the end user. Each participant was tasked with creating a purchase order on the system while adhering to two key constraints: avoiding stock shortages and preventing overstocking. The participants were instructed to evaluate the system based on several criteria, including user experience (UX), user interface (UI), workflow simplicity, and knowledge awareness. They rated the system on a scale of 0-5 (bad to good) for each criterion.

In terms of user experience (UX), feedback from seven participants revealed a generally positive response to the system for creating or modifying purchase orders. Five participants rated the experience with a score of 5 out of 5, indicating satisfaction, while two gave a score of 4, suggesting a desire for added features like shortcuts. Regarding the user interface (UI), six participants praised the new design with a score of 5, although one participant gave a score of 3 due to colour preferences. Evaluating workflow simplicity, three participants without procurement expertise rated it 4 for ease of following step-by-step instructions. In contrast, four procurement team members rated it 5 for consistency and accuracy. In terms of knowledge awareness, four participants rated it 5 for facilitating decisions on quantity, delivery, pricing, and supplier selection, while three desired more empirical data to bolster the system's recommendations.

5. CONCLUSION

In this paper, we proposed a multi-aspectual knowledge elicitation framework (MAKE4ML) for optimizing business processes through the design of machine-learning models. Our approach involves conducting interviews with domain experts and parameterize machine-learning models that can reproduce the expertise of the experts and provide insights for decision making. We applied the proposed framework in a food warehouse company to optimize the procurement process, resulting in a significant improvement in the accuracy of forecasting.

This framework allows us to extract concepts that were relevant to the business and useful to optimize the learning objectives of the machine learning models. Our approach can be extended to other business processes, enabling efficient knowledge elicitation, and contributing to the design of machine-learning models that can optimize operations, reduce costs, and increase efficiency.

Furthermore, we plan to investigate the combination of multi-aspectual knowledge elicitation techniques with the active learning. Active learning has been shown to be effective in reducing the amount of labelled data required for training machine learning models. We believe that combining active learning and the multi-aspectual knowledge elicitation technique MAKE4ML can lead to even more efficient and effective optimization of machine learning models.

Overall, our multi-aspectual knowledge elicitation framework can be a valuable tool for optimizing business processes through the design of machine-learning models. By leveraging the knowledge and expertise of domain experts, we can develop more effective machine learning models that can lead to cost savings, improved efficiency, and better decision-making. We hope that this paper provides a valuable contribution to the field and inspires further research in this area.

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