TOWARDS THE AUTOMATIC EXTRACTION OF DECISION MODEL & NOTATION FROM DUTCH LEGAL TEXT

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The translation from laws and regulations into actionable business rules remains challenging due to the complexity of Dutch legal text. In addition, the (semi-)manual translation of law into business rules is both time-consuming and error-prone. To address these issues, this research explores the use of Natural Language Processing (NLP) to automatically extract legal decisions and represent them in a Decision Model and Notation (DMN) model. For this purpose, existing research was reviewed to define requirements, which formed the basis for the NLP prototype. The current prototype evaluates an existing approach and aims to process unstructured Dutch legal text. However, a theoretical extension is proposed to address the structural complexity of extracting a DMN model from structured Dutch legal texts. Therefore, future research should focus on implementing the proposed approach and validating it in collaboration with legal analysts to extract a DMN model from structured Dutch legal texts.

Keywords:
BRM,
DMN,
NLP,
Legislation,
legal text

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1 Introduction

Operational decisions play a crucial role in highly regulated industries (e.g., government) as they determine how laws, regulations, and policies are implemented in practice. These decisions are defined as: "*the act of determining an output value from a number of input values, using decision logic defining how the output is determined from the inputs*" (Object Management Group, 2019a). Organizations use business rules to structure and automate such operational decisions. Business rules are defined as: "*a statement that defines or constrains some aspect of the business intending to assert business structure or to control the behaviour of the business*" (Hay & Healy, 2000). Implementing well-defined business rules within an organization, such as in IT systems, can help prevent errors, save time, and reduce costs in software projects by, e.g., ensuring compliance with regulatory requirements (Morgan, 2002). However, for business rules to deliver these benefits, organizations must design, execute, and manage them. This could be achieved through Business Rule Management (BRM) (Graham, 2007). BRM is defined as: "*a systematic and controlled approach that supports the elicitation, design, specification, verification, validation, deployment, execution, evaluation, and governance of business decisions and business logic*" (Boyer & Mili, 2011; Morgan, 2002; Schlosser et al., 2014). Within BRM, the *elicitation* capability, in particular, remains time-consuming, e.g., as addressed by (Nelson et al. 2008). In addition, formalizing Dutch legal texts remains challenging due to their complex structure, with long sentences, passive voice, and extensive relative clauses (Bakker, de Boer, et al., 2022). For example, in the Netherlands, the translation process has caused years of delays in IT projects within the Dutch Tax Administration (Nederlandse Omroep Stichting, 2024). Moreover, mistranslation can have serious consequences, such as the Dutch childcare benefits scandal (Amnesty International, 2021) or fraud with personal budgets (Nederlandse Omproep Stichting, 2019).

Supporting governmental institutions in translating laws and regulations into business rules through the application of Natural Language Processing (NLP) could help law and rule analysts. NLP is used to extract semantics from text (Nadkarni et al., 2011). For example, research applied NLP in the legal domain to help save time (Barale et al., 2023; Hendrycks et al., 2021; Mokashi et al., 2024; Vayadande et al., 2024) and reduce errors (Barale et al., 2023; Vayadande et al., 2024). To facilitate the translation to business rules, several modeling languages have been developed that support the specification of business rules for subsequent implementation in IT systems. These include the Semantics of Business Vocabulary and Business Rules (SBVR) (Object Management Group, 2019b), The Decision Model framework (TDM) (Von Halle & Goldberg, 2009), RuleSpeak (Ross, 2009), and Decision Model and Notation (DMN) (Object Management Group, 2019a). Among these, DMN is considered the industry standard for modeling decisions that define how business rules are implemented (Hasić et al., 2017; Leewis et al., 2020). In recent years, research has been conducted on NLP-based approaches for extracting (elements of) DMN models from natural language text (Arco et al., 2021; Etikala, 2021; Etikala et al., 2020; Goossens et al., 2021, 2022, 2023; Quishpi et al., 2021). For example, Goossens et al. (2023) use NLP to extract decision dependencies and decision logic for the creation of DMN models, while Quishpi et al. (2021) combine NLP with patterns to create DMN models. However, to the best of the authors' knowledge, no research has been conducted on an NLP-based approach for extracting DMN models from (Dutch) legal texts, nor on the requirements for such an approach. Therefore, the following research question is raised: "*In what way can a DMN model be automatically discovered from Dutch legal texts using NLP?*"

2 Background and Related Work

Before discussing DMN and the existing literature on the (semi-)automatic extraction of (elements of) DMN models from natural language text, the concept of BRM is further introduced. BRM consists of nine capabilities, which are performed (semi-)manually, as shown in Figure 1.

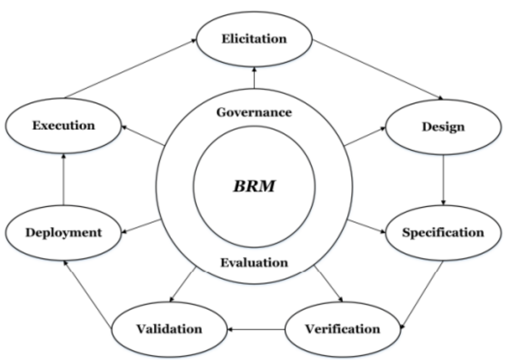

Figure 1: The nine BRM Capabilities (Smit, 2018)

First, an operational decision can be identified or modified through *elicitation*, based on, e.g., relevant legal knowledge. Second, *design* involves structuring the relevant information into a business rules architecture using a modeling language. Third, *specification* concerns defining the business logic. Fourth and fifth, *verification* focuses on ensuring logical consistency, while *validation* concerns confirming intended behavior. Sixth, *deployment* involves translating decisions into, e.g., implementation-dependent systems. Seventh, *execution* focuses on implementing business rules. Eighth and ninth, in parallel with the other capabilities, *governance* concerns ensuring traceability and version management, while *evaluation* involves monitoring implementation and performance (Boyer & Mili, 2011; Morgan, 2002; Smit, 2018). The business rules architecture defined in the *design* capability can, e.g., be modeled using SVBR (Object Management Group, 2019b), TDM (Von Halle & Goldberg, 2009), RuleSpeak (Ross, 2009), or DMN (Object Management Group, 2019a). Since DMN is considered an industry standard, it is used in this research.

DMN consists of two levels: the decision requirements level and the decision logic level (Hasić et al., 2017). The decision requirements level is represented by a Decision Requirement Diagram (DRD), which illustrates the requirements and dependencies of each decision. The decision logic level consists of a decision table for each decision in a DRD (Hasić et al., 2017). An example of both is shown in Figure 2. On the left, a decision is represented by (1), a dependency by (2), input data by (3), a knowledge source by (4), and business knowledge by (5) (Object Management Group, 2019a). On the right, a fact type is represented by (6) and a fact value by (7). An example of a decision rule would be: if the *Purpose of Use* is 'Education' and the *Type of Work* is 'Video,' then the *Permission Required* is 'false.'

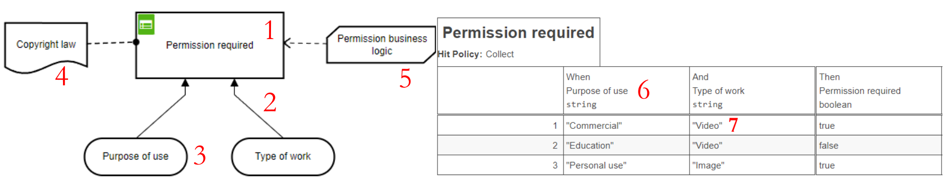

Figure 2: DRD (Left) and Decision Table (Right)

Research has been conducted on the NLP-based (semi-)automatic extraction of (elements of) DMN from natural language text. For example, a more recent approach is described by Goossens et al. (2023), which builds on previous work as described in (Goossens et al., 2021, 2022). Goossens et al. (2023) present a three-step approach to extract a DRD and a single decision table, as also indicated in Figure 3:

1. The unstructured text undergoes coreference resolution (identifying words referring to the same concept (Ng & Cardie, 2001), followed by preprocessing, including lowercasing, sentence tokenization (e.g., specifying words or commas), and adding tokens to the glossary of the deep learning model.
2. A deep learning classifier then identifies relevant sentences containing decision-related information.
3. Next, Named Entity Recognition (NER) extracts decision logic and dependencies from these sentences. NER is used to identify entities of interest in text documents (Nadeau & Sekine, 2007).

The extracted information, i.e., decision dependencies and decision logic, is used to create a DMN model (Goossens et al., 2023). Goossens et al. (2023) concluded that the Bidirectional Encoder Representations from Transformers (BERT) outperformed the Bi-LSTM-CRF deep learning model in extracting dependencies. For text classification, BERT also achieved the best performance compared to traditional machine learning methods, including logistic regression, naive bayes, and Support Vector Machines (SVM). Since the authors did not focus on decision logic extraction, BERT was applied for that task without comparison to other approaches.

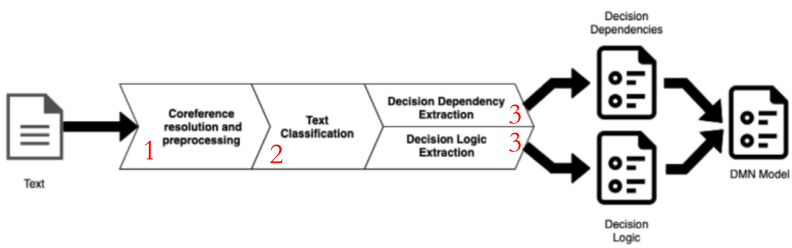

Figure 3: Implementation by Goossens et al. (2023)

One advantage of their approach is its language independence; for example, BERTje (De Vries et al., 2019) can be applied to Dutch and CamemBERT (Martin et al., 2020) to French. The use of BERT makes the approach more resilient to emerging patterns. However, it has a limitation, as it uses only one decision table for all decisions, meaning that each decision does not have its dedicated table. In addition, BERT has been trained only to consider a maximum of two decision dependency levels. Quishpi et al. (2021) also present an NLP-based semi-automatic approach for extracting a DMN model, similar to Goossens et al. (2023) in utilizing NLP to preprocess or parse natural language text. However, while Goossens et al. (2023) use NER for extraction, Quishpi et al. (2021) rely on English pattern-based rules (e.g., specific word structures) to identify decision logic and dependencies. This pattern-based method requires custom patterns for each case, making it less flexible compared to the approach by Goossens et al. (2023). In addition, not all decision expressions are covered by these patterns. However, the approach has the advantages of being extensible (by defining more patterns) and precise due to the clear pattern definitions. Furthermore, the authors extract both a DRD and corresponding decision tables. Two other NLP-based, framework-oriented automatic DMN extraction approaches are proposed by Etikala (2021) and Arco et al. (2021). Both address linguistic challenges, such as multiple interpretations and/or references in text. Etikala (2021) follows a pattern-based approach, similar to Quishpi et al. (2021), by identifying English decision patterns in sentences. The author also extracts a DRD and corresponding decision tables. In contrast, Arco et al. (2021) focus exclusively on extracting decision tables. Moreover, their approach does not support Dutch, as it relies on the Stanford NLP library, which does not support the Dutch language.

Although Goossens et al. (2023), Quishpi et al. (2021), Etikala (2021), and Arco et al. (2021) present approaches for the (semi-)automatic NLP-based extraction of (elements of) a DMN model from natural language text, there is currently no known approach for extracting a DMN model from Dutch legal text. In this regard, research has been conducted on automatic knowledge discovery from legal texts (Bartolini et al., 2004; Biagioli et al., 2005; Boella et al., 2013; Dragoni et al., 2018; Guissé et al., 2012; Kacfah Emani, 2014; Michel et al., 2022; Palmirani et al., 2011; Sleimi et al., 2018, 2019; Spinosa et al., 2009; Wyner & Peters, 2011). While some of these extract DMN-related elements, e.g., decision rules (Michel et al., 2022), none of these approaches directly address DMN.

3 Research Method

This research adopted a Design Science Research (DSR) (Hevner et al., 2004) approach, supported by a narrative literature review (Paré et al., 2015), as illustrated in Figure 4. First, the relevant literature was reviewed. Second, requirements were defined based on the literature. Third and last, an artifact (prototype) was developed, assessed, and refined to support the extraction of DMN models from Dutch legal texts. Following DSR, the prototype was designed to address a practical business need, i.e., assisting with the manual translation of legal texts into executable business rules, and was informed by applicable frameworks and methods identified in the literature.

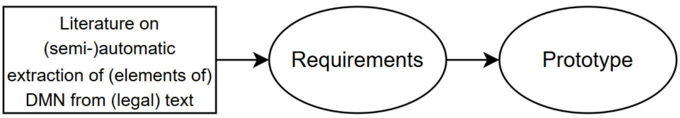

Figure 4: Steps used to implement the prototype

A narrative review was selected for this research, as it allows for a flexible examination of the most relevant literature. While this approach has the limitation of reduced transparency and reproducibility, it was appropriate for this research given the exploratory nature of the research and the goal of identifying relevant methods, frameworks, and requirements that can guide prototype development. Specifically, the objective was to identify existing solutions that extract structure using NLP from (legal) texts and generate (elements of) DMN models as output. To conduct the review, Google Scholar was used as the primary search engine as it is considered to be the most comprehensive academic databank (Gusenbauer, 2019). Based on the findings from this review, one or more of the following actions were taken:

- If an existing solution met the identified requirements, it was described and evaluated.
- If modifications or extensions were needed, the solution was refined based on insights from the literature.
- If an adequate solution was not found, a new approach was developed, integrating best practices and requirements extracted from prior research.

4 Data Collection and Analysis

The data collection for this research occurred between February and March 2025. Literature focused on extracting (elements of) DMN from natural language text was identified. It became evident that the body of literature on the (semi-)automatic extraction of DMN elements from (legal) texts is limited. To ensure completeness, the reference lists of the selected studies were examined (backward snowballing), confirming that no additional relevant sources were overlooked. This resulted in four relevant studies, as shown in Table 1. It is important to note that Etikala et al. (2020) and Goossens et al. (2021, 2022) were excluded as newer research provides a more comprehensive DMN extraction approach. The advantages and disadvantages relevant to the purpose of this research, specifically considering the extraction of DMN elements, robustness to new patterns (i.e., managing business rules can aid in maintaining systems in changing environments (Bajec et al., 2004)), especially with many Dutch laws having been in effect (Klein Haarhuis & Niemeijer, 2008), applicability to Dutch, and the consideration of edge cases, are outlined as follows:

Table 1: Advantages and disadvantages of relevant literature

Source	Advantages	Disadvantages
Goossens et al. (2023)	- Extracts DRD and one general decision table. - Natural language-independent. - More robust to changes.	- No decision table per decision. - Tested only on shallow (2-level) decision dependencies.
Quishpi et al. (2021)	- Extracts DRD and decision tables.	- Natural language-dependent; need to define Dutch patterns. - Does not cover all decision expressions. - Less robust to change; requires new patterns.
Etikala (2021)	- Extracts DRD and decision tables. - Addresses some natural language and decision modeling challenges.	- Natural language-dependent; need to define Dutch patterns. - Does not cover all decision expressions. - Less robust to change; requires new patterns.
Arco et al. (2021)	- Extracts decision tables. - More robust to changes. - Addresses some natural language characteristics.	- Does not extract DRD. - Single sentence analysis limits aggregating decision tables. - Does not support Dutch.

Based on the four studies focused on extracting DMN elements from natural language text, requirements for extracting a DMN model from Dutch legal texts were defined, as outlined in Table 2. Based on commonalities between the studies, these requirements consist of having a text as input, being able to extract decision dependencies and/or logic, and modeling a DRD and/or logic. In addition, the requirement to address edge cases (i.e., ensuring all potential decision scenarios are accounted for) is added for completeness, such as potential errors in a DMN model or legal text, which is crucial for validating the DMN model or legal text. In this table, 'X' indicates full support, 'x' indicates partial support, and '-' indicates no support. As shown in Table 2, Quishpi et al. (2021) do not fully address decision dependency extraction, decision logic extraction, or edge case coverage, as they acknowledge their approach's limitations. A similar limitation applies to Etikala (2021), whose pattern-based approach suggests incomplete coverage of decision expressions. Arco et al. (2021) focus on decision tables rather than the DRD, while Goossens et al. (2023) only partially address edge cases due to a maximum of two-level decision dependencies.

Table 2: Identified requirements

High-Level Requirement / Source	Text as input	Decision dependency extraction	Decision logic extraction	Modeling DRD	Modeling decision logic	Edge case coverage
Goossens et al. (2023)	X	X	X	X	X	x
Quishpi et al. (2021)	X	x	x	X	X	x
Etikala (2021)	X	x	x	X	X	x
Arco et al. (2021)	X	x	X	-	X	-

The prototype must meet the requirements outlined in Table 2. Therefore, to develop a solution through a prototype, the approach by Goossens et al. (2023) was selected to evaluate whether it could work with (unstructured) Dutch legal text or if an extension would be necessary, as their approach best meets the requirements. Moreover, Goossens et al. (2023) was chosen because it is language-independent, does not require manual pattern definition, is more resistant to changes in legal texts, and facilitates the extraction of an (almost) complete DMN model, including a DRD and a general decision table with executable business rules. In contrast, Quishpi et al. (2021) and Etikala (2021) require predefined Dutch patterns, while Arco et al. (2021) focus only on decision logic and do not support Dutch. As a result, the approach by Goossens et al. (2023) is the most suitable for this research.

5 Prototype Development

The prototype follows the implementation by Goossens et al. (2023); for further details, we refer the to their paper. Three BERTje models were fine-tuned in this study, which is a BERT model trained in the Dutch language (De Vries et al., 2019). This required three labeled datasets, including Dutch unstructured text: one for text classification to categorize sentences and two for decision dependency and logic extraction using NER. The datasets were labeled using IOB tagging, as described by Goossens et al. (2023), and included unique sentences collected via ChatGPT: 400 decision dependency sentences, 400 decision logic sentences, and 200 irrelevant sentences. Furthermore, some of these sentences represented one of the four special cases described by Goossens et al. (2023), such as two if-else statements or three dependency levels. The text classification dataset contained all types of sentences, while the NER datasets included only decision dependency or decision logic sentences. The results of the BERTje models are presented in Table 3.

Table 3: Fine-tuned BERTje metrics

Text Classification	Precision	Recall	F1-Score
Micro Average	0.99 ± 0	0.99 ± 0	0.99 ± 0
Macro Average	0.99 ± 0	0.99 ± 0	0.99 ± 0
Weighted Average	0.99 ± 0	0.99 ± 0	0.99 ± 0
NER Dependency	**Precision**	**Recall**	**F1-Score**
Micro Average	0.82 ± 0.0078	0.89 ± 0.0084	0.86 ± 0.0082
Macro Average	0.83 ± 0.0085	0.89 ± 0.0079	0.86 ± 0.0082
Weighted Average	0.83 ± 0.0106	0.89 ± 0.0084	0.86 ± 0.0063
NER Logic	**Precision**	**Recall**	**F1-Score**
Micro Average	0.93 ± 0.014	0.94 ± 0.0094	0.93 ± 0.0097
Macro Average	0.88 ± 0.0329	0.88 ± 0.0227	0.88 ± 0.0274
Weighted Average	0.93 ± 0.0133	0.94 ± 0.0094	0.93 ± 0.0097

After fine-tuning three pre-trained BERTje models, the steps defined by Goossens et al. (2023) are followed. It is important to note that coreference resolution was not included in the prototype, as it might address errors that should instead be reflected in the DMN model. Therefore, as indicated by Goossens et al. (2023), the resulting prototype takes unstructured text as input, extracts decision dependencies and logic after text classification, and creates a DMN model using a single general decision table and DRD based on the extracted data. The source code, pseudocode, and HuggingFace links to the BERTje models can be found in an Open Science Framework repository (OSF) (Anonymous, 2025).

6 Validation

After the prototype was implemented, an unstructured Dutch legal text excerpt was used, as the prototype was inspired by the implementation of Goossens et al. (2023). For example, the following sentence from Article 15e of the Dutch copyright law illustrates a decision dependency used to model a DRD: "*Disputes concerning **Article 15c, Section 1**, referred **compensation** will be decided in the **first instance** by **exclusion** by the **District Court of The Hague**.*" Here, both **Article 15c, Section 1, compensation first instance** and **District Court of the Hague** are input to the **exclusion** decision. After this was given as input to the prototype, the DRD in Figure 5 was given as output. Besides the fact that the input data on the right-hand side should be modeled as a knowledge source, the DRD aligns well with the excerpt of the Dutch legal text.

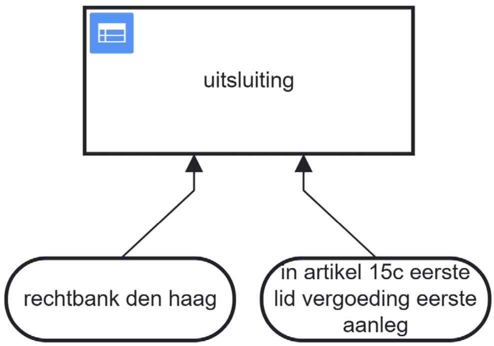

Figure 5: Results of using unstructured legal texts.

However, one apparent issue is that it is unclear which article the excerpt is from and how it refers to Article 15c, due to the structure of legal texts. In addition, as noted by Arco et al. (2021) and Etikala (2021), natural language challenges include bullet lists, a challenge also present in Dutch legal texts (De Maat & Winkels, 2010). Furthermore, Dutch legal texts contain long, complex sentences (Bakker, De Boer, et al., 2022; Sunkle et al., 2020) and, as shown in the DRD in Figure 5, include references to other legal sources (De Maat & Winkels, 2010). Therefore, the current prototype based on Goossens et al. (2023) needs to be extended to consider the structural complexity of Dutch legal texts. This results in the following additional requirements: R1) Support references to other legal sources, R2) Split text (e.g., lists) into individual sentences, R3) Handle special cases involving long and complex sentences, R4) Support the full DMN syntax. These additional requirements led to a theoretical extension, shown in Figure 5, which extends the prototype implemented based on Goossens et al. (2023). In this regard, references (R1) and lists are now accounted for (R2). Two additional features are the need to handle long, complex sentences (R3), which could be addressed by labeling a dataset containing Dutch legal text, and the ability to model the full DMN syntax within the prototype, e.g., knowledge sources and decision tables per decision (R4).

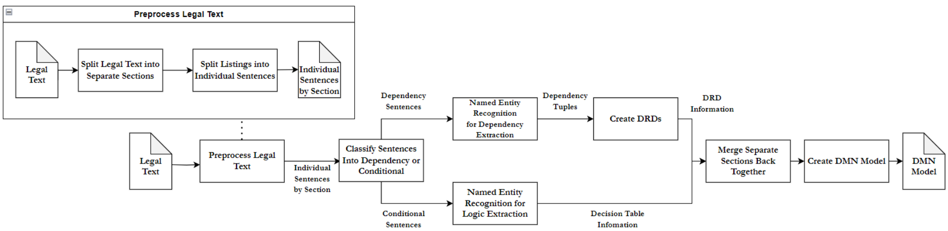

Figure 5: Proposed prototype extension.

7 Discussion and Future Research

This research has several limitations:

- *Limited data collection*: The data may have overlooked techniques such as context-aware deep learning (Nascimento et al., 2018). In addition, by focusing on natural language text, other sources, such as policy documents (Lopez et al., 2022), were excluded. However, these may also be relevant for future research to explore whether they can be utilized to automatically extract Dutch legal text.
- *Prototype limitations*: The prototype does not replace human judgment due to the inherent uncertainty of deep learning models and is not meant for direct implementation. Legal stakeholders should collaborate with NLP experts to understand the prototype's capabilities and interpret results appropriately.
- *BERTje results*: The high results (above 0.8) were influenced by ChatGPT-generated datasets and similar training and test data. This raises concerns such as model collapse, i.e., reduced diversity and increased repetitiveness in generated sentences. However, ChatGPT was chosen for its efficiency in

quickly generating sentences, with a focus on demonstrating the prototype's functionality. In addition, the pre-trained BERTje model already has a general understanding of the Dutch language.

- *No Dutch legal texts*: The absence of labeled Dutch legal texts, partly due to the authors' technological background, and the use of synthetic data in the first iteration of the DSR process highlights the need for future labeled datasets. These datasets are also needed for fine-tuning three corresponding BERT models trained on legal texts (e.g., RechtBERT (Looijenga, 2024)) in subsequent DSR iterations.
- *Manual parameter selection*: The parameters for fine-tuning were manually selected and may not be optimal. A grid search should be conducted when fine-tuning the three BERTje models for Dutch legal texts.
- *Prototype visualization*: The current prototype visualizes only part of the DMN. Future research should incorporate multiple decision tables using context-aware models to capture sentence context, as well as additional elements such as knowledge sources.

Furthermore, future research should assess whether the proposed prototype extension can handle the structural complexity of Dutch legal texts through implementation, and validation by legal professionals. Therefore, future research will involve the next iteration, refining the prototype, and evaluating it with legal analysts to have a specific legislation prototype that meets the proposed requirements.

8 Conclusion

To implement legislation, legal texts are translated into business rules, but the manual process is labor-intensive, time-consuming, and error-prone. An NLP-based approach can help address these challenges. Therefore, the following main question is addressed: "*In what way can a DMN model be automatically discovered from Dutch legal texts using NLP?*" From a theoretical viewpoint, this research: (1) contributes to the body of knowledge in BRM by providing a foundation for the automatic extraction of a DMN model from Dutch legal texts, adding to the *elicitation*, *design*, and *specification* capabilities. From a practical viewpoint, this research: (2) addresses several challenges in translating Dutch legal texts into executable business rules, such as reducing time and minimizing errors; (3) demonstrates how NLP can be applied to analyze legislation; (4) makes complex Dutch legal texts more comprehensible to more people than a select few in society by modeling them using a more easy-to-understand DMN model; and (5) facilitates the implementation of business rules due to the executable nature of DMN in, e.g., IT systems, making it easier for rule and law analysts to implement them.

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