The Value of Proactive Data for Intelligent Contracts

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Abstract. Intelligent Contracts (iContracts) is a new branch of research at the intersection of AI and law. It has many challenges, among which including the quality of data used. In our research we focus on generating and including quality Proactive Control Data (PCD) to improve iContracts, which is a novel research scope in literature. Our scope is defined by the main challenge in regards to emerging legal technologies. Currently, the legal system is more reactive than proactive, leading to high consequential legal costs. By shifting the focus to proactiveness, we discuss and improve upon the available methodologies (Bow-Tie Method and Logocratic Method) and technologies (Ontology Engineering, Software Engineering and Large Language Models [LLMs]) to demonstrate a higher degree of proactiveness in iContracts. Our results are threefold. First, we prove that the generation of PCD is possible with the development of a prototype that leverages the foundations of the Bow-Tie Method. Second, we demonstrate that the impact of PCD on contract drafting is significant, as the explicit inclusion of PCD in prompt engineering alters significantly the content of an LLM-drafted contract. Third, we show how the quality of PCD can be assessed and improved upon with the application of the Logocratic Method. The discussion highlights the feasibility of the research with available technologies. Ultimately, the implementation of our research depends on organisational considerations and resource allocation. We conclude that the generation of PCD is feasible, their impact on contract drafting is significant and their quality assessment is both possible and novel.

Keywords: Preventive/Proactive Law · Legal Technology · Contract Automation · Intelligent Contracts · Bow-Tie Method · Ontology Engineering · Software Engineering · Large Language Models · Logocratic Method.

1 Introduction

While innovation is accelerating and induces rapid changes around the world, the legal system is—to a large extent—still relying on traditional processes established over the course of the past few centuries [1]. The disconnection between *innovation* and *tradition* in the legal system is particularly amplified by the introduction of more complex technologies [2]. As a result, we see that each year the development of laws increases in *number* and the resolution of legal problems significantly grows in *complexity* [3]. One of the consequences of this growing legal complexity is a problem that has recently arisen: how can the legal needs of millions of people be safeguarded? [4].

As Susskind already remarked in 2019, in some court systems there are staggering backlogs of court cases (e.g., 100 million in Brazil and 30 million in India—according to the OECD, fewer than 50 percent of people on earth live under the protection of the law) [5]. Even earlier, in his 1996 book *The Future of Law*, Susskind predicted that with technology our approach to legal problems will switch from *problem solving* to *problem prevention*, through the use of proactive facilities supporting Legal Risk Management (LRM) [6]. He believes that our legal system is subject to the paradox of *reactive legal services*; a paradox which will be replaced by *proactive practices* induced by technology [6]. What we can observe here is that, since 1996, when Susskind first made the prediction, until today the legal system has not notably changed. Taking into consideration the massive case backlog, it would be reasonable to state that the legal system still seems to be more *reactive* than *proactive*.

Currently, we see that the growing complexity drives the need for introducing technologies to be applied in law (also called LegalTech). Intelligent Contracts (iContracts) is one example of contract automation in LegalTech. iContracts will contribute to the reduction of contractual dispute resolution by helping to (1) minimise the likelihood of dispute resolution, and (2) reduce its complexity. The main idea is to help reduce operational expenses during the resolution of disputes [7]. Even though the literature clearly supports the benefits of iContracts for reduced dispute resolution [8], thus far no research has *measured* the extent to which iContracts contribute to that end. The reason is that researchers have not sufficiently focused on *measuring* the proactive value of iContracts. To be precise, they have thus far not paid any attention to measuring the *explicit data* that contribute to the prevention of legal problems.

Our contribution aims to make the hidden data transparent and explicit by leveraging the Enriched Bow-Tie Ontology (EBTO), the primary ontology structure for managing contract risk in iContracts [9]. We start with an introduction of the basic concepts. In agreement with the EBTO terminology, we distinguish (1) *Proactive Controls* (hereinafter "Proactive Control Data" or "PCD"), which play an important role as soon as we have arrived at the identification of a (2) *Hazardous Event* and have produced an analysis of a (3) *Cause* [in the remainder of this article (1), (2) and (3) will be called "Proactive Data"]. Proactive Data **determine** the PCD necessary to prevent a contract from incurring legal risks. By measuring and leveraging PCD qualitatively and quantitatively, iContracts are able to maximise their value towards reducing the likelihood of dispute resolution, which are the main drivers of consequential legal costs.

Our research scope follows the direction of the members of the the school of Preventive/Proactive Law (PPL). They advocate for more *proactiveness* in contracting [10].

In earlier research we developed the Onassis Ontology, which provides deep insight into all data that can be generated with iContracts [7]. PCD forms part of such data. However, the *number* and *quality* of PCD that iContracts are able to generate for a more preventive automated contract is still unknown. More concrete insight into the quantity and quality of PCD that iContracts are able to generate is necessary. At that point, legal experts can be empowered with improved contract drafting. This may result in protecting contractors to a greater extent and consequently reducing reactivity in the field of contracting. As demonstrated in our previous research, the identification of PCD occurs during the risk analysis stage [9]. However, that research did not focus on any criteria to determine the quality of PCD. Hence, it is now necessary to investigate how to develop quality assessment criteria to measure PCD qualitatively. Following a qualitative analysis, the criteria can be measured quantitatively and will be able to impact contract drafting. A difficult point here is that in order to examine their impact on contract drafting, legal experts have divergent writing styles. Therefore, we are going to leverage Large Language Models (LLMs) [11] as a research methodology to reduce diversity in writing styles. LLMs present an opportunity to investigate the extent to which the Proactive Control-specific prompt engineering alters LLM's contract drafting for similar clauses and contexts in order to validate the impact of PCD.

All in all, our research goals are threefold. First, we demonstrate whether the Onassis Ontology is able to generate PCD, by building a prototype validating (1) our ontology design, and (2) the generation of PCD. Second, we investigate the impact of the generated PCD on contract drafting via the use of LLMs to draft contracts, replacing the legal expert for a higher degree of experimental accuracy. Third, we examine whether PCD can be qualitatively assessed so as to improve their quality.

Our paper will make a big step forward for six reasons: (1) it introduces the value of Proactive Data for iContracts, (2) it reports on a prototype web application that uses the Onassis Ontology and the EBTO structure, (3) it introduces the use of LLMs as a methodology for reducing the variety of contract drafting styles, and (4) it measures PCD quantitatively in iContracts. Then, (5) it establishes qualitative assessment criteria for PCD, and (6) it helps legal experts to overall improve data management and decision making during contract drafting within the context of iContracts for the purposes of reducing the likelihood of contractual dispute resolution. Finally, (7) it introduces a direction for measuring the value of Proactive Data for iContracts.

The foregoing discussion leads us to the following **Research Question (RQ):** *To what extent is it possible to generate quality Proactive Control Data to improve an Intelligent Contract?*

To answer the RQ, we structured the paper as follows. In Section 2, the literature is described. Section 3 presents the method of research, which includes the use of a survey. Then, Section 4 describes our field work and formulates the results of our research and Section 5 discusses them. Finally, Section 6 answers the RQ and yields our conclusion.

2 Literature

The section is structured into six parts. Subsection 2.1 introduces the literature on the topic of Preventive/Proactive Law. Then, Section 2.2 presents sources on the intersection of PPL and legal technology. Section 2.3 shows the relevant sources on Proactive Control Data. Section 2.4 discusses the qualitative assessment criteria options for PCD. Section 2.5 introduces literature on Large Language Models as a contract drafting medium. Finally, Section 2.6 presents literature on ontology engineering and linked data. The reference section does not contain an exhaustive list of literature on the topic of iContracts and the Onassis Ontology, contract risk management, and the EBTO, nor does it fully cover end user risk visualisation. In our previous work, which may be consulted in [7], [9] and [12], we introduced these sources.

2.1 Preventive/Proactive Law

The birth of PPL was in 1950, when Louis M. Brown introduced the concept of *preventive law* [13]. Brown (1950) believed that preventive law concerns the cost difference between entering into and avoiding legal costs [13]. He remarked that a complete avoidance of legal costs is not always possible; however, prevention is still an ever-present possibility. After preventive law took hold, it gave rise to two main schools of thought. One is *therapeutic jurisprudence* [14], which is concerned with the health of legal subjects, and the other *proactive law* [15], which focuses on proactive contracting. During the past decade, the research of preventive law and proactive law started to converge, leading to the creation of the term Preventive/Proactive Law [1]. Recently, PPL is endowed with the visualisation of legal information and the effects of technology on PPL [16]. Last but not least, while risk management was growing as a field of study and practice around the year 2000, the field of Legal Risk Management (LRM) emerged [17]. Gradually, the connection between LRM with PPL was established [18].

2.2 Preventive/Proactive Law and Legal Technology

Susskind was the first to notice the relation between preventive law and technology [6]. PPL researchers reinforced that notion by stating that the emerging technological culture is largely compatible with the assumptions underlying PPL [1]. Hence, they are proposing a re-design of the legal system, which reconsiders the relation between law and society, to guide a reform of law in a technologically-based society [19]. They are also questioning and investigating the effects of new technologies for PPL and legal design [20]. Most of the research on PPL and legal technology focuses on legal design and smart contracts. In particular, the focus is on: (1) the fundamental consideration by Susskind, namely that with legal technology, the law can become *more proactive*, and (2) the usual work by PPL researchers related to *legal design* and *smart contracts*. To date, no further scientific progress has been made on integrating PPL with legal technology. This is one of our research goals.

2.3 Proactive Control Data

The concept of PCD is based on the bow-tie method terminology. The bow-tie method helps in performing visual legal risk analysis [21]. It is extensively used in enterprises, projects, and energy risk management. In such cases, the bow-tie method is used for visualising risk in a holistic manner by taking into consideration *proactive* and *reactive* risk measures [22]. In this article we only concentrate on the proactive risk measures, since they are directly relevant to the prevention of a hazardous event. Reactive measures play a mitigation role once a hazardous event has already occurred.

The bow-tie methods guides us through the *hazardous events* (also '*Event*'). For each *event* to occur there is at least one *cause*. Thus, each *hazardous* event has a *cause*. As such, knowledge on the *hazardous events* and *causes* is necessary before defining the *Proactive Controls*, whose role is to minimise the likelihood of a *hazardous event* occurring.

PCDs help in identifying measures that reduce the likelihood for a hazardous event from occurring. The higher the quality of PCD, the less the likelihood a hazardous event will take place. To identify the relevant PCD, it is necessary to characterise (1) a hazardous event, and (2) the sources that may lead to a hazardous event (which together amount to Proactive Data). Proactive Data can be identified by applying along the following line (a) deductive reasoning (also called ingenuity), (b) inductive reasoning (also called ingenuity), and (c) abductive reasoning (also called intuition) (also known as Inferential Reasoning). Successfully avoiding a hazardous event depends on the availability of prior Proactive Data [23], which at present is not systematically structured. Currently, deductive reasoning is modelled with expert systems, and inductive reasoning with machine learning, while abductive reasoning cannot be modelled yet [24]. Still, Van den Herik believes that intuition can be programmed [25, 26]. However, as matters stand now, the programming of intuition is only in its experimental stage. For the moment we will accept that the automated identification of Proactive Data can be achieved with expert systems and machine learning. As an example of intuition programming, we point to the adjacent topic of *scenario planning*; within this area exists a technology developed by Pandora Intelligence and its founder Peter de Kock [27]. Thus far, Pandora Intelligence relies on future scenario prediction based on historical and present data via technology that combines expert systems and machine learning [28].

2.4 Quality Assessment of Proactive Data

One way to assess the quality of Proactive Data is to examine their identification process, which may be viewed as argumentation schemes open to interpretation within the context of forming contracts. Pieter Schlag, who has examined the interpretative nature of constitutions, has developed a theory which may be useful in this direction, as long as we examine the nature of contracting within the sphere of constitutional legal theory. Schlag believes that interpretation is key to recognizing the ontological emptiness of constitutions [29], which also holds for contracts. Hence, inquiring about the nature of the ontology of a contract can end in a perpetual process. An interesting explanation is given by H.L.A. Hart, who argues that the meaning of law is generally clear, certain, and stable at its core, but less so at its penumbra [30]. Therefore, legal experts have learned to deal with the law in non-ontological manners. Those manners may include technical, normative, or epistemic approaches [29]. As a result, legal experts have learned to deal with the law from the perspective of legal pragmatism [29]. Legal pragmatism means that in order to solve legal problems, a legal analyst should use everyday tools that come to hand such as precedent, tradition, legal text, and social policy [31]. As a result, the law leads away from the ontological to the epistemic, away from the epistemic to the normative, and away from the normative to the technical [29]. Taking into consideration the context of ontological emptiness of contracts, legal arguments can hardly be absolute as the closer they reach the ontological nature of the contract, the larger the role of emptiness. Currently, however, as contracts have become more concrete—though not necessarily more true—the closer they have come to the technical aspects of the contract, the better we can assess them. Hence, the closer the identification of Proactive Data comes to technical contractual parameters (rather than ontological), the greater the degree of certainty about their quality.

Contextual Identification of Proactive Data To identify Proactive Data, as mentioned above, it is imperative to apply inferential reasoning. Inferential reasoning is normally applied within the context of implicit argumentation. Within the context of law, a method to make such argumentation explicit and that helps examine its relative validity is the Logocratic Method developed by Scott Brewer [32]. The purpose of the Logocratic Method is to explain the nature of an argument, and it is applied to two main types of arguments: (1) arguments of which premises provide evidential support for conclusions (such as in the case of identifying Proactive Data), as well as to (2) agonic arguments (such as in case of legal argumentation in litigation). As Brewer contends (motivated by John Dewey), the Logocratic Method is a system of analysis where "it is a whole whose wholeness is particularly tied to the interrelations between its parts; it has elements that have some independent existence; those elements have formally specifiable relations and the relations form a structure" [33].

Defeasible Arguments A challenge with arguments, according to Douglas Walton, is that they are not always based on necessarily valid premises [34].

Such arguments are presumptive or defeasible, and their validity is dependent on contextual factors, depending on whether their premises are believed or accepted to be true [35]. Due to the ontological emptiness of contracts, there will always be premises in which the validity can only be examined probabilistically. Bart Verheij demonstrates how the representation of defeasible arguments within the context of the law is possible and how the benefits of this practice are helpful for improved argumentation. [36]. Larry Simon contends that "as we confront the multiple language-meanings permitted by many of the open-textured provisions of the Constitution, the only apparent standard we can bring to bear in evaluating competing arguments for one or another interpretative methodology (...) is the extent to which they promote a good and just society" [37]. Our conclusion is that when following the argumentative analysis of Proactive Data, their value ultimately depends largely on the extent to which they contribute to the prevention of a hazardous event.

2.5 Large Language Models as a Contract Drafting Medium

Large Language Models (LLMs) have emerged as a cornerstone in the field of natural language processing (NLP), enabling transformative advances in diverse applications such as machine translation, sentiment analysis, and text summarisation [11]. By leveraging vast amounts of training data and employing advanced neural architectures, such as the transformer [38], LLMs have demonstrated remarkable proficiency in generating coherent and contextually relevant text. One promising application of LLMs is in the domain of contract drafting. There they can be employed to generate, analyse, and optimise legal documents with minimal human intervention. LLMs, such as GPT3 or GPT4, can be fine-tuned with domain-specific training data, such as legal texts and contracts, to create specialised models with a deep understanding of legal jargon and contractual structures. In addition, employing fine-tuning techniques allows LLMs to generate contextually relevant and legally accurate language, for enabling the automation of contract drafting and reducing the time and cost associated with manual contract creation [39]. Following this line of action, [40] proposes that incorporating established legal principles in guidelines can assist AI systems in comprehending human objectives, subsequently minimising the likelihood of the AI system executing actions with unforeseen consequences or externalities. We believe that by incorporating to these standards, AI systems can better align with the underlying essence of a directive rather than strictly adhering to the explicit wording of the stated intention.

While the application of LLMs in contract drafting offers numerous benefits, it is not without challenges. Ensuring the privacy and security of sensitive legal data during the training process is of paramount importance. This necessitates the implementation of secure and privacy-preserving machine learning techniques [41]. Additionally, the interpretability and explainability of LLM-generated content are critical concerns, as legal professionals must be able to comprehend and justify the rationale behind the generated text [42].

2.6 Ontology and Linked Data

An **ontology** refers to a formal domain model in which concepts and relationships between concepts are described [43]. The classes and relationships in an ontology can be used for organising contract, risk, and proactive control data in a contract definition. Each distinct ontology class and relationship has properties and descriptions that explicitly define their meaning (i.e., *semantics*), allowing different possible contract users (legal experts, contractors, laymen, automated software systems and databases) to interpret them consistently and unambiguously. Relationships in an ontology allow its users to see how contract details (e.g., scope, contractors, questions, signature), risk, and proactive control instances in the text of a contract are interrelated; for example, "*Contract X has risks Y and proactive control Z*", and thereby improves traceability between contract data. The instantiations of an ontology, the actual contract text, contractors, scope, signature, risk, and proactive controls, can be stored as triples (subject, predicate, object: "*contract1 has_id 1*", *contract1 rdf:type Contract*, *contract1 hasRisk risk1*, etc.). As a result, they can be generated, processed, and accessed systematically.

3 Method

This section presents the methodology of our research. The methodology concerns four main topics: (3.1) the introduction of an iContracts Proactive Data case study, (3.2) the development of an iContracts prototype to validate to what extent the development of PCD is possible, (3.3) the development of an experiment to measure the effect of PCD on contract drafting, and (3.4) the application of the Logocratic Method on an example of Proactive Data to examine qualitative assessment possibilities.

3.1 Case Study

Our case study will focus on a freelancer agreement between a freelancer and a client (contractors). The legal expert will define the scope of the agreement, conduct the risk analysis, define the legal questions for the two contractors and visualise the risk analysis next to the questions. Then, the contractors answer the legal questions and the legal expert may process potential modal information before the contract is generated and sent to the contractors. The case study will concentrate on a specific risk, i.e., payment risk. An example of applying the EBTO to a payment risk case study has already been presented in our previous work [12] and its visualisation is accessible via GitHub [44].

3.2 Prototype Development

We have built a prototype web application that uses the Onassis and Enriched Bow-Tie Ontology structure to guide users in identifying legal risks and proactive controls during the negotiation and generation of a contract [45]. See [46] for a visual overview of the user interface and the user interaction. The prototype contains several web pages with input forms and interaction elements to interactively draft a freelancer contract, based on a text template and contract-specific questions. After a freelancer and client answer contract-specific questions, a legal expert uses those answers to fill in text in a template contract. The expert can add legal risks and possible proactive controls next to a visible predefined set of specified risks. Additional questions can be interactively asked to both the client and freelancer. The additional questions can be about the (new or predefined) risks, proactive controls, or about the initial questions about the contract to which the client and freelancer gave conflicting answers, e.g., about the milestones or payment, or about the need for negotiation/mediation. Finally, the questions, answers, risks, controls, and legal text are stored as data consisting of semantic subject+predicate+object triples (in Turtle *.ttl format) specified according to the Onassis and Enriched Bow-Tie Ontology Structure (or 'model'). We explain the stored data in more detail with examples of data actually generated by the prototype website in the Results section [47]. Via the stored data, the isolation of PCD becomes possible.

3.3 Large Language Models Experiment

According to Onassis Ontology research, text generation can be applied to minimise the involvement of the legal expert during the contract drafting process [7]. Instead of using legal experts as an experimental subject, who have inconsistent contract drafting styles, we are going to leverage ChatGPT, which has a consistent contract drafting style and which is more measurable for research purposes.

ChatGPT is an artificial intelligence chatbot developed by OpenAI and launched in November 2022 [48]. It is built on top of OpenAI's GPT Plus family of large language models and has been fine-tuned using both supervised and reinforcement learning techniques [48]. ChatGPT can be used to generate text data, which includes drafting contracts. Some of its limitations and potential biases are that: (1) its training data are vast and perhaps over-exhaustive, which means that its data potentially already takes PCD into consideration for our case study which has a limited scope, (2) ChatGPT lacks intuition, whereas a legal expert could draft a contract with greater safety based on PCD.

The command we provided to ChatGPT *without* explicitly mentioning PCD is: "Write a payment clause for a freelancer contract." The command we provided to ChatGPT that *explicitly* mentions PCD is: "Write a payment clause for a freelancer contract that includes PCD1, PCD2, PCD3, etc." In order to measure the content differences we used open-source text comparison technology [49].

3.4 Logocratic Method

To apply the Logocratic Method to the case study we needed to translate the application of deductive, inductive, and abductive reasoning via propositional logic statements. Brewer demonstrates that is possible, based on the fair formal representation of enthymemes (syllogisms with an unexpressed but assumed premise), by adapting the classical conception of enthymemes to any rule or argument in which the mode of logical inference is not explicit in its original mode of representation [50]. An example enthymeme (E) is as follows.

1. E1 = Men die, Socrates dies

Below we borrow Brewer's representation of enthymemes. First, for the deductive representation we see how—based on this representation of certain enthymemes—it is possible to derive a hypothesis (H).

1. E1 = All men are mortal
2. E2 = Socrates is a man
3. H = Socrates is mortal

Second, regarding the inductive representation, we see that it is possible to derive a hypothesis based on the probabilistic analysis of a collection of enthymemes.

1. E1 = X1 is a man and X1 is mortal
2. E2 = X2 is a man and X2 is mortal
3. ...
4. E1000 = X1000 is a man and X1000 is mortal
5. H1/E1001 = All men are mortal
6. E1002 = Socrates is a man
7. H2 = Socrates is mortal

Third, in relation to abductive representation, the representation of abduction is only possible as a meta-abduction, according to Brewer, due to significant reliance on an *enterprise conception of a point of view*, which is *explanatory* in nature [50]. Below we attempt to represent only the essential elements of Brewer's theory of abduction for our case study. We can see that based on the best conditional explanation of a (plausible) explanatory hypothesis, which is based on an *explanandum*, a hypothesis can be derived.

Abstract structure of abduction

1. Q = stands for an *explanandum*
2. F1... Fn = stands for (*plausible*) explanatory hypotheses (one or more *explanantia*)
3. If Fi $\rightarrow$ Q = stands for a sufficient explanation conditional: If Fn *were true, that would (plausibly) explain* Q
4. If Fn $\rightarrow$ Q = stands for *best explanation conditional*: Fn *explains* Q *better than any* Fi *where* Fi Fn

The schema for abduction

1. E1 = Q
2. E2 = For each candidate Fi, Fi $\rightarrow$ Q is true.
3. E3 = For candidate Fn, Fn $\rightarrow$ Q is true.
   Therefore
4. H = Fn

4 Results

The section presents the results of our research, of which there are three types. First, the generation of PCD via the experiment is presented (4.1). Second, the impact of PCD on contract drafting based on the LLM experiment is demonstrated (4.2). Third, the application of the Logocratic Method on an example of Proactive Data is presented (4.3).

4.1 Proactive Control Data Generation

We built a prototype web application that uses the Onassis and Enriched Bow-Tie Ontology structure to guide users in identifying legal risks and proactive controls during the negotiation and drafting stages of a contract. The source code for the prototype web application is accessible via Github [47] [46]. This includes the Docker specification for installing, running, and hosting the website, including a docker-compose script that can be used to start the front-end, back-end, and underlying database in a single command. Several screenshots stored in the readme.md of the front-end repository on Github [51] show the user interface and exemplify the user interaction of the web application.

The prototype validates two main points. First, (1a) that the development of iContracts based on the Onassis and Enriched Bow-Tie Ontology structure is possible and (1b) that the integration of APIs is possible. Second, that the extraction of isolated PCD is possible via the integration of the EBTO in the Onassis Ontology structure.

4.2 Impact on Contract Drafting

The experiment we conducted with ChatGPT demonstrated that the PCD-specific prompt engineering influences the generation of text by altering its contents by more than ninety (90) percent. The alterations in the text included ten (10) content removals and fourteen (14) content additions. The results can be accessed via [52].

The experiment validates the significant impact PCD has on contract drafting. The PCD-specific prompt engineering provides additional protection through the explicit inclusion of PCD-based clauses. Having validated the impact of PCD on contract drafting, the ChatGPT API can be integrated with the prototype web application we developed for a higher level of automation.

4.3 Quality Assessment

To apply the Logocratic Method to the Proactive Data of the visualisation of payment risk we used a specific example of a proactive control from the case study, with the purpose of demonstrating how it can be applied to more use cases. Our proactive control example is the timeline. The application of the Logocratic Method to the timeline example can be accessed via [53].

This example demonstrates that the quality assessment of a proactive control is possible via all three modes of inference, including deduction, induction, and abduction. Moreover, it makes clear that both the Onassis and Enriched Bow-Tie Ontology structures as well as the Logocratic Method are based on First Order Logic (FOL), therefore the application of the Logocratic Method can be engineered an ontology with the purpose of achieving a higher level of automation. Due to the high reliance of the Logocratic Method on the data required to validate the enthymemes, such automation would be preferable assuming the availability of data at a larger scale.

5 Discussion

The discussion concentrates on (5.1) prototype feasibility, (5.2) the impact of Proactive Control Data on contract drafting, (5.3) the validity of Proactive Data and (5.4) the value of Proactive Data.

5.1 Prototype Feasibility

The prototype demonstrates that it is feasible to generate PCD in a linked open data format. It also demonstrates that it is possible to link such data with LLM APIs, such as ChatGPT's API. Hence, technologically speaking, our research is practically feasible. One main obstacle is the lack of available data and friendly end-user interfaces that can support legal experts with the application of the EBTO and the Logocratic Method. As a consequence, it becomes imperative to examine the development of such innovation in commercial settings, next to furthering the scientific development of the theory in academia.

The application of the Logocratic Method is also technologically possible at this point for inferencing purposes on the ontology. Its implementation can be automatically executed via ontology reasoners. The Logocratic Method uses the inferencing system as employed in FOL. Ontology Web Language - Description Logic (OWL DL) (i.e., the semantics used to build the Onassis Ontology and the EBTO) follows description logic which is a branch of FOL. The inferencing system used in the Logocratic Method mirrors the one followed by OWL, and there are also reasoners (e.g., PELLET, HERMIT) implemented that perform the exact same inferencing displayed by the Logocratic Method. The added value of the Logocratic Method is the contribution it provides to quality assessment, beyond the assessment of consistency and contradictions that automated reasoners are able to achieve today. This is an innovative way to carry out an ontological quality assessment.

5.2 Impact of Proactive Control Data on Contract Drafting

During the application of PCD on prompt engineering it became evident that the generated text changes significantly. A higher level of detail, focused on the explicit PCD requested, is produced by the LLM. However, the quality of the drafted contract may not be ensured. Hence, a review by a legal expert is necessary. The examination of the quality of contract drafting remains a difficult task, even after the significant improvement of an automatically generated contract. To assess the quality of the drafted contract, it is also necessary to implement methods for assessing the quality of rules for generating the contract.

An example of such a method that can be applied in this case—and which also follows OWL DL—is the Calculemus-Flint Method which is being developed at TNO, the Netherlands Institute for Applied Scientific Research. It makes explicit rule-based interpretations via an action-based interpretation instead of using a deontic-based interpretative framework. As a result, rules become explicit, explainable, and understandable from an action-oriented perspective. The software, ontology, and documentation relating to the Calculemus-FLINT Method is accessible at the following GitLab repository [54].

5.3 Proactive Data Validity

The application of the EBTO to a case study has successfully generated Proactive Data. However, the quality of the generated Proactive Data is uncertain. The Logocratic Method can help investigate the quality of the Proactive Data based on their examination as argumentation schemes. We admit that the application of the EBTO is a time-consuming process and the application of the Logocratic Method further increases the time investment of a legal expert. This is the reason why the implemented reasoners can be leveraged for assessing consistency and contradictions and the quality assessment can be implemented only if necessary.

Moreover, even with the application of the Logocratic Method, the quality of the Proactive Data is not absolutely certain. The representation of enthymemes relies on assumed premises, of which the quality should also be examined, possibly with the additional application of the Logocratic Method. According to the theory of pragmatism, on which the Logocratic Method is based to a large extent, abduction assumes an infinite amount of deductive, inductive, as well as abductive statements [55]. Therefore, as the inferential structure deepens, complexity also increases and makes the task of representing reality in absolute terms eventually impossible.

Here we remark that based on the results of the application of the Logocratic Method, the prioritisation of the deductive, inductive, or abductive representation of argumentation schemes seems to depend on the specific context and needs for the quality assessment of Proactive Data. It appears that (1) an abductive representation is more useful in gaining a more complete understanding of Proactive Data, (2) inductive representation is more useful for the probabilistic analysis of Proactive Data, and (3) deductive representation is more useful in structuring the identified Proactive Data sequentially and explicitly. Moreover, we note that each representation is closely interrelated since the three representations are mutually relying on each other.

It, therefore, becomes evident that the quality analysis of argumentation schemes can result in a process resembling an infinite spiral. Hence, what becomes imperative is the identification of a sufficient abstraction level for quality assessment. That abstraction level is very much dependent on the use case at hand. For example, a legal expert from the previous century would normally prefer to conduct the whole contract drafting manually, relying on implicit risk analysis. However, a legal expert from the next century, depending on how technology develops, may only be focused on evaluating Proactive Data as argumentation schemes, deriving from the automated Bow-Tie analysis. Hence, depending on the context, resources, and culture of an organisation, the appropriate working process should be defined. The quality of Proactive Data improves with deeper examination, although the time investment for legal experts increases. Perhaps with the introduction of new technologies, this time-commitment may decrease. One potential way to experiment with technological innovation in this direction is with the generation of abductive representations via LLMs. In that way, the conditional automation of abduction becomes possible to some extent and the legal expert can significantly reduce the amount of manual review needed.

Consequently, automating the quality assessment of Proactive Data is both relevant and possible with available technologies, assuming the availability of data. Hence, it becomes eminent to apply this innovation in practice and further experiment with the tools at hand.

5.4 Value of Proactive Data

The title of our research is the *Value of Proactive Data*. To measure that value we can either approach it qualitatively or quantitatively. From a qualitative point of view, we see that Proactive Data is significantly influential in helping reduce the risk of disputes and minimising the subsequent legal costs. In this article, we demonstrate how its generation is possible, its impact, and how it can be further assessed and improved qualitatively.

Moreover, it would also be useful to examine their value from a quantitative perspective. Any quantitative measurement is limited at this point in time due to the lack of data. It is therefore very difficult to make an estimation. We can only arrive at a reasonable estimation with follow-up experimental research. The analysis we can make for now is limited to the payment risk case study and is as follows. According to the freelancers union, the payment risk for a freelancer and a client today is seventy-one (71) percent [56]. Hence, according to the EBTO case study on payment risk, the likelihood for payment risk according to available data is 0.7 [44]. The question remains as to how this percentage is affected once a freelancer agreement includes the identified PCD. To arrive at that estimation we would need to measure the extent to which each PCD reduces the likelihood for the hazardous event of non-payment to occur, for which we require data. Hence, it becomes evident yet again that the application of our results in practice and further experimentation is extremely relevant. By measuring the value of Proactive Data quantitatively, it also becomes possible to conduct an economic analysis of how an investment in Proactive Data reduces subsequent legal costs, and how a reallocation of investments targeted towards dispute prevention can save millions of people from unnecessary legal costs.

6 Conclusion

This section presents: (a) the answer to the RQ, (b) further research suggestions, and (c) the novelty of the research.

Regarding our RQ (viz. *To what extent is it possible to generate quality Proactive Control Data to improve an Intelligent Contract?*), we provide the following answer. Proactive Data is valuable in shifting iContracts towards minimising the likelihood of hazardous events, including that of a dispute that leads to consequential legal costs. The extent to which Proactive Data impacts an Intelligent Contract depends on their quantitative identification and qualitative assessment, as well as the use of relevant technologies that integrate the risk assessment (based on communication) data when a contract is generated. Our article demonstrates that the plain generation of PCD is possible with available technologies. Moreover, it shows that PCD can be quantitatively generated with the application of the EBTO and can be qualitatively assessed with the Logocratic Method. To achieve a higher degree of quality, efficiency is reduced; although we estimate that with the advancement of technology, this ratio will gradually improve towards a higher level of efficiency. Even though the application of the Logocratic Method does not guarantee "absolute truth", its application is highly valuable and preferable—or as the well-known statistician George Box stated: "all models are wrong, but some are useful" [57]. Available technologies are already sufficient in implementing the findings of our research. Hence, the impact of Proactive Data on iContracts has the potential to be significant in the future, yet it depends on the specific application preferences of an organisation, their resource allocation, and issues related to technological innovation. Therefore, the answer to the RQ is that the generation of PCD is possible, their impact on contract drafting is significant, and the generation of quality PCD is sufficiently possible.

In relation to further research, three key research areas appear to be relevant. The first is the conditional abductive reasoning automation of Proactive Data on iContracts via the use of the Logocratic Method within the context of LLM technology. Within this research scope it is possible to examine with a higher degree of certainty whether intuition is indeed implementable in the Logocratic Method and to what extent (having in mind Van den Herik's research statement on the possibility of programming intuition [26]). The second is the quality assessment of LLM-generated contract text via the integration of the Calculemus-Flint Method with the Onassis Ontology. The third is the conducting of experiments to generate data to measure the quantitative value of Proactive Data. Since the quality assessment is higher in order of priority for improving iContracts, our follow-up research will focus on the first of the identified research areas.

The novelty of this research is that we have demonstrated how it is possible to practically generate Proactive Data quantitatively as well as examine them qualitatively. Moreover, the research is novel because it develops one of the first practical prototypes of iContracts that demonstrates that the generation of Proactive Data in linked open data format is possible. Additionally, the

Logocratic Method, which is still a developing method in literature, is applied to a proactive case study rather than its traditional application on litigation arguments, which follows the reactive nature of legal systems. The research also demonstrates how it is possible to measure the value of Proactive Data for iContracts, which can help in scaling up iContract technology innovation in commercial settings, depending on architectural choices for improving the ratio of quality and efficiency. Moreover, the research is novel because it combines multiple FOL methodologies and technologies, and it proves that the automation of the aforementioned results is possible. Finally, our research introduces the value of Proactive Data and proposes a direction for measuring their value both technologically and economically.

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