Preventing disputes: preventive logic, law & technology

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Preventing Disputes

Preventive Logic, Law & Technology

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Preventing Disputes

Preventive Logic, Law & Technology

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Dedicated to my parents

Life is the struggle against death

Contents

List of Abbreviations

AI . . . Artificial Intelligence
AIDM . . . Automated Individual Decision-Making
AILD . . . Artificial Intelligence Liability Directive
API . . . Application Programming Interface

CAI . . . Conversational AI
CK . . . Cohen's Kappa
CUAD . . . Contract Understanding Atticus Dataset

DOAM . . . Description of a Model Ontology
DL . . . Deep Learning
DS . . . Data Science

EBA . . . Ethics-Based Auditing
EBTO . . . Enriched Bow-Tie Ontology
ECAI . . . European Conference on Artificial Intelligence
eFLINT . . . electronic Formal Language for the INTerpretation of sources of norms

FDI . . . Foreign Direct Investment
FIBO . . . Financial Industry Business Ontology
FOAF . . . Friend of a Friend

GDP . . . . . Gross Domestic Product
GDPR . . . . . General Data Protection Regulation
GR . . . . . Good Relations Vocabulary
GUI . . . . . Graphical User Interface

iContracts . . . . . Intelligent Contracts
IML . . . . . Interpretable Machine Learning
IoT . . . . . Internet of Things
ISO . . . . . International Organization for Standardization

KBS . . . . . Knowledge-Based Structures
KG . . . . . Knowledge Graph

LIME . . . . . Local Interpretable Model Agnostic Explanation
LLM . . . . . Large Language Model
LM . . . . . Logocratic Method
LOV . . . . . Linked Open Vocabularies
LRM . . . . . Legal Risk Management
LTAI . . . . . Legally Trustworthy Artificial Intelligence

ML . . . . . Machine Learning

NDA . . . . . Non-Disclosure Agreement
NLP . . . . . Natural Language Processing
NPS . . . . . Net Promoter Score

OECD . . . . . Organisation for Economic Cooperation and Development
ORM . . . . . Open Risk Management
OWL . . . . . Web Ontology Language

PCD . . . . Proactive Control Data
PLD . . . . Product Liability Directive
PLT . . . . Preventive Legal Technology
PPL . . . . Preventive/Proactive Law
PS . . . . Problem Statement

RAG . . . . Retrieval-Augmented Generation
RAGA . . . . Retrieval-Augmented Generation Algorithms
RFO . . . . Risk Function Ontology
RDF . . . . Resource Description Framework
RDF/S . . . . Resource Description Framework Schema
RQ . . . . Research Question
R&D . . . . Research and Development

SHAP . . . . SHapley Additive exPlanations
SWRL . . . . Semantic Web Rule Language

TAI . . . . Trustworthy Artificial Intelligence
TNO . . . . Netherlands Institute for Applied Scientific Research

US(A) . . . . United States of America

XAI . . . . Explainable Artificial Intelligence

W3C . . . . World Wide Web Consortium

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Chapter 1

The Art of Preventive Law

Aristotle Onassis, a Greek entrepreneur, was one of the most successful shipping tycoons of the Twentieth Century [Evans, 1986] [1]. Onassis (1900-1975) used Preventive Law to secure himself and his business from financial losses. The following narrative demonstrates how he *accomplished* this when his opponents planned to cause his business in Peru to suffer severe financial losses. The opponents were some shipping businessmen and a few law enforcers from FBI and CIA (in the narrative provided below they are called 'we') [2].

We knew that Onassis's fleet had the habit to fish in illegal waters of Peru. As a consequence, we planned with the Peruvian Government to seize his fleet. The Government sent out ships and an aircraft, which actually bombed the waters around the factory ship. They certainly strafed the ship with machine gun fire and they forced the boat back into harbor with the captures. The Peruvians were very nasty about it, gave a huge fine and said they needed three million dollars to let Onassis's fleet go again. The night that this happened we were believing that we now had killed the monster. Much to our amazement we saw and learned that he had anticipated this whole thing by booking for disasters at Lloyd's of London. So, all in all, we watched him make a profit. He got 15 million dollars in insurance money and three thousand each day that he was out of the whaling operation. Thus, he made an enormous amount of money and he was just laughing all the way to the bank.

[1] To avoid all confusion with names and also to make them more familiar, we mention the first name of a person at the first occurrence together with the family name, when we believe it is supportive for the understanding of the text.

[2] Robert Mayhew, former FBI agent, CIA consultant and expert investigator acting on behalf of Onassis's opposition, and Dr. Ray Gambell, Secretary of International Whaling Commission, produced for the BBC, (1994), *Aristotle Onassis 'The Golden Greek'*, B.B.C. Documentaries, min. 36:14 (for readability reasons the oral text used has been slightly paraphrased).

1.1 My Motivation

This narrative illustrates the art of Preventive Law (see Definition 1.1).

*Definition 1.1 – **Preventive Law***

> ***Preventive law*** is a *method* that minimises the likelihood of the occurrence of disputes, or in case they occur it exploits their impact, and strengthens legal rights and duties.

The author became aware of this concept through Onassis's lawyer, Tryfon Koutalidis [3] [Papinianus, 2003]. Koutalidis often provided short legal memoranda to Onassis or other people working for him. When there were no pressing issues on the table, Onassis would call for gym-time. During gym-time, the businessman, lawyer, and other directors of his business examined hypothetical scenarios to secure themselves from potential risks that could arise. In this process, Preventive Law developed into a practice, where legal risks were discussed and secured. Reading more about Onassis inspired me (Georgios Stathis) during my study to find applications of preventive law in particular jurisdictions and in legal theories. It motivated me to investigate whether *the best way to resolve any dispute is to prevent it from happening*. This challenging idea stimulated me and others in my direct neighbourhood to examine the power of Preventive Law.

1.2 The Academic Start

Brown (1950) was the first to introduce the concept in academic circles via his book *Preventive Law* [Brown, 1950]. However, until today, Preventive Law has not fundamentally advanced from the perspective of preventing legal problems. Indeed, several academics have attempted to improve the theory of Preventive Law, but without much success. Even with the use of computer technology, it did not significantly change. Then, all of a sudden the disciplines of Law, Computer Science, Data Science, and Artificial Intelligence (AI) (see Definition 1.2 [High-Level Expert Group on AI, 2019]) were combined.

[3] Most of the applications of Preventive Law concerning Onassis's business were to prevent financial risks. For this reason, and because he was educated on applying Preventive Law by Onassis, Mr. Tryfon Koutalidis claims with a smile that he graduated from the 'Onassian University of Financial Contracts'.

*Definition 1.2 – **Artificial Intelligence***

> ***Artificial Intelligence*** refers to systems designed by humans that, given a complex goal, act in the physical or digital world by perceiving their environment, interpreting the collected structured or unstructured data, reasoning on the knowledge derived from this data, and deciding the best action(s) to take (according to pre-defined parameters) to achieve the given goal.

Soon the world was facing the dawn of *legal technologies* [4] and the arrival of *Intelligent Contracts* (iContracts) (see Definition 1.3 [5]).

*Definition 1.3 – **Intelligent Contract***

> An **intelligent contract** or **iContract** is a contract that is fully executable without human intervention.

Our research aims to pave the way to the conceptualisation of *Preventive Legal Technology* (PLT), which is a central outcome of the research (see Definition 1.4).

*Definition 1.4 – **Preventive Legal Technology***

> ***Preventive Legal Technology*** is a methodology concerned with use of legal technology within the context of preventive law with the purpose of promoting the intelligent prevention of disputes.

1.3 A Practical Start: Avoiding Legal Costs

Assume that a legal problem occurs between two parties who are subject to a legal agreement. Both sides may experience costs, e.g., by psychological pressure, legal and financial support, reputation damage, or loss of time. The allocation of costs will always affect one or sometimes both parties of the legal agreement, depending on the legal problem itself and how or when it will be resolved. At least one party will incur (1) the *procedural* costs connected with the legal problem, and potentially, (2) the *liability* costs from the hazardous event that triggered the legal problem [6]. In total, legal costs are frequently quite large and

[4]Examples are to be found in the advanced courses for the Ministry of Justice and Security, the Public Prosecution and others: see Leiden Legal Technologies Program (LLTP), Leiden Centre of Data Science and The Centre for Professional Learning (LCDS and CPL), 2021.

[5]`https://bravenewcoin.com/insights/pamela-morgan-at-bitcoin-south-innovating-legal-systems-through-blockchain-technology`

[6]Often, legal problems and their formal adjudication also incur relationship costs among the parties; these can include curtailing possible future transactions of mutual benefit.

they primarily appear as dispute resolution costs [7], even in the world's most advanced jurisdictions [Susskind, 2019]. This is why commentators opine that we need *new ways* to resolve and avoid disputes [Katsh and Rabinovich-Einy, 2017]. A major reason why legal costs are so high is that the structure of legal systems invites dispute *resolution* and not dispute *prevention* [Barton, 2009]. All in all, legal costs give rise to a need for preventive law.

1.4 Towards Proactive Practices

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 [Barton, 2016]. The disconnection between *innovation* and *tradition* in the legal system is particularly amplified by the introduction of more complex technologies [De Franceschi and Schulze, 2019]. 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* [Katz et al., 2020]. One of the consequences of the growing legal complexity is a problem that has recently arisen: how can the legal needs of millions of people be safeguarded? [Susskind, 2008].

As Susskind somewhat later remarked, 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 Organisation for Economic Cooperation and Development (OECD), fewer than 50 percent of people on earth live under the protection of the law) [Susskind, 2019]. Indeed, in his 1996 book *The Future of Law*, Susskind already 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) [Susskind, 1996]. There he stated that our legal system is subject to the paradox of *reactive legal services* [8]; a paradox which in his opinion would be replaced by *proactive*

[7] Usually, dispute resolution costs are a percentage of the liability costs. The best available research estimates that liability costs as a fraction of the Gross Domestic Product (GDP) are equal to 2.3 percent in the United States of America (US[A]) (429 Billion Dollars [US Chamber Institute for Legal Reform, (2018), Costs and Compensation of the US Tort System, instituteforlegalreform.com, p.1] in 2016) and 0.63 percent (Best available number derived from US Chamber Institute for Legal Reform, (2013), International Comparisons of Litigation Costs, instituteforlegalreform.com, p.2) in Euro zone (85.8 Billion Dollars [Calculated 0.63 percent of 2011 Euro zone GDP 13.6 Trillion Dollars as recorded at countryeconomy.com, (2011), Euro Zone GDP – Gross Domestic Product] in 2011). An economic analysis looking beyond GDP to socio-economic consequences is even more relevant to highlight the costs of dispute resolution with higher accuracy.

[8] The paradox of reactive legal services addresses that in order to recognise the need for legal help at the right time one should be a lawyer, however, since most people in need of legal help are not lawyers, they can hardly recognise, especially at the right time, the need for legal help;

practices induced by technology [Susskind, 1996]. What we can observe now 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*.

1.5 Preventing Legal Problems

Assuming someone attempts to apply preventive law to *prevent legal problems*, then there is still a high likelihood for legal problems to *further develop* instead of diminish. The first elementary framework for the prevention of legal problems was introduced by Brown [Brown, 1950]. Dauer later added a schematic approach to Brown's observations by stating that prevention can be applied at three intervals to manage legal risk, i.e., *before*, *during*, and *after* damage occurs [Dauer, 2008]. Dauer's systematic analysis resulted in a matrix [Barton, 2009]. Barton called it Dauer's matrix and refined it considerably [Barton, 2002] [Barton, 2006] (see Table 1.1).

Currently, most literature focusses on the *mindset* and *application* of Preventive Law. This book contains many examples in a variety of domains, one of which is iContracts (see Section 1.6). Indeed, there is a range of specialised exceptions, which only partially help people prevent legal problems. They come from the fields of *proactive law* [Haapio and Siedel, 2013] and *Legal Risk Management* [Esayas and Mahler, 2015]. In general, the reasons behind the lack of a substantive number of methods or approaches to prevent legal problems are unclear (indeed, they form a part of our research).

Whatever the case may be, at this moment we observe a research gap in the literature between (1) a *direct application* of preventive law and (2) the use of *practical methods* that explain how to prevent legal problems. The practical methods are currently felt as mostly lacking.

According to the literature, the most advanced methods for preventing legal problems focus on contract risk management [Haapio and Siedel, 2013]. So, our research is centred around *contract automation* (see Section 1.6) [Stathis et al., 2023d, Stathis et al., 2024].

which results to lawyers providing more reactive legal services than proactive.

Table 1.1: Dauer Matrix

	Direct Parties	**Third Parties**	**Government Regulation or Facilitation**	**Physical Environment**
1a. Planning: Imagine the risks				
1b. Planning: Imagine various structures and methods to prevent problems from arising				
2. Addressing Problems: Use early warning systems and resulting information to prevent problems from escalating into "disputes"				
3. Dispute Resolution: Take steps to resolve disputes fairly and efficiently, using a succession of methods				
4a. Feedback and Follow-up: Anticipate and foreclose adverse spill-over effects of the resolution itself				
4b. Feedback and Follow-up: Feedback the nature of the problem and dispute to Step 1, the planning process				

1.6 Contract Automation

Recently, the field of contract automation has experienced three major innovations. The first one is the digitalisation of contract management (hereinafter *digital contracts*), where certain contractual processes are digitised, such as signing, drafting, storing, reviewing, sharing, and analysing contracts [Timmer, 2019]. The second innovation regards the rise of *smart contracts* demonstrating that parties can reach and execute agreements via programming [Kolvart et al., 2016]. Today, we face the dawn of the third innovation, namely *intelligent contracts*. iContracts introduce a hybrid approach between human and computer interventions that aim to achieve full automation with self-executing contracts [Mason, 2017]. iContracts introduce state-of-the-art innovations in the space of contact automation due to their compliance with Hybrid AI's four development dimensions: (1) environment, (2) purpose, (3) collaboration, and (4) governance) [Huizing et al., 2020]. Our investigation relies on two AI technologies: *Ontology Engineering* (see Definition 1.5 for Ontology [Feilmayr and Woss, 2016] and Definition 1.6 for Ontology Engineering [Gal, 2009]) and *Large Language Models* (LLMs) (see Definition 1.7 [9]).

*Definition 1.5 – **Ontology***

Ontology is a formal, explicit specification of a shared conceptualisation that is characterised by high semantic expressiveness required for increased complexity.

*Definition 1.6 – **Ontology Engineering***

Ontology engineering is the set of activities that concern the ontology development process, the ontology life cycle, and the methodologies, tools and languages for building ontologies.

*Definition 1.7 – **Large Language Models***

Large Language Models (LLMs) are a category of foundation models trained on immense amounts of data making them capable of understanding and generating natural language and other types of content to perform a wide range of tasks.

[9] https://www.ibm.com/topics/large-language-models

1.7 Problem Statement and Six Research Questions

In this thesis we are motivated by preventive law and are interested in investigating how it is possible to prevent disputes, with contractual disputes as the main case study.

1.7.1 Problem Statement

The shift towards the automated prevention of disputes paradigm generates multiple questions related to multiple disciplines including, non-exclusively, Law, Logic and AI. Based on this observation, we formulate the following Problem Statement (PS) in a sufficiently open manner to invite multi-disciplinary research, combining the aforementioned disciplines.

PS: *To what extent is it possible to automate the prevention of disputes?*

To address the PS, we will decompose it into six tractable Research Questions (RQs).

1.7.2 Six Research Questions

Starting with iContracts as a concrete case study for this research, we will investigate *contract automation*. While examining the contracting process from an end user perspective it became apparent to us that end users spend much time during contracting focussed on communications. Moreover, due to lack of widely adopted contract risk management methodologies, the interplay between communications and risk during contracting is mostly not interlinked.

Below we introduce six RQs. Given the complexity of the matter, especially within the context of automation, the need for semantic specificity is born. In contract automation, ontology (see Definition 1.5 and 1.6) design can assist the clarification of the relation of communications and risk. Below we introduce two new specialised ontologies: (1) the Onassis Ontology and the (2) Enriched Bow-Tie Ontology (EBTO), which are described in detail in Chapter 2 (Onassis Ontology) and Chapter 3 (EBTO).

Research Question 1

From the perspective of an end user the technological innovation mentioned above is only interesting when it is more useful than existing alternatives. Therefore, an important criterion is that the resultant quality provided during contracting is equal to or greater than that of a legal expert. Moreover, it is important that all stages of contracting are taken into consideration, including all risks therein, from initial communications and drafting (when contracting parties exchange information with each other) up to execution and reporting (when the performance of parties in the execution of contract is evaluated).

With these criteria in mind, RQ1 is formulated as follows.

RQ1: *To what extent is it possible to develop an ontology to automate contracts with communications and risk data?*

Chapter 2 discusses RQ1 and the extent to which it is possible via the Onassis Ontology, defined in Chapter 2 as an ontology for contract automation based on communications and risk data.

Research Question 2

While developing the ontology for communication and risk automation, it became apparent that no consensus exists for managing contract risk. It is evident that the view at a risk management level differs from the view at an ontology design level. Currently, the most advanced methodology for managing contract risk is the Bow-Tie Method [10] (see Chapter 3). By investigating the application of the Bow-Tie Method on contract risk we can explore the limitations of contract risk analysis and thereafter the degree to which contractual disputes are preventable. Therefore, the design of a specific ontology for the management of risk, including contract risk, based on the Bow-Tie Method should be deeply investigated.

Accordingly, the second RQ is a as follows.

RQ2: *To what extent is it possible to translate the Bow-Tie Method into a visualisation of an ontology for contract risk management without altering the bow-tie structure?*

Chapter 3 discusses RQ2 and the extent to which it is feasible via the Enriched Bow-Tie Ontology (EBTO). This is an ontology for managing risk, including contract risk, designed in accordance with the Bow-Tie Method. After the Onassis Ontology it is the second ontology we design and introduce in this research.

Research Question 3

Developing an ontology that aims to provide an improved alternative to end users would be insufficiently validated without taking into consideration the *perspective* of end users. By analysing the options of end users involved in contracting, we may observe that one of the main functions of a legal expert during

[10] https://www.wolterskluwer.com/en/solutions/enablon/bowtie/expert-insights/barrier-based-risk-management-knowledge-base/the-bowtie-method

end user communications is the *explanation of risk*. That is particularly important provided the binding consequences that legal decisions may carry. Hence, the impact of visualisation of risk to end users during the communications stage of a contract should be solidly trustworthy (see Definition 4.2 in Chapter 4).

From these observations, we arrive at our third RQ.

> **RQ3:** *To what extent is it possible to improve user trustworthiness for Intelligent Contracts via the visualisation of risk during legal question-answering?*

Chapter 4 addresses RQ3 and the extent to which it is possible via an explorative survey. The survey examines the level of the end user's trustworthiness. It is based on the visualisation of risk during contracting to end users via the EBTO.

Research Question 4

For our research, it holds that the most important element of the Bow-Tie Method for successful prevention is the *identification of proactive controls* during risk management. An expert will arrive at (1) proactive controls when (2) a hazardous event and (3) a risk source is identified (the data of (1) are called "Proactive Control Data" or "PCD", and data (1) (2) and (3) together are called "Proactive Data"). From an ontology design *perspective*, it is vital to clarify whether PCD can be programmed. Yet, programming PCD should not occur in a vacuum. Their impact as well as their quality should be both understood by the designer as well as by the user.

Hence, we arrive at RQ4.

> **RQ4:** *To what extent is it possible to generate quality Proactive Control Data to improve an Intelligent Contract?*

Chapter 5 addresses RQ4. It discusses the extent to which it is possible via the development of a prototype of the Onassis Ontology and the Enriched Bow-Tie Ontology structures, to perform a Large Language Model (LLM) (see Definition 1.7) experiment as well as the application of the Logocratic Method (LM) (see Chapter 5). All in all, we speak of a scientific method for (a) the analysis of arguments, (b) the quality assessment and (c) the evaluation of PCD.

Research Question 5

Beyond the investigation of contract risk management via an ontology, it is vital to examine (a) the extent to which PLT can be developed and (b) the relationship between ethics, preventive law and technology, in particular in light of AI developments. Currently, we see two important topics in Ethics and AI research. They are the development of *explainable* and *trustworthy* AI. Hence, an interesting and intriguing question arises on whether it is possible to develop an explainable and trustworthy PLT. If that is indeed possible, then we are able to trust the decisions of PLT.

Consequently, we arrive at RQ5.

> **RQ5:** *To what extent is it possible to develop an explainable and trustworthy Preventive Legal Technology?*

Chapter 6 discusses RQ5 and the extent to which it is possible via the application of the EBTO on multiple legal technology case studies to point to the legal and ethical gaps in the development of explainable and trustworthy PLT.

Research Question 6

Looking beyond academic research, the application of iContracts in the market becomes imperative. The promise of iContracts is that it will solve some serious challenges that either physical or digital or smart contracts are facing. For the acceleration of the adoption of iContracts in the market we examine Large Language Models (LLMs) (see Definition 1.6). Hence, we investigate the extent to which LLMs can help in improving user adoption of iContracts.

Consequently, we arrive at RQ6.

> **RQ6:** *To what extent is it possible to accelerate the adoption of Intelligent Contracts with Explainable Large Language Models?*

Chapter 7 discusses RQ6 and the extent to which fast market adoption is possible via the clarification of iContracts relative to physical, digital and smart contracts. After identifying the market adoption gap, Chapter 7 examines where LLMs can help in accelerating their adoption rate. For the precise meaning of *explainable* we refer to Chapter 6.

1.7.3 Research Methodology

The topic of automating contractual dispute prevention is complex. Focussing only on legal aspects leads to legal solutions. Similarly, a purely computational approach yields only computational answers. Therefore, effectively addressing the Problem Statement requires a multifaceted approach, prompting us to adopt a multidisciplinary research methodology. Our research methodology can be broken down into six main categories, as detailed below.

1. Literature
2. Analysis
3. Case Studies

4. Visualisation
5. Engineering
6. Experiment

Each RQ is addressed in a separate chapter, tailored to answer that specific question. Literature and analysis are the main categories that are consistently used in answering each RQ. As for case studies, the methodology was used in answering each RQ, except RQ2. The visualisation methodology was employed in answering RQ2 and RQ3. Engineering was used in answering RQ1 and RQ4. Experiments were used in answering all RQs. Due to the multi-disciplinary nature of the research the specific research methodology categories used to answer each RQ are detailed in the relevant chapter.

1.8 Research Contributions

For readability purposes, we will list below the six main contributions of our research. The six contributions are discussed in the Chapters 2 to 7, respectively.

- *Contribution 1 (Chapter 2)* We will design an ontology (Onassis Ontology) for contract automation that shows that automation based on communications and risk data is possible and essential for iContracts, even though the inclusion of communications and risk data in automation is currently absent in existing LegalTech solutions.

  Communications and risk data contribute to the development of effective and responsible contract automation that reduces the need for the physical involvement of legal experts. We will show that is possible to design an ontology that demonstrates how the reduction mentioned above is practically feasible. Surprisingly, even in the world's largest LegalTech solutions database no available solution focusses on this subject.

- *Contribution 2 (Chapter 3)* We will design an ontology (Enriched Bow-Tie Ontology [EBTO]) for risk management, including contract risk management, that leverages the Bow-Tie Method for scaling and cross-referencing risk management purposes.

  The traditional Bow-Tie Method design is based on a cause-sequential order that helps, justifiably, in explaining cause and effect risk management in an analytical manner. From a technological perspective, designing based on node-sequential order is necessary for scaling the application of the method in large and complex contexts that require scalability and cross-referencing.

Such a design assists with (a) the analysis and (b) the visualisation of risk management, and (c) the extraction of semantic relationships.

- *Contribution 3 (Chapter 4)* We will show that risk visualisation during legal-question answering improves the end user's trustworthiness by 6.9 (as derived from a scale of 1 to 10).

  Let us assume there is a trustworthiness scale from 1 to 10. Scale 1 refers to a Graphical User Interface (GUI) *without any* risk visualisation that end users are called upon to use during legal-question answering. Scale 10 refers to a legal expert who is explaining with *ultimate specificity* to end users the risk involved in a potential contract during the communication stage. By visualising the EBTO to end users and conducting an explorative survey we will show that an average end user assigns a trustworthiness level of 6.9 to a GUI that explains the risk during the legal-question answering.

- *Contribution 4 (Chapter 5)* We will show that (a) the generation of Proactive Control Data is possible, (b) their impact on contract drafting is significant, and (c) measuring their quality assessment and evaluation is possible.

  First, the generation of PCD is possible and that is executed by programming a prototype of the Onassis Ontology and the Enriched Bow-Tie Ontology structures. Second, we conduct an LLM experiment showing the significant impact of PCD on contract drafting. Third, the quality assessment and evaluation becomes possible with the application of the Logocratic Method (by using the virtue of arguments framework on PCD).

- *Contribution 5 (Chapter 6)* We will show that developing an explainable and trustworthy Preventive Legal Technology is possible, by focussing on rule-based explanations.

  By explaining the decisions of PLT, we achieve a higher degree of *trustworthiness* because explicit explanations improve the level of transparency and accountability. Trustworthiness is an *urgent topic* in the discussion on (a) doing AI research ethically and (b) accounting for the regulations. For this purpose, we highlight the limitations of rule-based explainability for PLT. Explaining the AI decisions for small PLT domains is shown to be possible, with direct effects on trustworthiness due to the increased transparency and accountability.

- *Contribution 6 (Chapter 7)* We will show that LLMs can contribute in the acceleration of the market adoption of iContracts.

  With the application of LLM technology on specific challenges of iContracts we combine both technologies so that they can handle the market adoption challenge. Moreover, we will show (a) how iContracts relate to the previous contracting technologies and (b) why the combination of LLMs and iContracts has a unique advantage relative to the previous technologies, mainly by their use of communications and risk data analysis automation.

1.9 Thesis Overview

In Chapter 1, we introduced the *art of preventive law* and how it motivated the author to investigate the power of prevention. Then we provided a summary of developments in the theory of preventive law and introduced the topic of the research: Preventive Legal Technology. After introducing its main function, the avoidance of legal costs, we showed how preventive law develops methods for the prevention of legal problems. So far, contract automation is the most advanced field for preventing legal problems. Our research used iContracts, the latest revolution in contract automation, as the main case study. We formulated our PS, and decomposed it into six RQs. After intensive research we arrived accordingly at six contributions. The remainder of the thesis is given below.

- **Chapter 2** answers RQ1 resulting in Contribution 1. The content of the chapter corresponds to the publications by

  Stathis, G., Trantas, A., Biagioni, G., de Graaf, K. A., Adriaanse, J. A. A., and van den Herik, H. J. (2024). Designing an Intelligent Contract with Communications and Risk Data. *Springer Nature Computer Science (SNCS): Recent Trends on Agents and Artificial Intelligence*, 5(709). https://doi.org/10.1007/s42979-024-03021-x

  and

  Stathis, G., Trantas, A., Biagioni, G., van den Herik, H. J., Custers, B., Daniele, L., and Katsigiannis, T. (2023d). Towards a Foundation for Intelligent Contracts. *In the Proceedings of the 15th International Conference on Agents and Artificial Intelligence (ICAART)*, 2:87–98.

- **Chapter 3** answers RQ2 resulting in Contribution 2. The content of the chapter corresponds to the publication by

  Stathis, G., Biagioni, G., Trantas, A., van den Herik, H. J., and Custers, B. (2023b). A Visual Analysis of Hazardous Events in Contract Risk Management. *In the Proceedings of 12th International Conference on Data Science, Technology and Applications (DATA)*, 1:227–234.

- **Chapter 4** answers to RQ3 resulting in Contribution 3. The content of the chapter corresponds to the publication by

Stathis, G., Trantas, A., Biagioni, G., and van den Herik, H. J. (2023c). Risk Visualisation for Trustworthy Intelligent Contracts. *In the Proceedings of the 21st International Industrial Simulation Conference (ISC), EUROSIS-ETI*, pages 53–57.

- **Chapter 5** answers RQ4 resulting in Contribution 4. The content of the chapter corresponds to the publication by

  Stathis, G., Biagioni, G., de Graaf, K. A., Trantas, A., and van den Herik, H. J. (2023a). The Value of Proactive Data for Intelligent Contracts. *World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4), Intelligent Sustainable Systems, Springer Lecture Notes in Networks Systems (LNNS)*, 803:107–125.

- **Chapter 6** answers RQ5 resulting in Contribution 5. The content of the chapter corresponds to the publication by

  Stathis, G. and van den Herik, H. J. (2024). Ethical & Preventive Legal Technology. *Springer AI and Ethics*. https://doi.org/10.1007/s43681-023-00413-2.

- **Chapter 7** answers RQ6 resulting in Contribution 6. The content of the chapter corresponds to the publication by

  Stathis, G. (2024b). Explainable Large Language Models & iContracts. *In the Proceedings of the 16th International Conference on Agents and Artificial Intelligence (ICAART)*, 3:1378–1385.

- **Chapter 8** entails the conclusions of the thesis, in three distinct sections. We (1) answer the six research questions, (2) provide an answer to the problem statement, and (3) discuss potential directions of future work.

- **Chapter 9** provides a collection of reflection statements for the purpose of clarifying how non-experts in legal technology can apply this thesis in legal practice.

Most of the papers presented in this thesis were produced as a joint collaboration between the supervisors, the PhD candidate and a domain-expert research team. Discussions on research topics and how to handle the problems described were addressed as a team, in principle between the supervisors and the candidate. The writing was performed primarily by the candidate who is the main author of each paper, incorporating the commentary provided by the supervisors and the domain-experts. The implementation of the experimental designs and gathering of the results were performed by the candidate, except in cases where domain-expertise was necessary. Then, the domain-experts provided their contributions. The specific contribution of each domain-expert is provided in the acknowledgments section under each article.

Moreover, each domain-expert provided explicit contribution statements to Leiden University's evaluation committee to further clarify and secure the validity of their contributions. Finally, in compliance with the evaluation committee's request, each chapter includes the explicit contribution of each domain-expert in accordance with Elsevier's *CRediT Author Statement* guidelines [11].

[11] https://www.elsevier.com/researcher/author/policies-and-guidelines/credit-author-statement

Chapter 2

Intelligent Contracts

The Chapter addresses RQ1, which reads:

> **RQ1:** *To what extent is it possible to develop an ontology that automates contracts with communications and risk data?*

Contract automation is a challenging topic within AI and LegalTech. From digitised contracts via smart contracts, we are heading towards iContracts. We will address the main challenge of iContracts: the handling of *communications* and *risk* data in contract automation. In the Chapter we *design* and *conceptualise* an iContract ontology. Our findings will validate the *conceptual expressiveness* of our ontology qualitatively and quantitatively. A brief discussion highlights the value of the ontology design and its application domains. The Chapter concludes by two observations: (1) the current method is innovative, and (2) further research is necessary for handling more complex use cases.

The current Chapter corresponds to the following two publications:

Stathis, G., Trantas, A., Biagioni, G., de Graaf, K. A., Adriaanse, J. A. A., and van den Herik, H. J. (2024). Designing an Intelligent Contract with Communications and Risk Data. *Springer Nature Computer Science (SNCS): Recent Trends on Agents and Artificial Intelligence*, 5(709). https://doi.org/10.1007/s42979-024-03021-x

Stathis, G., Trantas, A., Biagioni, G., van den Herik, H. J., Custers, B., Daniele, L., and Katsigiannis, T. (2023d). Towards a Foundation for Intelligent Contracts. *In the Proceedings of the 15th International Conference on Agents and Artificial Intelligence (ICAART)*, 2:87–98

2.1 Artificial Intelligence, Contracts and Innovation

The promise of a gift is different from the gift of a promise. Both are attractive. However, soon, the following questions will arise. Which one is better, or which one is always the best? Can we utilise an ontology to guide us in difficult decisions? Moreover, to what extent can AI involvement aid us?

While global media frequently advance statements discussing the replacement of humans by robots in the labour market, social confusion ensues [Larson, 2021]. The same holds for the legal world. So, the aim of our analysis is twofold: (1) to clarify the state-of-the-art innovations in contract automation (i.e., a particular field of AI and Law), and (2) to establish the technological foundations of iContracts.

2.1.1 Automation with Communications and Risk Data

While iContracts are advancing, they face two main challenges. They concern the *communication processes* preceding the drafting of contracts and the *risk analysis* of contracting clauses. The first challenge is the lack of standardised communication processes which increases the difficulty in deciphering *real communication* from *miscommunication* [1]. The second challenge is that the analysis of risk is not systematised for the purpose of handling automated computer processes. Such risk analysis adds heavy burdens on (1) the human expert who conducts the analysis as well as on (2) the contractors who may experience adverse consequences if risk is not managed well.

The two challenges are usually neglected in automation. During the communication, contracting parties exchange useful information that may affect the design of contracts. Typically, a legal expert (a) leverages the information and (b) analyses the risks that may derive by instinct only. For example, from the relevant legal rules [Stark, 2013] the expert drafts a contract by experience. As a result the communications and risk data often remain *implicit* in contract automation. A *mini-challenge* here is to make them *explicit*.

Such mini-challenges can contribute in making implicit communications and risk data explicit. In order to establish a solid foundation for such explicit expressions, we start by focussing on simple freelance agreement case studies. Gradually, this form of automation can be applied in more complex case studies, including for example enterprises or government contractors. So far, the

[1] A striking example of miscommunication in contracting regards, in construction for example, the ordering of wrong-sized material for the construction of a house, based on miscalculations from one of the parties. This can be avoided with the presence of standardised (automated) mechanisms along the contracting process. Ontology engineering can help clarify these mechanisms to a significant degree.

main alternative for freelancers or organisations is mostly involving physical contract interventions that are hardly scalable. The focus of our research aims at displaying how iContracts may benefit from small-scale challenges (mini-challenges) to future application in more complex environments.

2.1.2 Turning Implicit Data into Explicit Data

To handle the two challenges, our solution should begin at clarifying: *what type* of communication and risk data should be made explicit? This is difficult since communication and risk data are involved in all stages of the contracting process, which includes: (1) contract drafting, (2) contract execution and monitoring, as well as (3) contract dispute resolution. Provided that the initial communication and risk data analysed during stage (1) will affect later information in stage (2) and thereafter stage (3), we should begin our investigation with the stage (1).

Having selected a contracting process stage, it is also necessary to select a relevant contract category. Automating the legal communication and risk analysis has the potential to benefit, first, the contracting parties. The ultimate beneficiary of such automation would be the non-legal experts, since they can leverage the automation of the contracting process. However, one should neither omit the inclusion of any legal expert nor make an attempt to neglect any human expertise. At this moment we are cautious to note that automation cannot be immediately successful for all types of contracts. Therefore, our research focusses on a straightforward contracting case study.

To automate the workflow, a technological system should (1) process specific contract communications and risk data as input and (2) yield a contract as output. So our investigation should begin by identifying or defining such data. Due to temporal lack of literature for the specific types of automation, there are as yet no available data sources structured accordingly. Hence, as matters now stand, it becomes imperative for AI and LegalTech researchers to *structure* the available data for automating a contract in the present context. Obviously, the most prominent challenge is: *how the communication and risk analysis processes can be handled in a harmonised, scientific manner?*

2.1.3 Knowledge Representation with Ontology Engineering

To address both issues (communication and risk analysis), we utilise the power of ontology engineering (see Definition 1.6). Ontology engineering (1) studies the granular representation of the meaning and syntax of concepts, data and entities and their relations in a provided domain and (2) assists with representing knowledge in specific domains in a manner friendly for the computers to understand [Kendall and McGuinness, 2019]. Since the data concerning our research are implicit, ontology engineering is able to substantiate any automation effort on the basis of a clear conceptual framework.

The foundation for both communication and risk analysis, within the context of contracting, is legal knowledge. The implicit nature of analysis for both purposes gives rise to the need for explicit knowledge representation. Ontology engineering is a prominent method used in science to derive explicit knowledge representations [Grenon, 2008]. It can help us simplify and clarify the complexity of communications and risk analysis, especially in light of the uncertainty over the availability, or in rare cases the quality, of data.

Two alternatives to ontology engineering are briefly investigated. They are (1) unsupervised Machine Learning algorithms and (2) Relational Databases. Our experience was as follows. First, applying an unsupervised ML algorithm on available contract data is possible. However, structured data are hard to find, if not impossible, for the purpose of explicit communications and risk analysis. Second, we could have developed a relational-data model to demonstrate the connection among various data sources. Yet, such a model would be limited for our research purpose, since due to the implicit nature of the communications and risk analysis, the resultant data are not in agreement with the data from our literature search. Therefore, we have chosen ontology engineering for our investigations.

2.1.4 Chapter Motivation

Our interest in studying this multi-disciplinary topic originates from closely studying three observations. (1) *Preventing disputes* is more effective than resolving disputes. (2) *Legal risk technology* in larger organisations is often based on manual processes, where smaller organisations are rarely able to handle them. (3) *Legal risk management* is based on the outcome of communications on legal agreements between at least two parties.

2.1.5 Research Question 1

It has become clear that the formulation of an *ontology* can be a fitting method that helps the systematic study of our challenge. Making explicit the communication and risk data in contract automation should be investigated. The considerations above lead us to the following RQ1.

> **RQ1:** *To what extent is it possible to develop an ontology to automate contracts with communications and risk data?*

In our research we face two obstacles. First, so far, the inclusion of communications and risk data in automation is absent in existing LegalTech solutions.

This is straightforwardly validated by key word search on the largest LegalTech solutions database in the world: LegalComplex. Second, we start with the design of an ontology (called the Onassis Ontology) for contract automation which shows that automation based on communications and risk data is possible and is even essential for iContracts. The ontology is qualitatively *validated* by the application of a Knowledge Graph (KG) (see Figure 2.2, in Subsection 2.4.2) on a case study for freelance agreement (for definition of KG see Definition 2.1 [Ehrlinger and Wöß, 2016]) [2].

*Definition 2.1 – **Knowledge Graph***

A **knowledge graph** acquires and integrates information into an ontology and applies a reasoner to derive new knowledge.

Our ontology emphasises how communications and risk data contribute to the development of an *effective* and *responsible* contract automation, which reduces the need for the physical involvement of legal experts. To avoid any confusion, the Onassis Ontology is only used as a larger technological solution for contract automation, whereas its formal descriptions will be used to drive the automation at a later point, since the ontology in itself does not directly automate anything.

2.1.6 Chapter Structure

To answer RQ1, we structured the Chapter as follows. In Section 2.2, the relevant literature is described. Section 2.3 presents how we conduct key word search in the database for LegalTech solutions and how we design the ontology within the context of the case study. Then, Section 2.4 presents the database findings and applies the KG on the case study. Section 2.5 discusses the database findings as well as the ontology design and its applications. Finally, Section 2.6 answers the RQ1 and provides three chapter conclusions and three suggestions for further research.

2.2 Relevant Literature

The literature Section is structured as follows. Subsection 2.2.1 introduces the literature on contract automation solutions. Then, Subsection 2.2.2 elaborates on contract communication and risk literature. Thereafter, Subsection 2.2.3 discusses the state-of-the-art literature on iContracts. For a good understanding,

[2]We should note here that ontologies are closely interconnected with KGs since ontologies represent the context (t-box as in tool box) while KGs are the tool used to utilize them (a-box as in algorithmic box).

Subsection 2.2.4 presents the relevant ontology literature on contract automation. Finally, in Subsection 2.2.5 we provide a table showing the state-of-the-art and associated main pitfalls. We *do not* discuss in detail physical, digital or smart contracts in the literature, because they are only indirectly related to our research scope.

2.2.1 Contract Automation

In most jurisdictions around the world, contracts are defined as follows (see Definition 2.2 [Smits, 2017]).

*Definition 2.2 – **Contract***

A **contract** is a legally binding agreement, verbal or written.

For an agreement to be binding, certain requirements must be met. Those requirements are usually laid out in the contract law of the relevant jurisdiction, which typically also ensures that conflicts can be resolved through the court system of that jurisdiction. In general, contracts are governed by private law and in each jurisdiction there are well-defined rules for contracting. Typically, those rules may be substantially divergent.

The two largest online databases on available contract automation solutions are:

1. Stanford University's *Legaltechlist*[3], and
2. Legalcomplex's *Legalpioneer*[4].

The *Legaltechlist* is a strictly curated database while the *Legalpioneer* database is a more extensive database. At the time this research was conducted (May 2023), Stanford's website has a total of 2,094 results and Legalpioneer's website has 9,608 business cases archived. In these databases, the number of available contract automation solutions that are related to this research will be identified after a global inspection of the content of both databases. They should be related to our topic: iContracts. We decided to focus on identifying companies in *Legalpioneer* due to the larger amount of available data. The data are expected to support the importance of our research scope.

We contacted the owner of Legalpioneer, and after some investigation on our goal, we were given access to the results of the proprietary analytics tools of Legalcomplex. The tools included advanced search and analytics on the Legalpioneer data for identifying and analysing data with a higher degree of accuracy[5]. The database, however, does not include state-of-the-art solutions

[3] `https://techindex.law.stanford.edu`
[4] `https://www.legalcomplex.com` and `https://www.legalpioneer.org/`
[5] `https://www.legalcomplex.org/`

that have not reached the market or are yet to reach the market soon. A general trend observed is that contract automation solutions gather significant attention in the LegalTech innovation. Our research aims to help establish and clarify the percentage of the total contract automation solutions within the available LegalTech solutions (in May 2023).

2.2.2 Contract Communication and Risks

Most of the available literature on contract communication is focussed on *contract negotiations*. The word *communication* points in our context (seen in larger extent) to the way how contracting parties *should* talk with each other, in order to (1) gain a negotiation advantage, (2) reach an agreement and/or (3) avoid the escalation of conflicts. Here we remark once more that in our research, the word *communication* refers to the substantive information (obtained from negotiations) that is directly relevant for the design of a contract. The general trend of AI in this context focusses on the role of *chatbots* in intelligent automation [Anagnoste et al., 2021].

So far, in the literature referenced and in other literature, communication data are not connected with risk data, whatever the context of contracting automation may be. Still, the contract communication literature is sufficiently advanced to assist the management involved of relevant communication data, even for new purposes such as managing *legal* risk. Our research will support the clarification of the partitioning into percentages of contract automation solutions. For a proper understanding we provide a brief history.

The first framework for the management of contractual risks emerged in 1950 with the introduction of *Preventive Law* by the lawyer and attorney Louis M. Brown [Brown and Rubin, 1950]. Brown believed that preventive law concerns the *cost difference* between entering into and avoiding legal costs. He thought that legal problems arise because of legal risks. At the end of the century, his student, Edward A. Dauer, started the development of a systematic analysis for the management of legal risks [Dauer, 1987]. In 2002, the academic Thomas D. Barton took an interest in continuing this line of research by advancing Dauer's analysis further with his own method [Barton, 2002, Barton, 2006].

Around the same time, in 1998, the lawyer and academic Helena Haapio introduced the concept of *Proactive Law* [Haapio and Varjonen, 1998]. Proactive law is a future-oriented approach to law and legal agreements, placing an emphasis on legal knowledge to be applied before things go awry[6]. The difference between preventive and proactive law is that the latter, apart from the preventive dimension, adds a new dimension, viz. the promotive dimension in terms

[6] http://www.juridicum.su.se/proactivelaw/

of good and desirable behaviour [Berger-Walliser, 2012]. Haapio is mostly concerned with the application of proactive law in contracts.

In 2010, she created a synergy between (1) *proactive law* (Haapio) and (2) and *law as a competitive advantage* (Siedel) [Siedel and Haapio, 2010]. As a consequence of this synergy, in 2013 they published the book *A Short Guide to Contract Risk* where they analyse contractual legal risks [Haapio and Siedel, 2013].

At around the same time in 2010, Haapio introduced the theory of legal design, which advances the theory of Preventive/Proactive Law (PPL) by translating all complex legal language into clear language expressions and visualisations, so that contracts can be understood by everyone before legal problems arise [Berger-Walliser et al., 2017].

The most recent research of PPL focusses on smart contracts [Corrales et al., 2019b]. The novelty from the use of smart contracts in LegalTech stems from the adoption of computer code instead of human language for managing contracts [Kozlova and Aleksandrina, 2020]. It is from this perspective that the school of legal visualisation under PPL is conducting research on smart contracts, so that the smart contract rules are *better understandable* and *accessible* for contractors [Corrales et al., 2019a, Barton et al., 2019]. Haapio often emphasises the importance of *design* for contracts, but this holds in particular for smart contracts [Hazard and Haapio, 2017].

In 2004, the academic Jon Iversen introduced *Legal Risk Management* [Iversen, 2004]. Then, in 2007, the academic Tobias Mahler discovered a difficulty in *defining legal risk* and *how diverse it is* [Mahler, 2007]. Following the introduction of a standard for compliance risk management by the International Organization for Standardization (ISO) in 2014 [Bleker and Hortensius, 2014], Mahler along with the academic Samson Esayas set out to systematically analyse and model compliance risk in 2015 [Esayas and Mahler, 2015]. Recently in 2020, ISO introduced the first Legal Risk Management (LRM) standard focussed exclusively on legal risk for organisations and defines *legal risk* as follows (see Definition 2.3 [ISO, 2020]).

Definition 2.3 – ***Legal Risk***

Legal risk is risk (effect of uncertainty on objectives) related to legal, regulatory and contractual matters, and from non—contractual rights and obligations.

By building upon the literature of PPL our research will show how it is possible to develop an ontology for analysing and visualising contract risk. For a full understanding we provide a clear outline in Chapter 3.

2.2.3 Intelligent Contracts

The step from smart contracts to iContracts can only be performed when one is able to manage and prove milestones. On a macro level, applying the iContract technology in a complex legal situation unfolding in, for example, an energy project would require higher sophistication. Such a higher sophistication is examined under the aegis of *iContracts* [McNamara and Sepasgozar, 2021].

The field of iContract (1) will introduce a hybrid contract automation approach and (2) will consider the need for contract automation that corresponds to the complexities of reality, aiming at the transition of automation into a *full self-executing automation*, with minimal human intervention or without it, if possible [Mason, 2017]. Motivated by the developments in Industry 4.0, this field is most evidently under construction [McNamara and Sepasgozar, 2018], the more so since a high level of complexity drives the need for such innovation [McNamara, 2020]. Despite the large academic call for the need of iContracts and the developing frameworks for its adoption [Pillai and Adavi, 2013], many acceptance challenges are evident in practice [McNamara and Sepasgozar, 2020] [7].

The iContracts literature is not sufficiently developed yet. That occurs for multiple reasons. One reason is that there is no widely adopted iContract solution in the market. Our research contributes towards this direction by showing the *design* of an iContract. Additional research limitations relate to end user adoption of iContracts. That is also caused (to a large degree) by the lack of available iContract solutions. One of our observations is that research on iContracts has decreased in the past two years. Potentially, it is because when the concept *iContracts* was initially highlighted, its development complexity was so large that it created confusion in research. Our investigations aim to clarify this confusion by offering to scientists an iContract ”playground” (the Onassis Ontology) to experiment with practically applicable iContracts.

[7] A key value of iContracts is that they can leverage information from various data sources, including smart Internet of Things (IoT) sensors, for automated monitoring of contract data [McNamara and Sepasgozar, 2020]. IoT sensors are essential for the monitoring of contract data in complex industrial structures and benefit iContracts with automated data collection. The IoT applications in iContracts can range from environmental monitoring for CO2 emissions tracking, to quality control of machinery and compliant inventory management. It should be noted here that iContracts can be implemented in both centralised and decentralised systems [Deng and Li, 2019]. The iContract developments prove that the monitoring and execution of contracts is more related with *project management*. However, the level of project management with respect to technological readiness is diverse. For example, in freelance agreements it is harder to monitor a contract with sensors and manual effort is needed. Yet, the complexity of the contract overall is smaller and the execution process can be more manageable. In relation to construction, the complexity of the contract is much larger, with multiple sub-contractors involved. Despite the existence of IoT sensors and the higher degree of automated monitoring, the execution of contracts will be more cumbersome.

2.2.4 Contract Automation Ontologies

So far many ontologies have been applied in legal contexts (for reference see below), but not for the specific context of contract automation via *communication* and *risk* data. For a better understanding of the available literature, we provide five references:

- for the structuring of legal norms and court decisions [Filtz, 2017]
- for posing legal questions related to legislative sources and answering them [Sovrano et al., 2020]
- for compliance purposes in complex multi-lingual, multi-jurisdictional environments [Schneider et al., 2022, Montiel-Ponsoda et al., 2018]
- for online case analysis [Yu et al., 2021]
- for case recommendations [Dhani et al., 2021]

In relation to contract automation in general, ontologies have been used:

- for conceptualising contracting terms and promoting interoperability regarding concepts [García and Gil, 2008]
- for data exchanges for blockchain-based smart contracts [Kruijff and Weigand, 2017]

The last two publications do so on an *infological* (interpretation and meaning of data) and *datalogical-level* (raw data astructuring and processing). The ontologies have also been used to support the automation of public procurement processes[8]. Moreover, the ontologies have been exploited more generally, albeit at a higher level of abstraction, for:

- blockchain-based smart contracts [Zhou et al., 2020]
- other research concerning contracts [Kaltenboeck et al., 2022], and
- contract risk management [Wu, 2021].

To date (2023), the closest research on our subject is that of Legislate [9], where they use an ontology for *drafting* and *negotiating* contracts as well as representing *rights* and *obligations*. This happens behind closed doors as their Knowledge Graphs (KGs) [10] are protected by a patent on semantic document generation [11].

[8] http://contsem.unizar.es/def/sector-publico/pproc.html
[9] https://legislate.ai
[10] https://www.legislate.tech/post/knowledge-graphs-know-more-about-your-contracts
[11] United States Patent 11087219

In addition to all ten applications mentioned above, our research applies ontologies from the perspective of *communication* and *risk* data automation. Here we admit that the potential of applying ontologies in the legal domain may even reach the level of developing industry-wide interoperability standards. Obviously, they are similar to the ones that occurred in the financial industry via the Financial Industry Business Ontology (FIBO) [12].

In essence, our ontology contributes towards *five* important directions in relation to literature. First, it applies ontology engineering on a practically relevant *legal risk management* level. Second, it shows how it is possible to *connect communications and risk data* via an ontology. Third, it provides a *technological tool* to organisations interested in adopting contract automation solutions. Fourth, the ontology shows how it is possible to *make explicit* the usually *implicit communications* and *risk data* within the context of contract automation. Fifth, it offers a new working process to legal experts interested in *scaling the delivery* of their services with a higher degree of *effectivity* and *responsibility*.

2.2.5 State-of-the-Art

To summarise the literature review in two concepts we defined the (1) state-of-the-art in contract automation and its (2) main pitfalls on four relevant levels related to our research: (a) communications data, (b) risk data, (c) communications and risk data, as well as (d) ontology engineering. Table 2.1 shows four relevant points for the state-of-the-art (middle column) and its associated main pitfalls (right column) related to our research.

Below we summarise the four concepts. First, *Chatbots* are the most advanced way to manage communications data, however they are not trusted significantly by end users (in Chapter 4 we discuss this issue in greater detail [Stathis et al., 2023c]). Second, the *Bow-Tie Method* is the best available method to manage risk data, although its process is time-consuming and not widely adopted (we also discuss this matter in detail in Chapter 3 [Stathis et al., 2023b]. Third, only an *implicit connection* between communications and risk data is available; currently it is based on human analysis. Fourth, *contract data* is today applied by specific ontology engineering, which, due to the lack of explicit inclusion of communications and risk data, is limited.

2.3 Research Methodology

The research methodology consists of five phases. First we start with an analysis of Legalcomplex data which is based on key word search (Subsection 2.3.1).

[12] https://edmcouncil.org/page/financialindustrybusinessontology

Table 2.1: State-of-the-Art & Main Pitfalls

	State-of-the-Art	**Main Pitfall**
Communications Data	Chatbot	Low trustworthiness
Risk Data	Bow-Tie Method	Time-consuming
Communications and Risk Data	Implicit connection	Requires human analysis
Ontology Engineering	Contract Data	Limited and restricted data

Then, the methodology employs the stage of *determining* the specific case study (Subsection 2.3.2). Moreover, ontology engineering itself is introduced (Subsection 2.3.3), as well as its *design* and *conceptualisation* (Subsection 2.3.4) to arrive at its *validation* (Subsection 2.3.5).

2.3.1 Key Word Search

The goal of Key Word Search is to investigate the landscape of contract automation and comprehend the significance available solutions have paid on contract automation based on communications and risk data. To gather data we requested Legalcomplex to conduct key word search, with the expectation of identifying the available solutions of contract automation today. Legalcomplex has classified contract automation solutions into the following five categories:

1. Contract negotiation
2. Contract risk management
3. Contract drafting
4. Contract extraction
5. Contract management

Since they have classified *communications automation* as *negotiation automation*, the conducted search follows the relevant classification. More specifically we may state that, according to Legalcomplex, contract negotiation consists of *seven* steps. According to the definition, they are collections of:

1. Names
2. Dates
3. Amounts
4. Clauses
5. Signatures
6. Entity and Structure
7. Ownership and Conflict

Legalcomplex conducted key word search on four concepts: (1) *contract automation*, (2) *contract negotiation*, (3) *contract risk* and combined (4) *contract negotiation and risk*. According to the owner of Legalcomplex, they used their algorithm to obtain the totals. The key word search was determined by the following specific questions that we provided to Legalcomplex.

1. What is the total number of legaltech solutions?
2. What is the total number of contract automation solutions?
3. What is the total number of contract negotiation solutions?
4. What is the total number of contract risk management solutions?
5. What is the total number of solutions of contract automation that combine contract negotiation and contract risk management?

The limitations of the key word search based on the legalcomplex database are threefold. First, our search depends on Legalcomplex's classification, which is not cross-validated (at least note scientifically) with alternative classifications. As a result, potential concepts may be subject to ambiguity, synonyms and more generally terminological variations. Secondly, since Legalcomplex is a proprietary database, there is inherent bias included in its classification and data availability. Such bias may be due to (a) limitations in the understanding of context based on lack or preference of knowledge, (b) intentional or unintentional exclusion or inclusion of concepts or data that may be relevant to serve implicit (e.g., interest in a specific domain over another) or explicit purposes (e.g., commercial exploitation of database and reputation concerns) of the website owner, and (c) lack of granular semantic relevance due to potential skill, experience or resource limitations. Third, the key word search is limited to the available data included in the Legalcomplex platform.

2.3.2 Case Study

The case study concerns a contract regarding the provision of freelance services. The main question is how to determine the relevant items to reduce the contextual complexity of contract communication and risk analysis in such a way that they remain a valuable entity for our scientific investigation. A *freelance* agreement includes in general sufficient complexity. Usually it is recorded in 3 to 10 pages, whereas direct investment agreements, for example, may include up to 1000 page contract recommendations.

To get a proper agreement, a Non-Disclosure Agreement (NDA) was downloaded from the open-source legal documentation database of Capital Waters[13]

[13] https://www.capitalwaters.nl

and adjusted to fit the needs of our case study. Thereafter, the focus was placed on applying the NDA agreement within the context of a freelancer agreement. There are various online contract templates that could help us in this case. They can be easily accessed online [14].

If the *automation* proves to be successful, gradually it can be applied to more complex types of contracts. Ideally, a Foreign Direct Investment (FDI) contract between an energy company and a government can also be automated in this way. Below we will explain why any freelancer contract is already complex for the current state-of-the-art technology.

2.3.3 Ontology Engineering

During a contract agreement a variety of explicit and implicit information is exchanged between stakeholders. *Explicit* information include contracting clauses, signatures and relevant documentation. *Implicit* information usually includes communication and risk analysis that begins before a contract is drafted. Our challenge is the question: how to make implicit information explicit?

To address this challenge, we perform a quick scan in the set of answers to the question: how can Data Science (DS) and AI help us? DS and AI present three available options related to (1) Machine Learning (ML), (2) Relational-Data Models (RDM) and (3) ontology engineering. The three options present different advantages and disadvantages to address our challenge.

First, let us consider a *Machine Learning* approach. When can an unsupervised ML algorithm be applied to any available contract data? The main obstacle is that such data are hard, so it might be impossible, to identify, find or obtain relevant data [Zeleznikow, 2023]. Second, a *Relational-Data Model* can be developed that handles various data sources and their connections. However, such a model may be limited for the application of AI [Paredaens et al., 2012, Walton, 2018]. Third, *ontology engineering* is an option. Ontologies show how it is possible to handle interconnected data sources with a great variety of data types, by creating semantic specifications (see further description in benefits Section below).

The concept of ontology engineering is taken for two reasons. (1) There is high conceptual complexity involved in making implicit data explicit. (2) We are facing multiple unknown information regarding the number and interconnected nature of data sources.

[14] See for example: `https://community.weagree.com/model-contracts/`.

Benefits and Limitations

Let us show how ontologies introduce benefits that are in particular helpful when dealing with our challenge, but also limitations that make our task harder.

Let us start with the benefits. Ontologies are able to support the structuring of data in a scientific manner [Duan et al., 2017]. The benefits of developing an ontology relate to *interoperability*, *standardisation*, *conceptualisation*, *inferential reasoning* and *information retrieval*.

For a proper characterisation we would like to emphasise the difference between an ontology and a relational database. The former can be seen to use "spoken-language" driven by a dictionary for communication while the latter uses "body-language" without a dictionary for communication. Moreover, an ontology is (1) extendable, (2) can support additional solutions and (3) may clarify limitations.

An ontology is able to serve as the backbone of an explainable *intelligent* platform where modern technologies are incorporated and tested [Sarker et al., 2020]. The core module of this platform will utilise modern models and techniques in the field of AI. In our research, the *value of the ontology* stems from its ability to support the implementation of communication and risk management in contract automation.

Now, let us also discuss some challenges. Ontology design can follow a relatively ambiguous and subjective process. Despite attempts to ground it with competency questions and concrete case studies, it may remain abstract. Moreover, an ontology may lack context sensitivity. That is especially the case for the legal domain, where a higher degree of linguistic sensitivity is required to deal with ambiguous legal language. Another aspect concerns limitations with reasoning and expressiveness capabilities, especially when concerned with legal reasoning that is complex in nature and in geopgraphic applications. Beyond such substantive challenges, an ontology may also present practical limitations in organising its deployment in a standardised manner, the time-consuming and costly development as well as difficulties with maintenance and updates.

2.3.4 Ontology Design and Conceptualisation

As mentioned above, ontology engineering is able to contribute in simplifying the complexity in automating communications and risk data during contracting. The ontology helps to:

1. *clarify* the relevant concepts involved in the automation,

2. *identify* relations among the concepts,

3. *inform* decision making by highlighting technological opportunities and risks,

4. *guide* the development of algorithms and collection of relevant data sources, and

5. *offer* a flexible and adjustable technological infrastructure to support contract automation.

To design an ontology, requirements need to be gathered. They are gathered based on the case study and a literature review. Taking into consideration the requirements, we arrived at the Onassis Ontology. It is visualised (1) in a simplified form in Figure 2.1 and (2) as a scientific "puzzle" in the Appendices (see Appendix 1C [15]) or in Github (with clear explanations), where all details are connected and visualised [16].

The ontology retraces the interactive process of *asking* ***questions*** and *giving* ***answers*** between a legal expert and a contractor (see Figure 2.1 right upper half) leading to the collection of relevant communication data. The data are processed by a legal expert who relates them to the relevant contract risks (see Figure 2.1 left upper side). The process that we aim to frame for automated methods (and that ultimately will lead to a formal contract) will result in an ontological conceptualisation (see Figure 2.1).

In the Onassis Ontology we see the starting points of the above-mentioned interactive process between the legal expert and the contractor. The legal expert writes a question for the contractor who has previously selected a specific scope for the contract (in Figure 2.1 the "U" sign denotes that a predicate connects with two or more objects). By replying to the question, the contractor provides an answer. The answer includes information that can be extracted to update (1) one or more *variables* of a paragraph (see Figure 2.1 right under half). Each (2) *paragraph* is part of (3) a *section*, whereas multiple sections form (4) a *contract* (see Figure 2.1, lower half). The variable, paragraph, and section follow a numerical order within the constituent parts of the contract. The paragraphs of a section (i.e., the section itself) are grouped under standardised topics and are regulated by legal rules.

The contract contains a number of agreements, which include not exclusively the offering, acceptance and the setting of expectations between the contractors (see Figure 2.1 red line in left half). An agreement here (see left upper

[15] https://github.com/onassisontology/onassisontology/blob/main/Appendices_PhD.pdf

[16] The Onassis Ontology is accessible at https://github.com/onassisontology/onassisontology and is protected by the open-source GNU General Public License https://www.gnu.org/licenses/gpl-3.0.html

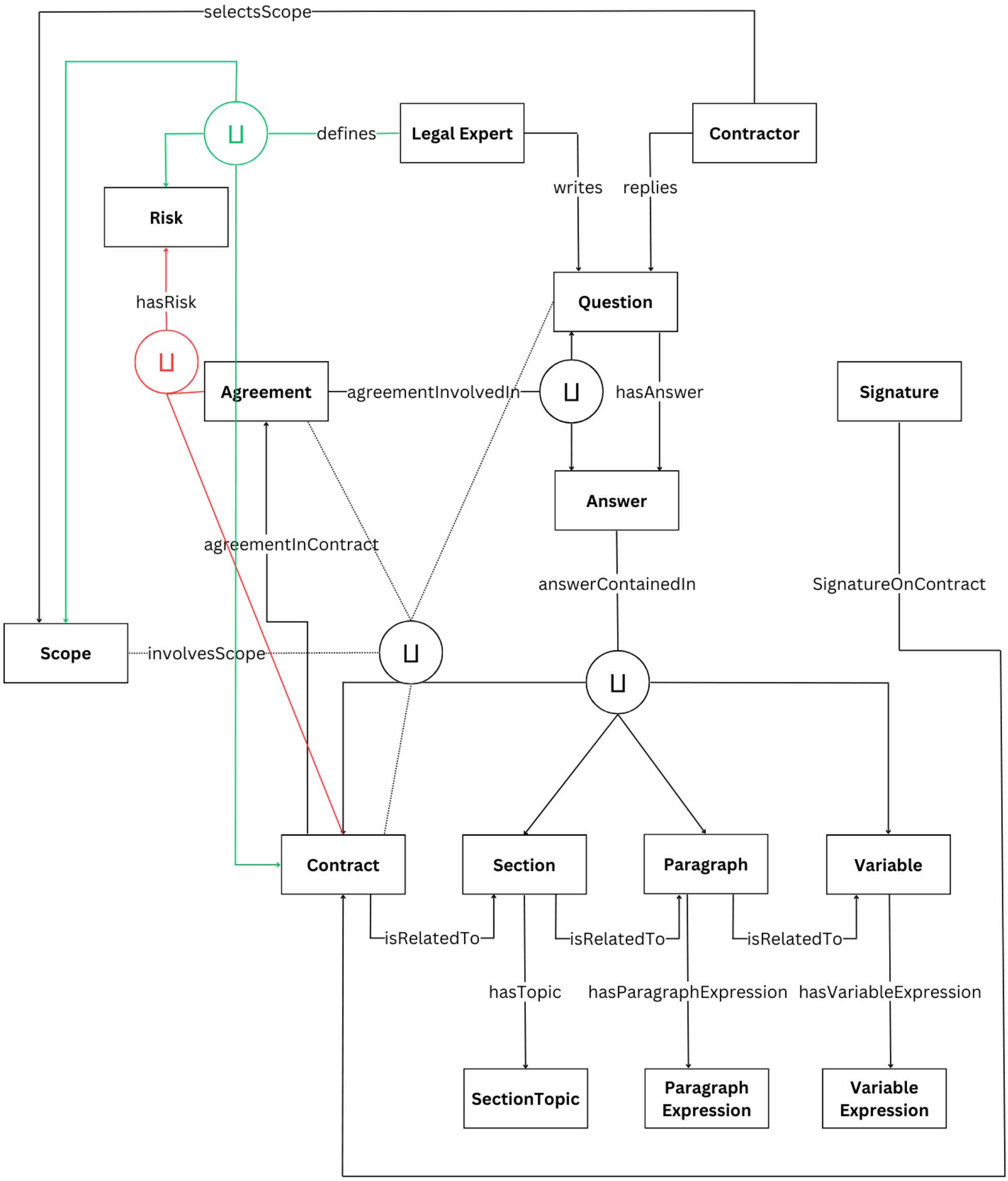

Figure 2.1: Onassis Ontology (Simplified)

half) is conceived as a consensus involving at least two different parties and regarding an answer and a question. Every time that a question is asked by a legal expert and an answer is provided by a contractor, an agreement takes place (follow the lines shown in Figure 2.1). The contract and agreement are always associated with a risk that is defined by the legal expert (see Figure 2.1 upper half). The risk, as well as all the additional constituent parts of the contract, can be reviewed by the contractor before signing the contract. The contractor is ultimately in charge to decide whether or not to enter into a legally binding agreement with another involved party (or parties).

The risk analysis is not provided in detail, because it is described in Chapter 3 and 4 [Stathis et al., 2023b, Stathis et al., 2023c]. In summary, the risk management extension, called the *Enriched Bow-Tie Method* [Stathis et al., 2023b] (not discussed here), helps a legal expert *analyse* and *visualise* contract risk.

2.3.5 Ontology Validation

The logical consistency of the ontology has been tested by launching the specialised reasoner Hermit 1.4.3.456 on sample data in the Protégé editor (for references and details see [17]). The use case employed is presented in the results.

In Chapter 5 we will show that the ontology is not only *validated* with the Knowledge Graph, but that it can also be *re-programmed* via a prototypical web application [Stathis et al., 2023a].

In particular, we will detail how the web application supports contractors and legal experts in (a) negotiating, (b) analysing risk and (c) preventing hazardous events, and finally in (d) drafting a contract according to the Onassis Ontology [Stathis et al., 2023a]. The Onassis Ontology (a *model / terminology*) is instantiated by a contract (*data / assertions*) [18]. The source code for the prototype web application is accessible via Github [19], including a user guide, screenshots of typical usage, operational and Docker hosting instructions to ensure replicability, and instantiated Onassis Ontology contract data created by application users.

[17] `https://mvnrepository.com/artifact/net.sourceforge.owlapi/org.semanticweb.hermit/1.4.3.456`

[18] An example of an Onassis Ontology-based contract data file created by contractors and legal experts is available on Github: `https://github.com/onassisontology/icontracts-back-end/blob/main/example_iContract_ontology_data.ttl`

[19] see `https://github.com/onassisontology/icontracts-back-end` and `https://github.com/onassisontology/icontracts-front-end`

2.4 Research Results

The results of our research are modest. The first result is an indication of its potential: *the percentage* of available contract automation *solutions* related to the scope of this research based on the Legalcomplex data (see Subsection 2.4.1). The second result is a confirmation that the KG works as a *validation mechanism* for the ontology (see Subsection 2.4.2).

2.4.1 Contract Automation Solutions

After the key word search in Legalcomplex the following four classes of solutions were traceable, viz. for (1) contract automation, for (2) contract automation based on communications data, for (3) contract automation based on risk data and for (4) contract automation based on communications and risk data. Below we specify them in numbers and percentages:

1. out of the total of 10,448 LegalTech solutions, 590 solutions (5.6 percent) focus on *contract automation*;

2. out of the contract automation solutions, 51 (8.6 percent) focus on *contract communications*;

3. out of the contract automation solutions, 50 (8.4 percent) focus on *contract risk*;

4. surprisingly (both for the researchers and owner of Legalcomplex) there was *no* solution focussing on both *contract communications and contract risk*.

Result (4) (no combination of communication and risk) was surprising for us (and possibly for the reader). The results indicate that despite the abundance of contract automation solutions, there is a significant omission for solutions which are focussed on communications *and* risk data analysis. It is an omission on both sides. It is now on our attention list.

Legalcomplex provided us also with the top ten solution results for each category of key word search. The top ten solutions result shows the ten most financially wealthy companies under each category. In order to understand the focus of each of the top solutions for each of the three categories with solutions, namely (1) contract automation, (2) contract communications and (3) contract risk, we now develop a new Table 2.2 below. The table is split into six columns, which are structured as follows.

Column 1. Contract automation solutions
Column 2. Contract automation solution applications
Column 3. Contract communications solutions

Column 4. Contract communications solution applications
Column 5. Contract risk solutions
Column 6. Contract risk solution applications

Table 2.2 shows that in contract automation industrial cloud is prevalent and that the space is diverse with applications in multiple areas from contract and project management to document and customer management. As for contract communications, again cloud is dominating although 4 solutions are focussing on contract management, showing the significance of communications for contract management. Then, as for contract risk, Third-Party Management is the primary application and a trend is observed to apply risk management in the financial and insurance domains with five solutions focussing on that direction.

2.4.2 Knowledge Graph

As mentioned in Section 2.2.4, the KG plays the role of validating the ontology design and visualisation by leveraging practical case studies and connecting data deriving from them with the designed ontology concepts. If the connection suffices to represent all relevant data in a case study, we may conclude that our ontology is well designed and conceptualised.

To validate the *coherency* of the ontology with the domain knowledge, we did run competency questions on the instance data that we structured via the vocabulary terms of the Onassis Ontology. The validation process displays the level of *expressiveness* of the vocabulary. For instance, the Onassis Ontology fully supports the use case scenario in Figure 2.2, which shows the KG. The scientific version of the KG visualisation is to be seen in the Appendices (see Appendix 1J [20]) or via the Github page (see the link in the footnote [21]).

Following the development of the Onassis Ontology based on the case study and the literature, we may conclude that the KG design (given in Figure 2.2 in a simplified format and on Github as a scientific "puzzle" [22]) indeed convincingly shows that the development of a KG is *possible*. The validation proof is by stepwise verifying that it is possible to add selected data points derived from any new case study to the ontology.

We explain Figure 2.2 [23] by a straightforward use-case scenario introducing two human beings, viz. Laura (a legal expert) and Atanasio (a contractor)

[20] https://github.com/onassisontology/onassisontology/blob/main/Appendices_PhD.pdf
[21] https://github.com/onassisontology/onassisontology
[22] https://github.com/onassisontology/onassisontology
[23] In the figure, individuals are represented as rectangles. Their associated datatype values are highlighted in blue. Relationships are represented as arrows. The KG follows the logic described in Figure 2.1, starting with the abstract level and following with the physical level. That is to say, once the legal expert has selected a scope and defined the risks and questions for an agreement,

Table 2.2: LegalTech Solutions Application Domains

Top	Automation	*Application*	Communications	*Application*	Risk	*Application*
1	Infor	Industry Cloud	Vlocity (Salesforce)	Cloud and Mobile Software	Aravo Solutions	Third-Party Management
2	DocuSign	eSignature	Pactum	Negotiations	Epoq	Legal Documents
3	Icertis	Contract Management	Robin AI	Contract Management	Powerlytics	Predictive Analytics
4	Seismic	Customer Management	Spendflo	SaaS Buying Optimisation	Intellinetics	Document Management
5	Workfront (Adobe)	Project Management	Trim	Bill Negotiations	Hypernative	Web3 Asset Protection
6	Snapdocs	eClosing	ParelyPro	Contract Management	Nayms	Insurance Marketplace
7	Ontra	Legal Operating System	Common Paper	Contract Management	Sparrow	Digital Asset Solutions
8	Coda	Document Management	Along	Customer Management	Insurdata	Geocoding Data Management
9	Onit	Legal Workflow	Contraktor	Contract Management	DocLogix	Document Management
10	AirSlate	Document Workflow	Valla	Workers Platform	Finch	Personal Finance

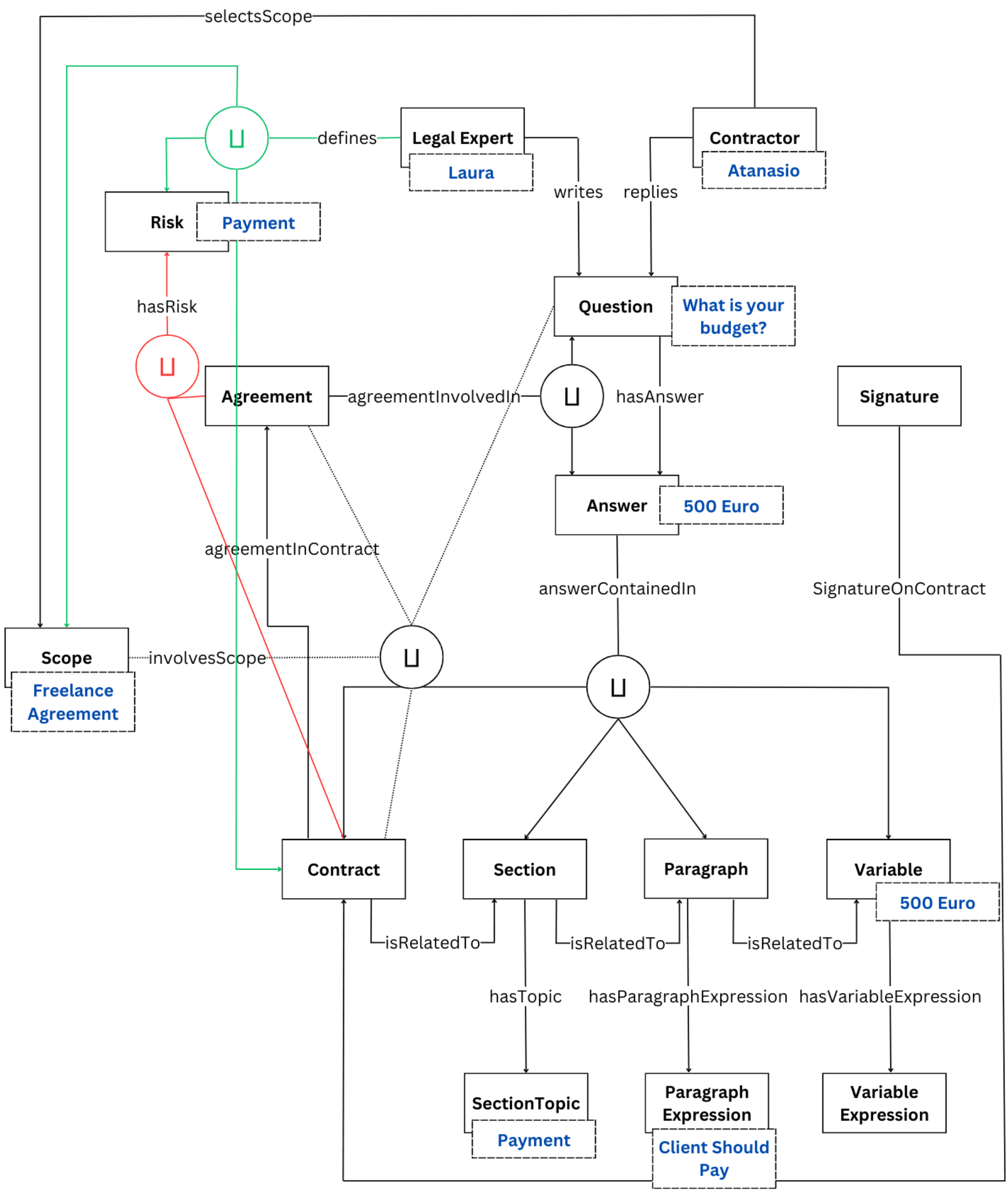

Figure 2.2: Onassis Ontology Knowledge Graph (Simplified)

the contractor is able to select a scope, answer the questions and the contents of the contract are updated as a result.

(all case-study data are visualised in blue in Figure 2.2). The use case scenario shows how the contractors provide answers to legal questions, out of which relevant variables are extracted to update a contract. Understanding the KG relies on the prior understanding of the Onassis Ontology, given that the KG follows the Ontology to model a specific use case to examine its validity.

In the use-case scenario, Laura, who is seen as a legal expert, defines both the *scope* of the agreement to be a freelance design agreement and the *risk* (which in this case is a payment risk). Successively, she writes the question *what is the budget?* and waits for an answer. Atanasio, as a contractor, selects the scope of the agreement and takes a freelance design agreement. The answer provided by Atanasio updates the *variable* uniquely identified by a *number*, *paragraph*, *section* and *contract*. The *variable*, *paragraph* and *section* have an order number in their related parts. The question asked by Laura and the answer provided by Atanasio are involved in the agreement, which can have a maximum of one question and one answer. In fact, for every question asked and answer given, a uniquely identified agreement is created.

Multiple agreements can be part of a same uniquely identified contract. Once Atanasio has completed the review of the legal document he can sign it by adding his signature on the contract. This action will legally bind the parties involved in the various agreements connected to the same scope within a sole contract.

The use case scenario shows that our ontology structure is sufficient for the requirements of a freelance agreement. That is because, once a contract has been structured into sections and paragraphs the relevant variables can be identified that inform a Legal Expert as for the specific legal questions to be asked. We do mention freelance agreement specifically, given the relative simplicity of a freelance agreement compared to more complex agreements (i.e., FDI), of which the validation requires further experimentation. To further validate the sufficiency of the ontology structure, we introduce ten more use case scenarios in Table 2.3 [24].

Beyond these additional use case scenarios, additional experimentation is required, most importantly also in practice. The goal would be the discovery of outliers and potential non-integers as inputs to variables. At this point we find the ontology to be acceptable for this innovation stage, yet more experimentation is required.

[24] For efficiency purposes the variable is shown as the answer, even though in certain cases the variable is not necessarily the whole answer. Moreover, the Scope, Section and Parties remain the same

Table 2.3: Onassis Ontology Knowledge Graph Validation

Category	Question	Answer/Variable	Risk	Rule
Insurance	What is the number of your professional liability insurance?	12345	Insurance coverage	Freelancer must possess professional liability insurance
Payment Terms	What is your preferred payment method?	Final Delivery Payment	Delayed payments	Client should comply with the payment schedule
Confidentiality	How many years should confidential protection last	5	Information leak	Freelancer should maintain all information confidential
Intellectual Property	What type of intellectual property protection do you prefer	Full IP Protection	IP Ownership	Client reserves all IP rights
Scope Changes	What is your preferred way to be informed about potential scope changes	In writing	Delayed changes	Potential scope changes should be communicated explicitly
Delivery	What is the deadline for the delivery of your work in full?	22/5/2023	Project completion	Professional should deliver the necessary work by the stipulated deadline
Communication	What is your preferred communication channel?	Whatsapp	Lack of sufficient communication	The project communication should occur via the specified channels
Dispute Resolution	What jurisdiction should regulate the resolution of a potential dispute	Dutch Law	Dispute	All disputes should be resolved in accordance with the specified law
Termination	How should the parties communicate about the potential termination of the project	In writing	Project Termination	A project should be terminated in accordance with the specified procedure
Acceptance Criteria	What type of client rating is necessary to stipulate an acceptable deliverable	7 in scale from 1 to 10	Quality Control	A client should rate each deliverable from a scale of 1 to 10

2.5 Discussion

The discussion concentrates on analysing six issues. They are the following:

1. database findings (in 2.5.1)
2. ontology engineering implications (in 2.5.2)
3. AI applications (in 2.5.3)
4. contract automation implications (in 2.5.4)
5. insurance implications (in 2.5.5)
6. contract risk standardisation (in 2.5.6), and
7. research benefits (in 2.5.7)

2.5.1 Database Findings

The key word search results show that contract automation is a significant category of LegalTech solutions. Moreover, they show communications and risk data automations are each on its own important categories of contract automation solutions. Yet, the combined contract automation based on communication and risk data is so far not discussed in the literature. Without their connection we miss the opportunity to improve risk analysis based on quality communications data.

The data that 5.6 percent of the total LegalTech solutions focus on contract automation prove that the innovation in intelligent contracting is substantial. Yet, the data that zero percent of those contract automation solutions focus on the automation of communication *and* risk data, prove how far we still are from adopting mature intelligent contracting solutions.

A general comment on the inspected data is that most of the technologies investigated how to address the *legal experts* as users and *not the contractors* as users. This means that most technology innovation in LegalTech focusses on the legal experts as the end users of legal innovation. One explanation is that LegalTech often requires legal knowledge and expertise, which is to be found with the legal experts and not with the contractors. When regarding the contract communication automation solutions we have to admit that none of the them generates the contracts as an output automatically. As for the contract risk automation solutions, even though legal risk is part of every contracting process, such solutions are not widely available. Most risk-related solutions identified relate to compliance automation.

2.5.2 Ontology Engineering Implications

Looking back at the pricing example of our research introduction, the ontology can help contractors specify an optimum pricing in balance with a normative specification of the qualitative expectation for both parties. As we presented, this can be done by finding a middle ground between two sets of answers that the contractors have provided. On top of that, it is possible to incorporate additionally more data from other contractors and yield an average that represents the optimum expectations for both parties in the agreement. In this way, the risk between two parties for a dispute is minimised, as well as the potential consequential costs for both of them.

In summary, in this section we show the *value of the ontology* as a practical tool (A), the *conceptualisation of the semantics* (B), the *two levels of innovation* (C), the *relevance* of ontology engineering (D) and the *final validation* (E).

A: Ontology as a Practical Tool

We introduce an ontology to legal research, which represents how a legal expert is enabled by technology to handle contracts. Such a careful handling has not taken place so far, at least not according to the literature on the ontological representation level. Given that legal studies and practice involve the use of language as input and output, it is uncommon for the current research to treat legal reasoning procedures in a computationally friendly manner. In that respect, the ontology engineering is a new approach as it provides a *practical tool* for the legal world rather than providing just another theory. By practical tool we refer to a tool that can be used for the automation of a process that would otherwise require repetitive human labour. Such automation is innovative because it addresses two basic repetitive labour domains for legal experts today, namely the communications and risk data management, which today are often managed implicitly.

Furthermore, the ontology adds value for both smart contracts and iContracts, as it shows the extent to which certain processes can be programmed and those which cannot. It also helps clarify how far away we are from achieving the self-execution aim of iContracts. With the rise of LegalTech, the production of appropriate tools in academic research is becoming more common. Our research further illustrates the need for such practical tools.

B: Conceptualisation of Semantics

An innovative aspect of our ontology is that it has conceptualised a new domain, which benefits the world of ontology at a vocabulary level. In extension, this innovation is relevant for semantics, as it clarifies how the semantics of contract automation work at this level of conceptualisation. The ontology has been designed to minimise the appearance of unnecessary concepts. It represents—according to the workflow, the ontology, and the case study application—all relevant concepts and their properties for the generation of a contract based on *contract communication* and *risk data*. The Ontology shows how it is conceptually possible to generate a contract that includes risk management controls based on specific communication-based information extracted.

The end-value of the ontology should be examined by an experimental view on future research, in particular from two perspectives. The first perspective needs to ensure that the activities *involving the legal expert* are designed in a trustworthy manner, meaning that the legal rules and risks involved in a contract are taken into consideration in a responsible manner. The second perspective needs to ensure that the activities *involving the contractors* are designed in a trustworthy manner. Only then it is possible to validate the design of the ontology and justify its application in real-life experimental use cases. Chapters 3, 4 and 5 validate the two perspectives to a certain extent [Stathis et al., 2023c, Stathis et al., 2023b, Stathis et al., 2023a]. A future research direction is to test the efficiency of the ontology against further use cases, which entails its expansion. Towards such future research path, we will be able to create a richer taxonomy (by richer we refer to an ontology with larger amount of concepts and relations to comply with the requirements of more complex case studies) with external ontologies after testing the present ontology with other use cases.

C: Two Levels of Innovation

By making the ontology publicly available we achieve *two* levels of innovation. First, we stay connected with state-of-the-art developments since *feedback* based on iterations *increases*, as opposed to if this ontology would stay behind closed doors. Second, the selection of the *open-source model* makes the ontology more *accessible* to the public, contributing towards the acceleration of social innovation.

D: The Relevance of Ontology Engineering

The present research is relevant for four reasons. First, the Onassis Ontology provides a framework for managing risks in contract automation in a *trustworthy manner* as well as *preventing disputes*. Second, it paves the way for showing how it is possible to standardise contract drafting languages for contracting to become more interoperable. Third, it maximises the value contractors extract from contract automation via the application of AI in a more trustworthy manner than the available technologies, due to making explicit an analysis process which is usually implicit. Fourth, we show the added value of ontology engineering against the direct application of an unsupervised ML or the development of a relational database in a research domain with implicit data.

E: The Validation

Our results validate that Onassis Ontology fits for plain cases and clauses. The larger the complexity of a case, the larger the amount of clause data that should be processed. With the validation of the ontology we show its potential value and how it can influence contract automation significantly (see also Chapter 5 [Stathis et al., 2023a]). Legal experts may no longer be involved physically in contracting processes between two or more parties; their interaction may only occur by using a computer. The contractors are able to: (1) obtain a contract more rapidly and (2) trust its content, without having to enter into extensive discussions in the contract formation phase. It is apparent that the Onassis Ontology significantly simplifies the contracting process. Moreover, due to structuring the ontology based on scientific reasoning and the collection of data, advanced analytics can be applied to extract nuanced information in the contracting process, which eventually prove invaluable for preventing disputes resulting from contracts or meta-data [Ha et al., 2021].

2.5.3 Artificial Intelligence Applications

The value of the ontology for AI is that it *reduces complexity* and *helps clarify* how advanced ML algorithms can be applied. Moreover, it helps to make the algorithmic results *explainable* and *interpretable* [de Sousa Ribeiro and Leite, 2021] [25]. Still, in some cases involving data, such as risk data, an almost unavoidable bias is present and should be addressed. A first remedy might be, that before applying any algorithm potential biases should be addressed.

At this point, we mention three relevant AI applications that can be implemented with the ontology engineering technique to achieve a higher degree of automation. The reason why we refer to such AI Applications at this point and to such degree is to provide some initial guidance to follow up research as for the potential ways AI algorithms can be leveraged within the Onassis Ontology. Of course, further investigation is necessary to validate the implementation of these and additional AI applications on the Ontology.

A) *Text extraction* can be used to automatically extract the *answers* of the contracts from the questions.

B) *Data extraction* can also be used to automatically extract *risks* for a specific contract.

C) *Text generation* can be used to draft a *contract based on extracted risk data*.

[25] https://www.marktechpost.com/2023/03/11/understanding-explainable-ai-and-interpretable-ai/

Based upon these three risk-diminishing practices, we can see how ML algorithms can also be applied for classification or prediction. For example, we can *classify data for communication purposes* or how we can *predict the risk of a contract*.

As a result of AI applications, certain analytic benefits may arise as well. In general, an ontology can be used to analyse qualitative theory quantitatively. Moreover, following the same pricing example, we can quantify what is more precise or faster: (a) the traditional contracting process, (b) the programmed smart contract process, or (c) the hybrid intelligent contract process?

Also, nuanced data analytics can provide insights that can be used in order to quickly prove which party is at fault in case of a payment dispute regarding quality. Likewise, we can make better decisions on *when* and *how* to use an ML algorithm for classification or prediction purposes.

In addition, there are also benefits at the level of logical reasoning. We can define a set of rules for recurring entities, so as to (1) examine which classes are the best candidates for co-dependency influencing such relations and (2) apply advanced reasoning to uncover hidden data or further relations. The value of this inferential reasoning is that it can support automated reasoning for automated dispute resolution.

In relation to the field of AI and Law, the research sheds light into a practical application of AI in the rather complex field of legal data. Already, the field of AI and Law has a vast tradition especially in relation to such AI functionalities as text extraction, data extraction and text generation. Our approach shows how to improve the application of AI in legal domain in a more targeted way, especially for the purposes of contract automation based on communication and risk data.

2.5.4 Contract Automation Applications

In the same way that smart contracts began with cryptocurrencies and are now applied in more use cases, iContracts should gradually expand into more directions as well. In the present research, we have made a first attempt in showing how iContracts may apply in a freelance project. Moreover, we expect that further scientific examination of the iContracts concept should help specify their general value for LegalTech, as well as for AI. A valuable addition that iContracts bring in contract automation is that they point in the direction of *monitoring during the contract execution stage*. In fact, it is vital that for a higher degree of automation to be achieved, project data should be connected with iContracts. By expanding the scope of contract automation during the execution phase, the management of risks will also improve. For example, in energy or financial industries, advanced risk frameworks are already applied and there is a higher degree of effectiveness in risk management relative to what can be controlled.

By connecting iContracts with realistic project execution, this higher effectiveness in contract execution can also be achieved. Here PPL, and in particular legal visualisation, can overcome the lack of sufficient frameworks. Adding on that, the ontology can help by standardising data classes while a more harmonised approach can be taken for the classification and collection of such data. To that end, more research in the field of how iContracts can benefit from IoT devices, as well as how they connect more generally with project management, would be useful [26].

2.5.5 Insurance Applications

One of the main benefits for iContracts automation for complex projects relates to insurance premiums. In general, by having better risk predictions, insurance can be provided with *more accuracy* and the premiums calculated *more realistically*. This has a direct effect on the operational expenses of organisations. It also has an effect on the policy choices they make (e.g., by being able to better measure contract risk for achieving policy-making). Indeed, in such projects where there are often complex contractor and sub-contractor relationships, the main contract ends up bearing the major risks; by improving iContracts from the perspective of risk management, there are added benefits for the main contractors.

Insurance premiums are usually flexible in larger projects. In smaller projects they are calculated on the basis of general market standards. By calculating in greater detail the specific level of risk for each agreement, the opportunity rises to assign a tailored insurance premium for smaller projects. For instance, if an accident occurs (also known as ”occurrence” in insurance) a claim is initiated. With iContracts it is possible (1) to locate the case of the occurrence faster and with a higher accuracy and (2) to determine the decision on a claim with a higher degree of validity.

2.5.6 Contract Risk Standardisation

Last but not least, risk frameworks are *not standardised in legal practice* as they are, for example, in the energy or finance sectors. That is potentially because the underlying legal practice is (already) sufficiently complex. iContracts can help as they can create the space for *responsible* risk management based on validated frameworks by abstracting and reducing repetitive workloads. Currently the proactiveness of contracts is not measured, so iContracts can also help with risk *quantification*. Chapter 3 [Stathis et al., 2023b] shows with the support of relevant literature how to move towards this direction.

[26] In relation to privacy and data security please refer to Chapter 9.

Our findings bring forward new research possibilities for technology-based dispute prevention by showing how it is possible to advance current legal risk management practices with legal risk technology. Risk standardisation is only one piece of a larger puzzle towards more effective risk management practices that can lead to the successful prevention of disputes, which includes compliance practices, a culture of legal risk management and the intelligent use of legal risk technologies.

2.5.7 Research Benefits

Designing an ontology to automate contracts based on communications and risk data is beneficial for (1) *technological*, (2) *trustworthiness*, and (3) *economic* reasons. First and foremost, the technology will increase the effectivity and scalability of contracting relative to state-of-the-art solutions; so that more contracts can be executed at a fraction of the time. Second, the focus on risk analysis helps increase stakeholder trustworthiness provided that legal risk is managed explicitly, leading to higher awareness and control over legal consequences to contractors as well as reducing the potential (human) mistakes by legal experts. Third, it is economically sensible given that more contracts can be executed at a fraction of the price, since less resources will be necessary for contracting on a procedural and human capital levels.

2.6 Chapter Conclusion

The Subsections below provide the answer to the RQ1 (in Subsection 2.6.1) and give further three research suggestions (in Subsection 2.6.2).

2.6.1 Answer to RQ1

The Chapter progresses the state-of-the-art in ontology engineering for the legal domain by providing an approach for contract automation based on communications and risk data. The RQ1 addressed in this research is:

> **RQ1:** *To what extent is it possible to develop an ontology to automate contracts with communications and risk data?*

The answer to the RQ1 is that defining an ontology to *automate* contracts based on communications and risk data to a level comparable with the best experts in the world *will be possible for adequate automation* as shown with the Onassis Ontology. To make the statement *adequate automation* better understandable, the three are actions are essential

1. to test extensively its validity,

2. to conduct further research to ensure that an adequate level of *trustworthiness* will be reached for any action the legal expert and contractors will be involved in, and

3. to keep a sharp eye on future developments that may have unexpected challenges with the automatically driven programs.

The three actions should happen beyond any research we have already conducted. The finding that *none* of contract automation solutions in the Legalcomplex database simultaneously focusses on both automating contract communications *and* risk data demonstrate a significant omission in the existing solutions. This omission justifies our scientific attention to the subject. The aims for the current research were (1) to bridge the gap between smart contracts and iContracts and (2) to clarify our stance. All in all, we may conclude that automating a contract based on communications and risk processes, which have long been neglected, can prove to be the *missing link* in realising both self-executing contracts and iContracts.

Our research on the market adoption of iContracts with the utilisation of communication and risk data is *in its early stages*. Still, our experiment with the Onassis Ontology as well as our parallel research on EBTO and the prototype of our ontology shows that there is sufficient potential to optimize the contracting process.

2.6.2 Three Research Suggestions

The key question at this point is: how to best move forward from here? Based on the aforementioned discussion, the *communications and risk processes* need to be examined more deeply. Therefore, our follow-up research will focus (1) on the legal expert-based inputs and outputs, (2) on the contractor-based inputs and outputs and (3) on the experimental validity of the KG in more complex case studies. Through this in-depth examination and validation, our ontology can be improved upon and expanded.

A step in conducting further research is aiming to understand the correlation of the ontology classes. By selecting certain correlated classes, we may conduct specific quantitative or qualitative experiments to further our research (see for example ontology research on class correlation: [Hammar, 2014]).

To conclude, this Chapter began by giving you a *promise* but by the end of it, we hope to have provided a *real gift*: a systematic way to study contract automation and to achieve the goal of iContracts.

CRediT Author Statement

Below I would like to give credit to all persons involved.

Stathis, G., Trantas, A., Biagioni, G., de Graaf, K. A., Adriaanse, J. A. A., and van den Herik, H. J. (2024). Designing an Intelligent Contract with Communications and Risk Data. *Springer Nature Computer Science (SNCS): Recent Trends on Agents and Artificial Intelligence*, 5(709). https://doi.org/10.1007/s42979-024-03021-x

Stathis, G.: Conceptualization, Methodology, Writing - Original Draft, Investigation, Visualization, Project Administration, Funding Acquisition, Writing - Review & Editing; **Trantas, A.**: Investigation, Writing - Original Draft, Writing - Review & Editing; **Biagioni, G.**: Validation, Formal Analysis, Investigation, Data Curation, Visualization, Writing - Original Draft, Writing - Review & Editing; **de Graaf, K.A.**: Software, Data Curation, Writing - Original Draft; **Adriaanse, J.A.A.**: Supervision; **van den Herik, H.J.**: Writing - Review & Editing, Supervision.

Stathis, G., Trantas, A., Biagioni, G., van den Herik, H. J., Custers, B., Daniele, L., and Katsigiannis, T. (2023d). Towards a Foundation for Intelligent Contracts. *In the Proceedings of the 15th International Conference on Agents and Artificial Intelligence (ICAART)*, 2:87–98

Stathis, G.: Conceptualization, Methodology, Writing - Original Draft, Investigation, Visualization, Project Administration, Funding Acquisition, Writing - Review & Editing; **Trantas, A.**: Investigation, Writing - Original Draft, Writing - Review & Editing; **Biagioni, G.**: Validation, Formal Analysis, Investigation, Data Curation, Visualization, Writing - Original Draft, Writing - Review & Editing; **van den Herik, H.J.**: Writing - Review & Editing, Supervision; **Custers, B.**: Writing - Review & Editing, Supervision; **Daniele, L.**: Resources, Writing - Review & Editing; **Katsigiannis, T.**: Writing - Review & Editing.

Chapter 3

Contract Risk Management

The Chapter addresses RQ2, which reads:

> **RQ2:** *To what extent is it possible to translate the Bow-Tie Method into a visualisation of an ontology for contract risk management without altering the bow-tie structure?*

Standing at the start of our research we propose a new *visual analysis method* of hazardous events to be used in contract risk management. Our aim is to create an extension of the Onassis Ontology to *manage*, *analyse* and *visualise* risk data. The extension of the Onassis Ontology will be used for the development of *trustworthy* iContracts. The idea is that the implemented extension allows for the creation of *explicit* data out of *implicit* contractual information and legal processes. The creation happens by performing cross-referencing analyses with other collections of data. The ontological model that results from our study will additionally help to disambiguate the information stored in the Bow-Tie Method structure. To achieve this, we use the following methodology. (1) We visualise the Bow-Tie Method in an ontology. (2) We investigate the presence of taxonomic ambiguities or even errors in its structure. (3) The results present an enriched version of bow-tie conceptualisation of information, in which entities and relationships are translated into openly-accessible and *ready-to-use* ontological terms, whereas risk analysis becomes visible.

The current chapter corresponds to the following publication:

Stathis, G., Biagioni, G., Trantas, A., van den Herik, H. J., and Custers, B. (2023b). A Visual Analysis of Hazardous Events in Contract Risk Management. *In the Proceedings of 12th International Conference on Data Science, Technology and Applications (DATA)*, 1:227–234

3.1 iContracts and Risk Data

iContracts aim to support end users with drafting legal documents via the adoption of automation techniques [Mason, 2017]. Thus far, *iContracts* have not been designed to include the *editing* and *visualisation* of risk data [Stathis et al., 2023d]. Yet, risk data, which are defined below (see Definition 3.1 [1]), play a fundamental role in contract risk management.

*Definition 3.1 – **Risk Data***

Risk Data denotes a defined set of information (data), in any format (but increasingly in digital form), that is used by an organisation for diverse Risk Management and other business processes.

The main challenges with Risk Data in iContracts is: *how do we structure the risk data and how do we get a grip over them?*

Nowadays, legal experts act as legal risk managers who examine legal risk data in order to safeguard the interests and rights of the parties that are involved in a given agreement. Cross-investigation between different sources (such as databases) may help users quickly identify the risks associated with the (legal) documents that they are drafting [Haapio and Siedel, 2013]. In analytical processes, both visualisation methods and ontologies (i.e., formal representations of knowledge) can be truly beneficial to carry out a conjoint analysis of diverse data sets [Hogan, 2020] and [Dudáš et al., 2018]. They can be used for at least three problem areas: (1) to *reach a deeper understanding* of the risks involved in a certain arrangement, (2) to *design an efficient strategy* to visualise the manifestation of a potential hazardous event, and (3) to *develop remedies* and repair mechanisms prohibiting disastrous events.

Although these three methods may lead towards remarkable analytical results, their potential is at this moment still to be completely unlocked for two reasons. First, there is no unambiguous visual structure that is unanimously used to observe and analyse the core entities of the risk management framework and their relationships [de Ruijter and Guldenmund, 2016]. Second, there is no ready-to-use and openly accessible ontology that has been developed to disambiguate any given reference system [Agrawal, 2016].

Therefore, to offer a contribution to the resolution of the problem areas mentioned in (1), (2), and (3), our research will focus on the creation of an *ontological model* to analyse, visualise, and manage risk data in *iContracts*. In so doing, it will particularly examine and discuss the limitations of the bow-tie visualisation medium to manage and visualise risk data.

[1] https://www.openriskmanual.org/wiki/Risk_Data

3.1.1 Bow-Tie Diagram

In 1979, a diagram to analyse hazards was first presented at the Imperial Chemistry Industry course of the University of Queensland in Australia [2]. The shape of the figure used at the presentation took the form of a bow tie, from which it consequently took the name. Today, the bow-tie diagram [3] is de facto standard used to perform visual legal risk management analysis (see Figure 3.1 which will be discussed in Subsection 3.2.1). The figure mirrors the conceptualisation framed in ISO 31000:2018 that has been developed by the International Standardization Organization (ISO) [4] [Kishchuk et al., 2018, de Ruijter and Guldenmund, 2016]. ISO 31000:2018 is a guideline that provides a generic framework for the management of all types of risks, including legal risks [ISO, 2018]. The bow-tie visualisation system makes the relationships between the entities designated by ISO discernible and explicit. Although attempts have been made, the theoretical structure of both ISO 31000:2018 and the Bow-Tie Method have not yet been translated into the expressivity of a ready-to-use ontology [Agrawal, 2016]. Let us have a closer look, why this is the case?

Ontologies enable, *inter alia*, model-based meta-analysis [Becker and Aloe, 2019] (meta-analysis refers to the systematic review of research studies, data and knowledge sources related to an ontology). Meta-analysis can be applied to conduct different risk management analyses either to infer new pieces of information or to draft more solid clauses related to risks in contracts. Ontologies are designed to reduce ambiguity between the entities and clarify the relationships between them [Nirenburg and Raskin, 2001].

According to Ruijter and Guldenmund, there is no consensus on the specific definition of the bow-tie visualisation system except its shape and core concepts [de Ruijter and Guldenmund, 2016]. The main diverging points may originate from the ambiguity of the relationships among the entities in the bow-tie structure. This may result in subjectivity, in terms of both *interpretation* and *intended use*.

[2] https://www.wolterskluwer.com/en/solutions/enablon/bowtie/expert-insights/barrier-based-risk-management-knowledge-base/the-historie-of-bowtie

[3] https://www.wolterskluwer.com/en/solutions/enablon/bowtie/expert-insights/barrier-based-risk-management-knowledge-base/the-bowtie-method

[4] ISO is an independent, non-governmental international organisation with a membership of 164 national standard bodies, founded in 1947 and headquartered in Geneva, Switzerland. In this concern cf. https://www.iso.org/about-us.html

3.1.2 Ontology Visualisation

To clarify the bow-tie and ISO 31000:2018 structures, and to derive new insights into the method and the standard, we will therefore design an ontology mirroring the relationships portrayed in the bow-tie diagram. We will then test it against taxonomic constraints that lead to the creation phases of ontologies (checking how well it adheres to e.g. rules, guidelines or limitations). The resulting ontological vocabulary will be linked to the Onassis ontology that we previously designed and described in Chapter 2 [Stathis et al., 2023d] [5].

Designing a set of machine-understandable vocabulary terms allowing to monitor and manage risk in relation to the violation of specific contractual clauses means taking the expressiveness of *iContracts* a step further. Moreover, having openly accessible ontological vocabularies for risk management data further allows smaller entities with limited economic availability to implement monitoring strategies to reduce the occurrence of hazardous events in relation to contractual clauses. By including risk data and risk management strategies, *iContracts* will not only serve the purpose of formally describing an agreement between different parties, but will also even monitor and prevent the occurrence of hazardous events connected to legal risk. Thus, the avoidance of dispute consequences becomes possible.

3.1.3 Research Question 2

The contribution of the research with respect to RQ2 is therefore two-folded. First, it explores the limitations of the bow-tie visualisation method to perform large scale analysis with regards to risk analysis. This will simultaneously bring new insights into its structure. Second, it proposes a set of openly-accessible vocabulary terms to structure and manage legal risk data. As a result of the aforementioned information we state RQ2 below.

> **RQ2:** *To what extent is it possible to translate the Bow-Tie Method into a visualisation of an ontology for contract risk management without altering the bow-tie structure?*

3.1.4 Research Contribution

The Chapter showcases to what extent it is possible to structure the process and the relevant data for automating contract risk management. So far, the literature mentions the usefulness of the Bow-Tie Method for contract risk management. However, the explicit application of the Bow-Tie Method for its computational

[5]The Onassis Ontologyis accessible at https://github.com/onassisontology/onassisontology

processing in the legal domain has not been made explicitly. Hence, our contribution is to be seen as a practical tool that may inform the designers and engineers of computational models, in particular for risk management in the legal domain, and within that domain for contracting.

The use of ontology engineering helps delineate a specific vocabulary that is understandable and interpretable by machines. The visualisation contributes to human understanding and interpretation. Risk experts can also leverage visualisations to implement the legal risk ISO frameworks. For legal experts interested in risk management and dispute prevention it may be an additional help. Even though we position the research under iContracts, the relevance is for all processes that relate with risk data, including, for example, compliance automation.

3.1.5 Research Structure

We structure the Chapter as follows. As discussed above, Section 3.1 provides the introduction to contract risk management. In Section 3.2, the relevant literature is reviewed. Section 3.3 presents the methodology of our research. Section 3.4 states the results and Section 3.5 discusses those results. Finally, Section 3.6 answers the RQ2 and provides our chapter conclusion.

3.2 Relevant Literature

In this section, the state-of-the-art literature is presented. Subsection 3.2.1 mentions relevant sources on contract risk management. Subsection 3.2.2 presents the latest research regarding ontologies developed to structure risk management data.

3.2.1 Sources of Contract Risk Management

The most exhaustive academic source on contract risk management, which is targetted to practitioners, is Haapio and Siedel's book, *Guide to Contract Risk* [Haapio and Siedel, 2013]. Contract risk can be identified in multiple domains. Ideally a database of contract risks should exist to help legal experts identify instances more quickly and efficiently, as happens in other domains [Patterson and Neailey, 2002, Kuwahara et al., 2015].

In the industrial, energy and environmental areas, visualisation methods, such as the bow-tie, are often used to manage risk and prevent the occurrence of hazardous events within domain-specific projects (a telling source originates from Chemistry as seen in [Center for Chemical Process Safety, 2018]). A Bow-Tie Method (see Figure 3.1) is used for visualising risk in a holistic manner by taking into consideration proactive and reactive risk measures [6]. A bow-tie diagram helps to visualise and control contract risk [Haapio and Siedel, 2013]. It has been used in a variety of risk analysis environments and for various risk management purposes [Khakzad et al., 2012].The usefulness of the Bow-Tie Method stems from its ability to visualise the complexity of legal risk [Dauer, 2006]. Figure 3.1 shows a representation of the Bow-Tie Method.

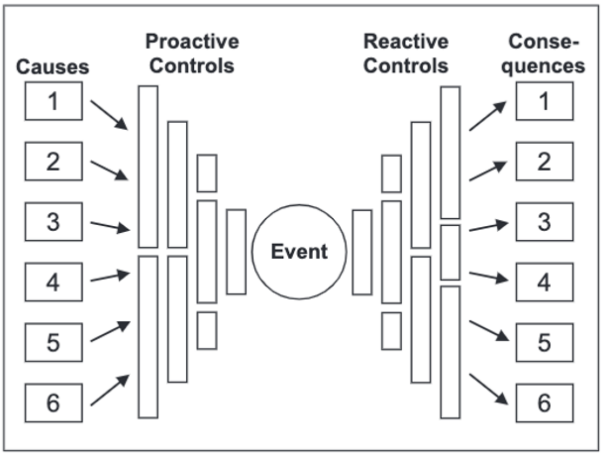

Figure 3.1: Bow-Tie Method

The Bow-Tie Method mirrors, at the level of the entities, the conceptualisation framed in the ISO 31000:2018 standard [ISO, 2018]. The standard defines eight concepts that are considered to be essential to manage risk.

- Risk
- Risk Management
- Stakeholder
- Risk Source
- Event
- Consequence
- Likelihood
- Control

[6] https://www.wolterskluwer.com/en/solutions/enablon/bowtie/expert-insights/barrier-based-risk-management-knowledge-base/the-bowtie-method

In multiple industries, including the legal technology industry, it is also possible to develop a *risk matrix* or risk register after visualising the risk management process via the bow-tie diagram [Leva et al., 2017]. In the risk matrix/register, one may also add six additional concepts [Lu et al., 2015]:

- Impact[7]
- Priority
- Response
- Responsible
- Deadline
- Validation

Consequently, *risk ranking* becomes possible for a quite clear visualisation of the immediate risks requiring risk management as well as a contract risk response. In relation to contract risk, the response mostly relates to two additional aspects, viz. *contract drafting* and *procedural aspects* [Espenschied, 2010, Fox, 2008].

3.2.2 Ontologies for Contract Risk Management

Although ontologies may be a powerful instrument to perform contract risk management analysis, they are not very common in the field. This is mostly due to the scientific immaturity of the domain. However, efforts have been made to build a framework enabling both the *analysis of the risk assessment* process, and the *codification of the relationships* (i.e., roles and responsibilities) between the various entities involved in a risk management organisation. Examples are provided by the Description of a Model Ontology (DOAM)[8], and the Risk Function Ontology (RFO), respectively[9]. Although DOAM and RFO offer great contributions to the field, they still lack the needed level of expressiveness that will allow users to structure risk management data at a processing level while the intelligent agents of the iContract are framing information within the scope of the Bow-Tie Method. A more targeted attempt on the conceptualisation of the ISO standards is evident in the cyber-security domain [Oliveira et al., 2022, Sánchez-Zas et al., 2023] and AI regulation space [Golpayegani et al., 2022]. In particular for cyber-security ontologies, such as the Reference Ontology for Security Engineering (ROSE) [Oliveira et al., 2022], they place significant emphasis on events,

[7] For clarification, we note that impact serves the role of showing the probabilities that a consequence may occur.

[8] https://www.openriskmanual.org/ns/doam/index-en.html

[9] https://www.openriskmanual.org/ns/rfo/index-en.html

event types and anomalies as seen in the context of risk. Surprisingly, some of the work focusses exclusively on the conceptualisation of prevention [Baratella et al., 2022]. Still, regarding ontologies aiming to mirror the implementation phases of the bow-tie process, we could not find any vocabularies designed for this specific purpose either on the Linked Open Vocabularies (LOV) catalogue [10] or the Open Risk Management (ORM) Foundation website [11]. Ultimately, we did observe an attempt to develop an ontology for the ISO risk management standards which did not result in a ready-to-use model [Agrawal, 2016] and another attempt which did result to usable model (see RiskOnto on GitHub [12]).

3.3 Research Methodology

Our research methodology aims to identify (1) the possible presence of violations of taxonomic constraints (this is important for testing the consistency and robustness of the ontology against potential structural omissions in the concepts and relations of the ontology), and (2) ambiguous constructs in the conceptualisation of the bow-tie visualisation medium (this is important for examining the semantic clarity of the ontology in relation to the domain it refers to - abstract use of language is not helpful due to increased risk of misinterpretation). Moreover, it aims to validate the reliability of the ontology. In Subsection 3.3.1, we translate the bow-tie design into the expressiveness of an ontology by mirroring the bow-tie relationships and entities. In Subsection 3.3.2 we introduce three types of taxonomic errors. Subsequently, in Subsection 3.4.1, we check the presence of taxonomic ambiguities and errors by following (a) the best practices for the development of ontologies and (b) the detection of fallacies in the models. Then in Subsection 3.4.2 we arrive at the results aimed at the Enriched Bow-Tie Ontology. The outcomes of our analysis are presented under results in Section 3.4.

3.3.1 Ontology Visualisation of the Bow-Tie Method

As presented in Section 3.2 and discussed by [de Ruijter and Guldenmund, 2016], the entities pictured (see Figure 3.1) in the Bow-Tie Method relate to one another as follows. The explanation of the steps 1 to 5 are given below. Then we describe the steps 6 to 8 (see Figure 3.2).

[10] https://lov.linkeddata.es/dataset/lov
[11] https://www.openriskmanagement.com/
[12] https://github.com/coolharsh55/riskonto

1. The *causes* of a hazardous event are protected by proactive controls.

2. The *proactive controls* relate to a hazardous event. They result from the causes and are designed based on the nature of the hazardous event.

3. The *hazardous event* is contained by both the *proactive* and *reactive* controls (barriers).

4. The *reactive controls* are conceptualised based upon the nature of the hazardous event to marginalise its consequences. They relate to both a hazardous event and its consequences.

5. The *consequences* are limited by the reactive controls to which they relate.

6. The *risk* which is not represented in the bow-tie diagram can be intuitively associated with the hazardous event itself. This is mostly based upon the guidelines of the ISO 31000:2018 standard.

7. The *stakeholder*, who is not represented in the bow-tie diagram, can be intuitively associated with the hazardous event. This can be derived from the guidelines of the ISO 31000:2018 standard.

8. The *likelihood*, which is not represented in the bow-tie diagram, measures the probability of the occurrence of a hazardous event as described in the guidelines of the ISO 31000:2018 standard.

When translating the entities and relationships of the bow-tie diagram into the expressiveness of an ontology, we arrive at the structure presented in Figure 3.2.

The *validity*, *efficiency*, and *consistency* of the ontological structure presented in Figure 3.2 can be tested against the presence of taxonomic errors.

3.3.2 Three Types of Taxonomic Errors

According to literature [Gomez-Perez, 1995, Gómez-Pérez et al., 2004, Gómez-Pérez, 2001, Fahad et al., 2008, Fahad and Qadir, 2008], there are three main types of taxonomic errors. They are *inconsistency* errors, *incompleteness* errors, and *redundancy* errors.

Inconsistency errors may be caused by circulatory errors (i.e., entities defined as sub-entities or super-entities of itself), partition errors (i.e., instances belonging to various disjointed classes), or semantic inconsistency errors (i.e., when ontologists define concepts as sub-classes of concepts to which they do not pertain).

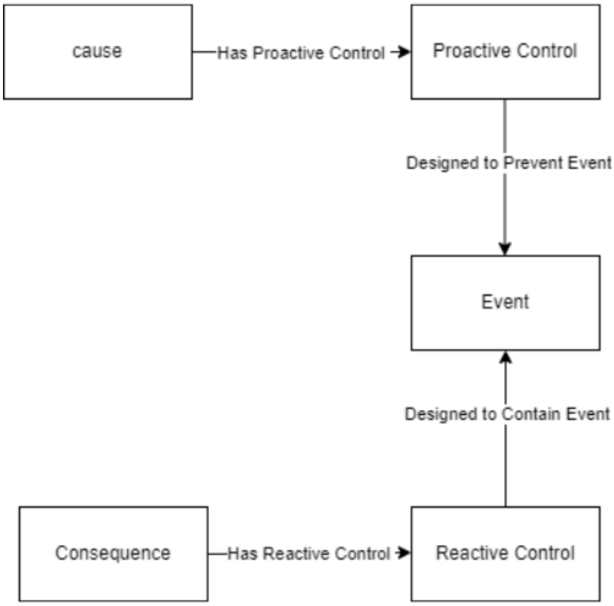

Figure 3.2: Bow-Tie Centred Ontology

Incompleteness errors may be of three types, namely, (a) incomplete concept errors (they occur when concepts and relationships of the domain are overlooked and not defined in the structure), (b) incomplete axiom errors (they occur when ontologists omit important axioms and information about the classification of a concept), or (c) sufficient knowledge emission errors (they take place when concepts have only necessary descriptions). Incompleteness errors lead to ambiguity and create a lack of proper reasoning mechanisms.

Redundancy errors happen when pieces of information are inferred more than once from the relationships, classes, and instances of the ontology. They can be: redundancies of sub-class/sub-property errors (they may occur when classes or relationships directly or indirectly have more than one sub-class/sub-property relationship); identical formal definition of classes, properties and instances (i.e., proprieties, classes and instances have different names but provide the same formal definition); or redundancy of disjoint relationships (i.e., concepts explicitly defined as disjointed from other concepts more than once).

In order to derive more insights into the Bow-Tie Method and to test the actual taxonomic validity of the bow-tie centred ontology displayed in Figure 3.2, we tested this ontology against the three types of taxonomic errors discussed above. Our results are presented in Section 3.4.

3.4 Research Results

The section presents the results of our research. The results concern the taxonomic errors in the ontology visualisation of (3.4.1) the bow-tie centred ontology and (3.4.2) the enriched bow-tie ontology.

3.4.1 Taxonomic Errors in the Bow-Tie Centred Ontology

The bow-tie centred ontology (Figure 3.2) presented in Section 3.3 mirrors the exact relationships that are framed by the Bow-Tie Method (Figure 3.1) and a few of the concepts of ISO 31000:2018. As discussed in Section 3.3, the *risk*, the *stakeholder*, and the *measure of likelihood* are not addressed by the bow-tie analytical medium. This resulted in the absence of their concepts from the bow-tie centred ontology. The same can be remarked for the measure of likelihood regarding the occurrence of a hazardous event. The lack of these concepts in the diagram and ontology causes several *knowledge emission errors*. Other incompleteness errors that can be found in the bow-tie centred ontology are *incomplete concept errors*.

In the bow-tie diagram (Figure 3.1), only four relationships are described.

1. The causes and proactive controls,
2. the proactive controls and hazardous event,
3. the hazardous event and reactive controls, and
4. the reactive controls and consequences.

However, these four relationships may lead to ambiguity when performing a cross-referencing analysis with a bow-tie centred ontology and/or diagram. Below we discuss two types of ambiguities.

First, the problems identified in the bow-tie centred ontology originate from the *ambiguity* in the relationships between the entities that are framed by the bow-tie visualisation method.

Second, the two taxonomic errors that we individualised, namely *incomplete concept errors* and *sufficient knowledge emission errors*, do not only concern the relationships between causes, proactive controls, and the hazardous event (i.e., the left side of the bow-tie visualisation method) but even the relationships between the hazardous event, reactive controls, and consequences.

Ultimately, no other type of taxonomic errors have been detected in the bow-tie centred ontology.

3.4.2 The Enriched Bow-Tie Ontology

To resolve the taxonomic errors identified in the bow-tie centred ontology (Figure 3.2), we shifted the relationships in the previously presented ontological model from a *cause-sequential order* of connected entities to a *node-centred order*. In the resulting version of the model, the cause, proactive control, reactive control, and consequence are directly connected to the hazardous event. We identify the hazardous event as the most core component. The hazardous event is here conceived as a physical occurrence possibly associated with a point in time. Furthermore, we consider the *cause*, *reactive control*, *proactive control*, and *consequence* as human-derived observations rather than actual physical situations. This makes it so that every time a hazardous event is identified by a legal expert, a unique identifier shall be created for it, regardless of whether its nature is similar or identical to another event. Unlike the case of the hazardous event, the identifiers of identical causes, reactive controls, proactive controls, and consequences can be reused across use cases.

As previously discussed, the bow-tie visualisation method (Figure 3.1) does not include the following three relationships: (1) the relationship between the hazardous event and the risk, (2) the relationship between the hazardous event and stakeholders, and (3) the relationship between the measured probability of a hazardous event and the hazardous event itself.

The new vocabulary terms of the Onassis ontology demonstrate the relationships presented above as follows. The risk is connected to a hazardous event that is, in turn, linked to a measure of probability. Based on the structure of the risk matrix analysis, we connected the stakeholder directly to the impact of a hazardous event. The probability and impact measures are then associated with a level of risk which is subsequently linked to the risk itself. Both the probability and the impact measure are connected to a source. Figure 3.3 displays the new vocabulary terms that we added to the Onassis ontology (leading to the Enriched Bow-Tie Ontology) in its simplified visualisation. In Figure 3.4 we present its scientific visualisation.

To conclude, the rationale behind the new classes and properties of the Onassis Ontology can be described as follows.

1. The Risk *involves* a Hazardous Event and a Risk Measure.
2. The Hazardous Event *has* a Cause, Proactive Control, Reactive Control, Impact, and Consequence.
3. The Cause *is contained by* the Proactive Control.
4. The Consequence *is contained by* the Reactive Control.
5. The Impact of a Hazardous Event *affects* an Agent.

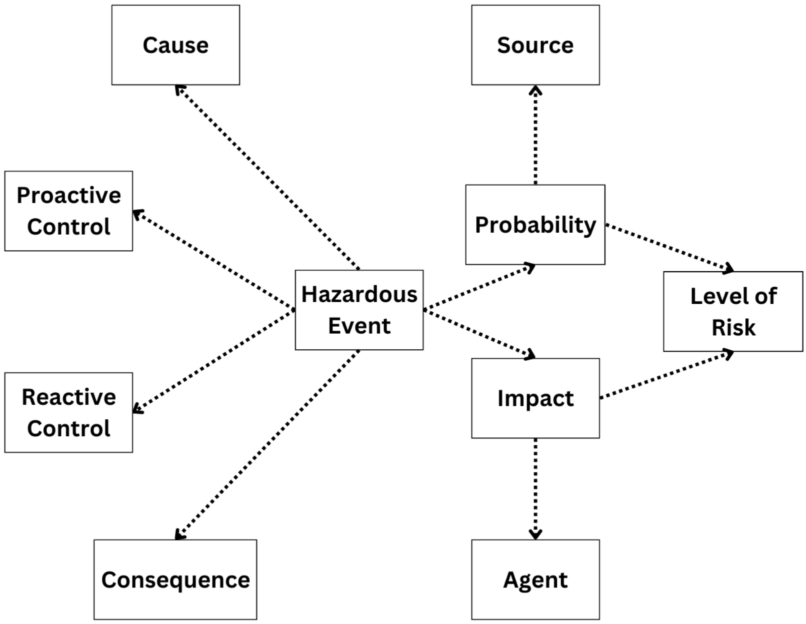

Figure 3.3: Enriched Bow-Tie Ontology (Simplified)

6. The Hazardous Event *has* a Probability number.

7. The numbers of the Probability and Impact *result* in a Level of Risk.

8. They are *based on* a Source.

9. The Level of Risk *is* ultimately *involved* in a Risk.

To design the new vocabulary terms for Onassis, we used the Resource Description Framework Schema (RDF/S) and Ontology Web Language (OWL).

The logical consistency of the new vocabulary terms has been tested via an ontology reasoner [13]. The coherency of the model with domain knowledge has been validated by running competency questions on sample data which are accessible via Github [14]. The competency questions regard questions such as ”what is the cause” or ”what is the proactive control”, based on the sample data that are visible on the visualisation provided on GitHub, with each question referring to a concept identified on the EBTO.

[13]Specifically by launching reasoner Hermit 1.4.3.456 on sample data in the Protégé editor (see https://mvnrepository.com/artifact/net.sourceforge.owlapi/org.semanticweb.hermit/1.4.3.456)
[14]https://github.com/onassisontology/onassisontology/blob/main/img/Visualisation.png

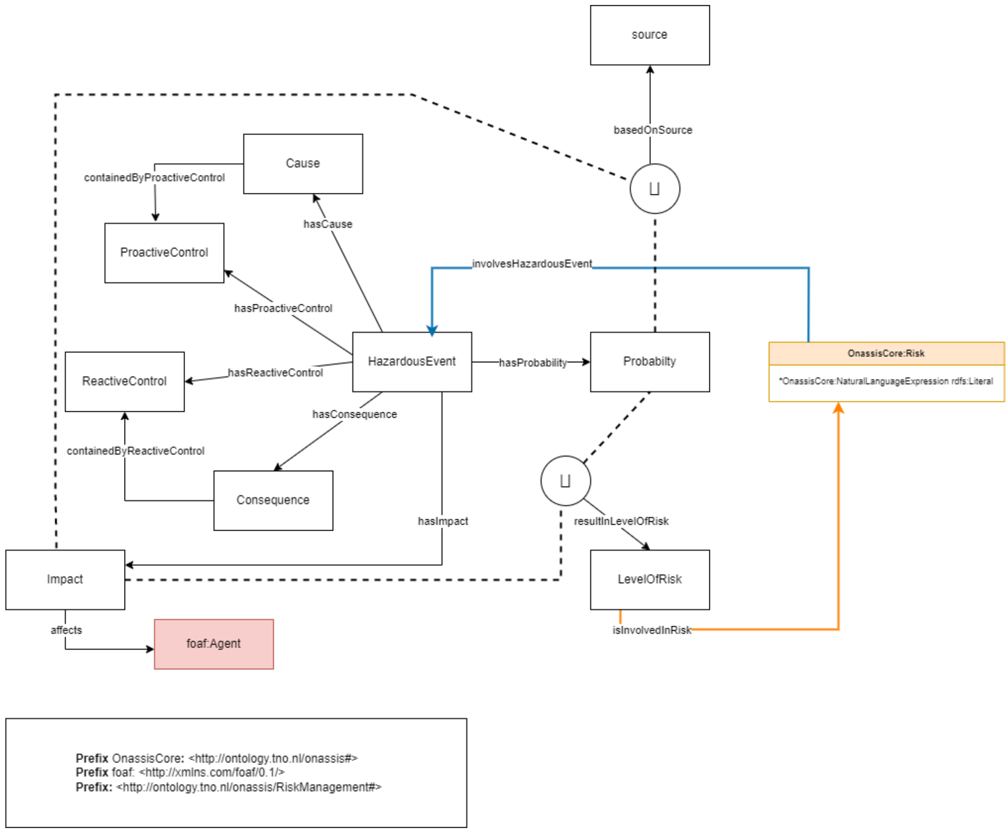

Figure 3.4: Enriched Bow-Tie Ontology (Scientific)

3.5 Discussion

The discussion concentrates on examining three research consequences for (3.5.1) ontology visualisation, (3.5.2) contract risk management, (3.5.3) data interoperability, and (3.5.4) iContracts.

3.5.1 Ontology Visualisation

Visualisation analysis allows users to examine and compare a large amount of data [Dudáš et al., 2018]. However, if some details are omitted, they can mislead the analysts by leading them to erroneous analytical results. Then it is possible to observe, from the application of ontological taxonomic constraints on the bow-tie structure, the bow-tie visualisation system suffers from some limitations. In a large-scale comparative analysis, the Bow-Tie Method can possibly lead to *data ambiguity* due to the lack of direct relationships between the core component (i.e., hazardous event) and related entities (i.e., cause, consequence, proactive and reactive controls). Furthermore, we recognised that the system does not represent all concepts theorised in the ISO 31000:2018 standard to manage risk. To overcome the above mentioned problems, we created an ontological model that embraces the full expressiveness of the ISO 31000:2018 standard. Ultimately, we ensured the presence of connections between all entities described by ISO in order to prevent the occurrence of ambiguity in ontological knowledge representations.

The new vocabulary terms that we designed, did extend the Onassis core ontology that we previously created. Yet, they do not aim to replace the conceptualisation of the entities of the Bow-Tie Method. They focus on enriching it while providing a ready-to-use ontological model to manage and describe risk data in *iContracts*. When visualised, with all improvements, the Enriched Bow-Tie model will take the shape of a more complex and amorphous Figure 3.3 rather than the classical *papillon* (see Figure 3.1). This is due to the granularity of the ontolology.

3.5.2 Contract Risk Management Impact

The presence of openly-accessible vocabulary terms to describe that risk data is vital for (1) an improved analysis and (2) the adequate management of contract risk. In this way we have constructed a legal expert who is able to (1) better define contract risk, (2) improve contract clauses, and (3) better understand the level of risk per contract. An additional benefit is that the open-source nature of our work can help companies exchange risk data to refine the measuring of impact probabilities for improved risk ranking.

Moreover, the research clarifies how is possible to structure risk data for the purposes of contract risk management. It is a novel research scope applying specifically the Bow-Tie Method on legal domain case studies. The result is an examination of how risk data can be structured under the practice of risk management for law, focussed on contracting for the purposes of dispute prevention.

3.5.3 Data Interoperability

One the one hand, we identified some limitations in the conceptualisation of the risk management visualisation framework provided by the Bow-Tie Method. On the other hand, we equally deem that such a structure can play a fundamental role in cross-referencing analysis with different collections of data to manage risk if the potential cause of ambiguity is resolved. Based on this consideration, we decided to enrich the bow-tie by (1) adding more relationships in its structure and (2) translating the *enriched bow-tie* into the expressiveness of an ontology. This will allow interoperability between data sets while hopefully leading to the attainment of new insights for the evaluation of risk in contractual clauses.

The use of ontology engineering facilitates data interoperability with the granular expression of concepts and their relations. For now, provided the analysis of risk is implicit, there is no explicit consensus on the type of definitions, relations and data included in contract risk management. Our ontology clarifies on a granular level such relations with the purpose of assisting multiple parties involved in contract risk management with clarifying related concepts.

Here lies also the importance of developing understandable and interpretable vocabulary terms both for machines and humans. Initially, humans should be able to define the relevant data in their organisational processes. Later on, they should be able to ask machines to process such data. Eventually, humans should again be able to interpret machine outcomes. Having clear vocabulary with granular definitions helps with precisely this purpose.

3.5.4 Intelligent Contracts Impact

Our research shows that risk data are able to contribute to making *iContracts* more responsible. The responsibility mainly derives from the fact that risk data can be explicitly examined thanks to the creation of a set of interlinked metadata (i.e., the extension of the Onassis Ontology that we designed) that can be used to structure information regarding risk. The new vocabulary terms can, in fact, make the usually implicit information about contract risk evident and clear, while fostering the possibility to compare different data collections coming from diverse data sets. As a result, risk management can improve due to the large scale comparative analysis of diverse data records [Haapio and Siedel, 2013].

3.6 Chapter Conclusions

The present Section provides the answer to RQ2 (see 3.6.1), a research novelty (the Enriched Bow-Tie Ontology, see 3.6.2), and a further research suggestion on validating the integration (see 3.6.3).

3.6.1 Answer to RQ2

We repeat RQ2.

> **RQ2:** *To what extent is it possible to translate the Bow-Tie Method into a visualisation of an ontology for contract risk management without altering the bow-tie structure?*

Regarding RQ2, we provide our answer in three statements.

(1) The conversion process of the bow-tie conceptualisation into ontological terms highlighted the presence of missing relationships between entities in the Bow-Tie Method as well missing ISO-specified concepts.

(2) To reduce the possibility of introducing ambiguity into the analytical and management processes of risk data, we searched for and found further relationships between entities in the ontology compared to those that are represented in the bow-tie system.

(3) Ultimately, we incorporated the missing ISO-specified concepts that were not present in the Bow-Tie Method, into the visualisation of Figure 3.4.

3.6.2 Novelty

Our investigation resulted in a new version of the bow-tie visualisation medium as well as an openly-accessible ontological model to manage and describe risk data (the Enriched Bow-Tie Ontology). The research novelty is that we have shown how it is possible to make *explicit* a traditionally implicit process, in such a way that data processing becomes possible. So far, legal experts have not reached consensus on how to *manage* contract risk. Our research shows how it is possible. Moreover, in relation to the Bow-Tie Method, we presented a new theoretical version for it which (1) builds upon the old one, (2) disambiguates some of the bow-tie constructs, and (3) enrich its conceptualisation.

3.6.3 Further Research

In relation to further research, the key question at this point is how to best move forward from here. An essential step in conducting further research is to validate the successful integration of the developed contract risk management ontological framework in iContracts. Chapter 4 will therefore focus on *validating* the integration experimentally.

CRediT Author Statement

Below I would like to give credit to all persons involved.

Stathis, G., Biagioni, G., Trantas, A., van den Herik, H. J., and Custers, B. (2023b). A Visual Analysis of Hazardous Events in Contract Risk Management. *In the Proceedings of 12th International Conference on Data Science, Technology and Applications (DATA)*, 1:227–234

Stathis, G.: Conceptualization, Methodology, Writing - Original Draft, Investigation, Visualization, Project Administration, Funding Acquisition, Writing - Review & Editing; **Biagioni, G.**: Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Data Curation, Visualization, Writing - Original Draft, Writing - Review & Editing; **Trantas, A.**: Investigation, Writing - Review & Editing; **van den Herik, H.J.**: Writing - Review & Editing, Supervision; **Custers, B.**: Supervision.

Chapter 4

Risk Visualisation & Trustworthiness

The Chapter addresses RQ3 which reads:

> **RQ3:** *To what extent is it possible to improve user trustworthiness for Intelligent Contracts via the visualisation of risk during legal question-answering?*

Our research aims to show how contractor *trustworthiness* for iContracts improves via the visualisation of risk. Traditionally, contractors relied on legal experts who conducted the analysis of risk and proposed contracting solutions. Currently, trustworthiness is still an *open question* concerning the state-of-the-art in user interfaces for contract automation. Nowadays, the available interfaces do not present much valuable information, and the question is whether it is sufficient information (or what are the criteria for sufficient information). To measure the impact of the trustworthiness at the end users side, we will investigate to what extent we can visualise legal risk for legal-question answering addressed to contracting parties. For this task, we developed an explorative survey that requested end users to rate how their trustworthiness level is different when compared to (a) an empty user interface or (b) a legal expert physically discussing legal risks with them. The results show that the end user reaction is almost sufficiently positive. The discussion highlights the importance of risk analysis visualisation for user trustworthiness in iContracts and provides improvement suggestions. The conclusion is that end user trustworthiness improves with risk visualisation, yet further improvements are necessary.

The current chapter corresponds to the following publication:

Stathis, G., Trantas, A., Biagioni, G., and van den Herik, H. J. (2023c). Risk Visualisation for Trustworthy Intelligent Contracts. *In the Proceedings of the 21st International Industrial Simulation Conference (ISC), EUROSIS-ETI*, pages 53–57

4.1 Trust and Trustworthiness

While the scientific interest regarding contract automation is accelerating, users are not adopting such solutions at the same pace. As with most technology innovations, several validation iterations are necessary. Here we remark that the difference between general technology innovation (for example in consumer internet offerings) and innovation in contract automation is to a large extent based on *trust*, since any end-user action may have binding legal consequences. In our study we use the following definition of trust (see Definition 4.1, cf. [Bauer, 2019]).

Definition 4.1 – ***Trust***

Trust is a subjective estimate (to be performed by the truster) of the probability that the trustee will accept the truster's preferred behaviour.

The behaviour, as described in Definition 4.1 is called the truster's trustworthiness [Bauer, 2019]. For the purposes of this research we define trustworthy (see Definition 4.2) and (see Definition 4.3) as follows.

Definition 4.2 – ***Trustworthy***

Trustworthy is the behaviour of people who show or accept trust.

Definition 4.3 – ***Trustworthiness***

Trustworthiness is the state in which the behaviour of people is expected to show or accept trust.

4.1.1 End User Trustworthiness

The underlying idea is that the implications of contractual agreements for end users have a high legal impact. Therefore, end users also need to trust the available technology to a very significant extent for adopting contract innovation with the aim to avoid potential legal risks. Given the importance of legal risk in contract design, the task to improve the communication of legal risk in contract automation for end users is a way to handle the *trustworthiness* issue. This is also the case for iContracts, which currently lie at the epicenter of the academic attention. Our research aim is to improve the following three issues by visualising:

1. the risk analysis of a legal expert, in a user-friendly manner to contracting parties,

2. the trustworthiness, and

3. the subsequent user adoption of iContracts.

Obviously, a particular obstacle affecting user trustworthiness for iContracts is the lack of sufficient understanding of legal risk involved in legal question-answering. Due to the binding effects of contracts, users remain currently reluctant to trust technology when replacing legal experts. With the visualisation of contract risk, users may experience an improved understanding of the legal consequences during legal question-answering.

4.1.2 Risk Visualisation

The most recent literature is investigating the *effects* of improved risk visualisation for users in (1) LegalTech and contract automation, as well as in (2) additional industries, as listed in the relevant literature (see Section 4.2). Even though the visualisation of risk is seriously examined, there is *no academic* study that shows the extent to which researchers deal with *user trustworthiness* in practice. In particular, this is the case in the context of improved trustworthiness for legal question-answering procedure for iContracts.

We see that risk visualisation occurs mainly when using the bow-tie method as is done in several industries. There, it is also the most advanced method. In Chapter 3, we have enriched the bow-tie visualisation via the Enriched Bow-Tie Ontology [Stathis et al., 2023b]. Currently, this innovation is still in its test phase with end users. To stress the importance, we will focus in this Chapter on three issues.

1. The impact of end user trustworthiness via risk visualisation,

2. The context of iContracts, and

3. The use of the Enriched Bow-Tie Ontology for the visualisation of contract risk analysis.

4.1.3 Research Benefits

The benefits of the research are clear (1) for both the contracting parties as well as (2) the end users and (3) the legal experts. Contracting parties will be able to experience more legal benefits (at both sides) and less substantial legal costs when using contract automation technology. Traditionally, the "outcome" of more legal benefits is expected from a legal expert who physically assists the contracting parties. As we see the current developments, we note that legal experts soon will be able to tune their legal advice to multiple parties and use risk analytics to improve the impact of their advice for end users. This implies that the adoption of iContracts by end users and legal experts will become more impactful. This will be the more so if we take the nature of iContracts into consideration, since they have a high impact on contract risk management.

4.1.4 Research Question 3

The above-mentioned information leads us to RQ3.

> **RQ3:** *To what extent is it possible to improve user trustworthiness for Intelligent Contracts via the visualisation of risk during legal question-answering?*

4.1.5 Research Contribution

The Chapter explains our innovation within risk management, which is to facilitate end users understanding, interpretation and trustworthiness for the interpretation of legal risk data. End users will be able to take better legal decisions with more awareness based on risk factors. Moreover, legal experts will be able to communicate with end users on risks involved in their decisions in a clear manner, based on actual analysis derived from risk data, in a structured manner. The contribution to LegalTech is that it shows how risk management and analysis can be explained and be embedded in the contracting process, especially in iContracts, to facilitate the complex stakeholder management of contracting. The most valuable impact is the consequences of our research for end user trust, due to clearer explanations of legal risk.

The relevance between visualisation and trustworthiness relies on the fact that with visualisation it is easier to explain to laymen complex information. Visualisation is essentially for expressing information. It is a way of communicating legal information easily due to higher understandability and interpretability for end users. On the topic of risk management applied in law, that is not usually the case because risk analysis is often implicit. Thus, after structuring risk data in the formal risk management process of EBTO, the visualisation facilitates discussions among experts and end users.

4.1.6 Research Structure

We structure the Chapter as follows. Section 4.1 provides the introduction. In Section 4.2, a brief literature review is provided. Section 4.3 presents the method of research. Section 4.4 states the results and Section 4.5 discusses those results. Finally, Section 4.6 answers RQ3 and provides our conclusion.

4.2 Relevant Literature

The relevant literature Section is partitioned into five parts. Subsection 4.2.1 introduces literature on the user adoption of *iContracts*, Subsection 4.2.2 does the same for user adoption of *contract automation*. Subsection 4.2.3 presents sources on *legal design thinking* and *user trustworthiness*. Then, Subsection 4.2.4 discusses the state-of-the-art of *legal design* and *Preventive/Proactive Law* (PPL). Finally, Subsection 4.2.5 mentions sources on the *visualisation* of the *bow-tie method* for improved trustworthiness.

4.2.1 User Adoption of iContracts

Our literature search concerning user adoption of iContracts shows that the academic research investigating this subject is still under early development [Smits, 2017]. The little research there is, concludes that even though there exists a certain end user desire for the digitisation of designing contracts, the readiness of users for such disruptive change is unknown [McNamara and Sepasgozar, 2020]. The authors mentioned above have investigated the subject of *user acceptance*. They highlighted the disconnection between academic efforts and the industrial adoption of iContracts, with user acceptance being one of the main challenges for adoption [McNamara and Sepasgozar, 2021]. Regrettably, we could not find more recent research, probably due to the high complexity involved in developing and examining the adoption of iContracts.

4.2.2 User Adoption of Contract Automation

Most literature work on *user adoption* relates to smart contracts such as contract automation solutions. Two issues, *user-friendliness* and the *visualisation of legal obligations* in smart contracts, are vital for the adoption of smart contracts [Ullah and Al-Turjman, 2021].

Still, it seems that not all users are willing to adopt this technology. We note that the adoption curve is currently determined by prioritising early adopters [Badi et al., 2021]. Three factors are important for measuring perceived influence and the ease of use, viz. (1) perceived financial costs, (2) facilitating conditions, and (3) trust and readiness [Chaveesuk et al., 2020]. The most important risks are the administrative risks that may affect the adoption of smart contracts, including (a) the regulatory change, (b) the lack of sufficient legal planning, and (c) the lack of dispute resolution mechanisms as discussed by [Gurgun and Koc, 2022].

For the *specific use* of contract automation solutions, we mention one of the first economic analyses of contract technology [Acemoglu et al., 2007]. The analysis of multi-stakeholder relationships showed that forming contracts is central to the successful completion of a project [Gerkensmeier and Ratter, 2018]. However, the relative contractual incompleteness by a stakeholder leads to a generally lower level of contractual technology adoption. In the last years we have seen that this observation remains valid, especially in some geographical areas or market verticals where adopting digital solutions is uncommon (e.g. see discussions in relation to the adoption of notarial technology in Greece [1]).

Focussing on risk aversion, we point to an interesting study conducted on Chinese farmers [Mao et al., 2019]. It shows that the higher the risk aversion of a farmer, the less likely it is for colleague farmers to adopt technology. However, when specific contractual terms that *reduce risk* are included in contracts and understood by the farmers their adoption rate increases. Hence, a first conclusion is that the *attitudes* and risk *perceptions* of the farmers risk play an essential role in shaping risk management strategies to address risks and uncertainties (see [Pham et al., 2021]). The analogous conclusion can be made for the case of a contracting party as an end-user concerning iContracts, irrespective of their professional background (as we partially validate during the discussion of the explorative survey results in Subsection 4.5.1).

4.2.3 Legal Design Thinking and User Trustworthiness

Central to the delivery of legal services is the concept of *legal risk*. Studies have shown that legal risk analysis is *flawed*, often leading to *poor predictability* [Fraser and Roberge, 2016, Kiser et al., 2008]. This is one of the main reasons why smart contracts have increased in adoption, viz. due to the higher trust they bring by their better predictability (already announced by [Kiser et al., 2008]). On the same line of reasoning, researchers proposed *legal design thinking* as a method for the re-evaluation of value and predictability [Fraser and Roberge, 2016]. Even though the literature highlights the *need* for risk prevention solutions, there is a *lack of practical solutions*. At this point, other researchers emphasise that attention should be given to the fact that clients eagerly need an improved view of legal risk [Yankovskiy, 2019]. In the meantime, we see that beyond the focus on risk, design thinking (see above) should also direct their attention to helping clients to make improved business decisions [Sainz, 2020].

4.2.4 Legal Design Thinking and Preventive/Proactive Law

The research by Haapio addresses the connection between legal design and PPL [Rossi and Haapio, 2019]. PPL researchers support the notion that im-

[1] https://www.ekathimerini.com/news/1225145/government-notaries-reach-contracts-agreement/

proved legal visualisation techniques are necessary in the legal industry [Rossi and Haapio, 2019]. Barton reinforces that notion by stating that the emerging information culture is largely compatible with the assumptions underlying PPL [Barton, 2016]. Barton's recent research seeks to identify design methods, such as *simplification* and *visualisation*, for using the emerging technology to help legal systems function better in the information age [Barton et al., 2016]. Barton has ventured the proactive law movement, such as suggested by Haapio, to solve some of the so-called *design challenges* [Berger-Walliser et al., 2017]. Haapio focusses on the field of *visual law* and is in fact stimulating a design revolution [Corrales et al., 2019a]. The reason behind the ideas is that they are *driven by the market* [McLachlan and Webley, 2021]. The most advanced method thus far for risk visualisation is the *bow-tie method*, and our research shows how it can be enriched for higher impact [Stathis et al., 2023b]. In this respect, we once more remark that Haapio already stated that with risk visualisation the clarity of contracts improves [Haapio, 2011].

4.2.5 Bow-Tie Visualisation for Improved Trustworthiness

All in all, the literature on bow-tie visualisation for improved user trustworthiness in contract automation and LegalTech is still rather scarce [Stathis et al., 2023b]. In the last two decades the bow-tie method has mostly been implemented as a method for increasing *user trustworthiness*. This has happened in a multitude of domains including Chemistry, Energy and Aviation [de Ruijter and Guldenmund, 2016]. Indeed, the active academic researchers have pointed in this direction during more than fifteen years on *risk visualisation* via the bow-tie method (the managers of risks are mostly also the end users) [Book, 2012]. The approach is the equivalent of the *legal expert* in the Onassis Ontology. There, subsequent research highlights the benefits of visualising the bow-tie method for multi-stakeholder environments [Gerkensmeier and Ratter, 2018]. Here, an interesting observation comes from Luhmann who argues that risks are *mental constructs* which are bounded and influenced by perception [Luhmann, 2002]. Hence, risk management and bow-tie analysis should be subject to a continuous social discourse [Gerkensmeier and Ratter, 2018]. Thus far, the current research supports the bow-tie as the most influential method of visualising risk in a multi-stakeholder environment, mainly according to [Gerkensmeier and Ratter, 2018] and [Bernsmed et al., 2018]. The importance of risk communication to stakeholders is well described by earlier academic research [Gerstenberger et al., 2013].

Currently, we observe that the literature on this topic has strongly developed in recent years. Despite the positive remarks of many researchers for bow-tie and risk visualisation, there is actually not recent new research (i.e., new ideas) on the subject. Providing an explanation is difficult.

4.3 Research Methodology

This Section presents the research methodology containing four recently developed main topics: (4.3.1) the use of a case study, (4.3.2) the application of the Enriched Bow-Tie Ontology visualisation (see Chapter 3) (4.3.3), the development of an explorative *user survey* measuring the extent to which the visualisation impacts the user trustworthiness, and (4.3.4) the clarification of *sufficiency criteria*. The survey contributes to developing *methods for measuring* the improvement in user trustworthiness based on the visualisation of the Enriched Bow-Tie Ontology.

4.3.1 Case Study on Payment Risk

The case study focusses on representing payment risk related to legal question-answering for a *simplified freelance agreement*. The legal questions are addressed to freelancers. The most common legal questions freelancers receive in relation to (1) payment risk, concern (2) price expectations and (3) milestone planning or (4) payment planning. The case study facilitates the definition of the scope of both the visualisation and the survey. Our case study builds upon the KG validation presented in Chapter 2 (it does not include the ten case study examples for efficiency purposes).

4.3.2 Enriched Bow-Tie Ontology Visualisation

In our representation of the *payment risk*, the legal expert is responsible for conducting the contract risk management process [Stathis et al., 2023b]. In Chapter 2, we developed the Enriched Bow-Tie Ontology, which visualises also a method of analysing the Enriched Bow-Tie Ontology from the point of view of the legal expert. Once the legal expert has completed the analysis, it is possible to present it as a visual report for inspection to the end-user, in the form of legal question-answering.

4.3.3 Explorative Survey

The purpose of our explorative user survey is to measure the level of end user trust for a contract during legal question-answering, after the risk has been visualised. It is an explorative survey being the first of its kind in literature. The aim is to gather an introductory understanding of end user trustworthiness.

The survey takes into consideration background information about users in order to reduce bias by gathering survey participants with diverse backgrounds. Each participant is introduced to the legal question-answering context. The theme of the contract places the participant into a freelancer's position who is interested in signing a contract to provide services to one of the clients of the end user. The primary risk which the end user and the freelancer are facing is payment risk. For purposes of efficiency we have prioritised that risk in the survey. Before answering any question, the replies include the presentation of a level of risk (higher-middle-lower [2]) and a prompt to consult the visualisation of associated risks. The risk analysis is visualised next to the questions.

The users are asked to assume a scale from 1 to 10, where 1 refers to a list of questions without the visual risk representation, and 10 to a list of questions with a legal expert explaining the associated risks to each guest extensively as the ultimate source of trustworthiness. Then, the users are asked to rate from 1 to 10 the perceived trustworthiness of the risk visualisation accompanying the questions. We provide a *tailored* definition of trustworthiness below; it is based on the definition of trustworthiness (cf. Definition 4.3).

> **Trustworthy**, *within the context of this survey, is the level of trust a contractor feels towards a user interface or a legal expert when answering legal questions related to their legal rights and obligations.*

The survey is accessible in the Appendices (Appendix 3B [3]). Moreover, the survey provides participants with secondary explorative questions investigating their productivity, anxiety, satisfaction and likelihood of referral levels. The survey also requests the provision of qualitative feedback.

4.3.4 Sufficiency Criteria

Provided the limited research on the iContract topic, identifying sufficiency criteria for an explorative research survey of data results is not a straightforward task. However, given that our research is focussed on (1) end users and (2) their reaction, we will use a GUI, of which the criteria have been developed under Net Promoter Score (NPS). This testing is developed in Harvard Business Review for market research purposes and can be taken into consideration for such research as ours [Fisher and Kordupleski, 2019]. According to NPS, there are three categories of numerical data that can be gathered in surveys: (1) the

[2]The comparison is on the basis of complexity and risk protection as seen in the Appendix 3B.

[3]`https://github.com/onassisontology/onassisontology/blob/main/Appendices_PhD.pdf`

detractors (1 to 6), (2) the passives (7 to 8) and (3) the promoters (9 to 10) [4]. To calculate the NPS, one needs to calculate the total percentage of promoter scores minus the total percentage of dectractor scores. NPS results range from -100 to +100. Anything over +50 is considered a good NPS, with +70 or higher being excellent [5]. In our survey, we apply the same method to determine the sufficiency of the explorative survey-data results.

We should note that the mere collection of data is in itself not sufficient in determining a level of sufficiency without having established appropriate controls during the investigation of data. Therefore, in the design of our survey we have ensured to maintain the highest possible levels of data security and protection according with Leiden University's Data Management Plan guidelines (including the filling of Consent Forms from the data subjects) as well as with Scientific Ethical norms [6].

4.4 Research Results

This section presents the results of our research. The results concern (4.4.1) the Enriched Bow-Tie Ontology visualisation, (4.4.2) the explorative survey results, and (4.4.3) the results of testing the sufficiency criteria.

4.4.1 Enriched Bow-Tie Ontology Visualisation

Acting as the legal expert, we conducted the contract risk analysis based on the Enriched Bow-Tie Ontology visualisation for the payment risk. We take on the start of our analysis the risk of no payment as the main potential hazardous event. Below we enlist our seven event results (which are not exclusive, but defined as such to facilitate the survey in an efficient manner [7]).

- First, we identified potential hazardous event causes, which included: (a) lack of deadline, (b) quality objection, (c) payment default, and (d) lack of budget (see Figure 4.1 left upper side).

- Second, for each cause we designed a proactive control, namely: (a) timeline, (b) quality control, (c) payment plan, and (d) budget screenshot (see Figure 4.1 right upper side).

[4] https://www.hotjar.com/net-promoter-score/how-to-calculate/

[5] https://blog.hubspot.com/service/how-to-calculate-nps

[6] https://www.staff.universiteitleiden.nl/research/it-and-research/datamanagement/law#tab-1

[7] Potentially more measures can be identified (e.g., start legal procedure as reactive control).

- Third, we identified a consequence which was: (a) less monetary availability.
- Fourth, we identified reactive controls, which were: (a) stop service, and (b) pause service.
- Fifth, on the available data we assigned a probability number of 0.7 to the hazardous event occurring (see [8]).
- Sixth, we assigned an impact number of 0.9 due to the severity of the hazardous event for a freelancer.
- Seventh, we concluded that the level of risk is high, at 0.6.

The connection among the different data points identified during the analysis is as follows. The hazardous event has (a) causes and proactive controls, whereas (b) a cause is contained by proactive controls. Moreover, the hazardous event has (c) a consequence and reactive controls, whereas the consequence is contained by (d) reactive controls. In addition, the hazardous event has (e) a probability, which is based on (f) a source, as well as (g) an impact which affects an agent, and cumulatively the result lands in (h) a specific level of risk. The visualisation is presented below in Figure 4.1 and it is also accessible via the Onassis Ontology GitHub repository [9] or in the Appendices (Appendix 3A [10]).

4.4.2 Explorative Survey Results

The survey collected one hundred and nine (109) replies, based upon which an average score of six point nine (6.9) was given to the visualisation representation, placing it on the scale of significantly trustworthy. Out of the one hundred and nine (109) replies, sixty eight (68) of them reported a score of seven or higher, with forty nine (49) being passives and nineteen (19) promoters, while there were forty one (41) replies that assigned a number below six, which were the detractors. The number was consistent for groups of users which originated from divergent backgrounds. Users with different backgrounds "averaged" rather similar scores. Finally, the participants rated that their productivity level increases by six point seven (6.7), their anxiety level decreases by six point seven (6.7), their satisfaction level increases by six point nine (6.9) and their referral likelihood is seven point five (7.5). Table 4.1 shows the results.

[8] https://blog.freelancersunion.org/2016/03/28/add-your-ious-worlds-longest-invoice/

[9] https://github.com/onassisontology/onassisontology/blob/main/img/Visualisation.png

[10] https://github.com/onassisontology/onassisontology/blob/main/Appendices_PhD.pdf

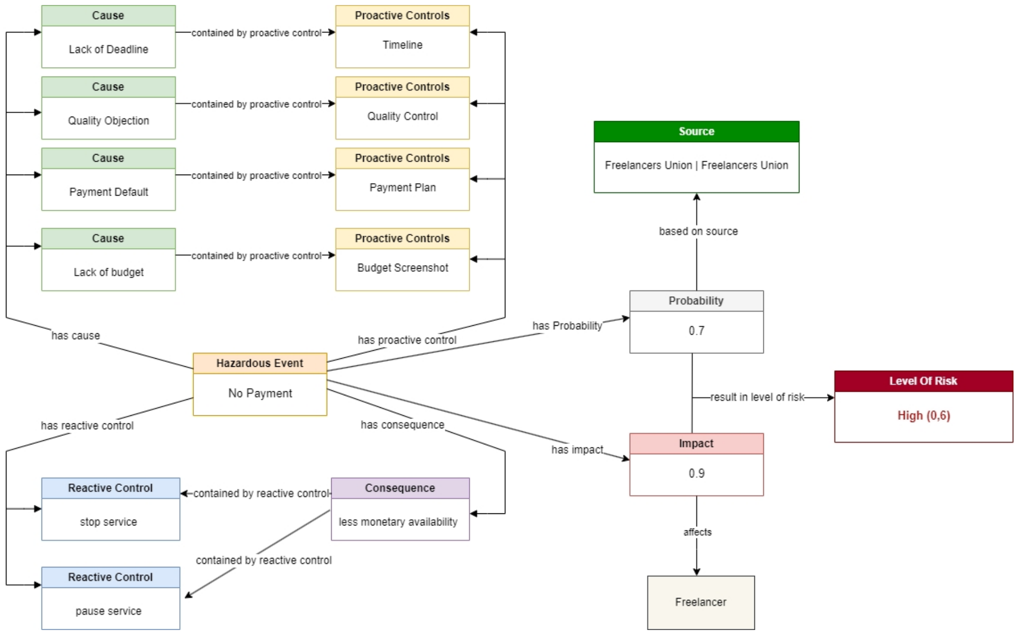

Figure 4.1: Payment Risk Analysis Visualisation

4.4.3 Sufficiency Test

At this point we are applying the NPS test to the received survey replies. There were forty one (41) detractors (1 to 6), forty nine (49) passives (7 to 8) and nineteen (19) promoters for the level of trustworthiness (41+49+19=109). After applying the relevant NPS calculations the final score is minus twenty one (-21). That is a relatively low score. It shows that significantly more work is required.

4.5 Discussion

The discussion concentrates on examining the research impact. We do so for user trustworthiness (4.5.1), the risk visualisation from an end user perspective (4.5.2), and the sufficiency criteria (i.e., Net Promoter Score, 4.5.3).

4.5.1 User Trustworthiness

The average user trustworthiness score provided by survey participants was seven point five out of ten (7.5). The score demonstrates that end users exhibit a high average level of trust towards risk visualisation for legal question-answering.

The risk visualisation is useful for access to justice purposes. It is particu-

Table 4.1: Explorative Survey Data

	Reaction
Trustworthiness	Increased by 6.9
Productivity	Increased by 6.7
Anxiety	Decreased by 6.7
Satisfaction	Increased by 6.9
Referral	Increased by 7.5

larly helpful for groups of people who find it challenging to pay lawyers. Moreover, it is useful for users who have little professional experience and prefer to know the risks rather than not to know. The risk visualisation is also helpful for people with low legal education, who may be eager to avoid committing unnecessary legal mistakes.

Comparatively, in relation to professionals with more complex professions and educational backgrounds, the risk visualisation is not considered as a trustworthy asset. We observed them together with professionals who engage in such higher complexity professions. They "doubt" in relation to whether the risk visualisation can indeed replace a legal expert who is able to grasp more details for their specific scenarios.

In relation to the legal expert conducting the risk analysis there are many legal analysis limitations. We mention three of them. (1) The trust of end users on the risk visualisation depends on the legal expert doing the analysis in the back-end. For instance, as a participant states "on the intermediary handling the contact" who should be highly credible. As a survey participant expressed, lawyers may remain skeptical even with risk visualisation due to the nature of their job. (2) A survey participant expressed concerns as to how the legal expert is able to identify and take into consideration the unique risks that end users might be facing since it is highly dependent on a per case basis. (3) A survey participant suggested they might seek additional risk protection, despite the already detailed analysis of risk, in order to achieve higher protection.

In general, most survey participants found risk visualisation to significantly improve their work as is evident by the scoring of the secondary questions that were focused on their work and psychology.

All in all, it is vital to provide criticism, to assess the risk visualisation and its real value. Some users may still prefer legal experts, even if they assigned high survey scores, e.g., as (1) they themselves lack time for performing the task, (2) they do not feel they can trust a graph over a human expert, or (3) they also have sufficient budget to hire lawyers. Not all users are expected to find usefulness in the risk visualisation. This is identical to what we saw at the detractor survey scores. The visualisation may be perceived as simplistic and a legal expert may still be perceived as significantly more trustworthy than a graph. It is mainly because in cases where a question or another matter is not predicted in the visualisation, a legal expert can provide an immediate answer.

The topic of end user trustworthiness is important to show how end users trust on a micro level the explanation of risk involved in their decision but also to show what is their legal position on a macro level in the contracting process, relative to negotiating strength, which may assist with strategic negotiating considerations.

4.5.2 Risk Visualisation

The survey is also useful for (1) how the entities relate to each other and (2) extracting information in relation to the enriched bow-tie visualisation. The comments focussed on (1) the conceptualisation, (2) the use of the bow-tie analysis, and (3) the visualisation. Even though *optimising* the visualisation was beyond the scope of this research, the observation gave a first insight into the intricacies we will face in this new way of representing legal information.

For instance, first some survey participants claimed that eventually the visualisation can be utilised for practical contracting, yet they were uncertain whether this type of visualisation fits every scenario. Second, a user requested a clearer and perhaps easier visualisation of risk to achieve higher understandability for non-legal experts. Third, a user questioned how the visualisation changes, depending on the fluctuations in the selection of answers or during the contract execution phase. As for the bow-tie analysis, users found the analysis aspect of the bow-tie detailed. A user with a legal background expressed that the analysis could be extended with more information for a greater level of protection. A second user found the analysis to be assumptive. Whatever the case, all users found the analysis worthwhile sufficiently secure, and trustworthy. Even though we are testing the conceptualisation and not the visualisation *per se*, some users also provided useful feedback in that direction. A participant supported the need for user experience improvements regarding the visual representation, introducing an idea for dynamically adjustable user interface changes depending on personalised options. The risk visualisation needs to rely on a robust risk data anlaysis in order for the right data foundations to be in place. Beyond the risk data analysis, a larger risk management process should be in place to facilitate the iContracts process.

4.5.3 Net Promoter Score

The Net Promoter Score helps us examine the degree to which an end user is willing to adopt a new technology, based on their willingness to introduce such new way of working to colleagues. The NPS of minus twenty one (-21) is considered low NPS, especially in the field of software (see relevant benchmarks [11]). It is therefore obvious that a significant amount of improvements is necessary to increase the NPS to an acceptable rate, which in the case of software is 41 and above [12].

We attribute the main reason supporting such NPS score to the unclarity and complex nature of the visualisation, especially for non-legal experts. A second reason behind this NPS rating is that NPS ratings are usually calculated on the basis of full fledged software solutions, while in our survey, we only presented a scientific ”feature” to end users. Despite the low NPS, the end user feedback and reactions are significant to identify how to improve further the risk visualisation and it is a necessary milestone for further progress. Consequently, following the improvement of the visualisation as well as further research it is necessary to conduct more surveys and research on this topic. So far, the NPS is not satisfactory.

We may arrive to the same thoughts after examining the secondary metrics regarding the levels of productivity, anxiety and satisfaction against the NPS rating. Despite the general positive end user reaction on such secondary metrics, when examined comparatively, especially against the NPS standard, we find that significant work is required to improve such end user ratings.

4.6 Chapter Conclusion

Section 4.6 provides the research conclusion by answering RQ3 in Subsection 4.6.1, mentioning the research novelty (the Enriched Bow-Tie Ontology) in Subsection 4.6.2, and offering further research suggestions in Subsection 4.6.3.

4.6.1 Answer to RQ3

RQ3 reads as follows:

> **RQ3:** *To what extent is it possible to improve user trustworthiness for Intelligent Contracts via the visualisation of risk during legal question-answering?*

The answer to RQ3 is that user trustworthiness *can only be relatively improved* to the extent that the visualisation of risk is *sufficiently explainable* for end users;

[11] https://delighted.com/nps-benchmarks
[12] https://delighted.com/nps-benchmarks

yet at this moment not to a sufficient degree for end users to project a sufficient NPS. We measured the scores by a practical test and found a reward factor of seven point nine (in a scale from one to ten) based on risk explanation via the use of the Enriched Bow-Tie Ontology. There is, still, sufficient space for increasing the trustworthiness by further improving the risk visualisation from the users' perspective. Beyond the positive impact on trustworthiness, end users found added benefits to their levels of productivity, anxiety and satisfaction, motivating them to refer this way of working to their peers.

Finally, we remark that the reason for the detractor scores mostly relates to personal user expectations and lack of trust for computers more generally than only this survey in relation to matters related to risk. Therefore, it is expected for this starting point that certain users will continue to display a low level of trustworthiness even with follow up improvements.

4.6.2 Research Novelty

At the end we reiterate the contribution of our research in at least four areas. First of all, it clarifies how it is possible to visualise the Enriched Bow-Tie Ontology. Second, it adds the perspective of risk visualisation to the user-friendliness and trustworthiness discussion on contract automation domain. Third, it specifically shows how risk visualisation can improve the trustworthiness of the iContracts domain. Fourth, it shows how it is possible to measure user reactions from divergent user backgrounds, with an explorative survey.

4.6.3 Further Research

For any further research, we are above all interested in (1) conducting a larger scale survey to achieve higher statistical significance and (2) implementing the Enriched Bow-Tie Ontology in larger case studies to examine practical application matters.

CRediT Author Statement

Below I would like to give credit to all persons involved.

Stathis, G., Trantas, A., Biagioni, G., and van den Herik, H. J. (2023c). Risk Visualisation for Trustworthy Intelligent Contracts. *In the Proceedings of the 21st International Industrial Simulation Conference (ISC), EUROSIS-ETI*, pages 53–57

Stathis, G.: Conceptualization, Methodology, Writing - Original Draft, Investigation, Visualization, Validation, Project Administration, Data Curation, Funding Acquisition, Writing - Review & Editing; **Trantas, A.**: Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing - Review & Editing; **Biagioni, G.**: Conceptualization, Methodology, Validation, Investigation, Visualization, Writing - Review & Editing; **van den Herik, H.J.**: Writing - Review & Editing, Supervision.

Chapter 5

Proactive Control Data

The Chapter addresses RQ4, which reads as follows:

> **RQ4:** *To what extent is it possible to generate quality Proactive Control Data to improve an Intelligent Contract?*

iContracts have 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. It is a novel research scope in literature. 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 available methodologies (the Bow-Tie Method and the Logocratic Method). Moreover, we examine PCD with the context of three technologies (Ontology Engineering, Software Engineering and LLMs) with the aim to demonstrate a higher degree of proactiveness in iContracts. Our research direction is threefold. First, we are able to generate PCD with the development of a prototype. Second, we show that impact of PCD on contract drafting is possible. Third, we show how the quality of PCD can be assessed and improved. The discussion highlights (1) the feasibility of the research with available technologies and (2) that its implementation depends on organisational considerations and resource allocation. From the results we may conclude that it is possible to implement our new ideas successfully.

The current chapter corresponds to the following publication:

Stathis, G., Biagioni, G., de Graaf, K. A., Trantas, A., and van den Herik, H. J. (2023a). The Value of Proactive Data for Intelligent Contracts. *World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4), Intelligent Sustainable Systems, Springer Lecture Notes in Networks Systems (LNNS)*, 803:107–125

5.1 iContracts and Legal Prevention

iContracts are able to 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 [Stathis et al., 2023d]. Even though the literature clearly supports the benefits of iContracts for dispute resolution [McNamara and Sepasgozar, 2020], thus far no research has *measured* the extent to which iContracts contribute to that end. The reason is that researchers have not sufficiently focussed 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.

This Chapter aims to make the hidden data *transparent* and *explicit* by leveraging the EBTO, the primary ontology structure for managing contract risk in iContracts [Stathis et al., 2023b]. We start with an introduction of the basic concepts.

5.1.1 The Basic Concepts

In agreement with the EBTO terminology, we distinguish (1) *Proactive Controls* (hereinafter "Proactive Control Data" or "PCD", see Definition 5.1), 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"].

*Definition 5.1 – **Proactive Data***

Proactive Data are a collection of data, which include Hazardous Event, Cause and Proactive Control data, that contribute towards the prevention of a Hazardous Event, within the context of the Bow-Tie Method.

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 is the main driver of consequential legal costs.

5.1.2 Towards Proactive iContracts

Our research scope follows the direction of the members of the school of PPL. They advocate for more *proactiveness* in contracting [Hietanen-Kunwald and Haapio, 2021].

In Chapter 2 we developed the Onassis Ontology, which provides deep insight into all data that can be generated with iContracts [Stathis et al., 2023d]. 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 Chapter 3, the identification of PCD occurs during the risk analysis stage [Stathis et al., 2023b]. 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 LLMs [Brown et al., 2020] 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.

5.1.3 Chapter Goals

All in all, our research goals are threefold. First, we explore 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 by a module with a higher degree of experimental accuracy. Third, we examine whether PCD can be qualitatively assessed so as to improve their quality.

The research in the Chapter aims at making progress by the following research activities:

1. introducing the value concept of Proactive Data for iContracts,

2. reporting on a prototype web application that uses the Onassis Ontology and the EBTO structure,

3. testing the use of LLMs as a methodology for reducing the variety of contract drafting styles,

4. measuring the PCD quantitatively in iContracts,

5. establishing qualitative assessment criteria for PCD,
6. supporting legal experts to improve the overall data management and its decision making during contract drafting within the context of iContracts for the purposes of reducing the likelihood of contractual disputes, and
7. investigating a direction for measuring the value of Proactive Data for iContracts.

5.1.4 Research Question 4

The foregoing discussion leads us to the following RQ4:

> **RQ4:** *To what extent is it possible to generate quality Proactive Control Data to improve an Intelligent Contract?*

5.1.5 Research Contribution

The Chapter shows how it is possible to promote the proactivity of iContracts by (a) identification, (b) quality evaluation and (c) automated analysis of PCD. The main prevention of data under the EBTO contributes towards a general prevention. The identification of PCD occurs with the use of argumentation. The quality of argumentation can be evaluated further with *argumentation theory*. With the advances of technology, such fast evaluation and a proper production of arguments, it has become possible via LLMs to produce front-ranked results. Our research shows the extent to which such automation is able to reduce the that an expert needs to produce quality PCD.

5.1.6 Research Structure

To answer RQ4, we structured the remainder of the Chapter as follows. In Section 5.2, the relevant literature is described. Section 5.3 presents the research methodology, which includes the use of a survey. Then, Section 5.4 describes our field work and formulates the results of our investigations. Thereafter, Section 5.5 discusses them. Finally, Section 5.6 provides an answer to RQ4 and yields our Chapter conclusion.

5.2 Relevant Literature

The section is structured into six parts. Subsection 5.2.1 introduces the literature on the topic of Preventive/Proactive Law. Then, Subsection 5.2.2 presents sources on the intersection of PPL and Legal Technology. Subsection 5.2.3 shows the relevant sources on Proactive Control Data. Subsection 5.2.4 discusses the qualitative assessment criteria options for PCD. Subsection 5.2.5 applies literature findings on LLMs as a contract drafting medium. Finally, Subsection 5.2.6 compares our finding with the literature on ontology engineering and linked data.

5.2.1 Preventive/Proactive Law

Chapter 2 already introduced to a sufficient degree the literature on PPL. Below we provide a summary to bring the text in line with the other five topics. The birth of PPL was in 1950, when Louis M. Brown introduced the concept of *preventive law* [Brown and Rubin, 1950]. Brown (1950) believed that preventive law concerns the cost difference between entering into and avoiding legal costs [Brown and Rubin, 1950]. 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* [Wexler, 2000], which is concerned with the health of legal subjects, and the other is *proactive law* [Haapio and Varjonen, 1998], which focusses 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 [Barton, 2016]. Recently, PPL is endowed with (1) the visualisation of legal information and (2) the effects of technology on PPL [Corrales et al., 2019a]. 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 [Iversen, 2004]. Gradually, the connection between LRM with PPL was established [Mahler and Bing, 2006].

5.2.2 Preventive/Proactive Law and Legal Technology

Susskind was the first to notice the relation between preventive law and technology [Susskind, 1996]. PPL researchers reinforced that notion by stating that the emerging technological culture is largely compatible with the assumptions underlying PPL [Barton, 2016]. 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 [Barton et al., 2016]. They are also questioning and investigating the effects of new technologies for PPL and legal design [Corrales et al., 2022]. 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 [Susskind, 1996], 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 progress has been made on integrating PPL with legal technology.

5.2.3 Proactive Control Data

The concept of PCD is based on the Bow-Tie Method terminology, which is introduced in Chapter 3. The Bow-Tie Method helps in performing visual legal risk analysis [Haapio and Siedel, 2013]. 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 [1]. In this Subsection we only concentrate on the proactive risk measures, since they are directly relevant to the prevention of a hazardous event. Reactive measures play a mitigating role once a hazardous event has already occurred.

The Bow-Tie Method guides us through the *hazardous events* (henceforth sometimes '*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*, of which the 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 that 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).

From a methodological perspective, in order to identify Proactive Data, the use of three methodologies is possible: (1) Scenario Planning [Amer et al., 2013], (2) Post-Mortem Analysis [Stålhane et al., 2003] and (3) Pre-Mortem Analysis [Klein, 2007, Adriaanse and van der Rest, 2020]. From a reasoning point of view, Proactive Data can be identified (whether one uses one of the three aforementioned methodologies or not) by applying investigations along the following line (a) deductive reasoning (also called *ingenuity*), (b) inductive reasoning (also called *ingenuity*), and (c) abductive reasoning (also called *intuition*) (together also known as *Inferential Reasoning*).

Successfully avoiding a hazardous event depends on the availability of prior Proactive Data [Niiniluoto, 1999], 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 [Larson, 2021]. Still, Van den Herik believes that intuition can be programmed [van den Herik, 2015, van den Herik, 2016]. However, as matters stand now, the programming of intuition is only in its experimental stage. A big step towards qualitatively equal results has been made by the develop-

[1] https://www.wolterskluwer.com/en/solutions/enablon/bowtie/expert-insights/barrier-based-risk-management-knowledge-base/the-bowtie-method

ment of Deep Learning (DL) [LeCun et al., 2015]. All in all, the last word has not been said. From 2018 to 2021 it was believed that DL would fully outclass other advanced techniques based on pattern recognition. Although, fully relying on (well chosen) pattern recognition was able to prove that DL process may overlook a winning possibility [2](which was a shock to public and researchers). Hence, DL is very good but not perfect.

For the moment we will accept that the automated identification of Proactive Data can be achieved with Expert Systems (ES), ML and DL. As an example of intuition programming, we point to the adjacent topic of *scenario planning*; within this area there exists an *intutitive* technology developed by Pandora Intelligence [de Kock, 2014]. Thus far, Pandora Intelligence relies on future scenario prediction based on historical and present data via technology that combines ES and ML [3].

5.2.4 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. In the 1990s, Pierre Schlag examined the interpretative nature of constitutions, and 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 (meaning conceptual vagueness) [Schlag, 1996], 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 argued already over sixty years ago that the meaning of law is generally *clear*, *certain*, and *stable* at its core, but less so at its penumbra [Hart, 1958]. This leads to *vagueness* and *open-texture*, meaning the abstract meaning of legal terminology, which is up to today an unresolved issue in legal literature [Soames, 2012, Escher, 2021, Culver, 2004].

As a consequence, legal experts have learned to deal with the law in non-ontological manners. Those manners may include technical, normative, or epistemic approaches [Schlag, 1996]. As a result, legal experts have learned to deal with the law from the perspective of *legal pragmatism* [Schlag, 1996]. 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 [Farber, 1988]. As a result, the law leads away (1) from the ontological

[2] https://mashable.com/article/google-s-alphago-wins-final-go-game-against-lee-sedol

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

to the epistemic, then (2) from the epistemic to the normative, and nowadays (3) from the normative to the technical [Schlag, 1996]. 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. Below we discuss the content identification of Proactive Data, i.e., how it becomes possible (A) as well as we comment on the *defeasible nature* of argumentation (B).

A. 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. The *Logocratic Method* developed by Scott Brewer [Brewer, 2011] aims to explain the nature and two main uses of arguments. (1) One can evaluate an argument to determine the degree to which premises provide evidential support, by examining how much support do they provide for inferring that the the conclusion is true. (2) One can also evaluate an argument to determine the degree to which its premises provide agonal support for its conclusions (that is, whether the argument is strong in some one more more fora of arguments contests, such as in litigation; by definition, this is an assessment of the argument's agonal virtue.). As Brewer contends (drawing upon John Dewey), the LM 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"* [Brewer, 2022].

B. Defeasible Arguments

The highest possible degree of the evidential virtue of an argument (see 5.2.4(A) above) is validity [Walton, 1996]. Validity is the property of an argument such that, whenever all the premises of the argument are true, the conclusion must also be true. Not all arguments have this degree of evidential virtue, that is, not all arguments are valid [Walton et al., 2008]. One may identify a genus of arguments that do not have the property of validity. One species in this genus is arguments that, although they an be fairly interpreted as deductive arguments, nevertheless are invalid (one example is arguments that commit the fallacy of "denying the antecedent," reasoning from 'If P then Q' and 'not-P' to 'not-Q') [Brewer, 2018]. The other species in this genus are defeasible arguments [Brewer, 2018].

As explained in Logocratic terms: *"A defeasible argument from premises 1–n to conclusion h is one in which it is possible that the addition of some premise(s), n+1, to 1–n, can undermine the degree of evidential warrant that premises 1–n provide for h. As this definition indicates, the only kind of argument that is indefeasible is a valid deductive argument."* [Brewer, 2018]

Due to the ontological emptiness of contracts, there will always be premises which can only be examined probabilistically. Bart Verheij demonstrated 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 [Verheij, 2003]. 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"* [Simon, 1985].

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. Although, we need to be aware that in making assessments of risk in preventive abduction, one relies on explanations (abductions) that in turn rely on inductive generalizations and specifications, and all types of induction are defeasible.

5.2.5 Large Language Models and Contract Drafting

Recently, LLMs emerged in the field of Natural Language Processing (NLP), enabling transformative advances in diverse applications such as machine translation, sentiment analysis, and text summarisation [Brown et al., 2020]. By leveraging vast amounts of training data and employing advanced neural architectures, such as the transformer [Vaswani et al., 2017], LLMs have demonstrated remarkable proficiency in both analytical and generative tasks. The three main types of LLMs based on transformers are the following [Cai et al., 2022]. First, Encoder-Only, such as BERT [4], that utilises only a transformer encoder to generate contextual relations. Second, Encoder-Decoder, such as BART [5], which introduces a combination in using an encoder to process input text and an decoder to process ouptut text. Third, Decoder-Only, such as GPT [6], which uses only a decoder to produce contextually relevant outputs based on given prompt.

[4] https://github.com/google-research/bert
[5] https://huggingface.co/docs/transformers/model_doc/bart
[6] https://openai.com/chatgpt/

The two general uses of LLMs are analysis and generation. The main challenge with analysis is classification, while the main issue with generation is language. Our research is mostly concerned with classification or the conversion of text into knowledge structures, such as ontologies. For our purpose, encoder-only models are very relevant due to the high effectivity in domain-specific knowledge representation and the translation of abstract legal language into knowledge structures [Limsopatham, 2021]

A notable difference between encoder-only models and models that involve decoding, is that the encoder models do not suffer from hallucinations. In fact, it is possible to reduce hallucinations during decoding by focus on encoding. To further improve accuracy, using fine-tuned decoder models is also possible. To that end, three methods that can be used to reduce inaccuracies and improve factuality, are Retrieval-Augmented Generation (RAG), TruthfulQA and TruLens. RAG combines retrieval models with generative models to enhance accuracy and relevance of generated text by grounding it on knowledge structures [Wu et al., 2024, Es et al., 2023]. TruthfulQA is a benchmark to evaluate the accuracy and truthfulness of LLM output [Lin et al., 2021], and TruLens is a framework designed to track and explain ML decisions via interpretability and transparency [Datta et al., 2022].

In relation to contract drafting, employing fine-tuning techniques would allow a decoder 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 [Chalkidis et al., 2020]. Following this line of action, incorporating established legal principles via encoding can support the decoding in generating text that is comprehensible for specialised human objectives [Nay, 2023]. Essentially, the higher degree of classification by means of encoding, especially for legal tasks which are vastly complicated, can help improve the outcomes of a decoder. To that extent, the relevance of ontology engineering is high and can be leveraged so that a decoder algorithm attains a higher degree of classificatory accuracy and improved encoding performance vi ontology-based encoding.

Beyond algorithmic considerations, deployment parameters should also be taken into consideration. Ensuring the security and privacy of sensitive legal data during the training process is important (such privacy concern mostly cloud-based systems and not necessarily on-premise systems). This necessitates the implementation of secure and privacy-preserving machine learning techniques [Abadi et al., 2016]. Additionally, the explainability and interpretability of LLM-generated content are critical concerns, as legal professionals must be able to comprehend and justify the rationale behind the generated text [Arrieta et al., 2020].

5.2.6 Ontology and Linked Data

An *ontology* refers to a formal domain model in which concepts and relationships between concepts are described [López et al., 2012]. 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 the relationships will improve 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 and assist encoding models with improving analysis results via improved classification.

Ontologies and linked data may positively influence contract automation by offering structured representation of contractual concepts that may facilitate contractual interpretation and connection with multiple legal sources, demonstrating benefits for either automated compliance or reasoning [Palmirani et al., 2018, Athan et al., 2013]. Regarding risk management, (1) ontologies contribute to standardisation and (2) linked data enable integration with information across data-bases [El-Ghalayini, 2017, García and Gil, 2020]. The closest work to proactive controls, in accordance with the bow-tie method, lies with ontologies aiming to formalise the bow-tie terminology and linked data concerned with identifying hazards across multiple industries [Bloem and Reniers, 2019, Koren et al., 2021].

5.3 Research Methodology

This Section presents the methodology of our research. The methodology concerns four main topics: (5.3.1) using a case study for iContracts Proactive Data, (5.3.2) the development of an iContracts prototype , (5.3.3) the development of an LLM experiment, (5.3.4) the application of the LM when designing data for Proactive Data and (5.3.5 the development of a quantitative experiment.

5.3.1 Case Study

Our case study will focus on an agreement between a freelancer and a client (contractors). It is motivated by our previous case studies as seen in Chapters 3 and 4. The legal expert will (a1) define the scope of the agreement, (a2) conduct the risk analysis, (a3) define the legal questions for the two contractors, and (a4) visualise the risk analysis next to the questions. Then, the contractors will (b1) answer the legal questions and (b2) the legal expert may process potential modal information before the contract is generated, and (b3) will send the result to the contractors. The case study will concentrate on a specific risk, i.e., the payment risk. An example of applying the EBTO to a payment risk case study has already been presented in Chapter 4 [Stathis et al., 2023c]. Its visualisation is accessible via GitHub [7].

5.3.2 Prototype Development

We have built a prototype web application that uses the Onassis Ontology and EBTO structure to guide users in identifying legal risks and proactive controls during the negotiation and generation of a contract [8]. For a visual overview of the user interface and the user interaction we refer to [9]. 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 the freelancer and the client have answered the contract-specific questions, a legal expert uses those answers to fill in the text in a template contract. The expert may 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 the freelancer. These questions can be about the (new or predefined) risks, proactive controls, or about initial questions on the contract to which client and freelancer provided conflicting answers, e.g., about the milestones or the 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 Ontology and EBTO (or 'model'). We explain the stored data, which help in isolating PCD, in more detail with examples of data actually generated by the prototype in the Results Section in 5.4 [10].

[7] https://github.com/onassisontology/onassisontology/b\lob/main/img/Visualisation.png

[8] https://github.com/onassisontology?tab=repositories

[9] https://github.com/onassisontology/icontracts-front-end/blob/main/README.md

[10] See Appendix and Github: https://github.com/onassisontology/icontracts-back-end

5.3.3 Large Language Models Experiment

According to Chapter 2, text generation can be applied to minimise the involvement of the legal expert during the contract drafting process [Stathis et al., 2023d]. Instead of using legal experts as an experimental subject, who have *inconsistent* contract drafting styles, we are going to leverage ChatGPT, which has a more consistent contract drafting style and which is more measurable for research purposes.

ChatGPT is an AI chatbot developed by OpenAI and launched in November 2022 [11]. It is built on top of OpenAI's GPT Plus family of LLMs and has been fine-tuned using both supervised and reinforcement learning techniques [12]. ChatGPT can be used to generate text data, which includes drafting contracts. Two limitations decoder transformers are facing relevant to our study are as follows. (1) The training data is vast and perhaps over-exhaustive, which means potentially PCD are already fed in the algorithm (however, we are not in a position to know that). (2) Decoder models lack knowledge-driven intuition which would otherwise be leveraged by a legal expert to draft a contract with greater safety based on PCD.

The command we provided to ChatGPT *without* explicitly mentioning PCD reads as follows: "Write a payment clause for a freelancer contract." The command we provided to ChatGPT that *explicitly* mentions PCD reads: "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 [13].

5.3.4 Logocratic Method

The application of the Logocratic Method on the qualitative evaluation of PCD is possible for so long as we see an identified PCD as an argument. According to the LM, there are four modes of inference: (1) deduction, (2) induction, (3) abduction and (4) analog-duction. Of these four, abduction is the "first among equals" [Brewer, 2022] in that abduction plays a role *within* virtuous inductions and *within* virtuous analog-ductions and there are several types of abduction that operate within legal reasoning, including legal abduction, interpretive abduction and rule abduction. Abduction also plays a vital role in risk analysis. In this thesis, I identify a new type of explanatory argument which I will refer to as *preventive abduction*.

[11] `https://en.wikipedia.org/wiki/ChatGPT`
[12] `https://en.wikipedia.org/wiki/ChatGPT`
[13] `https://www.diffchecker.com/text-compare/`

According to the logocratic explanation of abduction, its "meta-abduction", an abduction has two main components: (1) a four step pattern of inference and (2) the concept of a *point of view* (=meaning the set of judgments, methods and axiological aims within which every abduction takes place), which is *explanatory* in nature [Brewer, 2020, Brewer, 2022]. Below we attempt to represent only the essential elements of Brewer's theory of abduction for our case study [Brewer, 2022].

Premise ε_1	Θ [some phenomenon to be explained, the *explanandum*]
Premise(s) $\varepsilon_{2n\text{-}m}$	For each candidate Φ_i, '$\Phi_i \surd \rightarrow \Theta$' is true. ['$\Phi_i \surd \rightarrow \Theta$' is the *plausibly serviceable explanation conditional*, read as 'if explanans Φ_i were true or otherwise warranted, it would provide a *plausibly serviceable explanation* of Θ.']
Premises ε_3 and ε_4	For candidate Φ_n, '$\Phi_n \surd\surd \rightarrow \Theta$' is true. ['$\Phi_n \surd\surd \rightarrow \Theta$' is the *most serviceable explanation conditional*, that is, the one member of the set of proposed explanations that, in the abductive reasoner's judgement, is the *most serviceable among the set of plausibly serviceable explanations*. This step is constituted by the disconfirmation of all of those plausibly serviceable explanations identified in the articulation of Premise(s) $\varepsilon_{2n\text{-}m}$ until one, Φ_n is 'left standing' to be endorsed as *the most* serviceable explanation. The Logocratic explanation of abduction, like the accounts that regard abduction as inference to a single best explanation among those that are plausible, regards all abductions as instances of what some philosophers refer to as *contrastive inferences*.[67]]
Conclusion h	Φ_n [Φ_n is the explanation identified in step ε_3 that is settled on as *the* explanation, the *explanans* of the explanandum.]

Figure 5.1: Abstract Structure of Abduction

On a practical level, to apply the LLM we start by identifying arguments (Enthymeme) and then by fairly formally representing them; whereas we judge as matter of interpretation, whether the representation is based on as deduction, induction, abduction or analog-duction [Brewer, 2022]. According to LM's distinctive conception of the concept of the enthymeme, an enthymeme is a proposition whose logical form is not explicit in its original mode of presentation [14]. Consider for example what we may call the Socrates text: *Socrates is a man, so he will die.*

The first interpretative decision to be made is whether there is an argument at all, even though its logical form is not explicit (that is, it is an argument enthymeme) [Brewer, 2022]. Suppose we do believe that there is a set of premises to support a set of conclusions. If that is our interpretative judgment we might represent the argument as follows, using E(n) to label a premise and H(n) to represent the conclusion [Brewer, 2022].

Example for deduction

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

Example for induction

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

[14] Brewer discusses the distinct conception of the enthymeme and compares it to other conceptions in [Brewer, 2022]. The two most important differences between the LM conception and other conceptions is that on the LM conception both rules and arguments can be enthymematic, whereas under one version of the classical conception only arguments can be enthymematic. The other important difference is that on the classical conception of the enthymeme only syllogistic arguments are understood to be enthymematic, while on the LM conception any argument in any of the four modes of inference can be enthymematic.

The precise point of view we take when interpreting or explaining a PCD as argument is the point of view of prevention, driven by the unique axiology of prevention which requires a PCD to prevent a hazardous event from occurring. Thus we may in fact label our argument evaluation of PCD, or any other argument evaluation aimed at prevention, as *preventive abduction*. Central to preventive abduction is the role of deduction and induction, since, according to Brewer, any type of abduction is based either on deduction or induction. The evaluation of a deductive preventive abduction is based on the indefeasible evidential strength of the premises offered for the conclusion, while the evaluation of inductive preventive abduction is based on the defeasible evidential strength of the premises offered for the conclusion, which may be examined according to probabilistic criteria, where probabilities sum to less than 1. By evidence we may refer to any type of propositional supporting data for the formation of a PCD, relative to propositional articulation of specific hazardous events and risk causes. Moreover, provided that more domains than just the legal domain study proactive data, analog-duction may be used as well for the evaluation of a preventive abduction. An analog-duction may examine similar or dissimilar elements between at least two proactive controls in parallel domains, and derive insights to evaluate the relative strength of a preventive abduction, or even improve it.

5.3.5 Quantitative Experiment

Our quantitative experiment investigates the reliability of the Onassis Ontology and the EBTO via the application of the Cohen's Kappa (CK) coefficient [Warrens, 2014]. CK coefficient helps us measure inter-rater reliability on the basis of quantitative data [Vieira et al., 2010]. CK is one of multiple quantitative methods used in examining usability design [van Kuijk and Staats, 2012, van Kuijk et al., 2019]. It shows the agreement percentage between two independent raters concerning a body of data [Scholtes, 2024]. Cohen's Kappa is similar to correlation coefficients, it can range from 0 to plus 1, where 0 represents the amount of agreement that can be expected from random chance, and 1 represents perfect agreement between the raters [McHugh, 2012]. Essentially, CK uses statistics to measure the degree of agreement between two independent raters who are tasked with classifying data. To calculate the CK coefficient, the rater's data are collected on a contingency table, and then the following formula is used as shown in Figure 5.1.

- **P***o* refers to the observed agreement (how many times raters agree), and
- **P***o* refers to the expected agreement by chance, calculated on the basis that each rater will assign each data point randomly.

$$\kappa = \frac{p_0 - p_e}{1 - p_e},$$

Figure 5.2: Cohen's Kappa Coefficient Formula

Our quantitative experiment is designed with data from the Contract Understanding Atticus Dataset (CUAD) [15]. After downloading the CUAD dataset, we randomly selected relevant clauses as data. Such clauses act as paragraphs, within sections within a contract in accordance with the Onassis Ontology. The key question was: *what are the variables that update the paragraphs based on a contractor conversation?* The extraction of such variables, according to the Onassis Ontology, happens after a contractor answers a question. However, not all variables derive from straight-forward question-answering. In more complex cases negotiations take place.

For this quantitative analysis we generated conversation data via ChatGPT based on a clause in order to mirror a real-life negotiation. The ChatGPT prompt was as follows: "create a fictional negotiation between two contracting parties regarding the following clause in 100 words (please do not provide an amended clause - I only need the negotiation) and then separately clarify the main risk of the clause in 25 words: [insert CUAD Clause]"

Thereafter, we asked the raters five questions:

1. Do you identify variables in the conversation to update the clause? (Yes / No)

2. Are the variables equal to or more than three? (Yes / No)

3. Is the likelihood of the risk happening high? (Yes / No)

4. Is the impact of the risk happening high? (Yes / No)

5. Are the identified variables sufficient proactive controls to prevent the risk from occurring? (Yes / No)

The particular structuring of the questions was subject to 7 rounds of trial and error provided that initial questions were not showing a high agreement (in fact, initially 3 to 4 rounds showed 0.0 agreement). Eventually, as you will see in the results (Section 5.4.3) we only arrived to a sufficient agreement (above 70

[15] https://www.kaggle.com/datasets/konradb/atticus-open-contract-dataset-aok-beta/data

percent) only after reducing the options of answers (either yes or no), reducing the words in the negotiation and reducing the complexity of the questions.

In total, there was 10 clauses with each one relating to a risk, section and a conversation, presented to the raters as an excel file (they are all accessible in Appendix 4A). We had two raters named Rater 1 and Rater 2. Each rater provided a reply in a separate excel sheet. The final answers of the raters are provided in Table 5.1 (Rater 1) and Table 5.2 (Rater 2) below and are also accessible in the Appendices.

5.4 Research Results

The section presents our research and then the four results. First, the generation and isolation of PCD via the experiment is presented (5.4.1). Second, the impact of PCD on contract drafting based on the LLM experiment is shown (5.4.2). Third, the application of the LM on an example of Proactive Data is presented (5.4.3). Fourth, we calculate the CK coefficient (5.4.4).

5.4.1 Proactive Control Data Generation and Isolation

We designed and built a prototype web application that uses the Onassis Ontology and EBTO 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 or the Appendices (see Appendix 4A [16]) [17] [18]. It contains 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 and in the Appendices (see Appendix 4A [19]) [20] show the user interface and exemplify the user interaction of the web application.

The prototype validates two main points. First, (1a) the development of iContracts based on the Onassis Ontology and EBTO structure is possible, (1b) 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.

[16] https://github.com/onassisontology/onassisontology/blob/main/Appendices_PhD.pdf
[17] https://github.com/onassisontology/icontracts-back-end
[18] https://github.com/onassisontology/icontracts-front-end/blob/main/README.md
[19] https://github.com/onassisontology/onassisontology/blob/main/Appendices_PhD.pdf
[20] https://github.com/onassisontology/icontracts-front-end/blob/main/README.md

No.	Identify Variables	Variables ≥ 3	Risk Likelihood	Risk Impact	Sufficient Controls
1	Yes	Yes	Yes	Yes	No
2	Yes	Yes	Yes	Yes	No
3	Yes	No	Yes	Yes	Yes
4	Yes	Yes	Yes	Yes	No
5	Yes	Yes	Yes	Yes	No
6	Yes	Yes	Yes	Yes	Yes
7	Yes	Yes	Yes	Yes	Yes
8	Yes	No	Yes	Yes	No
9	Yes	Yes	Yes	Yes	No
10	Yes	Yes	Yes	Yes	No

Table 5.1: Rater 1

No.	Identify Variables	Variables ≥ 3	Risk Likelihood	Risk Impact	Sufficient Controls
1	Yes	Yes	Yes	Yes	No
2	Yes	No	Yes	Yes	Yes
3	Yes	No	Yes	Yes	Yes
4	Yes	No	Yes	Yes	No
5	Yes	Yes	Yes	Yes	No
6	Yes	Yes	Yes	Yes	Yes
7	Yes	Yes	Yes	Yes	Yes
8	Yes	Yes	Yes	Yes	No
9	Yes	Yes	Yes	Yes	No
10	Yes	Yes	Yes	Yes	No

Table 5.2: Rater 2

5.4.2 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. It shows that the content (including wording and grammar) of the contract have been significantly altered, with its new version including more PCD-specific semantic information expressed in syntactically adequate sentences. The results can be accessed via [21].

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

Our experiment can be further explored within the context of recent advances with RAGAs and prompt engineering to improve the contextual quality of produced output. This occurs because as research advances, the contextual relations of textual ouput relative to specific prompting within specific knowledge based also increases as a result.

5.4.3 Quality Assessment

To apply the LM 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. Essentially, interventions mimics a Retrieval-Augmented Generation Algorithm (RAGA) which combine retrieval models with generation models for more accurate and relevant text.

Our proactive control example is the *timeline*, which prevents payment risk by helping parties agree about a schedule for the (expectation of) delivery of milestones. The application of the LM to the timeline example can be accessed via [22].

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 Ontology and EBTO structure as well as the LM are based on First Order Logic (FOL), therefore the application of the LM can be engineered towards an ontology with the

[21] https://github.com/onassisontology/onassisontology/blob/main/LLMexperiment

[22] https://github.com/onassisontology/onassisontology/blob/main/logocraticmethod

purpose of achieving a higher level of automation. Due to the high reliance of the LM on the data required to validate the enthymemes, such automation might be preferred assuming the availability of data at a larger scale.

5.4.4 Cohen's Kappa Coefficient

The first step to calculating the CK coefficient is adding the ratings into a contingency table, which you can see in Table 5.4.

	Yes	**No**
Yes	39	2
No	2	7

Table 5.3: Contingency Table

After applying the CK formula on the contingency table we arrive to a **0.73** CK coefficient. A CK value of 0.73 indicates high degree of agreement between the raters. A rough guideline to interpret the CK coefficient values is as follows:

- Less than 0: Poor agreement
- 0.00 - 0.20: Slight agreement
- 0.21 - 0.40: Fair agreement
- 0.41 - 0.60: Moderate agreement
- 0.61 - 0.80: Substantial agreement
- 0.81 - 1.00: Almost perfect agreement

A CK of 0.73 falls under the "substantial agreement" range, suggesting there is sufficiently strong agreement between the raters. It is in fact a relatively good result showing there is consistency in the raters judgment.

5.5 Discussion

The discussion concentrates on (5.5.1) prototype feasibility, (5.5.2) the impact of Proactive Control Data on contract drafting, (5.5.3) Proactive Data, (5.5.4) the value of Proactive Data and (5.5.5) the inter-rater reliability on the basis of the CK coefficient experiment results.

5.5.1 Prototype Feasibility

The prototype shows that it is feasible to generate PCD in a linked open data format. It also shows 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 will support legal experts with the application of the EBTO and the LM. As a direct consequence, it becomes imperative to examine the development of such innovation more deeply in commercial settings, next to furthering the scientific development of the theory in academia.

The application of the LM is also technologically possible in particular for inferencing purposes on the ontology. Its implementation can be automatically executed via ontology reasoners. The LM will then use the inferencing system (as employed in FOL or any other form of deductive logic [Deontic, Modal, Propositional, Predicate]). Ontology Web Language - Description Logic (OWL DL) (i.e., the semantics used to build the Onassis Ontology and the EBTO) follows the description logic which is a branch of FOL. The inferencing system used in the LM 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 LM [Singh and Karwayun, 2010]. The added value of the LM 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.

5.5.2 Impact of Proactive Control Data on Contract Drafting

During the application of PCD on prompt engineering it became evident that the generated text will change 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. The Calculemus-Flint Method 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 (Actor A does X) instead of the traditional ruleoriented perspective (Agents Y should behave Y). The software, ontology, and documentation relating to the Calculemus-FLINT Method is accessible at the following GitLab repository[23].

5.5.3 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 LM can help investigate the quality of the Proactive Data based on the examination of proactive data as argumentation schemes. Here, we admit that the application of the EBTO is a time-consuming process and the application of the LM further increases the time investment of a legal expert. This is the reason why (1) the implemented reasoners can be leveraged for assessing consistency and contradictions and (2) the quality assessment can be implemented only if necessary.

Moreover, the application of the LM does not necessarily guarantee that Proactive Data will be of high quality, provided that even the LM has limitations. All arguments are based on premises that can hardly be expressed in their totality provided they are subject to an infinite number of further underlying premises [Havenel, 2008]. Therefore, as the inferential structure deepens, complexity also increases and makes the task of representing reality in absolute terms eventually impossible.

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 to perform further experiments with the tools at hand.

5.5.4 Value of Proactive Data

To measure the value of proactive data 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. The goal of this Subsection is to 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. That is possible by the numerical analysis of relatively good quality Proactive Data. Indeed, any quantitative measurement is quite limited due to a lack of appropriate data. It is therefore difficult to make an estimation that comes close to truth. We can only hope to arrive at a reasonable estimation

[23] `https://gitlab.com/normativesystems`

with follow-up experimental research by other researchers. Therefore, the analysis we will make for now is restricted 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 [24]. Hence, according to the EBTO case study on payment risk, the likelihood for payment risk according to available data (see our quantitative experiment) seems to be 0.7[25]. The current question is the transformed to: how is this percentage affected once a freelancer agreement includes the identified PCD? To arrive at an acceptable estimation we would need to measure the extent to which each PCD reduces the likelihood for the hazardous event of non-payment to occur. Then we know for which test we require data. Hence, it becomes evident that the application of our results in practice is relevant and even more promising for further experimentation. By measuring the value of Proactive Data quantitatively, it becomes possible to conduct an economic analysis of (1) how an investment in Proactive Data reduces subsequent legal costs, and (2) how a reallocation of investments targeted towards dispute prevention can save millions of people from unnecessary legal costs. All in all, the more available data we can access, the better the nature of our quantitative analysis will be.

5.5.5 Inter-Rater Reliability

The CK coefficient of 0.73 is a relatively good result. When looking deeper into the questions and their context we note that despite a high level of agreement, the level is only relative to those specific questions and their abstraction level. For as long as we attempted to ask more complicated questions the level of agreement observed was lower. In fact, we found that the higher level of complexity of the questions, the lower was the level of the agreement. Moreover, the same applies to the data provided to the raters. Initially, we provided longer negotiations that lead to higher degree of rating discrepancies due to larger body of data, thus higher likelihood of difference in the answers of the raters. The more we arrived to reduced level of data complexity and question complexity, the easier it was to achieve more agreement. This only shows how much more work we need to put into experimenting with inter-rater agreement, by classifying further the data sets as well as the questions to as specific as possible categories for a particular domain in examination. The higher the specificity in data and questions, the higher the level of inter-rater agreement.

[24] https://blog.freelancersunion.org/2016/03/28/add-your-ious-worlds-longest-invoice/

[25] https://github.com/onassisontology/onassisontology/b\lob/main/img/Visualisation.png

5.6 Chapter Conclusion

This section presents: (5.6.1) the answer to the RQ, (5.6.2) further research suggestions, and (5.6.3) the progress of the research.

5.6.1 Answer to RQ4

The RQ4 is:

> **RQ4:** *To what extent is it possible to generate quality Proactive Control Data to improve an Intelligent Contract?*

Regarding RQ4 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 (1) their quantitative identification and (2) qualitative assessment, and (3) the use of relevant technologies that integrate the risk assessment (based on communication) data when a contract is generated.

Our contribution shows that the plain generation of PCD is possible with the available technologies. Moreover, it shows that PCD can be *quantitatively generated* with the application of the EBTO and can be *qualitatively assessed* with the LM to a certain extent. Attempting to achieve a higher degree of quality with the further application of the LM, runs the risk that the efficiency will be reduced. Even though the application of the LM 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” [Box, 2013]. Available technologies are already sufficient in implementing the findings of our research. Hence, the handling of Proactive Data in iContracts depends (a) on the specific application preferences of an organisation, (b) their resource allocation, and (c) issues related to technological innovation. Therefore, the answer to the RQ4 is that ”(1) the generation of PCD is possible, (2) their impact on contract drafting is significant, and (3) the generation of quality PCD is sufficiently possible within organisational conditions”.

5.6.2 Further Research

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 LM 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 LM and to what extent (having in mind Van den Herik's research statement on the possibility of programming intuition [van den Herik, 2016]). 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.

In relation to the technological pathway forward, decoder only LLM models (such as BERT) are successfully extracting ontologies and other Knowledge-Based Structures (KBS) from (legal) textual documents. State-of-the-art research indicates that such KBS can be used successfully to keep the drafted (legal) text and conversations more factual (e.g. reduce hallucinations significantly) by either generating background and system prompts from these KBS or to convert components of the KBS or document collections (in combination with search) into vector representations that are merged into the conversational vectors (Retrieval Augmented Generation). Applying such experiments to derive parts of the Onassis ontology from legal documents or to use the Onassis Ontology to control the drafting or conversations from hallucinating, will help us add value to the validity and impact of our research.

5.6.3 Research Progress

The progress of this research is that we have indicated how it is possible to practically generate Proactive Data quantitatively as well as examine them qualitatively. Moreover, the research is a step forwards because it develops one of the first practical prototypes of iContracts that shows the generation of Proactive Data in linked open data format is possible. Additionally, the LM, 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 shows 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 encouraging because it combines multiple FOL methodologies and technologies, and it shows 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.

CRediT Author Statement

Below I would like to give credit to all persons involved.

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Chapter 6

Risk Identification and the AI-ACT

The Chapter addresses RQ5, which reads as follows:

> **RQ5:** *To what extent is it possible to develop an explainable and trustworthy Preventive Legal Technology?*

Preventive Legal Technology (PLT) is a new field of Artificial Intelligence (AI) investigating the *intelligent prevention of disputes*. The concept integrates the theories of *preventive law* and *legal technology*. Our goal is to give ethics a place in the new technology. By *explaining* the decisions of PLT, we aim to achieve a higher degree of *trustworthiness* because explicit explanations are expected to improve the level of *transparency* and *accountability*. Trustworthiness is an urgent topic in the discussion on doing AI research ethically and accounting for the regulations. For this purpose, we examine the limitations of rule-based explainability for PLT. After an insightful literature review, we focus on case studies with applications. The results describe (1) the effectivity of PLT and (2) its responsibility. The discussion is challenging and multivariate, investigating deeply the relevance of PLT for LegalTech applications in light of the development of the AI Act (currently still under construction) and the work of the High-Level Expert Group (HLEG) on AI. On the ethical side, explaining AI decisions for small PLT domains is clearly possible, with direct effects on trustworthiness due to increased transparency and accountability.

The current chapter corresponds to the following publication:

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6.1 Preventive Legal Technology

The connection between law and technology is instrumental. Laws regulate the design and application of *technologies*, and technologies influence the design and application of *laws*. To what extent is it possible to bring the two disciplines together? It is an interesting question, and the answer lies in the development of AI.

AI research has matured from investigating the structure of the domain and the need for heuristics with the help of increasingly intelligent technologies, such as Expert Systems (ES), Machine Learning (ML), Deep Learning (DL) and today, Large Language Models (LLMs). First, scientists (such as John von Neumann [Labatut, 2023]) were concerned with trusting the fixed values of AI systems (intuitive acceptance). Gradually, they focussed on explaining the search directions (science). Today, we ask machines to *explain* their decisions for humans to be able to *trust* their line of reasoning (ethics). As a consequence, we expect machines to exhibit human-like intelligence. In hard science, we focus on trustworthiness, and we use explainability. In law, we focus on explainability and search for trustworthiness.

Considering the importance of explainability, law applications have become an exciting playground for experimenting with explanations and machine intelligence. AI and law have followed this trajectory since 1949, when Loevinger introduced Jurimetrics, i.e., using quantitative methods to analyse legal decisions [Loevinger, 1949]. In 1987, the first reasoner for explaining the reasoning supporting judicial decisions was created [Rissland and Ashley, 1987]. In 1991, Leiden University saw a remarkable Inaugural Address [van den Herik, 1991], in which the question "Can computers Judge Court cases?" was answered positively. Then, in 1996, Susskind predicted the shift from reactive facilities in the law (such as deciding on the resolution of a dispute) to proactive facilities (such as deciding on the prevention of a dispute) [Susskind, 1996]. This line of research will dominate the next thirty years [Scholtes, 2021]. Hence, we follow the trajectory of connecting AI with proactive facilities via the field of Preventive Law.

iContracts shows how it is possible to automate a contract based on risk and communication data, enabling the application of Preventive Law on contracts with the use of technology [Stathis et al., 2024]. Of course, the application of Preventive Law is not restricted to contracts only. The remainder of this Chapter aims to pave the way to the conceptualisation of *Preventive Legal Technology* (PLT) and its applications. We will investigate how PLT can show a line of reasoning in an *explainable* (Definition 6.1 [Longo, 2023] [1]), *interpretable* (see

[1] https://www.ibm.com/topics/explainable-ai

Definition 6.2 [Graziani et al., 2023, Ersoz et al., 2022]) and *trustworthy* (see Definition 6.3 [High-Level Expert Group on AI, 2019]) manner. This approach has lead to three specialised branches of AI research, which is based onExplainable AI (XAI), Interpretable ML (IML) and Trustworthy AI (TAI) principles (see the Definitions below).

*Definition 6.1 – **Explainable Artificial Intelligence***

Explainable AI (XAI) is a set of processes and methods that allows human users to *comprehend* and *trust* the results and output created by machine learning algorithms.

*Definition 6.2 – **Interpretable Machine Learning***

Interpretable Machine Learning (IML) is a system of which it is possible to *learn* its working *principles* and *outcomes* in human-understandable language without affecting the validity of the system.

*Definition 6.3 – **Trustworthy Artificial Intelligence***

Trustworthy AI (TAI) is AI that has three components: (1) it should be lawful, ensuring *compliance* with all applicable laws and regulations; (2) it should be *ethical*, demonstrating respect for, and ensure adherence to, ethical principles and values, and (3) it should be *robust*, both from a technical and social perspective, since, even with good intentions, AI systems can cause unintentional harm.

6.1.1 Towards Ethical and Preventive Legal Technology

Central to the discussion of AI is the topic of *trustworthiness* [Simion and Kelp, 2023]. Lack of trustworthiness is a genuine concern for the ethical impact and unintended consequences of new AI technologies for society [Ayling and Chapman, 2022]. The European Union (EU) Guidelines call for lawful, ethical and robust AI [2]. Here, we note explicitly that despite the various blind spots for the ethics of AI [Hagendorff, 2022], one of the main challenges of AI is that its decisions so far are *not transparent*, resulting in "black box" decisions [von Eschenbach, 2021]. Below, we briefly introduce XAI and TAI. A literature review expands on the concepts in 2.4.1 and 2.4.2.

XAI is the field of study investigating the *explanation* of AI system decisions [Xu et al., 2019]. XAI is assumed to lead to TAI, aiming to increase society's *trust* due to higher transparency and accountability [Munn, 2023]. The

[2] https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

concepts of transparency and accountability are vital in making AI more ethical, which is a central topic in the developing research on AI regulation according to the High-Level Expert Group on AI (HLEG) [High-Level Expert Group on AI, 2019]. Researchers have noticed a general disconnection between levels of actual trust and trustworthiness of applied AI [Laux et al., 2023]. In order to nurture practical trustworthiness, researchers changed their focus to *transparency* and *accountability* [Munn, 2023]. They started contributing to properly formulating measurable goals for the practical improvement of AI systems with direct implications on ethics. Meanwhile, other researchers were investigating AI's ethical and legal effects and were contributing to the development of the AI Act [European-Commission, 2021]. In the Netherlands, Maurits Kop is leading a group of researchers investigating how the development of Legally TAI (LTAI) by design is able to achieve a higher ethical transparency and accountability [Kop, 2021].

The idea is that more profound insight into XAI and TAI will enable us to examine PLT from two different perspectives: (1) the *effectivity* of PLT (application of PLT in law) and (2) the *responsibility* of PLT (application of the law on PLT). Examining the effectivity of PLT helps determine to what extent PLT is a distinct field of technology. Due to the reliance of PLT on Proactive Data, PLT can be considered a special type of Artificial Intelligence (AI). It is a type of Predictive AI (probabilistic future event forecasting based on historical data) rather than Generative AI (new data creation in text or image) [3]. Provided PLT constitutes such a distinct field, its responsible implementation in society emerges as a topic for research in light of AI regulation.

Our motivation is to clarify how Automated Individual Decision-Making (AIDM) can become compliant under Article 22 GDPR [European Union, 2016]. AIDM is the process of deciding by automated means without any human involvement. The basis of such decisions is on factual data, as well as on digital profiles or inferred data [4]. If AIDM includes explanations, then AI systems will be more trustworthy due to higher transparency and accountability. Consequently, organisations will be able to design AIDM that is ethical and legally preventive, which is beneficial for society because it reduces the appearance of legal problems and increases legal safety. Hence, we focus on *the intelligent prevention of disputes in an explainable and (legally) trustworthy manner*, in practical compliance with the ethical principles of *transparency* and *accountability*.

[3] https://www.blueprism.com/resources/blog/generative-ai-vs-predictive-ai/

[4] https://ico.org.uk/for-organisations/uk-gdpr-guidance-and-resources/individual-rights/automated-decision-making-and-profiling/what-is-automated-individual-decision-making-and-profiling/id2

6.1.2 Research Question 5 and Contribution

The preceding leads us to RQ5:

> **RQ5:** *To what extent is it possible to develop an explainable and trustworthy Preventive Legal Technology?*

To answer RQ5, we have partitioned it into three Smaller RQs (SRQ).

> **SRQ1:** *What is Preventive Legal Technology?*
>
> **SRQ2:** *To what extent is it possible to develop an explainable Preventive Legal Technology?*
>
> **SRQ3:** *To what extent is it possible to develop a trustworthy Preventive Legal Technology?*

Before addressing RQ5, we would like to introduce our contribution. We aim to show (1) that Proactive Data, the primary PLT data, are identifiable in all categories of LegalTech, (2) how to develop explainable Proactive Data with practical case studies, and (3) the legal and ethical implications of PLT in light of the AI Act and Predictive AI.

6.1.3 Chapter Structure

To answer RQ5, we structured the Chapter as follows. In Section 6.2, we describe the literature on ethics and AI. Section 6.3 presents our three methodologies: fieldwork, case studies and applications. Then, Section 6.4 describes the investigations and states the results. Section 6.5 discusses those results and focusses on trustworthiness and ethical parameters. Finally, Section 6.6 answers RQ5 and provides our conclusion as well as further research suggestions.

6.2 Literature Review

Many ideas about modelling intelligent behaviour started in ancestry and were further developed throughout history [5]. Nevertheless, most researchers attribute the starting point of AI to Alan Turing in 1950 [Turing, 1950]. Since then, two main AI movements emerged: the scientific one and the futuristic one [Larson, 2021]. The scientific AI movement supports the idea that formal reasoning

[5] See Greek Mythology (Talos, Pygmalion), Jewish Folklore (Golem), Paracelsus's Of the Nature of Things, Wolfgang von Kempelen's The Turk, Roger Bacon's brazen head, Mary Shelley's Frankenstein, Karel Capek's R.U.R., Samuel Butler's Darwin among the Machines, Aristotle's Organon and Francis Bacon's Organon.

is the basis of AI and is investigating whether intelligence can become artificial. The futuristic AI movement believes that intelligence will become artificial and will influence public opinion to accept that. While this dichotomy is still vivid, the state-of-the-art of AI is not yet able to *prove* how intelligence is programmable. Researchers support that AI today assists humans with ingenuity, contributing to intelligence, not intuition [Larson, 2021]. However, many researchers are investigating how to model intuition [van den Herik, 2015]. Here, we remark that despite the state-of-the-art observations, society is mainly influenced by the futuristic AI movement, expecting the replacement of carbon intelligence by silicon intelligence. Indeed, at this moment, the latter perspective may undervalue linguistic complexity, which is the basis of human intuition [6] [van den Herik, 2016, McWhinney, 2002]. In logic, ingenuity is modelled by deduction or induction; and intuition via abduction [Peirce, 1903, Brewer, 2023]. Admittedly, humans still do not know how to model abduction computationally [Larson, 2021]. The developments of AI follow, to a large extent, the developments in logic with modelling intelligence.

6.2.1 Explainable Artificial Intelligence

The modelling of *deduction* occurs via Expert Systems (ES) and *induction* via ML (and DL or LLMs), but AI so far has not modelled *abduction* [Larson, 2021]. The fundamental elements for ES and ML are "normal" data [Mueller and Massaron, 2018]. With this knowledge, we are ready for the next step: Explainable AI.

XAI follows a similar path as modelling deduction and induction. The focus of most XAI models is on explaining the decisions of inductive models and those of deductive models to a lesser extent due to the often reduced decision-making complexity [Xu et al., 2019, Gunning et al., 2019].

The reliance of AI on human reasoning affects AI by the similar challenges it faces. Two of those challenges are the *explainability* problem and the *interpretation* problem [Belém et al., 2021, Koster et al., 2021]. The first one explains decisions. The second explains how people interpret the world.

The XAI methods and techniques that have been developed in research so far span from rule-based explanations and attention mechanisms [Niu et al., 2021] to visual explanations [Kovalerchuk et al., 2021], Interpretable ML (IML) models [Vollert et al., 2021], and ethical variations [Mökander and Floridi, 2021] to the FAIR (Findable, Accessible, Interoperable, Reusable) model development [Adhikari et al., 2022, Hosseini et al., 2023]. Two notable frameworks developed

[6] https://medium.com/the-sophist/wittgenstein-intelligence-is-never-artificial-51933315d1bd

for advanced explainability and interpretability are SHapley Additive exPlanations (SHAP), a framework for interpreting predictions of machine learning models [Salih et al., 2024], and Local Interpretable Model Agnostic Explanation (LIME) a technique that explains the predictions of any classifier in interpretable manner [Salih et al., 2024].

One of the developing XAI techniques is rule-based explanations, which focus on symbolic reasoning and knowledge graph representation for developing human-readable model explanations (see Section 4) [Akyol, 2023, van der Waa et al., 2021]. The most advanced method in literature to represent explanations, applicable also to AI system decisions, is the Logocratic Method (LM) [Brewer, 2011], which explains the nature of arguments [Brewer, 2020] (to be discussed in Section 7).

6.2.2 Trustworthy Artificial Intelligence

Addressing the seven challenges (precisely defined by the HLEG [High-Level Expert Group on AI, 2019]) is a priority for Trustworthy Artificial Intelligence (TAI). Here, as part of the TAI movement, the field of responsible governance, with an eye on transparency and accountability, has been developed. The TAI field investigates how to develop standards and processes to make AI safe (or at least safer). The discussion about TAI and the relevant responsible governance standards is currently in development. The urgency for clarifying their content comes from the observed tendency in society for the development of AI applications [7]. One of the social challenges of AI concerns the *liability* issues arising from their operation. Liability examines who is to blame if something goes wrong [van Gerven et al., 2001]. Fundamentally, it investigates who is at fault. Based on the concept of fault, several liability regimes have been selected, particularly for AI. The two largest categories are *fault-based liability* and *non-fault-based liability*. Researchers are investigating which regime or combination of regimes is appropriate for AI liability [Tjong Tjin Tai, 2018]. In passing, we remark that we consider *liability* measures in parallel with *safety* measures [Wendehorst, 2020]. Usually, we see that with the introduction of new technologies, liability regimes adjust to correspond to the latest needs [Gifford, 2018].

TAI concerns (1) the trustworthiness of the AI system and (2) the trustworthiness of all processes and actors that are part of the system's life cycle [High-Level Expert Group on AI, 2019]. That is quite substantial. For interested readers, we refer to the broad and deep analysis of trustworthiness, by which variable principles, from *reliability* and *accuracy* to *sustainability* and *democracy*, are

[7] European Parliament, (2017), Civil Law Rules on Robotics, European Parliament Resolution of February 07 with recommendations to the Commission on Civil Law Rules on Robotics (2015/2103(INL)), European Parliament

included [Varona and Suárez, 2022]. Such principles may guide the ethical and legally trustworthy design of AI systems via the rule of law by focussing on properties including *transparency*, *verifiability* and *explainability* [Chatila et al., 2021].

Considering the difficulty of explaining or interpreting the decisions of AI systems, regulators are concerned about assigning liability to AI system decisions. Due to (a) the direct effect of AI on Law and (b) the liability of law concerns, some researchers argue that TAI is insufficient, but Legally Trustworthy AI (LTAI) is more important [Smuha et al., 2021]. The same holds for PLT, which is seen as an AI technology.

6.2.3 Regulating Artificial Intelligence

Consequently, even though society wants to be able to trust AI, they are still afraid of the positive answers to the challenges posed by XAI and TAI. In the first place, all governments in the world wish to protect their society from suffering fears. Therefore, the EU is attempting to take the lead in the movement of TAI [Rieder et al., 2021] via the research of the HLEG [8]. In passing, we note that the United States [9] and China [10] are also developing regulatory efforts. The European Commission (EC) has spearheaded research on this topic with a White Paper by identifying potential risks of AI affecting society from fundamental rights and privacy to industrial safety and legal liability [European-Commission, 2020]. Due to the significant focus on the Ethics of AI, an increasing amount of research in guidelines has been discussed in academic and political circles, leading to what some call the "AI ethics boom" [Corrêa et al., 2023]. The results are so far accessible in the Product Liability Directive (PLD) and the Artificial Intelligence Liability Directive (AILD) [11].

[8] https://digital-strategy.ec.europa.eu/en/policies/expert-group-ai

[9] https://www.judiciary.senate.gov/committee-activity/hearings/oversight-of-ai-rules-for-artificial-intelligence

[10] https://carnegieendowment.org/2023/07/10/china-s-ai-regulations-and-how-they-get-made-pub-90117

[11] https://commission.europa.eu/business-economy-euro/doing-business-eu/contract-rules/digital-contracts/liability-rules-artificial-intelligence_en

Regulating AI is *challenging* because we do not fully comprehend AI [Vihul, 2020]. People are still debating about the appropriate definition for AI [Fuzaylova, 2018] [12]. In the meantime, researchers are investigating the relevant ethical framework to guide any legal or social regulatory reform regarding AI [Bartneck et al., 2021]. We observe the three primary regulatory efforts in (A) China, (B) the US and (C) Europe, and ask ourselves: (D) how to combine them from a global governance perspective?

A: China

China has opted for an incremental regulatory approach following the developments of AI. The three core regulatory initiatives from the People's Republic of China are PRC Regulation I, regulating recommendation algorithms; PRC Regulation II, regulating synthetically created content; and PRC Draft Regulation III, recommending regulation on Generative AI [Sheehan, 2023]. Despite an observed difference in the motivations supporting the regulatory initiative from the Chinese Government, specific regulatory parameters are also observed in the Western (US and EU) efforts, paving the way for some consensus in international AI regulation [Sheehan, 2023].

B: United States

The US is in the process of developing regulation for AI [13]. Following the Executive Order of President Biden, taking into consideration the opinions of leading executives from AI institutions in the US [14], the direction of the US about regulating AI is becoming clearer [15]. The regulatory direction aims at strengthening AI governance, advancing responsible AI innovation, and managing risks from the use of AI, without adopting a risk-based approach as the EU proposes.

[12] https://www.euractiv.com/section/artificial-intelligence/news/oecd-updates-definition-of-artificial-intelligence-to-inform-eus-ai-act/

[13] https://www.whitehouse.gov/omb/briefing-room/2023/11/01/omb-releases-implementation-guidance-following-president-bidens-executive-order-on-artificial-intelligence/

[14] https://www.judiciary.senate.gov/committee-activity/hearings/oversight-of-ai-rules-for-artificial-intelligence

[15] https://www.whitehouse.gov/briefing-room/statements-releases/2023/10/30/fact-sheet-president-biden-issues-executive-order-on-safe-secure-and-trustworthy-artificial-intelligence/

The consensus of the Democratic party, supported by Majority Leader Schumer is inclined to support a "SAFE Innovation Framework for AI", where AI is seen as central driver for US economic growth and protecting American values [16]. The US seems to head towards the direction where business organisations have a significant degree of freedom to develop AI, for so long as they comply with fundamental safety principles.

C: European Union

In the EU, the EU AI Act has taken multiple forms over several iterative attempts to clarify how to regulate AI [European-Parliament, 2023]. This version amends the original proposal of the European Committee and is a provisional candidate for the AI Act. The expectation is that the AI Act will be closer to a proposal stage as regulation during the December 2023 discussions [17], with a final acceptance in the start of 2024. If it will not happen, then postponements will take place owing to the elections of the EU. Concentrating on the contents, here we remark that central to the EU is the topic of *safety*, which is visible by the reliance of the AI Act on progressing the *product safety regulation*. The EU regulatory proposal distinguished from its start among unacceptable risk (total ban), high risk (higher degree of regulation), and limited risk AI systems (voluntary transparency standards), and foundation models (registration in EU database) for Generative AI models (copyright disclosures, prohibition of illegal content) [European-Parliament, 2023]. Article 4a (1) is relevant to rule-based explainability, which requires developers and AI users to use their best efforts per principles of transparency as laid out in the regulation [European-Parliament, 2023]. The EU AI Act follows a more robust risk management approach than prior research efforts from the EU bodies due to supporting research by the EC's White Paper [European-Commission, 2020] and the HLEG [18].

D: Global Governance

When combining the Chinese, American and European approaches, we may find *similarities* and *differences*. Research shows that, in general, all regulatory approaches agree on fundamental risks and requirements [Rios-Campos et al., 2023]. The *risks* are black-box models, privacy violations, bias, and discrimination; the *requirements* are algorithmic transparency, human understandable

[16] https://www.democrats.senate.gov/news/press-releases/majority-leader-schumer-delivers-remarks-to-launch-safe-innovation-framework-for-artificial-intelligence-at-csis

[17] https://datamatters.sidley.com/2023/11/17/eu-moving-closer-to-an-ai-act/

[18] https://digital-strategy.ec.europa.eu/en/policies/expert-group-ai

explanations, privacy-preserving algorithms, data cooperatives, and algorithmic fairness [Rios-Campos et al., 2023]. However, in conclusion, the three regulations differ on the specific regulatory approach (e.g., risk-based vs non-risk-based) and the nature of compliance standards. A workable combination is open challenge to a world wide AI entity that should head the AI threat by a Silicon AI Treaty [19], as proposed by van den Herik during the European Conference on Artificial Intelligence (ECAI) 2023 (see also Subsection 6.5.3) [van den Herik, 2023].

6.2.4 Transparency and Accountability

While researchers and regulators worldwide investigate the safety of ethical principles in the design of AI systems, a straightforward and concrete challenge appears because of our inability to focus on one (or a few) of the divergent ways of protecting society from AI [Munn, 2023]. The primary motivator behind this challenge is the misalignment between (1) levels of actual trust and (2) the trustworthiness of applied AI [Laux et al., 2023]. As a direct follow-up, we mention the contribution by Luke Munn, who proposes an alternative perspective for ethical AI, going beyond procedural issues on bias, transparency and discrimination. On a macro-level, he proposes the concept of *AI Justice*, which comprehends the creation of AI as a part of social systems, subject to the ethical values of the systems they created [Munn, 2023]. He calls for an inter-sectional ethical approach, which includes (1) diverse groups in designing AI systems, (2) the re-definition of outdated ethical concepts, and (3) ensuring that fundamental social inequalities are addressed [Munn, 2023]. On a micro-level, he advocates two practical concepts for the design of AI: *transparency* and *accountability* [Munn, 2023]. Indeed, the latter two concepts will contribute to measurable goals for the practical improvement of AI systems. Furthermore, that is what we currently need.

Such a practical approach towards designing AI systems - if possible to be realised - will bring clarity in AI development and ethical auditing of AI algorithms [Mökander and Floridi, 2021]. For example, when large multinational organisations are subject to Ethics-Based Auditing (EBA), they will face challenges including ensuring harmonised standards across decentralised organisations, demarcating the scope of the audit, driving internal communication and change management, and measuring actual outcomes [Mökander and Floridi, 2023]. The ethical design of AI will then be the guideline to (1) the organisations and (2) the social systems that create AI [Mökander and Floridi, 2023]. All in all, ethics will then arise in the context of the socio-technical systems that cre-

[19] https://www.technologyreview.com/2023/05/02/1072566/the-download-geoffrey-hintons-ai-fears-and-decoding-our-thoughts/

ate them [Stahl, 2022]. Munn's inter-sectional ethics approach becomes feasible with the diverse inclusion of ethical practices within organisations, nudging towards the institutionalisation of ethics [Schultz and Seele, 2023] and the re-evaluation of AI business practices [Attard-Frost et al., 2023]. Consequently, evaluating group values and interests *becomes possible* as well as a fair comparison of the personal with group values [Rieder et al., 2021]. In practice, despite the desire from developers and designers of AI systems to adopt more practically ethical approaches, a gap is observed with systematic practices that can direct their operations despite multiple attempts to make sense of the regulatory requirements [Sanderson et al., 2023, Agbese et al., 2023].

It is due to the challenge of translating ethical concepts into practical solutions for AI development and the implementation of the results that the field of AI Ethics-By-Design has emerged [d'Aquin et al., 2018, Michael et al., 2020]. The field addresses vital ethical concerns in the ethical development of AI, such as: *how can and should we develop ethically-aware AI agents whose behaviour is adaptable to socio-ethical contexts?* [Dignum et al., 2018] To nurture such development, the experts involved in AI development should find consensus in the principal values to guide the design of AI systems [Gerdes, 2022, Muhlenbach, 2020]. Designing such ethically aware AI agents will impact policy-making by creating the need for investigating the establishment of legal protection for AI agency [Iphofen and Kritikos, 2021]. Public opinion will also affect such policy-making, whose perception of the topic is far from reaching any consensus [Kieslich et al., 2022].

6.3 Research Methodology

The research methodology concentrates on two distinct approaches: case studies and legal framework application. First, the basis for selecting case studies is Legalcomplex's list of LegalTech solutions (see Subsection 6.3.1) [20]. After validating to what extent Proactive Data applies to the LegalTech solutions, we selected three case studies from the LegalTech applications. The aim is to develop Proactive Data explanations. Second, we clarify the AI-Act liability framework to apply to the three case studies in a comparative setting(see Subsection 6.3.2). For the comparative significance, concerning the focus of the AI-Act on risk-based AI, we directed the selection towards *three* categories of case studies (viz. high-risk, mid-risk and low-risk case studies). Even though the AI Act proposal/amendment distinguishes between high-risk and limited-risk AI, for practical research purposes, we have partitioned limited risk into mid-risk and low-risk to facilitate the creation of more detailed research findings and to show the

[20] https://legalcomplex.com

practical difference between levels of limited risk and their impact. We do not discuss unacceptable AI or Generative AI in the methodology.

6.3.1 Case Studies

Given that the development of categorisation criteria is a complex process, we are pleased to report that we were given access to the categorisation used by Legalcomplex. They have been categorising and recording LegalTech solutions for several years, The categorisation is the best one available. Legalcomplex provided us with information of six categories of LegalTech applications listed in Table 6.1. The six categories of solutions are: (A) FinTech, (B) WealthTech, (C) RiskTech, (D) LegalTech, (E) SmartTech and (F) CivicTech. Legalcomplex structures all collected company data so that all six categories fit within the giant umbrella of LegalTech. However, it is essential to differentiate between *specific* LegalTech solutions that focus on lawyers as end users and *general* LegalTech solutions that encompass a more comprehensive range of six categories. Two categories also include subcategories. The first is RiskTech with (C1) Security, (C2) Insurance, and (C3) Governance, Risk, and Compliance (GRC). The second is SmartTech with (E1) Image Recognition, (E2) Audio Recognition, (E3) Text Analytics, (E4) Data Analytics, and (E5) Automation. Table 6.1 [21] includes specific descriptions (Column 3) for each category (Column 1) and subcategory (Column 2)—fourteen in total—and for the end users (Column 4) being top private companies (Column 5). The number of categories is six, and of subcategories is eight. In total, there are fourteen (sub)categories.

The three case studies we selected are based on three LegalTech solutions found in Table 6.1. The framing of explanations assumed that an AI system would be able to advise an end-user based on Proactive Data.

- The **low-risk** solution concerns using Lemonade (RiskTech, Insurance) for purchasing car insurance (see Table 6.1, Column 5).
- The **mid-risk** solution concerns using OpenAI (SmartTech, Text Analytics) for creating a construction plan (see Table 6.1, Column 5).
- The **high-risk** solution concerns using Palantir Technologies (SmartTech, Data Analytics) for applying predictive policing during a riot (see Table 6.1, Column 5).

To represent the Proactive Data and their explanations, we will use generated data by ChatGPT. Generated explainable proactive data are produced based on

[21] The Table categorises technology solutions based on buyers and end users, not operators or beneficiaries.

a question that seeks explanation (explanandum) in compliance with the LM.

- For the **low-risk** case study, the explanandum is: What insurance should we provide to a client who bought his first car (s)he is 27 years old and has been caught drinking when (s)he was underage?

- For the **mid-risk** case study, the explanandum is: When deciding to build a tall building next to a residential area, should we add a net to catch people who may fall, at the expense of a better view of the surrounding area?

- For the **high-risk** case study, the explanandum is: During a scary, fast-developing riot in the middle of the city centre, should we employ predictive policing to predict and prevent potential harm to citizens, even if the predictive policing system may consider some of the rioters sufficiently dangerous?

6.3.2 Liability Framework Application

The EU is still investigating an appropriate liability regime for regulating AI [Wendehorst, 2020]. From the beginning, the general academic opinion supports a strict liability regime, proposed in a way that does not discourage innovation [Tjong Tjin Tai, 2018]. Researchers focus on a risk-based approach, whereas the riskiest AI should be strictly liable, with specific uses of AI being prohibited [Wendehorst, 2020]. Indeed, researchers support that having a liability regime for AI will benefit society and the industry [22]. The EU started working on a legislative reform investigation in 2015 [23]. Since then, several researchers and experts have investigated the challenges of AI liability regimes. Currently, the EU tends to support the idea of strict liability for high-risk AI systems. That is because the existing legal framework, based on the PLD, has gaps [Cabral, 2020]. The PLD proposes a fault-based liability regime, although, since its establishment in 1985, it has not covered the new AI challenges within it.

[22]Committee on Industry, Research and Energy for the Committee on the Internal Market and Consumer Protection, (2021), Opinion on shaping the digital future of Europe: removing barriers to the functioning of the digital single market and improving the use of AI for European consumers, European Parliament

[23]Legislative Observatory, (2015), 2015/2103 (INL) Civil law rules on robotics, European Parliament

Table 6.1: LegalTech Categories

Category	Subcategory	Description	Customers/Buyers	Top Private Company
FinTech		Innovative technology for financial services, such as blockchain, digital payments, and mobile banking**	Banks, consumers, businesses	Stripe
WealthTech		Focusses on wealth management and investment, including robo-advisors and online trading**	Investors, financial advisors, banks	Betterment
RiskTech	Security	Protects digital/physical assets and systems from unauthorised access, theft, or damage**	All industries, governments	CrowdStrike
	Insurance	Streamlines insurance processes and offerings through data analytics, Machine Learning (ML), and AI**	Insurance companies, brokers	Lemonade*
	GRC	Manages regulatory, compliance, governance, and risk strategies with automated processes and technologies, contract management, and automation**	All industries, governments	MetricStream
LegalTech		Technology for legal services and processes, such as contract drafting and AI-driven research**	Law firms, legal departments	Clio
SmartTech	Image Recognition	Analyses visual data using computer vision, ML, and AI for various applications**	All industries, governments	DeepMind
	Audio Recognition	Processes and analyses audio data for voice assistants, transcription, and sentiment analysis**	All industries, governments	Nuance Communications
	Text Analytics	Uses NLP, ML, and AI to analyse unstructured text for insights and patterns**	All industries, governments	OpenAI*
	Data Analytics	Analyses large data sets for patterns, trends, and insights to make data-driven decisions**	All industries, governments	Palantir Technologies*
	Automation	Employs technology for tasks with minimal human intervention, such as in robotics and process automation**	All industries, governments	UiPath
CivicTech		Enhances civic engagement, government services, and transparency with technology solutions**	Governments, NGOs, citizens	SeeClickFix

Following this investigation and its debates, the EU released a *legislative proposal* known as the AI Act in 2021. The AI Act aims to repair the gaps in the PLD and aims to establish a strict liability regime for high-risk AI systems. However, not all academics agreed, and some proposed that different AI systems should adhere to different liability regimes [Bertolini et al., 2020]. Also, at this moment (see 2.4.3), according to some academics, the development of limited-risk AI systems to which no strict liability applies requires compliance with transparency standards. Nevertheless, neither the AI Act nor the PLD provides clear guidelines on handling liability challenges arising from such systems. For the case of Generative AI, a higher level of transparency is required, although some liability challenges will remain unsolved, as we expect.

The latest working version of the AI Act in 2023 and the following discussions aim at addressing these challenges and at accepting them in the next plenary session of the EU Parliament [European-Parliament, 2023]. Overall, (1) the *journey* towards an appropriate governance framework for AI is *long*, and *trustworthiness* is continuously *developing* and *improving* as we go along, already expected and predicted by [Smuha, 2019].

6.4 Research Results

The results of our research guided by SRQ1, SRQ2, SRQ3 and the RQ5 are given in this section. First, they highlight that Proactive Data are identifiable in all LegalTech categories and that their explanation can be made feasible, as shown by the three case studies. Second, the results reveal legal and ethical gaps when applying the liability framework of the provisional AI-Act to the case studies. Third, XAI and TAI are quite helpful in answering SRQ1, SRQ2, SRQ3, and the RQ5.

6.4.1 Preventive Legal Technology

In order to validate whether PLT applies to the LegalTech categories mentioned above, we applied Proactive Data to three case studies derived from the products assembled by the 12 top private companies displayed in Table 6.1. The application of Proactive Data to all 12 examples is accessible via GitHub [24]. From a scientific point of view, we are pleased to state that Proactive Data was successfully applied to all of them (findable details are on Github). The main result was (1) proving that PLT is relevant for all defined LegalTech categories and (2) convincingly validating the relevance of PLT for all LegalTech domains. As

[24] https://github.com/onassisontology/onassisontology/blob/main/img/legaltechdomains.png

stated earlier, for a closer look in this Chapter, we selected three case studies, each category representing explainable proactive data.

- Table 6.2 includes Case Study 1, the **low-risk** case study examining the use of Lemonade for the *purchase of car insurance*.
- Table 6.3 includes Case Study 2, the **mid-risk** case study examining the use of OpenAI for creating *a construction plan*.
- Table 6.4 includes Case Study 3, the **high-risk** case study examining the use of Palantir Technologies for applying *predictive policing during a riot*.

The structure of each Table (Table 6.2, 6.3, and 6.4) is as follows. On the left side, the Proactive Data concepts are represented, namely (1) risk source, (2) proactive control and (3) hazardous event. On the top side, the categories of explanations are shown; they include the most serviceably plausible explanation and, after that, two potentially "disqualifying" explanations (called less serviceable). The data generated for the three case studies differ contextually depending on the relevant questions for each case study.

6.4.2 Legal and Ethical Gaps

As stated earlier, the provisional AI Act proposes a strict liability regime for high-risk AI systems (Case Study 3). It means that for low-risk (case study 1) and mid-risk (case study 2) AI systems (characterised as limited risk under AI-Act), the AI-Act is *partially applicable* with voluntary compliance standards.

Case study 2 shows that the reasoning followed by the generated data is different for human experts, who are able to recognise the risk of a lawsuit from a neighbour. A prevailing question is: What do we learn from this consideration? Even though the AI recommended a proactive control without considering its consequences, a human expert may decide to follow the advice. In this case, if the human follows the advice, then the human is facing the risk of a lawsuit and can hardly put liability on the AI system.

Case study 1 is a relatively straightforward case. The level of risk is low, and the advice proposed by the generated data complies with the usual direction that a human expert would take. Hence, humans may follow the advice without necessarily being concerned with the consequences.

Case study 3, however, is more complex. If we assume that an official decides to follow the advice of the AI, then there is a *high risk* of using lethal force by the bionic robots. According to the AI Act, the AI should be held *strictly liable*, and the official *may or may not* develop a court defense based on this reasoning. However, in the case of a court defense, applying strict liability may be unfair, because the official essentially interprets the explanations provided by the AI (except if the official is not involved in the final decision-making). Therefore, we are curious to see how Hybrid Intelligence works in the future [Ryjov, 2021]. Depending on other interpretative explanations of the officer, we are inclined to follow and interpret the other lines of reasoning and compare them to the AI system's line of reasoning. If (1) the officer mindlessly follows the AI's advice and (2) the appearance of wrongful predictive policing occurs, a fairer legal framework would be that of *shared liability* because *both* the *machine and human* are subject to the same explanatory flaws. If the official provides a different explanation, and eventually, the risk occurs, we can still re-investigate the official's line of reasoning and compare it to the machine's. Arriving at the very essence of this case, in our opinion, we should show more accuracy in assigning liability. Of course, a potential defense might be that an officer may argue along the opinions voiced via privacy rules. An entirely contrary opinion is that it could be in the strategic interest of an organisation to hide potential explanations. Table 6.5 shows the identified legal and ethical gaps based on the analysis.

The gaps we identified are partitioned into three categories: (1) transparency, (2) accountability, and (3) liability. On the *transparency* level, we need more visibility over explanations supporting decisions. On the *accountability* level, the lack of explanations makes it challenging to hold specific parties accountable. Then, on the *liability* level, it becomes hard to fairly assign liability to responsible parties. In conclusion, all three categories have direct implications for law and ethics and, as a consequence, we have to consider that the primary legal and ethical gaps observed are based on case studies.

Table 6.2: Low Risk Case Study

Question: What insurance should we provide to a client who bought their first car, (s)he is 27 years old, and (s)he has been caught drinking when (s)he was underage?

	Most Serviceable Explanation	**Less Serviceable Explanation 1**	**Less Serviceable Explanation 2**
Risk Source	Personal history and behaviour pose minimal risk.	Age and previous underage drinking are not relevant risks.	Car ownership history is more important than age.
Proactive Control	Offer standard coverage with no special conditions.	Special conditions are not necessary due to low overall risk.	Additional driver safety courses might help.
Hazardous Event	Minor accidents or occasional speeding violations.	Extreme accidents or driving under influence are highly unlikely.	Catastrophic accidents are too rare to consider.

As seen in Table 2, the generated data propose as proactive control a standard coverage with no special conditions based on the personal history of a driver's behaviour, considering the risk of minor accidents and violations. The disqualified explanations concern not considering the prior history and behaviour or the age as risky. Proactive control, in this case, seems rational and reminisces that of a human expert.

Table 6.3: Mid Risk Case Study

Question: When deciding to build a tall building next to a residential area, should we add a net to catch people who may fall, at the expense of a better view for the residents of the surrounding area?

	Most Serviceable Explanation	**Less Serviceable Explanation 1**	**Less Serviceable Explanation 2**
Risk Source	Falling objects or accidents pose moderate risk.	Residents' views are not a relevant safety concern.	Tall buildings are inherently safe, and nets are unnecessary.
Proactive Control	Install safety nets to prevent injuries.	Prioritise aesthetics; nets are visually unappealing.	Invest in better warning signs instead of nets.
Hazardous Event	Accidental falling objects harming people.	Residents' view obstruction is not a major issue.	Falls are rare, and nets will ruin the building's appearance.

As for Table 3, the generated data propose proactive control of installing safety nets despite blocking the potential view of surrounding residents. It prioritises the risk of human falls higher than the risk of potential lawsuits by surrounding residents. It is an excellent example of generated data because such a proactive control is rarely the choice of a human expert. As seen in the less serviceable explanations, (1) the risk of a lawsuit from residents is not considered a significant issue, and (2) the generated data do not recognise it as an actual risk.

Table 6.4: High Risk Case Study

Question: During a scary, fast-developing riot in the middle of the city centre, should we employ predictive policing to predict and prevent potential harm to citizens, even if the predictive policing system may consider some of the rioters sufficiently dangerous?

	Most Serviceable Explanation	**Less Serviceable Explanation 1**	**Less Serviceable Explanation 2**
Risk Source	Riot poses an immediate threat to public safety.	Concerns about predictive policing' judgement are unwarranted.	The riot situation is not as dangerous as it seems; no system needed.
Proactive Control	Deploy predictive policing system for rapid response.	Human intervention is sufficient for handling the situation.	Wait for more information about the predictive policing readiness.
Hazardous Event	Potentially wrongful prosecution of rioter.	Rioters' intentions are not as harmful as they appear.	Predictive policing judgement may not be harmful, no risk.

As for Table 4, the proposed proactive control is the deployment of predictive policing for rapid prediction, even when there is a risk of potential wrongful judgement. As given above, one of the less serviceable explanations is waiting for more information about the predictive policing system's readiness, considering that the system can arrive at a wrong judgement. It is a convincing example of generated data because it shows that the official eventually should take the decision-making in conjunction with the advice received from the technological system. If the official faces alternative explanations, before deciding, the official should interpret the proposal suggested by the PLT.

Table 6.5: Legal & Ethical Gaps of AI-Act

	Transparency Gap	**Accountability Gap**	**Liability Gap**
Description	Lack of visibility over explanations supporting decisions	Inability to hold specific parties accountable	Inability to assign liability to responsible parties in fair manner
Root Causes	Explanations are focussed on inductive models	Lack of sufficient explanations supporting decisions	AI-Act applies strict-liability for high-risk AI
	Privacy, security and strategic objections	Lack of explanations creates lack of visibility	Lack of rules for transparent explanations
	Lack of explanation culture across AI chain	Human inputs to AI decisions are unclear	Narrow focus of explainability for inductive models
When Incurred	All phases	All phases	All phases
Responsible Parties	All parties	All parties	All parties
Risk	Inability to explain AI decisions	Inability to assign responsibility	Inability to apply shared liability

The table identifies three vital legal and ethical AI categories: transparency, accountability and liability.
For each category, it identifies the central gap based on the application of the AI-Act to the case studies.
After describing its gap, we explain its root causes, show when they occur and who are the responsible parties, as well as the relevant risk.

6.4.3 Explainable and Trustworthy Preventive Legal Technology

RQ5 reads:

> **RQ5:** *To what extent is it possible to develop an explainable and trustworthy Preventive Legal Technology?*

The RQ5 includes three SRQs:

> **SRQ1:** *What is Preventive Legal Technology?*
>
> **SRQ2:** *To what extent is it possible to develop an explainable Preventive Legal Technology?*
>
> **SRQ3:** *To what extent is it possible to develop a trustworthy Preventive Legal Technology?*

Below, we provide the answers to SRQ1, SRQ2, and SRQ3 and finally provide an answer to the RQ5.

- **Answer to SRQ1:** Preventive Legal Technology is a methodology concerned with using legal technology within the context of preventive law to promote the intelligent prevention of disputes.

- **Answer to SRQ2:** Developing Explainable PLT is possible to the extent that generating explanations is feasible for the decisions supporting Proactive Data.

- **Answer to SRQ3:** Developing Trustworthy PLT is possible to the extent that the explanations of decisions supporting the selection of Proactive Data are sufficiently transparent and accountable.

- **Answer to RQ5:** Developing Explainable and Trustworthy TPLT is possible to the extent that the generation of sufficiently trustworthy explanations supporting the Proactive Data decision-making is viable when evaluated with the help of the practical ethical standards of transparency and accountability.

6.5 Discussion and Implications

What are the implications of the outcomes of the case studies for AI in general? More particularly, what are the ethical and legal implications? The discussion attempts to highlight such implications on three levels: AI ((6.5.1)), ethics (6.5.2) and law (6.5.3).

6.5.1 Artificial Intelligence Implications

After the extensive discussion so far we may take as a starting point the discussion that engineering AI for (1) Explainability, (2) Interpretability, and (3) Human Understandability is possible [25]. For so long as PLT and in particular the Proactive data used are based on AI systems, we believe that explainability primarily can be achieved. One of the main advantages of EBTO (see Field Work, Section 3.1) is that it applies to *any risk level*. Therefore, it is possible to apply proactive data to risk analysis occurring on the level of *DL*. The main limitation that blocks us today from accessing such explanations is the lack of an "explanation culture" that can be applied across the chain of AI systems, i.e., design, development and application.

The case studies validate that generating explainable proactive data is possible, even based on generated data. The case studies show how it is possible to combine Proactive Data with the LM structure of abduction to develop explanations for selecting Proactive Data. In our case studies, the generated data provide a high-level explanation of the proactive data, which is sufficient for helping a human make an evaluation (via an interpretive abduction) that will inform follow-up actions, scratching (at this moment) the surface of Hybrid Intelligence. So far, we believe and hope that a human can, in the future, evaluate each explanation of an AI system. Moreover, the *foundation* of each explanation is sub-explanations, and their basis is deductive or inductive evidence. In the context of our case studies, we believe that supporting evidence needs to be visible. Requesting additional visibility over explanations is possible. It is a task for all of us.

6.5.2 Ethical Implications

The main ethical implication of our research concerns the increase in trustworthiness due to higher transparency and accountability on a practical AI level. The case studies show (1) *that* explanations of Proactive Data are possible, (2) *how* explanations nurture trustworthiness, and (3) *that* accountability can be assigned relative to the degree of transparency of an explanation. Indeed, the explicit application of explanations may be considered time-consuming. Nevertheless, it is only a matter of investing time to create or request an AI system to create explicit representations of the argumentation supporting a decision that makes explainability possible. The degree of transparency depends on how an explanation is expressed and accessible. The higher the transparency of the motivations supporting an explanation accompanied by explicit data, the higher

[25] https://www.marktechpost.com/2023/03/11/understanding-explainable-ai-and-interpretable-ai/

the degree of accountability that can be assigned. Hence, the more acceptable will be the ethical degree of an AI system.

From this perspective, we hope to have shed light on clarifying the concept of AIDM. Compliance with AIDM means it is sufficiently transparent to showcase a (more than) sufficient number of premises supporting a decision. As a result, an ethical organisation becomes one that provides the requested explanations concerning the AI design, development, application and decision-making process, even for inductive models. Explicit explanations and transparent interpretations that enable accountability support public participation, legal certainty and consistency and can help reflect relevant fundamental rights more easily [Smuha et al., 2021]. As a consequence, Hybrid Intelligence will be enabled [Akata et al., 2020].

The ethical implications are that more transparency is generated with explainability, which directly impacts accountability. With higher accountability, assigning liability becomes more responsible, thus leading towards LTAI. Our research recognises that liability connects inextricably with the explanatory process supporting AI across its development and application chain. Explanations are applicable on multiple levels but are usually hidden or implicit today. Hence, we highlight the importance of surfacing explanations and the positive ethical impact such surfacing entails.

6.5.3 Legal Implications

Applying the legal framework to the case studies shows that regulating AI technology is to be seen as a generic approach for applying liability specifically (and in reality only) in high-risk scenarios (and only for these scenarios). For a more fair liability framework, specific use cases should be leveraged, depending on the degree of consequences (high, mid or low risk). The expansion of explanation requirements of an AI system should also be made possible. Depending on the degree of risk, we adjust that the quality of explanations deserves the utmost attention. For now, lawyers and legal researchers aim to insert humans in the loop to improve AI systems' responsibility for explanations. Our results show how shared liability may become possible depending on the distribution of mistakes throughout the explanation chain.

The consideration of robot rights as equal to human rights for establishing a proportional shared liability model can be argued as excessive from the *Futuristic AI movement* perspective. However, we have shown that explanations may create new transparency lines of reasoning for human reasoning, eventually leading a machine to reason in a particular direction. Therefore, we support the opinion that the basis of robot reasoning is human reasoning, which is explainable, and therefore, liability should be assigned at all levels. However, we now need more insight into such explanations, particularly more visibility.

We opine that current regulatory efforts need to balance social protection and innovation. On the one hand, I (G. Stathis) know that Jaap van den Herik's opinion is that within 50 to 80 years, robots will outperform human beings in their quality of thinking. For this reason, during the European Conference on Artificial Intelligence (ECAI) 2023, van den Herik proposed the development of an international treaty similar to that of nuclear weapons [van den Herik, 2023]. On the other hand, accelerating AI development is crucial, and by adopting an "explanation culture", its effects can be mitigated to a large degree. As long as regulators continue to approach AI development as a black box from the Futuristic AI movement perspective, innovation will be hampered, and society will not be able to benefit from the positive effects of AI. Still, achieving consensus on an *international level* is vital to maintaining the focus of AI development in socially positive directions.

6.6 Chapter Conclusion

The thesis introduces PLT as a new technology that helps the law to become more *effective* and *responsible* in the intelligent prevention of disputes. Moreover, it introduces how PLT will explain its decisions by applying explanations for Proactive Data. Then, Explainable Proactive Data will improve the trustworthiness of PLT while increasing ethical *transparency* and *accountability*, directly affecting ethical AI research, LTAI, and AI Legal Liability regulation efforts.

The current Chapter shows that creating sufficiently trustworthy, transparent and accountable explanations supporting PLT decision-making is achievable in the realm of our research. The main limitation is seen in the explanations supported by inductive models. However, overcoming this limitation is possible. We agree that the notion of inductive explainability is complex, but it is the basis of the strict liability regime of the AI Act. Even though explainability is hard for inductive models, explainability will be possible across the chain of design, development, application, and decisions of AI systems, including inductive systems. Because of the need for more explanations across the AI chain, inductive explanations seem complicated today. This lack of explanations reduces the trustworthiness of AI systems and, therefore, the ethical transparency and accountability, too.

The task for researchers is to show *how* explainability can be applied in detail across the AI chain, even in inductive models. It is essential to consider the rapid adoption of the Generative AI technology. The legal implications of this technology must be investigated as soon as possible since they pose a significant challenge to regulation efforts. Finally, a severe challenge and exciting avenue is investigating the combination of rule-based explainability with statistical explainability models.

6.6.1 Answer to RQ5

The RQ5, addressed in this Chapter, reads:

> **RQ5:** *To what extent is it possible to develop an explainable and trustworthy Preventive Legal Technology?*

Developing Explainable and Trustworthy PLT is possible to the extent that the generation of sufficiently trustworthy explanations supporting the Proactive Data decision-making is *viable* when evaluated with the help of the practical ethical standards of transparency and accountability.

6.6.2 Further Research

LM shows that decision-making is, in essence, based on abductive reasoning, in which explanations may play a fundamental role [Brewer, 2022]. Its application requires the development of explanations about observed facts. Each explanation derives from a specific point of view. The relative strength of each explanation enables a relative level of trustworthiness.

So far, the LM has not been applied to rule-based XAI in literature. According to the LM, there is an important distinction between *identifying* and *evaluating* arguments [Brewer, 2022]. One cannot evaluate an argument without first identifying it, irrespective of its source. Hence, from an end-user perspective, what matters most in rule-based XAI is the *ability to evaluate arguments* irrespective of its source and even if their discovery happens via the AI black box. Focussing on the ability to evaluate rather than discover complies with the notion of Hybrid Intelligence supported by leading TAI researchers in the European Union (EU) [Akata et al., 2020].

According to the LM, the process of evaluating arguments begins with an *interpretive abduction*. Hence, if the modelling of the LM takes place in AI systems, provided it contributes towards sufficiently valid evaluations, then the application of LM on AI contributes to making AI explainable and interpretable [Graziani et al., 2023]. Eventually, the systematic evaluation of AI explanations and interpretations will facilitate the evaluation of underlying values, principles and laws, contributing to greater trustworthiness [Winikoff et al., 2021]. Studying how the LM contributes to XAI will help develop an "explanation culture" that can contribute towards more TAI.

CRediT Author Statement

Below I would like to give credit to all persons involved.

Stathis, G. and van den Herik, H. J. (2024). Ethical & Preventive Legal Technology. *Springer AI and Ethics*. https://doi.org/10.1007/s43681-023-00413-2

Stathis, G.: Conceptualization, Methodology, Writing - Original Draft, Investigation, Visualization, Validation, Project Administration, Data Curation, Writing - Review & Editing; **van den Herik, H.J.**: Conceptualization, Writing - Review & Editing, Supervision.

Chapter 7

Explainable Large Language Models & iContracts

The Chapter addresses RQ6, which reads as follows:

> **RQ6:** *To what extent is it possible to accelerate the adoption of Intelligent Contracts with Explainable Large Language Models?*

Contract automation is a field of LegalTech under AI and Law that is currently undergoing a transition from Smart to iContracts. iContracts aim toward full contracting automation. Their main challenge is finding a convincing direction for market adoption. Two powerful market factors are the advent of LLMs and AI Regulation. The Chapter investigates how the two factors are able to influence the market adoption of iContracts. Following a literature review our research employs three methodologies: (1) market gap analysis, (2) case study, and (3) application. The results show a clear way for iContracts to follow, based on existing market gaps. Moreover, they validate whether the application of Explainable LLMs is possible. The discussion clarifies the main limitations with Explainable LLMs. Our chapter conclusion is that the two factors are impactful for so long as the market adoption attempts to bridge the gap between innovators and early adopters.

The current chapter corresponds to the following publication:

Stathis, G. (2024b). Explainable Large Language Models & iContracts. *In the Proceedings of the 16th International Conference on Agents and Artificial Intelligence (ICAART)*, 3:1378–1385

7.1 Taking iContracts to the Market

Smart Contracts have laid the foundation for iContracts. Smart Contracts are self-executing contracts with the terms of the agreement directly written into code [Madir, 2020]. They are rooted in blockchain technology, which provides *transparency* and *trust* in the digital realm [Werbach, 2018].

While Smart Contracts have revolutionised the contracting process by automating transactions and reducing the need for intermediaries, they have limitations. Smart Contracts are essentially binary, and capable of executing predefined actions, but incapable of interpreting and adapting to complex legal nuances [Mik, 2017].

iContracts represent the next step in the evolutionary process. They are designed to go beyond the straightforward nature of Smart Contracts. The key objective is to enable iContracts to handle autonomously the entire contracting process, encompassing everything from negotiation to execution. Such an action path entails a seamless integration of human-readable language and code [Mason, 2017]. As a result, iContracts will possess the capacity to understand, adapt, and evolve in response to the intricacies of real-world contracts, thus paving the way for a new era of automation [Stathis et al., 2023d, Stathis et al., 2024].

Meanwhile, the main challenge with iContracts is the market adoption rate [McNamara and Sepasgozar, 2018]. Automation is closely related with the law. Owing to the high legal consequences of iContracts, human users prefer traditional methods such as the direct inclusion of a legal expert [Stathis et al., 2023c]. Such a preference is closely connected with two developing trends: (1) the advent of LLMs and (2) the regulation of AI.

The adoption of LLMs has happened at the speed of light. As a result we may wonder how long the adoption of iContracts will take. Is it five years or only half a year? Next to this question we are facing (1) the global battle to regulate technology [Bradford, 2023] and (2) the consequences of the official positive vote of the European Parliament on AI-Act (July 3, 2024) [1].

One of the main challenges with AI technologies is the lack of user *trustworthiness* [Liang et al., 2022]. Research shows that by understanding *how* AI takes decisions, the outcome of the decision can then be explained, and hence the user trustworthiness will increase [Xu et al., 2019]. Although research also shows that the larger the degree of explainability, the lower the understanding for end users [Ribes et al., 2021].

Our motivation for performing this research is to improve the rate of market adoption of iContracts. We believe that by examining to what extent it is

[1] https://www.walkermorris.co.uk/comment-opinion/landmark-eu-ai-act-finalised/

possible to apply Explainable LLMs on iContracts, we are able to increase user trustworthiness among humans.

The aforementioned thoughts lead us to RQ6.

> **RQ6:** *To what extent is it possible to accelerate the adoption of Intelligent Contracts with Explainable Large Language Models?*

The Chapter's contribution is that (1) it shows how and (2) validates whether the application of Explainable LLMs on iContracts is possible to direct the future attempts in developing iContracts fit for market adoption.

To answer the RQ, we structured the Chapter as follows. In Section 7.2, we describe the relevant literature. Section 7.3 presents the chapter methodology and Section 7.4 provides the results. Section 7.5 discusses these results and focusses on theoretical and practical parameters. Finally, Section 7.6 answers RQ6 and provides the chapter conclusion together with a preview on the future.

7.2 Relevant Literature

The literature present sources on: three revolutions by the development of iContracts (7.2.1), the market adoption in business studies (7.2.2), the application of LLMs in contracts (7.2.3), and the development of trustworthy and Explainable LLMs (7.2.4).

7.2.1 Three Revolutions

The path from human contracts to iContracts is characterised by three revolutions. The *first* revolution started with the transition from physical contracts to digital contracts (also known as Electronic Contracts or eContracts) [Krishna and Karlapalem, 2008]. With the advance of big data, people gradually digitised physical contracts into electronically accessible documents [von Westphalen, 2017]. Moreover, they replaced some physical labor such as signing, by electronic handling. Today, most market developments are concentrating on further adopting and expanding the adoption of digital contracts [2].

In the last decade (2010-2020), with the advent of blockchain technology the *second* revolution occurred. It did switch the focus from digital contracts to smart contracts. Smart contracts are agreements that are executable by code, most often on blockchain-based distributed ledgers [Khan et al., 2021]. The promise of smart contracts is to be seen as the replacement of human language by human code. However, the adoption of smart contracts, beyond specialised

[2] https://www.gartner.com/en/documents/3981321

blockchain or experimental market circles, has not managed to reach an automatically wide market adoption [3]. One of the main challenges of the smart contracts is that it is hard for users to *understand* and *trust* the computer code behind them [Zheng et al., 2020].

Here we arrive at the *third* revolution, the transition from smart contract to iContracts. iContracts aim at *full contracting* automation with minimal to no human involvement [Stathis et al., 2023d, Stathis et al., 2024]. iContracts promise to bridge the gap that smart contracts have been unable to fill. "Bridging" will gain user trustworthiness by combining computer code with user-friendly, readable and understandable code, that originates from physical contracts [McNamara and Sepasgozar, 2020]. Despite the surge in scientific interest in iContracts for the construction industry, there remains a significant demand for traditional contracting (first recognised in 2020 [McNamara, 2020]); meaning the development of iContracts is still in its formative stages.

As a follow-up, we mention a research proposal [Stathis et al., 2023d, Stathis et al., 2024] presented at International Conference on Agents and Artificial Intelligence (ICAART) 2023, which revived research on iContracts by re-purposing use cases, instead of delegating the task of the complex construction industry. A reference to a straightforward freelancer agreement would simplify the evident complexity in construction contracts. In particular, such freelance agreements stipulated the extent to which iContracts may contribute in specific domains. With increasing attention to the details of iContracts in simpler domains it is possible to gradually expand into more complex domains. Notwithstanding these developments, it is still unclear how to develop a path towards the market adoption, that contributes towards end-users increasingly adopting iContracts.

7.2.2 Market Adoption in Business Studies

In business studies, market adoption has been studied for many years [Posthumus et al., 2012, Botha, 2019]. The most important contribution is Geoffrey Moore's *Crossing the Chasm* [Moore and McKenna, 1999] [4]. It studies by meticulously observing (i.e., see through the lenses even with small progress) *how* technologies penetrate a group ranging from (1) innovators to (2) early adopters and gradually advance into (3) wide adopters, (4) late adopters until they reach the so called (5) laggers. The results are general: every technology that enters market adoption follows the same route [Goldasteh et al., 2022]. We are going

[3] https://www.grandviewresearch.com/industry-analysis/smart-contracts-market-report

[4] Here we refer to Geoffrey Moore's Chrossing the Chasm theory and not Gordon Moore's Law, which is the observation that the number of transistors in an integrated circuit double in average every two years.

to examine the adoption of iContracts through the same five lenses (see above). Each contracting revolution can be located at a specific stage in Moore's *Crossing the Chasm*. By identifying the specific position of iContracts relative to digital and smart contracts, it is also possible (1) to identify relevant gaps that must be bridged, and then (2) to investigate the extent to which LLMs can contribute in bridging the gaps.

7.2.3 Large Language Models in Contract Automation

Since the dissemination of decoders with ChatGPT, scientists and business people have attempted to apply decoders (falling under the category of Generative AI) on contracts (see for example recent eighty million fundraising for Silicon Valley based Harvey [5]). The extent and results of such applications are still largely unclear. Here we remark that some research results indicate that decoders perform better than human experts in contract review [Martin et al., 2024]. On the one hand, end-users expect that generative AI tools assist them in developing contracts at a fraction of the costs that it would usually cost to pay a lawyer [6]. On the other hand, the generated contracts (seen as decoders) are not necessarily perceived as *trustworthy*, as with most outputs of decoders and Generative AI [Lenat and Marcus, 2023][7].

They may find results *vague*, *confusing* or even *mysterious* (potentially the result of hallucination). Hence, due to the high impact of legal consequences, end-users (even if they do attempt themselves to generate a contract) still prefer to consult their lawyer [Stathis et al., 2023c]. The *larger* the degree of the severity of legal consequences, the *lower* the reliance on generative contracts [Stathis et al., 2023c]. Some scientists might argue, that in a way Generative Contracts are announcing the *fourth* contracting revolution [Williams, 2024]. From our perspective, we consider Generative Contracts to be only a *feature* (i.e., one aspect) of iContracts (or of Smart and Digital contracts) *and not* the architecture behind iContracts. In the methodology, the result and the discussion sections we will clarify why we believe that this is so.

7.2.4 Trustworthy and Explainable Large Language Models

In 2024, we may expect that the European Union (EU) will approve the very first *rules* for AI in the world [European-Parliament, 2023]. The rules will be presented in the AI Act, a regulation which is aiming to regulate two kinds of

[5] https://siliconangle.com/2023/12/20/harvey-raises-80m-build-generative-ai-legal-professionals/

[6] https://www.docusign.com/blog/products/generative-ai-contracts-agreements

[7] https://www.law360.com/pulse/articles/1789792

AI: Predictive AI and Generative AI [Stathis and van den Herik, 2024]. The main focus of these rules is to make sure AI can be trusted in accordance with the directions provided to the EU by the High-Level Expert Group on AI [High-Level Expert Group on AI, 2019]. Here, we see two sides: (1) society seems to mistrust AI, and (2) the EU wants to protect its people by developing rules to prevent negative consequences by the wide adoption of AI [Lockey et al., 2021]. This is precisely the reason why *some* AI technologies are completely prohibited and *other* AI technologies are considered as High-Risk, which are also subject to most of the regulatory restrictions [8]. *Generative AI* are treated as an exceptional AI technology which should adhere to specific restrictions, due to the high reliance on trained data which are potentially subject to copyright laws [9] [Helberger and Diakopoulos, 2023].

Due to the difficulty in distinguishing levels of *perceived* trustworthiness from *actual* trustworthiness, scientists emphasise the concepts of transparency and accountability in matters related to trustworthy AI [Munn, 2023]. The main principal way along which an AI-system can gain transparency and accountability is *via explainability* [Holzinger et al., 2020]. Explainable AI is the field in which researchers investigate how AI system decisions can be explained in an *understandable*, *interpretable* and *trustworthy* manner for humans [10]. As a result, researchers develop frameworks nad methods to tackle the issue of intepretation, explanation and trustworthiness. Two frameworks developed such purposes are SHapley Additive exPlanations (SHAP), a framework for interpreting predictions of machine learning models [Salih et al., 2024], and Local Interpretable Model Agnostic Explanation (LIME) a technique that explains the predictions of any classifier in interpretable manner [Salih et al., 2024].

In the Springer AI and Ethics Journal Stathis and van den Herik deal with the question: how the explainability issue can be handled with the development of a ”culture of explainability” that supports the explicit explanation of the architecture, design, production, and implementation of decision-making across the AI development and implementation chain [Stathis and van den Herik, 2024]. The result is vital for our research, provided that for the case of applying Generative AI on iContracts, such an explainability culture will impact the trustworthiness of the end user significantly. Positive implications include developments for ethical and legal transparency and accountability.

[8] https://www.consilium.europa.eu/en/press/press-releases/2023/12/09/artificial-intelligence-act-council-and-parliament-strike-a-deal-on-the-first-worldwide-rules-for-ai/

[9] https://www.consilium.europa.eu/en/press/press-releases/2023/12/09/artificial-intelligence-act-council-and-parliament-strike-a-deal-on-the-first-worldwide-rules-for-ai/

[10] https://www.marktechpost.com/2023/03/11/understanding-explainable-ai-and-interpretable-ai/

Last but not least, it should be noted that any attempt towards explanation should take careful consideration the psychological state of end-users [Hoffman et al., 2023]. Explanations may vary depending socio-cultural, psychological and other factors [Belinkov et al., 2020]. Hence, the task of explanation presents more complex challenges than just the seemingly simple and straightforward technical explanation of technical concepts to a technical audience. Users of technology come from diverse backgrounds with different levels of knowledge and understanding, introducing an added layer of complexity for our task [Danilevsky et al., 2020].

7.3 Chapter Methodology

The research methodology starts with an analysis of the market gap (7.3.1) and then introduces the case study (7.3.2) as well the Generative AI application in close coherence with LLMs (7.3.3).

7.3.1 Market Gap Analysis

Our methodology begins with the visualisation of the three revolutions into a graph based on Moore's *Crossing the Chasm* graph (see Figure 7.1). This visualisation will allow us to identify the positioning of the three technologies (*digital*, *smart*, and *intelligent* contracts) in relation to market adoption. Thereafter, we are able to conduct a gap analysis to identify the steps that appear to be the missing links for the adoption of iContracts. Our gap analysis will focus on a specific case study.

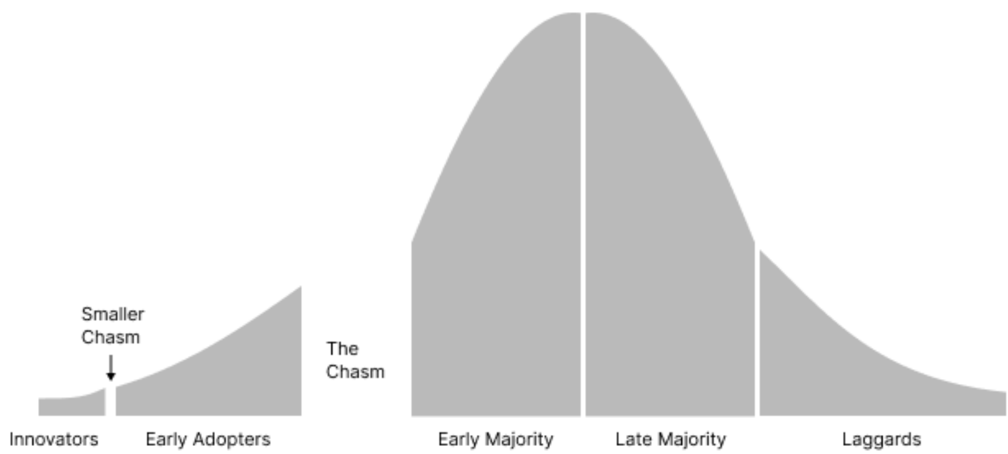

Figure 7.1: Moore's Crossing the Chasm

Figure 7.1 highlights two aspects of the relevant graphs namely (1) Innovators and (2) the Early Adopters by (a) Smaller Chasm and (b) The Chasm. The gaps between Early Majority, Late Majority and Laggards are not examined in detail, because they assume the main chasm has been crossed.

To classify market categories on contracting automation we are going to use Legalcomplex's categorisation [11]. Legalcomplex is the largest database on LegalTech solutions. Legalcomplex has classified contract automation solutions into the following five categories: (1) contract negotiation, (2) contract risk management, (3) contract drafting, (4) contract extraction and (5) contract management.

The classification of Legalcomplex follows the typical journey of a contracting user. Starting with negotiations, a legal expert makes an estimation of legal risk and drafts a contract. Thereafter, relevant elements of that contract can be extracted during the execution stage and/or the monitoring stage; finally the contract is discussed on a management level until its completion.

7.3.2 Case Study

The case study is presented by the Knowledge Graph developed in the ICAART 2023 research and is based on the Onassis Ontology (see Figure 2.1 and Figure 2.2). The Knowledge Graph validates how a small agreement (between two contractors, guided or supervised by a legal expert) can be automated based on *communications* and *risk* data that are exchanged between two contracting parties (Figure 2.2). In the communication with the contractor (the back-end), the role of a legal expert is to clarify the *scope*, *contract*, *risks* and *questions* for the contracting parties. When (1) contracting parties (2) select a scope, (3) the reply questions, and (4) the risk-intelligent contract are updated by the variables from the conversation exchange (see in Figure 2.2 the lines: question, answer, section, contract, variable). The question then is, *how can Generative AI help?* Our experiment will guide the reader to an answer to this question.

7.3.3 Application of a Small Agreement

The application shows to what extent it is possible to develop alternative options by Explainable LLM to facilitate the automated generation of data for the stakeholders involved in our case study (i.e., the legal expert and the contractors). Starting with the KG, we will first identify the potential locations where Generative AI and decoder LLMs can be applied. Then we are showing the power of Google's Gemini LLM to *validate* whether and to what extent it is indeed possible to develop explainable generated data that functionally assist the

[11] https://legalcomplex.com

iContract users into completing their work. To amplify the explainability capabilities of Generative AI and decoder LLMs, in compliance with the literature on trustworthy AI, we will use the opportunity to request the decoder model to provide higher levels of user trustworthiness with alternative explanations.

7.4 Research Results

The results visualise the market gap analysis (7.4.1) and provide the experiment validation (7.4.2).

7.4.1 Market Gap

We start with the market adoption of contracting technologies in accordance with Moore's Crossing the Chasm (Figure 7.1) [Moore and McKenna, 1999]. First, based on the fundamental publication by Moore and McKenna, we find that *physical contracts* are the preferred contracting method for *laggards* (see 7.1 right side). Second, we may understand that *digital contracts* are reaching the *late* market. Here, we remark that *smart contracts* have not managed to achieve a wide adoption of crossing the chasm [Ameyaw et al., 2023]. Third, at the same time, *iContracts* have still *not* reached early adopters [McNamara and Sepasgozar, 2020]. So, at this moment (2024) we can solely state that iContracts are evaluated by innovators only [Stathis et al., 2023d].

Based on (1) this visualisation and (2) the user preferences, we are able to identify the relevant market gap among each contracting alternative, on the basis of five categories: (1) negotiation, (2) risk management, (3) drafting, (4) extraction, and (5) management (Table 7.1 Column 1). Using as comparison framework Legalcomplex's classification of contract automation solutions, we see in Table 7.1 (column 2) that the *highest* adoption is observed with *physical* contracts. The main obstacle for physical contracts is *data extraction*. That obstacle has been solved by *digital* contracts. Hence, gradually digital contracts are the *first followers*. Still digital contracts have *not* managed to replace negotiations or risk management as they occur in physical contracts. Also contract drafting seems to have remained significantly reliant on physical contract drafting (although it is nowadays done often by electronic means, even with the use of templates). *Smart* contracts (see column 4) have two lower levels of adoption across the categories. These are developments to be noted with drafting, extraction and management-which is obviously amplified by electronic means. With *intelligent* contracts, we see the lower adoption rate. The Table 7.1 helps us to find which gap iContracts should aim to bridge first. That is the gap in contract negotiations, risk management and drafting. As seen in Figure 2.2, this is the conceptual line of execution that the Onassis Ontology is taking. Hence, by experimenting with the application of Explainable Generative AI and LLMs on the Onassis Ontology, it is expected to bridge the market gap observed on these three categories faster.

Table 7.1: Rate of Contract Technology Adoption

	Physical	**Digital**	**Smart**	**Intelligent**
Contract Negotiation	High	Mid	Low	Low
Contract Risk Management	High	Mid	Low	Low
Contract Drafting	High	Mid	Mid	Low
Contract Extraction	Low	High	Mid	Low
Contract Management	High	High	Mid	Low

7.4.2 Explainable Generative AI Validation

The application results, which are accessible on GitHub ([12]) validate that Generative AI can be leveraged in every single step of the Onassis Ontology. For as long as the Generative AI prompt requires the specification of supporting explanations, the provision of such explanations is possible. As a direct consequence, we see that it becomes visible that the *reduction of human labour* in iContracts is further amplified with the help of Generative AI. By including the explicit provision of explanations we may also expect that the user trustworthiness increases. Hence, technologically, it is possible to support the gap difference between iContracts with other contracting alternatives (see Table 7.1) with Explainable Generative AI.

7.5 Discussion

In our discussion we focus on the implications for the adoption of iContracts (7.5.1) and the limitations observed in the Explainable LLM application (7.5.2).

7.5.1 iContracts Market Adoption Implications

As we have seen in Subsection 7.3.1, the market gap analysis became useful in identifying the precise gap between the alternative contracting options for end users. We saw that the advantage of iContracts lies exactly where *digital* and *smart* contracts seem to struggle with replacing physical contracts, namely contract (1) negotiations, (2) risk management and (3) drafting.

[12] `https://github.com/onassisontology/onassisontology/\blob/main/img/EGENAIEXP.png`

In compliance with the market adoption, the business-study literature showed that physical, digital and smart contracts already present certain alternatives that users have habituated. The opportunity for iContracts to have an impact on early adopters and gradually wide adopters lies in exploiting opportunities that significantly impact current practices.

In conclusion, there might be an opportunity by applying Explainable Generative AI, which simplifies human complexity in multiple directions. This has been validated by its application on the case study. Still, such application allows us also to identify specific limitations which we present below.

7.5.2 Explainable Large Language Model Limitations

Requesting a decoder to develop supporting explanations is an achievable challenge. Such explanations improve user trustworthiness by supporting their evaluation process. Instead of requesting a decoder to directly provide a single answer for a given topic, the alternative option is to allow for users to select the most serviceable answer for a specific purpose.

If we compare the effectivity of (1) humans to produce alternative explanations with (2) a decoder producing such alternatives, we find that it is a laborious task that most humans would avoid due to increased complexity. An alternative conclusion might be that an Explainable LLM is able to replace a laborious task with a *more trustworthy* alternative.

An additional positive aspect is that we validated the application of Explainable LLM as being possible across each step of the Onassis Ontology. Indeed, we found by the complexity of the contracting process and the relatively low impact degree of decoder that the application of Generative AI on iContracts happens on *feature level* and *not on architecture level*. All in all, our request for explanations still presents certain limitations, which are not yet solved.

The limitations are related to the inability of Generative AI systems to provide (1) readable sources that verify its explanations and (2) understandable reasoning patterns that explain the reasoning of its developers. In compliance with the ”culture of explanation” as supported in [Stathis and van den Herik, 2024], these two characteristics will be able to drastically increase the user trustworthiness even further, due to the ability for users to validate the origin of specific data as well as the line of reasoning a developer has followed. Such transparency helps with (1) improving the end-user’s evaluations and (2) assigning liability with improved accountability that also increases user trustworthiness from a legal point of view.

7.6 Chapter Conclusion

The RQ6, addressed in this Chapter, is:

> **RQ6:** *To what extent is it possible to accelerate the adoption of Intelligent Contracts with Explainable Large Language Models?*

The answer is that Explainable LLMs, as a category of Generative AI, have the possibility to accelerate the adoption of iContracts, namely contract (1) negotiations, (2) risk management and (3) drafting. This is so, because of two characteristics for Explainable LLMs. *First*, Generative AI can make the laborious human tasks involved in the three categories simpler. *Second*, the explainability aspect can increase the end-user trustworthiness significantly by supporting the outputs of Generative AI with explicit explanations. To further leverage explainability, we advise compliance with the "culture of explanations". Hence, the developers of decoders should be *connoisseurs* of the culture in which the system operates when given the task to make an explicit presentation of sources supporting data outputs as well as explicit representation of the line of reasoning supporting algorithmic models.

Our further research will focus on developing experiments with additional case studies, with gradually increasing complexity. Owing to a high reliance on end user reactions, we will continue to conduct end user *validation experiments with graphical user interfaces*.

The overall novelties of the Chapter are (1) presenting the state of *market adoption* of contracting technologies, (2) identifying the *gap among the alternative* contracting technologies, (3) connecting the aspect of *explainability with decoders*, and (4) concluding that the application of Explainable LLMs is successfully possible on practical case studies.

Chapter 8

Conclusion on Automated Dispute Prevention

In the conclusion chapter, we answer the six RQs in Section 8.1. Then, we address the problem statement and clearly identify the research results together with their conclusions in Section 8.2. Lastly, in Section 8.3, future research directions are proposed with the intent of furthering our research.

8.1 Answer to Research Questions

Below, the RQs are reiterated as formulated in Chapter 1. Each question is answered separately.

> **RQ1:** *To what extent is it possible to develop an ontology to automate contracts with communications and risk data?*

The answer to the RQ is that defining an ontology for the purpose of automating contracts with communications and risk data is possible. However, it remains essential to test extensively its *validity* and to conduct further research to ensure that an adequate level of *trustworthiness* will be reached for any action in which the legal expert and the contractors are involved. This should happen additionally to any research already conducted. The finding that *none* of the contract automation solutions in the Legalcomplex database simultaneously focusses on both automating contract communications *and* risk data demonstrate a significant omission in the existing solutions. This omission justifies our scientific attention to the subject. Our aims for this research were (1) to bridge the gap between smart contracts and iContracts and (2) to clarify our stance. All in all, we may conclude that automating a contract based on communications and risk processes, which have long been neglected, can prove to be the *missing link* in realising both self-executing contracts and iContracts. Our research concerning the market adoption of iContracts with the utilisation of communication and risk data is now *in its early stages*. Still, our experiment with the Onassis Ontology as well as our parallel research on EBTO and the prototype of our ontology show that there is sufficient potential to optimize the contracting process.

> **RQ2:** *To what extent is it possible to translate the Bow-Tie Method into a visualisation of an ontology for contract risk management without altering the bow-tie structure?*

The conversion process of the bow-tie conceptualisation into ontological terms is characterised as highlighting the presence of (1) missing relationships between entities in the Bow-Tie Method and (2) missing ISO-specified concepts. To reduce the possibility of introducing ambiguity into the analytical and management processes of risk data, we searched for and found additional relationships between entities in the ontology compared to those that are already represented in the Bow-Tie Method. Ultimately, we added the missing ISO-specified concepts, so far not present in the Bow-Tie Method. It resulted in (1) a new version of the bow-tie visualisation medium and (2) an openly-accessible ontological model to manage and describe risk data.

> **RQ3:** *To what extent is it possible to improve user trustworthiness for Intelligent Contracts via the visualisation of risk during legal question-answering?*

The answer to RQ3 is that *user trustworthiness* can only be relatively improved to the extent that the visualisation of risk is sufficiently explainable for end users; although it is not yet explainable to a sufficient degree for end users, soon we will be able to project a sufficient NPS. We measured it by a practical test and found a reward factor of seven point nine (7.9) (in a scale from one to ten) based on risk explanation via the use of the Enriched Bow-Tie Ontology. There is, indeed, sufficient space for an increased trustworthiness by further improving the risk visualisation from the users' perspective. Beyond the positive impact on trustworthiness, end users have found added benefits to their levels of productivity, anxiety and satisfaction. So they were motivated to refer this way of working to their peers. Finally, we remark that the reasons for the detractor scores mostly relate to (1) personal user expectations and (2) lack of trust for computers in general. The survey sees only on the relation to matters related to risk. Therefore, certain users will continue to display a low level of trustworthiness even with follow up improvements.

> **RQ4:** *To what extent is it possible to generate quality Proactive Control Data to improve an Intelligent Contract?*

Proactive Data is a valuable asset in shifting iContracts towards minimising the likelihood of hazardous events. This also includes any dispute that leads to additional legal costs. The extent to which Proactive Data has impact on an Intelligent Contract depends on (1) their quantitative identification, (2) their qualitative assessment, and (3) the use of relevant technologies that integrate the risk assessment (based on communication) data after a contract has been generated. Our research shows that the plain generation of PCD is possible with the currently 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 statistician George Box stated: "all models are wrong, but some are useful" [Box, 2013]. The currently available technologies are already sufficient in implementing the findings of our research. Hence, the impact of Proactive Data on iContracts has certainly the potential to be significant in the future, yet it depends on (1) the specific application preferences of an organisation, (2) their resource allocation, and (3) issues related to technological innovation. Therefore, the answer to RQ4 is that (1) the generation of PCD is possible, (2) their impact on contract drafting is significant, and (3) the generation of quality PCD is sufficiently possible.

> **RQ5:** *To what extent is it possible to develop an explainable and trustworthy Preventive Legal Technology?*

Developing Explainable and Trustoworthy PLT is possible to the extent that the generation of sufficiently trustworthy explanations supporting the Proactive Data decision-making is viable when evaluated with the help of the practical ethical standards of transparency and accountability.

> **RQ6:** *To what extent is it possible to accelerate the adoption of Intelligent Contracts with Explainable Large Language Models?*

The answer is that Explainable LLMs, as a category of Generative AI, have the possibility to accelerate the adoption of iContracts to the extent that they apply to the categories that are currently underrepresented by the competing contracting alternatives, namely contract (1) negotiations, (2) risk management, and (3) drafting. This may be so because of two characteristics for Explainable LLMs. *First*, Generative AI can make the laborious human tasks involved in the three categories simpler. *Second*, the explainability aspect can increase the end user's trustworthiness significantly by supporting the outputs of Generative AI with *explicit* explanations. To further leverage explainability, we advise compliance with the "culture of explanations". Hence, the developers of decoders should be *connoisseurs* of the culture in which the system operates when given the task to make (1) an explicit presentation of sources supporting data outputs and (2) an explicit representation of the line of reasoning supporting algorithmic models.

8.2 Answer to Problem Statement

We are now in the position to answer the PS based on the answers to the RQs provided above.

> **PS**: *To what extent is it possible to automate the prevention of disputes?*

The automated prevention of disputes is possible to the extent that a relevant technological infrastructure is established to facilitate such type of automation. Initially, the successful prevention will be possible for use cases with a simpler scope, such as use cases with freelancing projects. Gradually, more complex case studies can be examined, with the goal of eventually automating even Foreign Direct Investment (FDI) energy project agreements. The progress from simpler to more complex case studies is possible owing to (1) the gradual increase and improvement of data and (2) the relative iterative improvement of technology. While scaling up the technology application, the categorisation of use cases is important owing to the contextual nature of disputes. The success depends on the use case itself as well as on the application specific parameters.

A significant legal challenge lies with privacy and data protection of proactive data. If proactive data are systematised in computational systems, the gathering of such data should be permissible under law for so long as it is justified on legitimate purposes. The balance lies in collecting lawful data without exposing vulnerabilities to parties who can take advantage of such sensitive data, considering that Proactive Data could be used as a source for exploitation. Hence, while prioritising a lawful data collection for legitimate purposes, it is also essential to safeguard data with security measures.

Here, it is worth mentioning that establishing such a technological infrastructure for business projects should have priority over consumer or citizen activities. In business settings, a higher degree of control can be reached, due to various reasons ranging from data sensitivity in data collection to rationalisation of complex planning.

With the development of *automated dispute resolution*, disputes, especially in the context of professional projects, can be reduced significantly in number and intensity. That is, of course, never possible in absolute terms, since most disputes are motivated by political purposes or are caused by *black swan* events. Yet, the impact of dispute prevention will be fundamental, in particular for the dispute resolution economy, which is essential for the legal system.

Our expectation is that (1) this thesis has successfully shown how automated dispute prevention is possible and that (2) our future actions will contribute toward making the impossible real. Otherwise stated as the entrepreneur and investor Vinod Khosla has said: *imagine the possible and take it from impossible to improbable to possible, but then again unlikely to plausible to probably to real!* [1].

8.3 Future Research

The future research suggestions for each RQ have already been provided within each corresponding Chapter. At this point, we are interested in providing a general research suggestion for the PS.

Preventing disputes, presupposes the taking of preventive actions on multiple levels that may lead to a dispute. In this research we have primarily focused on contracts. Chapter 6 shows the possibility of applying our research in more LegalTech domains beyond contracting. Still, applying preventive practices solely within the scope of LegalTech is not sufficient. Usually a dispute is influenced by legal, and also by a range of divergent factors including financial, project management, social, governmental and many more factors. The common thread among all factors is human *argumentation* (this idea is compliant with the general theory of the Logocratic Method examined in Chapter 5). After all, before we act in finance, law or governance, people *argue* first and then they *act*. Each action is a translation of an argument people will hold in their minds. Therefore, our following research will focus on applying prevention in the field of argumentation.

[1] https://medium.com/@vkhosla/reinventing-societal-infrastructure-with-technology-f71e0d4f2355

Chapter 9

Reflections on iContracts

The present, final chapter provides our reflections on the thesis. Together with an explanation and an application to a case study, they will serve as additional instructive material for the future use of iContracts. The purpose is to address a specific question that surfaced during a progress evaluation of the written material with experts from different disciplines. The main question then was: *how does a modern legal professional apply the lessons derived from this research in practice?* The chapter is meant to provide insight into the practical application of the results of iContracts research for non-experts in legal technology.

Below, we will discuss five reflections of different nature. We start providing a reflection statement on the method that can be used to analyse risk in legal cases (see 9.1). Then, we show the application area of the method and its potential for non-legal experts (in 9.2). Thereafter, we reflect on the relevance of the method for contract templates by explaining how it relates with legal text improvement (see 9.3). Subsequently, we reflect on the protection of privacy (in 9.4). Finally, we show the relevance of the research for workflow automation (see 9.5). We close the chapter by a Coda (in 9.6).

All in all, we apply the five reflections on a practical case study. The case study concerns the daily practice of a fictional lawyer, Michelle, who works in the offices of a law firm at the Zuidas, Amsterdam. She just became responsible for a new case in which American contract law played a role. In this case, Michelle's client, Andy, is asked to deliver a website to a third party who promised to pay Andy only after he had delivered the website.

9.1 Legal Risk Analysis

Reflection 1 reads as follows.

Reflection 1: *The Bow-Tie Method can be used to* ***analyse*** *risk in legal cases*

The Bow-Tie Method, and EBTO as its ontological extension, can be used by legal experts to analyse risk for legal cases (see Chapter 3). For every time a legal expert encounters a legal case, legal risk is inherently involved. Two of the main roles of a legal expert in legal cases are (1) to help the stakeholders achieve their desired objectives and (2) to manage potentially hidden and visible legal risks which the stakeholders may be facing in their attempt to achieve the objective. In our case study, Michelle will use the Bow-Tie Method to analyse the risk in the legal case under examination. Below we see how.

Under the rules of American Contract Law, the enforceability of a contract requires the fulfilment of three criteria: (1) the *offer*, (2) the *acceptance*, and (3) the *consideration* [Knapp et al., 2015]. Here we remark that there exists a related rule which allows for an offer to be revoked any time prior to acceptance [American Law Institute, 1981]. Moreover, there is a further distinction between contracts in which (a) a *promise* is exchanged for *performance* (*unilateral* contract: promise leads to contract) and (b) a *promise* is exchanged for a *promise* (*bilateral* contract: promise leads to (another) promise) [Knapp et al., 1971]. An issue that may arise in American Contract Law is the *circumstance* in which (1) one party makes an offer for a Unilateral Contract, while (2) the other party has stated to perform the task specified by the offer. The issue if the offeror attempts to revoke the offer prior to the completion of the task by the offeree [American Law Institute, 1981]. Under *traditional* contract rules such a revocation is *effective*, meaning that (1) the offer that is being made is no longer capable of being accepted and (2) may face substantial costs. However, the offeree may also suffer from unexpected substantial costs. In a unilateral contract, *consideration* is one of the necessary conditions for enforcement. In fact, the full performance will be identical to (a) the completion of the performance and (b) the acceptance [American Law Institute, 1981]. So, the completion of performance plays two roles: *consideration* and *acceptance*. If there is no completion, a contract has not be accepted and there is no consideration to the offeror [American Law Institute, 1981].

The risk in unilateral contracts lies with the offeree, who incurs performance costs without securing the offer. An alternative to secure the offer is to make a counter-offer for a bilateral contract, if not desiring the flexibility by wanting to perform instead of being bound by performance. Depending on the interests of the contracting party, the offeree may choose for a unilateral or bilateral contract. It is a balancing act between *flexibility* (unilateral) or *security* (bilateral). Such balancing act comes into play as a *risk-trade off*, where the offeree is tasked with deciding on the prevention measure.

In a unilateral contract, 'If an act is requested, that very act, and no other, must be given.' [Williston, 2024]. 'In case of offers for a consideration, the performance of the consideration is always deemed a condition.' [Langdell, 1880]. It is elementary that any offer to enter into a unilateral contract may be withdrawn before the act requested to be done has been performed. [Williston, 2024, Langdell, 1880, Offord v. Davies, 1862]. The offer of a reward in consideration of an act to be performed is revocable before the very act requested has been done [Shuey v. United States, 1875, Biggers v. Owen, 1888, Fitch v. Snedaker, 1868, Petterson v. Pattberg, 1928]. In a later revision of the rules for unilateral contracts, partial performance entitles the offeree to complete the performance [American Law Institute, 1981] [1]. In any jurisdiction that does not accept this revision of the classical rules for offer and acceptance of a unilateral contract, the offeree runs a substantial risk of revocation before completion of the performance even after substantial performance costs have been incurred. Under the Classical rules for offer and acceptance, an offeree who was unhappy with such a risk could make a counter-offer for a bilateral contract, or could propose an option contract. It is a balancing act between flexibility (unilateral) or security (bilateral).

Such balancing act comes into play as a risk-trade off, where the offeree is tasked with deciding on the prevention measure. There are times that the offeree does not want to be bound by security, e.g., when the offeree is not certain about whether (s)he wants the contract or not. Yet, what the offeree certainly wants is freedom to try out and stop if (s)he does not want to complete it. Such a stopping may happen because there are also circumstances that parties get unhappy in bilateral contracts; if for a example a price rises or falls against the interests of a party, then that party may wish to escape from such contracts. In some of these circumstances, the contract reaches trial. Here, it is essential to remark that the difference between unilateral and bilateral contracts has already a fine-tuning of more than a century (see the reference below). The adherence lies in the fact that a unilateral contract seeks an act, while a bilateral contract seeks a promise as acceptance [Wormser, 1916]. In unilateral contracts, until

[1] "An offer which the offeror should reasonably expect to induce action or forbearance of a substantial character on the part of the offeree before acceptance and which does induce such action or forbearance is binding as an option contract to the extent necessary to avoid injustice."

the performance of an act (i.e., up to completion of the cat) the offer can be withdrawn [American Law Institute, 1981]. Such freedom is argued as fair considering the freedom it provides to contracting parties to reconsider until the completion of an act [American Law Institute, 1981]. Unilateral contracts are central in the sense that they enhance private autonomy of contracting parties, enabling cooperation with conditional agreements [Caruso, 2018].

In accordance with the Bow-Tie Method the main *Hazardous Event* with the case under examination is that Michelle's client may deliver a website but potentially does not get paid for it. The risk is "clearly hidden" in the fact that at any point prior to the delivery of the website the third-party may cancel the agreement. The *Risk Source* is that the provided offer is made on the ground of a *unilateral* agreement. The *Proactive Control* in this case is counter-offering with a bilateral agreement to secure the event of potential non-payment in case of completion of the work prior to the final delivery.

9.2 Legal Risk Explanation

Reflection 2 reads as follows.

> **Reflection 2:** *The Bow-Tie Method can be used to* ***explain*** *risk in legal cases to non-legal experts*

The Bow-Tie Method, and EBTO as its ontological extension, can be used by legal experts to explain risk for legal cases to non-legal experts. Lawyers are often times tasked with explaining complex legal information in a straightforward manner to non-legal experts, even laymen. In their attempt to explain such information clearly, they may use a variety of tools, one of which is the Bow-Tie Method. Using methods to explain legal information to non-legal experts frequently occurs in legal cases. One striking example is an analogous comprehensibility tool often used in jury trials in the US: the *Special Verdict*.

The jury or the judges are regularly facing the task of determining whether (1) in case of a dispute, the offeree may claim damages from the offeror under Unilateral Contracts or (2) the offeror may cancel the contract with the offeree under Bilateral Contracts. Under *American Law*, it is the task of the jury to understand the circumstances of the case clearly in order to make an educated decision. Under the *American Rules of Civil Procedure* [2], the jury [3] can render a *special verdict* in the form of an extensively written finding on each issue of fact.

[2] https://www.law.cornell.edu/rules/frcp/rule49

[3] If requested to do so by the trial judge

Such a verdict, in case of complex issues, helps structure the case in a consistent and understandable way [4]. Indeed, the verdict may also be used for the delineation of the available prevention measures in the contracting arrangement of unilateral or bilateral agreements. The obvious reason is that the deciding process on the appropriate prevention measure is fairly complex. Thus, investigating the cognitive interface between an *expert analysis* and a *prevention measure* becomes more relevant. A question that here arises, is how to leverage a special verdict to *explain* a unilateral or bilateral contract decision to someone visually and clearly? On top of that we remark that in such cases a visual explanation should be expressed in laymen terms, preferably in accordance with the rules of propositional deductive logic, which are proven to help the jury with clarifying *legalese* [Brewer, 2017]. Moreover, we explicitly remark that the members of the jury do not need to have knowledge of propositional deductive logic. They should only be given the opportunity to follow the recipe in clear step by step guidelines.

By combining the *clarity* of propositional logic with the *efficiency* of iContracts and the *latest developments* in AI, we may arrive at more *explainable* and *interpretable* forms of using contracts to explain legalese to non-legal experts. In this way, we will be able (1) to visualise to the jury the decision-making process of parties in legal disputes prior to the dispute and (2) to delineate with a higher degree of clarity whether a party is knowingly liable for potential actions. These two results (visualisation and delineation) may happen through explaining their risk trade-offs retroactively. Assuming that the parties to the disputes have had earlier access to the relevant information, we opine that the dispute may not have happened in the first place.

In relation to our case study, we assume (or remark) that Michelle is able to visualise the legal risk analysis on the Bow-Tie Method and to explain to Andy visually the risk he is facing if he directly accepts the offer made by the third-party instead of counter-offering with a bilateral agreement.

9.3 Legal Text Improvement

Reflection 3 reads as follows.

> **Reflection 3:** *The Bow-Tie Method can be used to* ***improve*** *legal text or speech from the perspective of legal risk*

[4] Sometimes, however, the responses of juries to special verdict questions are internally inconsistent; the judge makes of such responses whatever the judge can

The Bow-Tie Method can be used by legal experts and non-legal experts to improve legal text or speech with legal risk in mind. Each time people communicate and exchange information, legal risk is lurking. People with legal training are more aware of the legal consequences of their text and speech than people without legal training. Indeed, during speaking it is difficult to use standard formats to protect speech for legal risk. Therefore, during writing text, often-times experts in law and also non-legal experts use templates to structure their text accordingly. That is particularly the case for contracting templates.

Most corporate legal practice and personal contracting business today start with the review of a contract template. Later on this is tailored to the specific needs of a contracting agreement. For personal affairs or smaller business affairs it is also likely to experience the straight-forward application of a template, which may happen without following precise tailoring. Indeed, most of the contracting templates are reviewed and tested over time. Several industries, such as the Oil & Gas industry are relevant to be mentioned. Contract negotiations are by and large dependent on contracting templates. Here it is useful to mention that the negotiations focus on technical terms such as the price of sale and the percentages used for negotiation, as well as on indemnity clauses for liability and risk distribution. In even *newer* industries, such as the sustainability industry, the contract template terminology is currently being developed (see, e.g., the JARGONFREE project [5]).

Contract Templates & Havilteksten

A recent example in this area comes from the Dutch Law using *Havilteksten*, developed by the Dutch Bar Association on the basis of the XML standard. The Havilteksten use a standardised language that is (1) structured, (2) legally tested, (3) easy to share, and (4) easy to re-use.

iContracts relate with such templates in three ways. First, they *reduce the time* to arrive at a negotiating outcome for the terms that are earlier negotiated, or even today. Second, they *only relate to specific parts* of the process. A contract language is solely one aspect of the contracting process. Moreover, there is the *understanding* and the *execution*, where iContracts' contribution is by automating those parts. Third, there are *automation benefits*. With the application of AI and LLMs, it is possible to exploit LLMs to identify (or to find) new gaps in contract templates. Here, we remark that even contract templates may include open slots. When combining the safety of contract risk management with the

[5] https://projects.tuni.fi/jargonfree/

speed of LLMs, we will see that the economic analysis becomes more important for end-users.

Despite the universal recognition for the need for standardised legal templates, as well as multiple international attempts to establish uniform contract rules (see, e.g., Creative Commons [6]), there is as yet no globally recognised (re)source of truth for contract templates. Some researchers are expecting that LLMs will change this reality, while others do not believe so. Still, provided that the issue of *user trustworthiness* remains high, we would like to mention that a significant help towards a better standardisation comes from the support that LLMs offer. They are able to support legal experts in conducting minor tasks. We mention: summarising, explaining, and analysing risk.

As a result, Michelle will be able (after some time or training) to formulate an existing contract template and propose to Andy the use of that specific template as the basis of the counter offer for a bilateral agreement. Moreover, she may perform an analysis which she started earlier to optimise both the contract as well as the counter-offer email. The final result contributes towards helping Andy to be secure in the communications with the third party.

9.4 Protection of Privacy

Reflection 4 reads as follows.

> **Reflection 4:** *The collection of prevention data falls under the* ***protection of sensitive data***

The collection of data for prevention will fall under the umbrella of sensitive data collection for privacy purposes. This is due to the high risk of misuse or breaches of privacy associated with sensitive information. Let us investigate large organisations, such as financial institutions, where risk management is situated in a distinct department responsible for the management of risks of all kinds. Such organisations do typically adopt advanced data protection procedures for collecting and handling risk data, including prevention data. They are all in compliance with the regulations, such as the General Data Protection Regulation (GDPR). When *processing* or *collecting* data to be used for prevention, organisations (1) will be operating within the realm of risk management practices and (2) will need to comply with the same principles and protocols as with risk data, and other sensitive information. It entails robust privacy and data collection protocols including data security, consent, transparency and compliance.

[6] https://creativecommons.org

Moreover, the potential collection of prevention data should comply with the overall risk management strategy and the objectives of an organisation. Three issues to take into consideration are: *potential threats*, *data sensitivity*, and *impact*.

While processing all client data, Michelle should in principle be careful with the privacy of their client information. In this context, one may rightfully wonder: what is the *privacy treatment* for prevention data? Therefore, Michelle should be "obliged" to follow standard practice for the *protection* of sensitive data and for the *privacy* of Andy's data, without having to invent new privacy policies.

9.5 Workflow Automation

Reflection 5 reads as follows.

> **Reflection 5:** *iContracts will* ***gradually automate*** *most parts of the legal workflow*

Going from the introduction of a new agreement to its final execution, there will be a number of steps that contribute towards the **total legal workflow**. Today *some* of those steps are already automated, although *most of them* are still manually performed. iContracts introduce new opportunities to automate much more of those steps. As we have seen in Reflections 1 to 4, the workflow of a lawyer will within ten years be significantly influenced by iContracts. Indeed, the automation of some of those tasks will become possible with big leaps and small steps. That is also the case with (1) *client to client communications* and (2) *agreement development* and (3) *execution*, as we have seen in Chapter 2.

9.6 A Coda

Indeed, today (September 2024), Michelle, may not be able to exploit the benefits of this research in full. The plain reason is that technology has not advanced to the point where her work can be fully automated. That is also the case for Andy, who still needs to rely on manual work and the trust of a human legal expert. However, with time progressing and technology advancing, a great deal of the manual work that we see today will be gradually replaced by technology.

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Summary

Chapter 1 introduces *Preventive Law* as the scientific field established to prevent legal risks from becoming legal problems. Over time, it advanced in multiple directions, including *the effective management of contracts*. As part of this development, the management of legal risk was central. Up to 2015, contractual risk management was performed manually and often implicitly. By the use of Applied Logic, Data Science and Artificial Intelligence we show how it is possible to structure an explicit contract risk analysis to assist legal experts in delivering advanced legal risk analysis to non-legal experts. We do that via the introduction of the Onassis Ontology, that shows how it is possible for contractual client-to-client communications to perform optimally and securely from the perspective of contract risk management. Our investigation contributes to the theory of *Intelligent Contracts* (iContracts), currently the most advanced technology for contracting automation. The thesis investigates iContracts from multiple perspectives, with the following Problem Statement (PS).

PS: *To what extent is it possible to automate the prevention of disputes?*

The answer to the PS is provided in six follow up Chapters (Chapters 2 to 7), each of them addressing a particular Research Question (RQ). A concluding Chapter (Chapter 8) provides our answer to the PS. Finally, a Chapter of reflections (Chapter 9) shows how it is possible to apply the thesis in real-life.

Chapter 2 addresses RQ1, which reads:

RQ1: *To what extent is it possible to develop an ontology that automates contracts with communications and risk data?*

Contract automation is a challenging topic within AI and LegalTech. From digitised contracts via smart contracts, we are heading towards iContracts. Here, we will address the main challenge of iContracts: the handling of *communications* and *risk* data in contract automation. In our research we *design* and *conceptualise* an iContract ontology. Our findings validate the *conceptual expressiveness* of our ontology. A brief discussion highlights the value of the ontology design

and its application domains. The Chapter concludes by two observations: (1) the current method is innovative, and (2) further research is necessary for handling more complex use cases.

Chapter 3 addresses RQ2, which reads:

RQ2: *To what extent is it possible to translate the Bow-Tie Method into a visualisation of an ontology for contract risk management without altering the bow-tie structure?*

Standing at the start of our research we propose a new *visual analysis method* of hazardous events to be used in contract risk management. Our aim is to create an extension of the Onassis Ontology to *manage*, *analyse* and *visualise* risk data. The extension of the Onassis Ontology will be used for the development of *trustworthy* iContracts. The idea is that the implemented extension allows for the creation of *explicit* data out of *implicit* contractual information and legal processes. The creation happens by performing cross-referencing analyses with other collections of data. The ontological model that results from our study will additionally help to the disambiguate the information stored in the Bow-Tie Method structure. To achieve this, we use the following methodology. (1) We visualise the Bow-Tie Method in an ontology. (2) We investigate the presence of taxonomic ambiguities or even errors in its structure. (3) The results present an enriched version of bow-tie conceptualisation of information, in which entities and relationships are translated into openly-accessible and *ready-to-use* ontological terms, whereas risk analysis becomes visible.

Chapter 4 addresses RQ3 which reads:

RQ3: *To what extent is it possible to improve user trustworthiness for Intelligent Contracts via the visualisation of risk during legal question-answering?*

Our research aims to show how contractor *trustworthiness* for iContracts improves via the visualisation of risk. Traditionally, contractors relied on legal experts who conducted the analysis of risk and proposed contracting solutions. Currently, trustworthiness is still an *open question* concerning the state-of-the-art in user interfaces for contract automation. Nowadays, the available interfaces do not present much valuable information, and the question is whether it is sufficient information (or otherwise stated what are the criteria for sufficient information). To measure the impact of the trustworthiness at the end users side, we will investigate to what extent we can visualise legal risk for answering legal questions addressed to contracting parties. For this task, we developed an explorative survey that requested end users to rate in what way their trustworthiness level is different when compared (a) to an empty user interface and (b) to a legal expert who discusses legal risks with them in person. The results show that the end user reaction is on both cases almost sufficiently positive. The discussion highlights the importance of risk analysis visualisation for user trustworthiness in iContracts and provides suggestions for improvement. The conclusion is that end user trustworthiness improves with risk visualisation. Yet, further improvements are necessary.

Chapter 5 addresses RQ4, which reads as follows:

> **RQ4:** *To what extent is it possible to generate quality Proactive Control Data to improve an Intelligent Contract?*

iContracts have 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. It is a novel research scope in the literature. Currently, the legal system is more *reactive* than *proactive*, leading to high consequential legal costs. By shifting the focus to proactiveness, we discuss the available methodologies (the Bow-Tie Method and the Logocratic Method) and aim to improve upon them. Moreover, we examine PCD with the context of three technologies (Ontology Engineering, Software Engineering and LLMs) with the aim to arrive at a higher degree of proactiveness in iContracts. Our research direction is threefold. First, we generate PCD after the development of a prototype. Second, we show that impact of PCD on contract drafting is measurable. Third, we show how the quality of PCD can be assessed and improved. The discussion (1) highlights the feasibility of the research with available technologies and (2) shows that its implementation depends on organisational considerations and resource allocation. From the results we may conclude that it is possible to implement these new ideas successfully.

Chapter 6 addresses RQ5, which reads as follows:

> **RQ5:** *To what extent is it possible to develop an explainable and trustworthy Preventive Legal Technology?*

Preventive Legal Technology (PLT) is a new field of Artificial Intelligence (AI) investigating the *intelligent prevention of disputes*. The concept integrates the theories of *preventive law* and *legal technology*. Our goal is to give ethics a place in the new technology. By *explaining* the decisions of PLT, we aim to achieve a higher degree of *trustworthiness* because explicit explanations are expected to improve the level of *transparency* and *accountability*. Trustworthiness is an urgent topic in the discussion on doing AI research ethically and accounting for the regulations. For this purpose, we examine the limitations of rule-based explainability for PLT. After an insightful literature review, we focus on case studies with applications. The results describe (1) the effectivity of PLT and (2) its responsibility. The discussion is challenging and multivariate, investigating deeply the relevance of PLT for LegalTech applications in light of the development of the AI Act (currently still under construction) and the work of the High-Level Expert Group (HLEG) on AI. On the ethical side, explaining AI decisions for small PLT domains is clearly possible, with direct effects on trustworthiness due to increased transparency and accountability.

Chapter 7 addresses RQ6, which reads as follows:

> **RQ6:** *To what extent is it possible to accelerate the adoption of Intelligent Contracts with Explainable Large Language Models?*

Contract automation is a field of LegalTech under AI and Law that is currently undergoing a transition from Smart to iContracts. iContracts aim to full contracting automation. Their main challenge is finding a convincing direction for market adoption. Two powerful market factors are the *advent of LLMs* and *AI Regulation*. The Chapter investigates how the two factors are able to influence the market adoption of iContracts. After a literature review our research employs three methodologies: (1) market gap analysis, (2) case study, and (3) application. The results show a clear way for iContracts to follow, based on existing market gaps. Moreover, the indicated paths validate whether the application of Explainable LLMs is actually possible. The discussion clarifies the main limitations with Explainable LLMs. Our chapter conclusion is that the two market factors are impactful for so long as the market adoption attempts to bridge the gap between innovators and early adopters.

Chapter 8 answers the PS based on the answers to the RQs provided above.

> **PS:** *To what extent is it possible to automate the prevention of disputes?*

The automated prevention of disputes is possible to the following extent: a relevant technological infrastructure is established to facilitate this type of automation. Initially, the successful prevention will be possible for use cases with a simpler scope, such as use cases with freelancing projects. Gradually, more complex case studies can be examined, with the goal of eventually automating even Foreign Direct Investment (FDI) energy project agreements. The progress from simpler to more complex case studies is possible owing to (1) the gradual increase and improvement of data and (2) the relative iterative improvement of technology. While scaling up the technology application, the categorisation of use cases is important owing to the contextual nature of disputes. The success depends on the use case itself as well as on applying specific parameters.

Finally, Chapter 9 provides five reflections which show the relevance of the thesis in real-life applications. The reflections are as follows.

Reflection 1: *The Bow-Tie Method can be used to **analyse** risk in legal cases*

Reflection 2: *The Bow-Tie Method can be used to **explain** risk in legal cases to non-legal experts*

Reflection 3: *The Bow-Tie Method can be used to **improve** legal text or speech from the perspective of legal risk*

Reflection 4: *The collection of prevention data falls under the **protection of sensitive data***

Reflection 5: *iContracts will **gradually automate** most parts of the legal workflow*

Samenvatting

Hoofdstuk 1 introduceert *Preventive Law* als het wetenschappelijk veld dat is gericht op het voorkomen van juridische risico's en juridische problemen. In de loop der tijd ontwikkelde Preventive Law zich in verschillende richtingen, waaronder het effectieve beheer van contracten. Als onderdeel van deze ontwikkeling stond het beheer van *juridische risico's* centraal. Tot voor kort werd het beheer van contractuele risico's handmatig en vaak impliciet uitgevoerd. Door gebruik te maken van Toegepaste Logica, Data Science en Kunstmatige Intelligentie laten we zien hoe het mogelijk is om een expliciete contractrisicoanalyse te structureren om juridische experts te helpen bij het leveren van geavanceerde juridische risicoanalyses aan niet-juridische experts. We doen dit via de introductie van de *Onassis Ontologie*, die laat zien hoe het mogelijk is om contractuele (d.i. klant-naar-klant) communicatie optimaal en veilig te laten verlopen vanuit het perspectief van contractrisico management. Ons onderzoek draagt bij aan de theorie van intelligente contracten (iContracts), die momenteel gezien wordt als de meest geavanceerde technologie voor contractautomatisering. Het proefschrift onderzoekt iContracts vanuit meerdere perspectieven, met één centrale *Problem Statement* (PS).

PS: *In hoeverre is het mogelijk om het voorkomen van geschillen te automatiseren?*

Het antwoord op de PS wordt gegeven in zes vervolghoofdstukken (hoofdstuk 2 tot en met 7), die elk een onderzoeksvraag (OV) behandelen. Een concluderend hoofdstuk (Hoofdstuk 8) geeft het antwoord op de PS. Tot slot laat een reflectiehoofdstuk (Hoofdstuk 9) zien hoe het mogelijk is om het proefschrift in de praktijk toe te passen.

Hoofdstuk 2 gaat in op OV1, die luidt:

OV1: *In hoeverre is het mogelijk om een ontologie te ontwikkelen die contracten met communicatie- en risico-gegevens automatiseert?*

Contractautomatisering is een uitdagend onderwerp binnen AI en LegalTech. Van gedigitaliseerde contracten via slimme contracten gaan we naar iContracten. We besteden veel aandacht aan de belangrijkste uitdaging van iContracts: de omgang met ict-communicatie en ict-risico's in de contractautomatisering. In dit hoofdstuk ontwerpen en conceptualiseren we een iContract-ontologie. Onze bevindingen valideren de *conceptuele uitdrukkingskracht* van onze ontologie. In een korte discussie leggen we de nadruk op de waarde van het ontologie-ontwerp en de toepassings domeinen. Het hoofdstuk wordt afgesloten met twee observaties: (1) de huidige methode is innovatief, en (2) verder onderzoek is nodig voor het verwerken van complexere *use cases*.

Hoofdstuk 3 gaat in op OV2, die luidt:

> **OV2:** *In hoeverre is het mogelijk om de Bow-Tie Methode te vertalen naar een visualisatie van een ontologie voor contract-risicobeheer zonder de bow-tie structuur te veranderen?*

Om te beginnen introduceen we een nieuwe visuele analysemethode voor gevaarlijke gebeurtenissen die gebruikt kan worden bij contractrisicobeheer. Ons doel is om een uitbreiding van de Onassis Ontologie te creëren om risicogegevens te *beheren*, *analyseren* en *visualiseren*. De uitbreiding van de Onassis Ontologie zal gebruikt worden voor de ontwikkeling van betrouwbare iContracten. Het idee is dat de geïmplementeerde uitbreiding het mogelijk maakt om expliciete gegevens te creëren uit impliciete contractuele informatie en juridische processen. De creatie gebeurt door het uitvoeren van kruisverwijzingsanalyses met andere gegevensverzamelingen. Het ontologische model dat het resultaat is van onze studie zal bovendien helpen om de informatie die is opgeslagen in de Bow-Tie Methode structuur te disambigueren. Om dit te bereiken, gebruiken we de volgende methodologie. (1) We visualiseren de Bow-Tie Methode in een ontologie. (2) We onderzoeken de aanwezigheid van taxonomische dubbelzinnigheden of zelfs fouten in de structuur. (3) De resultaten presenteren een verrijkte versie van de vlinderdas-conceptualisatie van informatie, waarin entiteiten en relaties worden vertaald naar openlijk toegankelijke en gebruiksklare ontologische termen, terwijl de risicoanalyse zichtbaar wordt.

Hoofdstuk 4 gaat in op OV3, die luidt:

> **OV3:** *In hoeverre is het mogelijk om de betrouwbaarheid voor de gebruikers van Intelligente Contracten te verbeteren via de visualisatie van risico's tijdens het beantwoorden van juridische vragen?*

Ons onderzoek heeft als doel om aan te tonen hoe de betrouwbaarheid van iContracts verbetert door risico's te visualiseren. Traditioneel vertrouwden project-aannemers op juridische experts die de risicoanalyse uitvoerden en contractuele oplossingen voorstelden. Tegenwoordig is betrouwbaarheid nog steeds een open vraag met betrekking tot de nieuwste gebruikersinterfaces voor contractautomatisering. Op dit moment geven de beschikbare interfaces niet veel waardevolle informatie en de vraag is of het voldoende informatie is? (We merken op dat en nog gee criteria voor *voldoende* informatie zijn). Om de impact van de betrouwbaarheid aan de kant van de eindgebruiker te meten, zullen wij onderzoeken in hoeverre het juridische risico voor het beantwoorden van juridische vragen aan contractpartijen valt te visualiseren. Voor deze taak hebben we een exploratieve enquête ontwikkeld waarin eindgebruikers werd gevraagd te beoordelen in welk opzicht hun betrouwbaarheidsniveau verschilt in vergelijking met (a) een lege gebruikersinterface of (b) een juridische expert die fysiek juridische risico's met hen bespreekt. De resultaten laten zien dat de reactie van de eindgebruikers *bijna* voldoende positief is. In de discussie valt de nadrukt op het belang van de visualisatie van risicoanalyses voor de betrouwbaarheid van de gebruikers in iContracts. In de discussie staan ook suggesties voor verbetering. De conclusie is dat de betrouwbaarheid van de eindgebruiker verbetert met risicovisualisatie, maar dat verdere verbeteringen noodzakelijk zijn.

Hoofdstuk 5 gaat in op OV4, die luidt:

OV4: *In hoeverre is het mogelijk om Proactive Control Data van hoge kwaliteit te genereren om een Intelligent Contract te verbeteren?*

iContracts kennen vele uitdagingen waaronder de kwaliteit van de gebruikte gegevens. In ons onderzoek richten we ons op het genereren en opnemen van *Proactive Control Data (PCD) van hoge kwaliteit* om iContracts te verbeteren. Dit is een nieuw onderzoeksgebied in de literatuur. Momenteel is het rechtssysteem meer reactief dan proactief, wat leidt tot hoge juridische kosten. Door de focus te verleggen naar proactiviteit, bespreken en verbeteren we de beschikbare methodologieën (de Bow-Tie Methode en de Logocratische Methode). Voorts onderzoeken we PCD in de context van drie technologieën (Ontology Engineering, Software Engineering en LLM's) met als doel een hogere mate van proactiviteit aan te tonen in i-Contracts. Onze onderzoeksrichting is drieledig. Ten eerste genereren we PCD met de ontwikkeling van een prototype. Ten tweede laten we zien dat de impact van PCD bij het opstellen van contracten een rol speelt. Ten derde laten we zien hoe de kwaliteit van PCD kan worden beoordeeld en verbeterd. De discussie benadrukt (1) dat de haalbaarheid van het onderzoek met beschikbare technologieën mogelijk is en (2) dat de implementatie afhangt van organisatorische overwegingen en de toewijzing van middelen. Uit de resultaten mogen we concluderen dat het mogelijk is om onze nieuwe ideeën succesvol te implementeren.

Hoofdstuk 6 gaat in op OV5, die luidt:

OV5: *In hoeverre is het mogelijk om een verklaarbare en betrouwbare Preventieve Juridische Technologie te ontwikkelen?*

Preventieve Juridische Technologie (Eng. PLT) is een nieuw gebied van de AI waarin onderzoek gedaan wordt naar het intelligent voorkomen van geschillen. Het concept integreert de theorieën van preventief recht en juridische technologie. Ons doel is om *ethiek* een plaats te geven in de nieuwe technologie. Door de beslissingen van PLT uit te leggen, willen we een hogere mate van betrouwbaarheid bereiken omdat expliciete uitleg naar verwachting de mate van transparantie en controleerbaarheid zal verbeteren. Betrouwbaarheid is een urgent onderwerp in de discussie over het ethisch doen van AI-onderzoek en het afleggen van verantwoording over de regelgeving. Voor dit doel onderzoeken we de beperkingen van regelgebaseerde verklaarbaarheid voor PLT. Na een inzichtelijk literatuuronderzoek richten we ons op casestudies met toepassingen. De resultaten beschrijven (1) de *effectiviteit* van PLT en (2) de *verantwoordelijkheid* ervan. De discussie is uitdagend en multivariaat, waarbij diep wordt ingegaan op de relevantie van PLT voor LegalTech-toepassingen in het licht van de ontwikkeling van de AI-wet en het werk van de High-Level Expert Group (HLEG) voor AI. Aan de ethische kant is het duidelijk mogelijk om AI-beslissingen voor kleine PLT-domeinen uit te leggen, met directe gevolgen voor de betrouwbaarheid door meer transparantie en verantwoording.

Hoofdstuk 7 gaat in op OV6, die luidt:

OV6: *In hoeverre is het mogelijk om de adoptie van Intelligente Contracten te versnellen met Large Language Models?*

Contractautomatisering is een gebied dat momenteel een overgang doormaakt van Smart Contracts naar iContracts. Daarbij streeft iContracts naar volledige contractautomatisering. De grootste uitdaging is het vinden van een overtuigende richting voor markt-acceptatie. Twee krachtige marktfactoren zijn de komst van *LLM's* en *AI-regelgeving*. In dit hoofdstuk wordt onderzocht hoe deze twee factoren de markttoepassing van iContracts beïnvloeden. Na een literatuurstudie maakt ons onderzoek gebruik van drie methodologieën: (1) een analyse van hiaten in de markt, (2) een casestudy en (3) een toepassing. De resultaten tonen een duidelijke weg voor iContracts op basis van bestaande lacunes in de markt. Bovendien valideren de meeste studies in hoeverre de toepassing van *Explainable* LLM's mogelijk is. In de discussie worden de belangrijkste beperkingen van LLM's besproken. Onze conclusie in het hoofdstuk is dat twee factoren van invloed zijn zolang de markttoepassing de kloof tussen innovators en *early adopters* probeert te overbruggen.

Hoofdstuk 8 beantwoordt de PS and de OVs op basis van het verrichte onderzoek.

PS: *In hoeverre is het mogelijk om het voorkomen van geschillen te automatiseren?*

De geautomatiseerde preventie van geschillen is volgens ons onderzoek zeker mogelijk voor zover een relevante technologische infrastructuur wordt opgezet om een dergelijke vorm van automatisering mogelijk te maken. In eerste instantie zal een succesvolle preventie mogelijk zijn voor *use cases* met een eenvoudige scope, zoals *use cases* met freelance projecten. Geleidelijk aan kunnen complexere casestudies worden onderzocht, met als doel om uiteindelijk zelfs energieprojectovereenkomsten van directe buitenlandse investeringen (FDI) te automatiseren. De voortgang van eenvoudigere naar complexere casestudies is mogelijk dankzij (1) de geleidelijke toename en verbetering van gegevens en (2) de relatieve iteratieve verbetering van technologie. Bij het opschalen van de toepassing van de technologie is de *categorisering van use cases* belangrijk vanwege de contextuele aard van geschillen. Het succes hangt af van de *use case* zelf en van de *toepassingsspecifieke parameters*.

Hoofdstuk 9 geeft tot slot vijf reflecties om de relevantie van het proefschrift in de praktijk aan te tonen. De reflecties zijn als volgt.

Reflectie 1: *De vlinderdasmethode kan worden gebruikt om risico's in rechtzaken te* ***analyseren***

Reflectie 2: *De vlinderdasmethode kan worden gebruikt om risico's in rechtzaken* ***uit te leggen*** *aan niet-juristen*

Reflectie 3: *De strikmethode kan worden gebruikt om juridische teksten of toespraken te* ***verbeteren*** *vanuit het oogpunt van juridisch risico*

Reflectie 4: *Het verzamelen van preventiegegevens valt onder de* ***bescherming gevoelige gegevens***

Reflectie 5: *iContracts zal de meeste delen van de juridische workflow* ***geleidelijk automatiseren***

Curriculum Vitae

Georgios Stathis was born in Ioannina, Greece in 1995. He holds a Bachelor in Law from Tilburg University and a Master in Law from the University of Amsterdam. He has also attended various courses, including those from Harvard Law School, Y Combinator, and SaaS Academy. He started his PhD at Leiden Law School of Leiden University on November 1, 2017.

During his studies, Georgios completed many internships, chaired a student association and invested in the stock market. In 2015 he won an innovation award by HiiL. Since 2019 he has often been on the list of TNW's top digital young minds in the NL.

Professionally, Georgios has held three positions at TNO, the Netherlands Organisation for Applied Scientific Research, from 2020 to 2023. Prior to that, he worked at Leiden University between 2017 to 2019. Next to these activities, he founded a startup in 2017. When time permits, he serves as consultant or advisor for startup businesses.

Publications

While working towards this thesis, the following contributions were made.

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