EU Regulation of Reinforcement Learning in Digital Finance

BART GEUGIES, University of Twente, The Netherlands

The integration of Artificial Intelligence (AI) into Digital Finance has grown significantly in recent years, driven by the potential to enhance decision-making and operational efficiency. This study aims to explore the various key application categories of Reinforcement Learning (RL) in Digital Finance, and evaluate their regulatory feasibility by identifying the current and future regulatory challenges within the European Union (EU). Through a Systematic Literature Review and a Grey Literature Search, key application areas were identified, including Portfolio Management, Risk Management, Trading, and Tax Management. The findings highlight that while RL can significantly enhance financial operations, its deployment can be complicated by regulatory frameworks such as the EU AI Act, which categorises AI applications based on risk levels and imposes stricter regulations on high risk applications. Analysis reveals however that most RL applications in finance are expected to fall under minimal to limited risk categories, which imposes few to no restrictions on development and deployment. This research further recommends the need for adaptive regulatory frameworks and interdisciplinary studies to fully understand the wider impact of RL in Finance while ensuring regulatory compliance and consumer protection.

Additional Key Words and Phrases: Fintech

1 INTRODUCTION

Reinforcement Learning (RL) is a Machine Learning technique in which an agent uses decision-making policies to select its actions. It learns and adapts these policies by interacting with a real or simulated environment and uses feedback from employing a policy to improve said policy. RL is capable of learning and continuously adapting based on new information, this makes RL well suited to the dynamic and partially observable environment of Digital Finance.

The current world of Digital Finance consists primarily of automated systems that run the vast majority of tasks, ranging from credit risk assessments to portfolio management and active equity trading. The usage of these systems is prevalent due to the benefits they provide over manually operated systems, such as a decrease in processing times as well as an increase in consistency.

While it is true that automated systems have become the primary actors in Digital Finance, the systems are still not perfect. They excel at structured and repetitive tasks, however complex tasks in dynamic environments can often result in inaccurate decisions or may still require intervention by a human actor. Reinforcement Learning, a branch of machine learning that is well known for its capability to operate in dynamic environments, has been identified as a possible solution to overcoming such challenges. However, the adoption of Reinforcement Learning algorithms in turn causes new challenges, some of which are on the regulatory side. Governments are actively evaluating if existing regulatory frameworks are sufficient for regulating Machine Learning applications or if new frameworks need to be created.

This research consists of two parts, a systematic literature research to identify gaps in current literature and propose directions for future research based on the potential applications of RL in digital finance, and a grey literature search to identify the current and future direction of regulation in the EU to the domain of Artificial Intelligence in Finance. Particularly the EU AI Act will be explored as a potential complicating factor in adopting RL.

2 MOTIVATION

The integration of Reinforcement Learning (RL) into Digital Finance has been a focal point of recent research. Several studies have explored the potential of RL to enhance various aspects of financial services, including but not limited to trading, risk management, and portfolio optimization. The aim of this section is to explore both existing academic literature on applications RL in Digital Finance as well as gain insight into the current state of relevant regulation.

2.1 Current Findings

Recent studies such as [Hambly et al. 2023] have reviewed modern applications of RL in finance, exploring their use in Optimal Order Execution, Portfolio Optimisation, Option Pricing, Hedging, Market Making, Robo-advising and Smart Order Routing. Their findings demonstrate the potential of RL to improve decision-making processes in the dynamic and uncertain financial environments.

Similarly, the study by [Malibari et al. 2023] conducted a systematic review on RL in Fintech with a primary focus on the technical implementations of RL systems, identifying similar use cases as [Hambly et al. 2023] such as Optimal Order Execution, Robo-advising, Portfolio Management, Peer-to-Peer Lending, Cryptocurrency Price Prediction, and Risk Optimisation. The paper also highlights a previously unexplored use case of chatbots, which can effectively serve as personalised brokers to the users.

[Veale and Zuiderveen Borgesius 2021] discuss the implications of the then recently proposed EU AI Act, focusing on its regulatory framework designed to ensure the ethical and safe use of AI in various sectors, including finance. The article emphasises the need for transparency, accountability and robust governance mechanism to mitigate risks associated with AI applications. The act categorises AI systems based on risk levels, proposing stricter regulations for high-risk applications to promote responsible AI practises.

The article by [Restoy et al. 2019] explores the challenges and opportunities in regulating fintech. The report emphasises the need for adaptive regulatory frameworks that can keep pace with the rapid technological advancements in the financial sector. It highlights the importance of striking the right balance between fostering

TScIT 41, July 5, 2024, Enschede, The Netherlands

innovation and ensuring consumer protection, emphasising the importance of collaboration between regulators, industry stakeholders and policymakers.

2.2 Research Goal

The goal of this research is to find the potential applications of Reinforcement Learning in Digital finance and explore the regulatory challenge posed by the EU AI Act or similar regulation within the European Union.

3 RESEARCH METHODOLOGY

This chapter outlines the research methodology for this study which includes a Systematic Literature Review (SLR) and a Grey Literature Search (GLS). The aim is to synthesise both results to address the gap between the technical capability and regulatory feasibility of application categories, thereby providing a holistic understanding of the opportunities and challenges of implementing RL in Digital Finance. This results in the following primary research question.

What are the regulatory-feasible and promising applications of Reinforcement Learning in Digital Finance?

3.1 Systematic Literature Review

The goal of the Systematic Literature Review (SLR) is to systematically identify existing applications of RL in Digital Finance by synthesising findings from various studies into a comprehensive overview of application areas.

3.1.1 Research Questions. To aid in partially answering the primary research question, the following sub questions will be used to guide the SLR:

What are the existing applications of reinforcement learning in digital finance? What are the key findings and contributions of existing studies on RL applications in digital finance?

3.1.2 Inclusion and Exclusion Criteria. To ensure that the SLR includes high-quality, relevant studies that provide valuable insights into the application of RL in Digital Finance, the following criteria were applied (Table 1):

Table 1. Inclusion and exclusion criteria

Inclusion Criteria
Papers published between 2014 and 2024, to ensure relevance.
Papers published as journal articles or conference papers.
Papers written in English.
Papers that explore the usage of RL in Digital Finance applications.
Exclusion Criteria
Papers without a significant emphasis on RL techniques.
Papers without a financial context.
Papers with a focus on one specific technical implementation.
Papers for which a newer version has already been included.
Papers with low quality title and abstract

3.1.3 Search Procedure. The search procedure for the SLR was designed to ensure a comprehensive and unbiased collection of studies that explore applications of RL in Finance while ignoring documents that focus on specific RL technical implementations for a particular application. The literature search was conducted across the academic database Scopus, which is well known for its extensive indexing of high quality research articles and conference papers.

3.1.4 Keywords and Queries. The main query for the search can be found in Table 2 along with the number of hits. Boolean operators (AND, OR) were used to combine keywords into search strings such as “Reinforcement Learning AND Digital Finance”. To ensure comprehensive coverage, synonyms and related terms for the primary keywords were included in the search string and where appropriate wildcard and truncation symbols were used to capture variations in keywords, such as “Risk Manag*” to capture Risk Management and Risk Managing and “RL, Reinforcement Learning” or “Finance, Fintech”. This helps find studies that might use different terminology for the same concepts.

Per the above, the following keywords were selected based on the research goal, scope and a preliminary review of related literature: *Reinforcement Learning*, *Digital Finance*, *Applications*, *Risk Management*, *Portfolio Management*, *Option Pricing*, *Market Making*, *Smart Order Routing* and *Robo-advising*.

Table 2. Scopus Search Query and Hits

Search Query
TITLE-ABS-KEY (("RL" OR "Reinforcement Learning") AND ("Financ*" OR "Fintech") AND ("Application*" OR (("Risk" OR "Portfolio") AND (manag* OR optimi*)) OR "Option Pricing" OR "Market Making" OR "Robo-advising" OR "Smart Order Routing")) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ar"))
Hits
504

This search query combines the two most important keywords and their variations, Reinforcement Learning and Finance, with the more descriptive and smaller scope keywords that have been selected.

3.1.5 Literature Selection. The studies that are of interest are those that explore the usage of RL in Digital Finance applications. Studies that explore a single and specific technical implementation in finance, such as a particular method to manage a portfolio are excluded. During the literature section the vast majority of the studies were in the latter category, diving into the different mathematical models to manage a portfolio or trade and comparing them against traditional benchmarks.

After applying the search query found in table 2, 504 studies of interest were found. Based on the inclusion and exclusion criteria from table 1 the titles and abstracts of these studies were screened, leading to a smaller selection of 34 studies and articles for a full text review. Finally the contents of these 34 studies were assessed in detail to confirm whether they complied with the criteria and truly explored the usage of RL in digital finance applications as previously described, resulting in the final selection 5 compliant studies.

3.1.6 Literature Synthesis. For the studies that passed the full-text review, a standardised data extraction form was used to collect key information, such as Authors, Publication Year, Study Objectives, Explored Financial Applications, and Key Findings. Following that the RL applications found in the studies were grouped together into categories.

3.1.7 Results. Despite casting a wide net of 504 studies within the initial scope, the final count of studies that met the criteria was rather small (n = 5). This shows that based on our criteria, this particular research area is underdeveloped and that most research studies in the space focus on the implementation of specific reinforcement learning frameworks in specific disciplines such as portfolio management and algorithmic trading. The results rely on 5 articles included in the review, published between 2019 and 2024, none of the papers selected were published before 2019. The discovered applications will be grouped and discussed in section 5.1.

3.2 Grey Literature Search

The goal of the Grey Literature Search (GLS) is to complement the Systematic Literature Search (SLR) by examining the existing and proposed regulatory frameworks within the European Union that can impact the deployment of RL in Digital Finance.

3.2.1 Research Questions. The research sub question that guides the the Grey Literature Search is:

What are the current and potential future regulatory directions for RL applications in Digital Finance within the European Union?

3.2.2 Material type Selection. The GLS focuses on the following material types in order to provide a comprehensive and high quality understanding of the regulatory environment:

- Government publications
- Regulatory publications, including white papers and reports
- Academic commentaries on policy

The following criteria will be used to screen articles:

- Publications from 2019-2024 to ensure relevance to the current state of AI.
- Materials in English.
- Materials specifically addressing AI, ML and RL in the context of regulation.
- Materials covering the financial sector directly or indirectly.
- Materials scoped within the European Union

3.2.3 Search Procedure. The search procedure for the GLS involves a semi-systematic approach to ensure consistent and comprehensive coverage of the available material. The search will be conducted across the academic database of Google Scholar and the search engine of Google as well as official EU websites, employing a mix of search queries and manual screening to identify relevant documents.

3.2.4 Keywords. To capture a broad range of documents a combination of keywords related to RL, AI, ML, Digital Finance, and Regulatory frameworks have been chosen. Similar to the SLR, where applicable synonyms and abbreviations were used to ensure comprehensive coverage, as well as truncation to include word variations. Examples are “Reinforcement Learning, RL” and “Finance, Financ*”

Reinforcement Learning, *Artificial Intelligence*, *Machine Learning*, *European Union*, *Compliance*, *Regulation*, *Finance*, *Digital Finance*, *Fintech*, *Policy*, and *Law*

Similar to the SLR, where applicable synonyms and abbreviations were used to ensure comprehensive coverage, as well as truncation to include word variations. Examples are “Reinforcement Learning, RL” and “Finance, Financ*”

3.2.5 Material Selection. The selection process involves an initial, manual screening based on the title and summary of publications, followed by a full text review to confirm relevance and quality before the final selection is made.

3.2.6 Results. The results of the GLS will be synthesised to provide an overview of the regulatory landscape of RL applications in Digital Finance. To inform the discussion on regulatory feasibility, key themes and insights in regulation will be identified with a focus on current regulatory frameworks and their impact as well as proposed regulations and their potential impact.

4 FINDINGS

4.1 Identified Applications

This section explores the various applications of RL in digital finance, categorising them by their respective areas and providing examples of how RL is being utilised in each domain. Table 3 presents an overview of the identified applications. Each application demonstrates how RL can be leveraged to enhance aspects of financial systems and decision-making processes.

Application details:

- Smart Taxation, [Scientific 2024]: RL can optimise tax strategies and compliance, ensuring that financial operations are tax-efficient and adhere to legal requirements.
- Portfolio Management, [Hambly et al. 2023] [Den Hengst et al. 2019] [Charpentier et al. 2021] [Scientific 2024]: RL enables the creation of dynamic investment portfolios that can adapt to changing market conditions, optimising returns and managing risk effectively.
- Optimal Order Execution, [Hambly et al. 2023]: RL algorithms can determine the best execution strategies for trades, minimising costs.
- Option Pricing, [Hambly et al. 2023]: RL can be used to price derivatives, taking into account the dynamic market conditions and risk factors.
- Hedging, [Hambly et al. 2023]: RL provides robust strategies for mitigating financial risks by adjusting positions dynamically to hedge against potential losses.
- Market Making, [Hambly et al. 2023]: RL algorithms provide liquidity in financial markets by continuously quoting buy and sell prices and adjusting them dynamically based on market movements.
- Robo-advising, [Hambly et al. 2023] [Den Hengst et al. 2019]: RL enables automated advisors to provide personalised investment

advice and dialogue, optimising asset selection and allocation based on user profiles.
- Smart Order Routing, [Hambly et al. 2023]: RL improves the routing of orders to different liquidity pools, ensuring the best possible execution for each trade.
- Risk Management, [Charpentier et al. 2021], [Amirzadeh et al. 2022]: RL identifies and manages financial risks more effectively, optimising risk-return profiles for financial institutions.
- Auction Design, [Charpentier et al. 2021]: RL optimises auction and bidding strategies, ensuring efficient and fair outcomes for those involved.
- Algorithmic Trading, [Amirzadeh et al. 2022]: RL enhances algorithmic trading strategies, improving trade execution and profitability through dynamic decision-making.
- Fraud Detection, [Amirzadeh et al. 2022]: RL models detect fraudulent activities by learning patterns of legitimate and illegitimate behaviour in financial transactions.
- Sentiment Analysis, [Amirzadeh et al. 2022]: RL is able to analyse and correlate market sentiment to market movements in order to predict price action and inform trading decisions.

4.2 Regulatory Challenges

One of the primary concerns by regulators is the existing regulatory frameworks' ability to keep pace with the rapid advancements in AI technologies. The Grey Literature Search revealed a regulatory challenge that can impact the deployment of RL applications in Digital Finance within the European Union.

The European Union's proposed AI Act[1] aims to make sure that AI systems used in the EU are safe, transparent, traceable, non-discriminatory and environmentally friendly by categorising AI systems based on risk levels and imposing stricter regulations on high risk applications or in extreme cases outright banning them. This will have an impact on the financial sector, [Parente 2024] mentions that applications such as creditworthiness assessments by banks as well as risk assessments in life and health insurance will be considered high risk AI use cases.

Furthermore, [KPMG International 2024] mentions that the AI Act's definition of AI is anticipated to be broad and as such will impact most AI applications. On top of categorising AI systems by risk levels, provisions have been added to impose increased transparency requirements on General AI systems that can be integrated into many different technological applications.

The publications by the European Union, [European Union 2024], and the European Parliament, [European Parliament 2023], clarify which risk levels exist and which systems belong in which category. The risk levels used are:

- **Unacceptable Risk**, Banned AI systems that are considered a threat to people, such as:
  - Cognitive behavioural manipulation of people or vulnerable groups, for example voice activated toys that encourage dangerous behaviour in children.
  - Social Scoring, classifying people based on personal characteristics, behaviour or social status.

[1] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52021PC0206

Table 3. Overview of identified applications

#	**Application Area**	**Category**	**Study**
1	Smart Taxation	Tax Management	[Scientific 2024]
2	Portfolio Management	Investment Management	[Hambly et al. 2023], [Den Hengst et al. 2019], [Charpentier et al. 2021], [Scientific 2024]
3	Optimal Order Execution	Trading	[Hambly et al. 2023]
4	Option Pricing	Trading	[Hambly et al. 2023]
5	Hedging	Risk Management	[Hambly et al. 2023]
6	Market Making	Trading	[Hambly et al. 2023]
7	Robo-advising	Investment Management	[Hambly et al. 2023]
8	Smart Order Routing	Trading	[Hambly et al. 2023]
9	Risk Management	Risk Management	[Charpentier et al. 2021], [Amirzadeh et al. 2022]
10	Auction Design	Market Mechanisms	[Charpentier et al. 2021]
11	Algorithmic Trading	Trading	[Amirzadeh et al. 2022]
12	Fraud Detection	Risk Management	[Amirzadeh et al. 2022]
13	Sentiment Analysis	Trading	[Amirzadeh et al. 2022]

  - Identification and categorisation of people through the use of biometric data.
  - Real-time and remote biometric identification systems, such as facial recognition. With the exception that for serious cases it may be allowed for law enforcement.
- **High Risk**, AI systems that will be subject to strict obligations before and during their lifecycle. Such obligations include good risk assessment and mitigation systems, high quality datasets to feed the system and minimise discriminatory outcomes, logging of activity to ensure traceability of results, detailed documentation about the system and its purpose so authorities can assess its compliance, appropriate human oversight measures, and high levels of security and accuracy. High risk applications are AI systems that are used in products covered by the EU's product safety legislation, [European Parliament 2001], which includes toys, aviation, cars, medical devices and lifts, as well as applications used in specific areas, such as:

  - Critical infrastructure.
  - Educational or vocational training.
  - Safety components of products.
  - (self-)Employment or worker management.
  - Essential private and public services.
  - Law enforcement.
  - Migration management.
  - Legal interpretation and application of the law.
- **Limited Risk**, AI systems where transparency or disclosure to the user is the most important risk factor. For example, when using chatbots, users should be made aware that they are interacting with a machine. Similarly, AI-generated content intended to inform the public on matters of public interest should be clearly disclosed as such.
- **Minimal Risk**, the remaining AI systems that do not fall into the other risk categories. These systems are free to use without restrictions, this includes applications such as AI enabled video games or spam filters.

[De Nederlansche Bank | AFM 2024] explains the need for Financial Institutions to use AI responsibly, highlighting that the objectives of supervision and the standards institutions are required to uphold are technology-agnostic, and apply just as well when AI is used, emphasising the importance of institutions to comply with requirements for high risk AI systems voluntarily by observing European guidelines on trustworthy AI.

4.3 Synthesis

The feasibility of RL applications in digital finance is influenced by both technical and regulatory factors as identified through the SLR and GLS. On the technical side RL offers substantial benefits, such as improved decision-making, dynamic adaptation to changing market conditions, and enhanced risk management.

Given the context of the proposed regulatory direction by the EU AI Act, it appears that the RL applications that have been discovered do not fall into the unacceptable risk category, with only Risk management potentially qualifying for the high risk category due to the possibility of dealing with essential private and public services such as risk management by credit services or dealing with legal interpretations for tax management.

Remaining applications such as investment management might fall under the limited risk category due to the primary risk being lack of transparency and disclosure. Without the user knowing they are talking to a robo-advisor or having their portfolio managed by AI, they cannot make informed decisions about the risk they are taking. The final applications, such as trading, are likely to be classified as minimal risk, resulting in no additional regulatory requirements over implementing traditional solutions.

5 CONCLUSION

Most promising Reinforcement Learning (RL) applications in digital finance are regulatory-feasible, applications such as tax management, investment management, trading and the design of market mechanisms pose little regulatory risk. The European Union's AI act imposes restrictions on the design an implementation of AI systems, however most digital finance applications of RL appear not to be impacted by these restrictions due to the general lack of dealing with sensitive data. Potential exceptions are risk management in the healthcare or credit sector, which may fall under the category of high-risk applications and will therefore require greater regulatory supervision and obligations. Other applications such as robo-advising or automated portfolio management will fall under the limited risk umbrella which will require the proper disclosures towards the user about interacting with an AI but no further adaptions. The remaining applications fall outside of these categories and under the minimal risk designation, which results in no adaptions whatsoever outside of the regular financial compliance requirements for digital systems.

5.1 Implications

The findings from this research indicate that the expected impact of these new AI regulations on applications of RL in finance will be minimal. The EU AI Act will require some financial institutions to adopt greater transparency and compliance measures, particularly those dealing with private or sensitive data, such as the health insurance or credit sectors. For these sectors it will mean a careful balancing act between leveraging the capabilities of RL while adhering to stricter regulatory standards, however for the other sectors the focus will lie on making sure the systems comply with the already existing broader regulation on digital finance.

5.2 Future Research

Despite the increase in literature on the subject, there are notable gaps that warrant further exploration. While many studies, including those by [Hambly et al. 2023] and [Malibari et al. 2023], emphasise the technical capabilities and potential applications of RL in finance, there is limited research on the regulatory challenges one will be faced with during real-world implementation.

Furthermore, while [Veale and Zuiderveen Borgesius 2021] address the required regulatory frameworks to ensure safe and ethical use of AI, there is a lack of detailed case studies or empirical data on how these regulations can be practically enforced and monitored. The proposed EU AI Act categorises AI systems by risk level, but the practicalities of categorising and monitoring these systems on an ongoing basis remains unclear.

[Restoy et al. 2019] highlights the need for adaptive regulatory frameworks to regulate modern AI, however there is a lack of discussion on the specific regulatory mechanism that can balance innovation with consumer protection effectively. Furthermore, unexplored areas such as the ethical and societal impact of these RL systems in finance are important to explore to understand the broader impact of these systems outside of their legality.

Future research should focus on addressing these gaps and challenges. Studies are needed to explore the practical and regulatory-compliant implementation of RL in the high risk financial applications, such as health insurance and credit assessments. These studies should provide detailed analysis on how institutions can meet the transparency and compliance requirements set by the AI act.

Appendix: Disclaimer(s)

During the preparation of this work the author(s) used GPT4o by OpenAI to identify style inconsistencies, spelling errors and grammatical errors. The tool/service was utilized purely for language purposes and after using this tool/service, the author(s) manually reviewed, corrected and edited the content as needed and take(s) full responsibility for the content of the work.

REFERENCES

Rasoul Amirzadeh, Asef Nazari, and Dhananjay Thiruvady. 2022. Applying artificial intelligence in cryptocurrency markets: A survey. *Algorithms* 15, 11 (2022), 428.

Arthur Charpentier, Romuald Elie, and Carl Remlinger. 2021. Reinforcement learning in economics and finance. *Computational Economics* (2021), 1–38.

De Nederlansche Bank | AFM. 2024. The impact of AI on the financial sector and supervision. https://www.dnb.nl/media/gepbbikm/ai.pdf

Floris Den Hengst, Mark Hoogendoorn, Frank Van Harmelen, and Joost Bosman. 2019. Reinforcement learning for personalized dialogue management. In *IEEE/WIC/ACM International Conference on Web Intelligence*. 59–67.

European Parliament. 2001. Consolidated text: Directive 2001/95/EC of the European Parliament and of the Council of 3 December 2001 on general product safety. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02001L0095-20100101

European Parliament. 2023. EU AI Act first regulation on artificial intelligence. https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence

European Union. 2024. AI Act. https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai

Ben Hambly, Renyuan Xu, and Huining Yang. 2023. Recent advances in reinforcement learning in finance. *Mathematical Finance* 33, 3 (2023), 437–503.

KPMG International. 2024. Decoding the EU AI Act. https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2024/02/decoding-the-eu-artificial-intelligence-act.pdf

Nadeem Malibari, Iyad Katib, and Rashid Mehmood. 2023. Systematic Review on Reinforcement Learning in the Field of Fintech. *arXiv preprint arXiv:2305.07466* (2023).

Fausto Parente. 2024. AI Act and its impacts on the European financial sector. https://www.eiopa.europa.eu/document/download/5dc730b7-29b6-44dd-819b-3a04476416ed_en?filename=ai-act-fausto-eurofi-magazine_ghent_february-2024%20128.pdf

Fernando Restoy et al. 2019. Regulating fintech: what is going on, and where are the challenges. *Bank for International Settlements* (2019), 1–7.

Little Lion Scientific. 2024. OPTIMIZATION OF SMART TAXATION USING ARTIFICIAL INTELLIGENCE: RISKS AND OPPORTUNITIES. *Journal of Theoretical and Applied Information Technology* 102, 5 (2024).

Michael Veale and Frederik Zuiderveen Borgesius. 2021. Demystifying the Draft EU Artificial Intelligence Act—Analysing the good, the bad, and the unclear elements of the proposed approach. *Computer Law Review International* 22, 4 (2021), 97–112.