JusGov Research Paper Series Paper 2021 - 03

Diogo Morgado Rebelo

"On the way to look at *Big Data* as an asset for CWA 4.0."

EU Right to Suggestion of an IDSS MAS-Based Scoring Case Study in Consumer Credit

This work is financed by national funds through FCT – Foundation for Science and Technology, I.P., under the project UID/05749/2020.

About this Research Paper Series

The JusGov Research Paper Series (editor: Sofia Pinto Oliveira) provides full articles submitted for publication by our researchers and by visiting researchers as well as speakers at our centre. The content is the responsibility of individual authors. All papers can be accessed from the JusGov Research Paper Series site on Social Science Research Network (SSRN) online platform (https://www.ssrn.com/index.cfm/en/jusgov-res/) and from our official site (https://www.jusgov.uminho.pt/pt-pt/publications/jusgov-research-paper-series/).

About this paper

The present work epitomises one of the author's Master's thesis topics. It was presented at the V Conference "AI and Robotics: Junior Researchers Panel" on 3 December 2021, a session co-organised by PhD Professors Eva Sónia Moreira and Pedro Miguel Freitas at the University of Minho, School of Law.

"On the way to look at *Big Data* as an asset for CWA 4.0." EU Right to Suggestion of an IDSS MAS-Based Scoring Case Study in Consumer Credit

Diogo Morgado Rebelo[1]

Summary: 1. Introduction; 2. CCD (in)effectiveness on CWA 4.0.; 3. Application scoring for credit in the age of Artificial Intelligence; 4. Intelligent-based CWA Profiling and ADM; 5. Interpretation for high-stake scoring in credit vis-à-vis data protection Jigsaw; 6. Right to Suggestive-Commoditization of an IDSS MAS-based classifier.

Abstract: Nowadays, consumers should fear how some of their demographic, financial, employment or behavioural information might impact their ability to be granted loans. DM approaches, applying ML models, often hide black box correlations. In the 2011 Fábio Silva's case study, the purposed credit suggestion agent settles the solution to the unenforceable entanglement of a right to explanation in consumer credit. When put into practice, the solvency profile automatically drawn up by the model-based decision agent operates by clustering clients as creditworthy. Alternatively, the suggestion agent operating next externalize a genetic automated counterfactual, revealing why a particular application ends up in a refusal of lending credit. By design, this methodology provides interpretations of which parameters were individually lacking and leads to inverse the non-acceptance outcome, being more feasible and effective for consumer applicants. EU representatives must once and for all perceive data as a real asset. Creditors shall be obliged to ascertain the duty by which clients would achieve specific transactional advantages for providing alternative or missing data.

1 Junior Researcher at JusGov Centre, E. Tec. Department & Postgraduate on Law and Informatics, both at the University of Minho, School of Law. E-mail: djmr1995@gmail.com.

ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Networks
ADM	Automated Decision-Making
CCD	Consumer Credit Directive
CRMC	Credit Risk Management Cycle
CSP	Credit Service Provider
CWA	Creditworthiness Assessment
DM	Data Mining
EC	European Commission
EDPS	European Data Protection Supervisor
ETL	Extract, Transformation & Loading
EU	European Union
FinTech	Financial Technology
IDSS	Intelligent Decision Support Systems
MAS	Multi-Agent Systems
PDCC	Proposal for a Directive on Consumer Credits
TRL	Technology Readiness Level
SME	Small and medium-sized enterprises
XAI	Explainable Artificial Intelligence

FIGURES

TABLES

1. Introduction

Article 22 of the Consumer Credit Directive (CCD)[2] enshrined imperative rules of maximum harmonisation, aprioristically meant to strengthen consumers' protection while simultaneously easing the crystallisation of a well-functioning European market on credit agreements. All 28 Member States have transposed Article 8 regarding the creditor's obligation to access the consumers' creditworthiness. However, the wide margin for legislative description has displayed structural flaws, especially in what esteems the type of data, sources and procedural lawful mechanisms used to infer customers' solvency. Therefore, the consumer credit regulation scenario figure now as a fragmented landscape on a European level.

Besides this legislative ineffectiveness, today's digital era exhibits renewed AI-based techniques for scoring individuals at the scale of big (alternative) data. Retail banking devoted to loan markets depicts the Creditworthiness Assessment (CWA) 4.0., the industrialisation of customers' increasing trust in machines. Scoring procedures in banking 4.0. outlines a helpful tool for predicting defaults risk with much better accuracy levels. Matured machine-made recommendations must, even from a psychological viewpoint, replace human beings in scoring at some point of the decision-making course.

As such, the more extensive availability, quality, and reliability of historical or alternative data sources across multiple borrower and loan products is the key to achieve the ML model's effectiveness or better accuracy in learning processes. Today, credit data drives the entire lending operation, especially whereabout automated IDSS output exclusively concede or influence consumer credit approvals or, alternatively, denials. It is no longer the programmers anymore who take on the status of the main characters. On the contrary, personal (often sensitive) data, jointly with the learning models, are responsible for predicting or prescribing who to accept next. The greater volume and diversity of input attributes at the primary layers of a given model will enhance benchmarking creditworthiness aptitude.

However, despite all the European attempts to uniformize sufficient legal grounds of privacy-preserving on exclusive credit-related Automated Decision-Making (ADM), data subjects still do not understand autonomous processing and have little control over how personal (credit) data is used to exhort predictions. As far as technical explanation vis-à-vis interpretation concerns, Article 18(6)(b) and Recital 48 of the Proposal for a Directive of the European Parliament and of the Council on consumer credits (COM(2021) 347 final), of 30 June 2021 (PCCD) reinforce the monodisciplinary nature of the European normative acts on Law and Technology. Until now, the European Commission (EC) suggests consumers must be granted the right to "meaningful explanation" before agreeing on credit. However, this European technophobic trend of explainability may stop. Instead, it is essential to come closer to the liveable and feasible technological reality, if necessary, adopting customer-friendlier solutions. With the establishment of a right to Automated Suggestion in application-related scoring, Fábio Silva's Multi-Agent System (MAS) provides, by default, SMEs, or FinTech Giants a straightforward privacy-friendly compliance solution through 'Law in Action'. The study presented in this paper aims to demonstrate how the use of counterfactual interpretations proves to be helpful and feasible tool in the current state-of-the-art. For this purpose, the term of comparison will be used, and the weaknesses associated with Explainable Artificial Intelligence (XAI) overlapping models will be clarified.

2. CCD (in)effectiveness on CWA 4.0.

Article 22 of the CCD encompasses imperative rules of maximum harmonisation. It aprioristically aimed to ease the emergence of a well-functioning internal market in credit agreements. Considering the various paragraphs that set, by exclusion, its material scope on Article 2, CCD provisions pertain to the several sorts of contracts regarding consumer credit. According to Article 3(c) of the CCD, contracts in consumer credit "*means an agreement whereby a creditor grants or promises to grant to a consumer credit in the form of a deferred payment, loan, or other similar financial accommodation, except for agreements for the provision continuingly of services or for the supply of goods of the same kind, where the consumer pays for such services or goods for the duration of their provision employing instalments*". As such, within the scope of this European act fall:

1 Personal loans to finance the acquisition of goods or services of long-lasting consumption.

2 Directive 2008/48/EC of the European Parliament and of the Council of 23 April 2008 on credit agreements for consumers and repealing Council Directive 87/102/EEC

2 Car loans, with or without reserve clause or ownership title, whether leasing or long-term rental.

3 Revolving credit, whether in the form of a credit card, overdraft facility, credit line, or even a current bank account.

4 Debt conversion credit agreements.

5 And, at final, supplier credits[3].

Some aspects of its material framework are also worth pointing out for scoping purposes. According to Article 2(a)(b), CCD shall not apply, respectively, to credit agreements that are secured either by a mortgage or agreements pursuing acquiring or retaining property rights in land or an existing or projected building. Contracts on consumer credit free of interest and without any other charges CCD provisions do not also apply, according to Article 2(f). Similar logic demands the agreements on credit where parties are involved in an employment relationship, as established in Article 2(g) of the CCD. As far as the amounts involved, Article 2(c) determine that credit agreements with a total amount of loan less than EUR 200 or more than EUR 75 000 are not covered by the material scope of CCD. Moreover, overdraft facilities that estipulate credit repayment within one month do not comprise the material scope of CCP, as envisaged by Article 2(e) of the CCD. In its rationale of "*buying now, paying later*"[4], it aims to avoid competitive distortions for creditors in the EU, also looking for an 'all-embracing' consumers protection, as established in its Article 22(1)[5]. By enshrining the obligation of means for assessing consumer affordability on credit agreements, CCD seeks to avert irresponsible lending[6] (and therefore, borrower's over-indebtedness[7]).

The relevance behind the notion of responsible lending is that creditors or intermediary parties should not act solely according to their benefits but should also consider the borrowers' interests and needs in both pre-contractual and post-contractual stages. It also encompasses the life cycle of credit products, from their inception through marketing until borrowers' full repayment. Hence, to avoid incremental risks portraying the detriment of consumers' ability and willingness to pay, banking institutions must assess their level of creditworthiness. Raymond Andersen list some of the practices of irresponsible lending that, in more severe cases, can lead to over-indebtedness of customers. Thus, creditors do not fulfil their duty to assess consumers' creditworthiness in the following situations when there are loan agreements underwritten under unclear terms and conditions, or it is conceivable the lack of credit checks to assess clients' affordability. Similar reasoning is applicable when offering pre-approved loans without proper care. Additionally, officers must not encourage debt transfers, offering higher limits and lower rates. The duty regarding CWA is also not fulfilled when the middlemen reduce payments to a minimum. Lastly, when issuing unsolicited cheques that can draw on the credit card account with no information of how interest and fees accrue, the adequate managing is not obeyed[8].

---

3 See NOVA SBE & ASFAC – Impacto do Crédito ao Consumo na Economia Portuguesa, Relatório Final, 2019, pp. 17-18.

4 See ANDERSON, Raymond - *The credit scoring toolkit: theory and practice for retail credit risk management and decision automation*. Oxford University Press, 2007, p. 3.

5 See, also in that sense, Recital 9 of the CCD; GOURIO, Alain – La reforme du crédit à la consommation. In: *La Semaine Juridique – Édition Enterprise et Affairs,* vol. 29, 2010 p. 8; and CRISTOFARO, Giovanni de – La Nuova Disciplina Comunitaria del credit al Consumo: La Diretiva 2008/48/CE E 1' Armonizzazione completa delle disposizioni nazionali concernenti "taluni aspetti" dei "contratti di credit ai consumatori. In: *Rivista di Diritto Civile,* vol. 54, no. 3, 2008, pp. 267-269.

6 See Judgment of the ECJ, of 27 March 2014, *LCL Le Crédit Lyonnais SA v Fesih Kalhan*, Case C-565/12 ECLI:EU:C:2014:190, paragraph 41. Creditors

7 See European Commission – *Evaluation of Directive 2008/48/EC on credit agreements for consumers,* Directorate-General for Justice and Consumers, 2020, p. 3.

8 See ANDERSON, Raymond – op. cit., 2007, pp. 629-631.

To make it clear and simple, detriment in customers' financial situation traduces the measure of harm they may experience when market outcomes fall short of their potential[9]. Over-indebtedness, in turn, traduces a situation of lasting or structural inability to pay one or more debts. Objectively, this term refers to the negative weighting between income and expenses. From the subjective side of understanding, over-indebtedness fits to the borrower's inability to meet his or her financial commitments, including even the incapacity to mobilize third-party assets[10]. Another way of classifying this undesirable phenomenon can be brought up here. From the defaulter perspective, being subjected to a situation of over-indebtedness may be fostered both passively and actively. Passive over-indebtedness arises from unforeseeable circumstances that make income insufficient to pay off loans taken out. Such circumstances occur when individuals become unemployed or get involved in life hazards such as unemployment, divorce, illness, amog others. In contrast, active over-indebtedness emerges when the customer's neglect to fulfil financial commitments already foreseeably (since previously agreed upon other contractual agreements) more than his or her financial capacity, or, on the other hand, due to low-income family budget management[11]. Of course, macroeconomic flows relative to interest rates, employment, inflation, taxes, and other events, must also be considered[12].

To avoid the scenarios described above, creditors must have the duty by which they are obliged to estimate consumers creditworthiness before the conclusion of the final agreement or any significant increase in the amount of credit afterwards. Article 8(1) generally specifies that "*Member States shall ensure that (…) the creditor assesses the consumer's creditworthiness on the basis of sufficient information, where appropriate obtained from the consumer and, where necessary, on the basis of a consultation of the relevant database*". Recital 26 further clarifies that moneylenders "*should be allowed to use information provided by the consumer not only during the preparation of the credit agreement in question, but also during a long-standing commercial relationship*".

In fact, all 28 Member States have transposed the relevant provisions on CWA. However, its accomplishment differs significantly, leading to a diverse regulatory landscape[13],as highlighted in the "*EC Consumer Financial Services Action Plan: Better Products, More Choice*"[14] and in the "*Second Progress Report on the Reduction of Non-Performing Loan in Europe*"[15]. From a comparative law standpoint, Member States adopted three different approaches at a national level. Firstly, a set of countries leave discretion to the lenders as to which types of information can use for CWA. Such open standards come from countries such as Germany, Malta, Denmark, Austria, and the Czech Republic. The second group of countries exhibit prescriptive approaches. Hence, in legal orders like, for instance, Ireland, France, Greece, Estonia, Sweden, Cyprus, Ireland, Finland, Spain, Poland, Slovenia, and Croatia, creditors must look upon specific information such as consumer's income, expenditures, debts and, in some cases, their assets. In some of these countries, it is still compulsorily required for creditors to check credit history within the organization's databases and further verify the existence of any payment default. At last, Belgium, Portugal, Slovak Republic, and Hungary introduce beyond formulas with the precise indebtedness threshold, clearly defining whether to grant credit to the

---

9 See European Coalition for Responsible Credit, Principles of Responsible Credit, in particular Principle 1:'Responsible and affordable credit must be provided for all', *ex vi* ALIYEV, Farid – Review of the Consumer Credit Directive, BEUC Position Paper 2019, pp. 6-7; FSUG – Responsible consumer credit lending, FSUG opinion and recommendations for the review of the Consumer Credit Directive, 2019, pp. 6-8; and MADJOUR, Oualid – *La responsabilité civile du banquier dispensatur de credit: Étude de droit compare français-algérien,* Thése de doctorate en droit prive, 2009, p 18. According to this principle, the lender should avoid granting excessive credit, observing specific criteria that exhort indebtedness rates, the borrower's ability to preserve financial stability, his or her ability to repay, and residual income. See *ibidem,* p. 176-178.

10 See FRADE, Catarina – Desemprego e Sobreendividamento dos Consumidores: Contornos de uma ligação perigosa, Projeto Desempree go e Endividamento das Famílias, Relatório Final, Centro de Estudos Sociais da Faculdade de Economia da Universidade de Coimbra (PIQS/ ECO/50119), 2003, p. 16

11 See FRADE, Catarina – Um perfil dos sobreendividados em Portugal. In: Observatório do Endividamento dos Consumidores do Centro de Estudos Sociais da Universidade de Coimbra (POCTI/JUR/40069/2001), 2008, p. 12.

12 See *ibidem,* p. 9

13 See European Commission – *Evaluation of Directive 2008/48/EC on credit agreements for consumers, … supra*, p. 63.

14 See Communication from the Commission to the European Parliament, the Council, the European Central Bank, The European Economic and Social Committee and the Committee of the Regions, Consumer Financial Services Action Plan: Better Products, More Choice, of 23 March 2017 (COM(2017) 139 final), p. 10.

15 See Communication from the Commission to the European Parliament, the European Council, The Council, and the European Central Bank, Second Progress Report on the Reduction of Non-Performing Loans in Europe, of 14 March 2018, (COM(2018) 133 final), p. 7.

borrower regarding his or her financial stability. These last approaches to CWA policies prevail as macroprudential recommendations regarding debt-to-income or debt-service-to-income, following the principle comply or explain[16].

As it is now clear, Article 8 of the CCD does not provide helpful guidance on the approach to take based on CWA. This abstract prescription undeniably leaves, by law in inaction, national lawmaker, primarily, and further, creditors or intermediaries, with an unconceivable margin of discretion to decide which sources and information types to collect to conclude whether the consumer is creditworthy[17].

Furthermore, if, from a contractual perspective, there are situations of clear duty's default on the part of the creditor, as mentioned above, many other concerns arise on data protection dictates. To make things as clear as possible. Today, customers live in the digital era. This is the period in which most of the products in credit loans began being provided on-boarding[18]. The digitalisation of our economy and society revolutionised how CWAs profile clients in their ability and willingness to pay fully[19]. Compared to the baseline, this phenomenon boosted the number and types of data about consumers, especially big sets that come from online sources. Technological breakthroughs, particularly those of AI engineering discipline, have huge impact on what CWA approaches to adopt. CWA 4.0. are evolving fast, with innovations focusing on CWA unstructured apps for data-scrubbing, social media, and advanced inferencing[20]. Therefore, an increasing number of moneylenders - i.e., in a fintech scenario, the ones that figure not only as banking corporations but also those with the scope of SMEs - use such benchmarking manoeuvres for assessments with solid credit histories and sound financial situations[21]. However, not everything that befalls in this technological revolution goes as expected. If, on the one hand, such novel techniques unveil ways to help borrowers by profiling several of their personal traits to obtain a loan which they would not receive under traditional means, on the other, AI-based techniques for scoring raise some privacy-preserving concerns. EC and EP recognise it remains doubtful if or how to fulfil the principles of data minimisation and purpose limitation, enshrined in Article 5(1)(b)(c) of the GDPR[22], respectively. The logic, data sources, significance and the consequences of AI-powered inferences that use algorithms to estimate consumers' reliability is still far from being sufficiently understood from the costumer's viewpoint[23]. Besides this, the International Committee on Credit Reporting raised additional challenges in ensuring the accuracy, quality, and completeness of credit-reporting data[24].

So, depending on the Member State, the type of data collected by the data controllers (i.e., creditors) and the mechanisms used to do so differ significantly. Partakers still do not know within what limits and which data types they can employ in AI-based tools to comply with this obligation. As Cherednychenko and Meindertsma noted in 2019, the structural flaws of this abstract's prescription expose themselves at the three procedural steps of a CWA

16 See European Commission – *Evaluation of Directive 2008/48/EC on credit agreements for consumers, … supra*, p. 132, *ex vi* European Commission – Mapping of national approaches in relation to creditworthiness assessment under Directive 2008/48/CE on credit agreements for consumers, Consumer Protection in Financial Services, 2018, pp. 5-10.

17 The ECJ confirmed this extensive boundary, stating "*the sufficient nature of the information may vary depending on the circumstances in which the credit agreement was concluded, the consumer's personal situation or the amount covered by the agreement*". See ECJ, of 18 December 2014, *CA Consumer Finance vs. Ingrid Bakkaus, Charline Savary, Florian Bonato,* Case C-449/13 ECLI:EU:C:2014:2464, paragraph. 36. A more recent ECJ judgment further determined that Article 8(1) of the CCD allows different interpretations of Member States, hence, even admitting the establishment of additional requirements. Consequently, the Court ruled that creditors may only enter into a credit agreement if it is possible to believe the consumer can fulfil the duties assigned reasonably. See ECJ, of 6 June 2019, *Michel Schyns vs Belfius Bank SA,* Case C-58/18 ECLI:EU:C:2019:467, paragraphs 37-49.

18 See ALCARVA, Paulo - *Banca 4.0: Revolução Digital: Fintechs, blockchain, criptomoedas, robotadvisers e crowdfunding,* Lisboa: Actual Editora, 2018, p. 106.

19 See European Commission – *Evaluation of Directive 2008/48/EC on credit agreements for consumers … supra,* p. 64.

20 See European Commission – Study on the role of digitalisation and innovation in creating a true single market European Commission, for retail financial services and insurance, Final Report (FISMA/2015/075D), 2016, p. 128.

21 See *ibidem,* p. 130.

22 Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)

23 See European Parliament - A governance framework for algorithmic accountability and transparency, EPRS Study, 2019, pp. 28-30.

24 See GPFI – Use of Alternative Data to Enhance Credit Reporting to Enable Access to Digital GPFI, 2018 Financial Services by Individuals and SMEs operating in the Informal Economy, 2018, paragraph 31.

Guidance Note.

operation, as follows: (1) obtaining appropriate information about the consumer's financial capacity; (2) estimating the consumer's creditworthiness; and (3) deciding on the consumer's credit application[25].

Even the Basel II Accord, which has contributed to Credit Service Providers' (CSPs) management development on their credit scoring systems[26], does not fix clients' issues on data protection. CSPs required to comply with the three Pillars of Basel II shall only generate internal rating-based approaches to estimate default probability for on- and off-balance exposures, henceforth, demonstrating competency to regulators. Indeed, CSPs who have no duty to comply with Basel II also have considered using in-house credit scoring methods to improve consistency and efficiency, bring down costs, and reduce losses[27]. Banks, not the customers, are better prepared for the future challenges of the new digital era. Basel II has overall enhanced the level of analytics and credit scoring in banks. This international committee introduced and formalized repeatable, transparent, and auditable means in banks for developing predictive models. At the very least, Basel international agreement has also assisted in creating genuinely independent arm-length risk functions and model validation teams to face compelling challenges. Basel II and Basel Committee on Banking Supervision (BCBS) regulation 239 have tried to make inferential data processes at banks far better than before. International Financial Reporting Standards and other current regulatory actions such as Comprehensive Capital Analysis and Review, Current Expected Credit Loss, and stress testing, as well as their global equivalents, will proceed to expand and test analytics on credit scoring[28]. However, regulatory challenges on privacy-preserving personal data will remain.

No matter what, to date, the forms of data processing have not received due attention from the European legislator or international authorities. There is an urgent need for more and better consumer protection when accessing solvency profile of customers in retail credit-based banking. After all, the European regulatory landscape of fragmentated nature, regarding CWA, reveals its difficult effectiveness[29]. Only to the abstraction magnitude of the GDPR disi cipline can the CWA regime in force be deemed consistent with the CCD. There are many inconsistent gaps between the CCD and data protection legislation, not considering the Proposal for the Artificial Intelligence Act of 21 April 2021[30]. For this time being - as there is (and, certainly, will) much more to point out in terms of AI - a better synergy between the CCD and GDPR would impact creditors on the referred vital aspects, above. The fact that Article 8 of the CCD does not mention which data can creditors insert on scoring models in any way ensure that consumers are provided with appropriate loans concerning their financial circumstances[31]. Presumably, the new directive shall better serve the new European consumer agenda, which (at least, we expect) will look further at the current CWA banking policies by introducing common standards and principles for lending to consumers, preferably, adequate to the new computerised statistics and mathematical procedures[32].

3. Application scoring for credit in the age of Artificial Intelligence

The creditors need to assess the customer's ability and willingness to repay credit debts no longer fit with traditional practices that solely used the officer's human judgment. Those practices considered his or her own experience and guidelines from banking corporations. Even traditional judgmental systems, eventually benefiting from hard skilled officers who make use of well-tries institutional guidelines, suffer several critical flaws. Besides lacking accuracy in identifying trustwor-

25 See CHEREDNYCHENKO, Olha; MEINDERTSMA, Jesse - Irresponsible lending in the post-crisis era: Is the EU consumer credit directive fit for its purpose?. In: *Journal of Consumer Policy*, vol. 42, no 4, 2019, p. 500.

26 See SIDDIQUI, Naem – *Intelligent Credit Scoring: Building and Implementing Better Credit Risk Scorecards,* 2nd ed, New York, Willey and Sons, 2017, pp. 2-3.

27 See KNUTSON, Melissa – *Credit Scoring Approaches Guidelines,* The World Bank, 2021, p. 5.

28 SIDDIQUI, Naem – op. cit., 2017, p. 16.

29 See European Commission – *Evaluation of Directive 2008/48/EC on credit agreements for consumers, … supra*, p. 63-64.

30 See European Commission - Proposal for a Regulation of the European Parliament and of the Council, laying down harmonised rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts (COM(2021 206 final), of 21 April 2021.

31 See European Commission – *Evaluation of Directive 2008/48/EC on credit agreements for consumers, … supra,* pp. 62-64.

32 See HUEMER, Marie-Astrid – Revision of the Directive 2008/48/EC on credit agreements for consumers, European Parliament, EPRS, Briefing Implementation Appraisal, 2021, p. 2; and, generally, European Commission- Proposal for a Directive of the European Parliament and of the Council on consumer credits (COM(2021) 347 final), of 30 June 2021 (hereinafter, PCCD)

thy applicants, credit policies of banks arose without any empirical verification, being unrealizable, accordingly. Apart from all these weaknesses, studies indicate that race, sex, and marital status may also receive undue and excessive consideration, consequently increasing prohibited discrimination[33].

Due to technological advancements, banking policies to access credit agreements represent mathematical theories, computational algorithms or statistical programmes that can ascertain more precisely how likely individual consumers are to pay back their debt obligations[34]. Currently, CSPs' running scoring procedures in consumer lending materialises the computerised operation of statistical models that extract insights from relevant data into numeric measures, thus guiding decision-making at AI-based levels[35]. The retail banking industry depicts the CWA 4.0. industrialisation of customer trust: further logical development of credit ratings first provided by nineteenth-century credit bureaux. It emerged because of the necessity for objective, fast, more consistent decisions made possible by technological progress[36]. A score in credit exists now broadly as any numerical expressions that betoken how likely individuals repay instalments regularly and fully, including any additional charges, such as interests and fees[37]. These systems, relying upon an alternative theory that large populations behave consistently, process statistically applications by noting the information disclosed and weighing them with other attributes from electronic data warehouses, analytical data marts, or other labels that do not fall into the scope of this paper[38]. With the boom of business intelligence in consumer credit for about the last decades, demystifying how to use scientific and technological means to score customers increasingly showed its urgency. Data Warehouses are relational databases that reduce business risk and promote the rapid development of Extract, Transformation and Loading (ETL) operations on CWA[39]. These tools are just as important, if not more so, as the business require to gather and organize the data together and communicate the results, accordingly. Through investments in data warehouses and analytical tools, scoring products execute a quick and proven means to use data to reduce losses while increasing profitability[40]. Usually, (short-term) consumer loans for individuals, are of low value in retail banking and granted on a large scale. (see, Table 1, below).

Table 1. Credit Scoring: a brief overview

	Application Credit Scoring
Subject	Individual customer
Data	Demographics | Financial | Employment | Behavioural
Method	Statistics
Controllers	CSRPs | CSP
Users	Credit Providers | Credit Managers | Public Authorities
Depth	Low value
Breadth	Short-term retail lending (various types) | Mortgage Lending
Scale	Any numerical range

The evaluation either meets or fails to meet a predetermined cut-off at the final. This assessment denotes the degree to which the historical experience of several customers statistically links creditworthiness to repayment probabilities[41]. To note: high CWA scores do not necessarily represent that all past applicants with equivalent attributes ended up repaying

33 See HSIA, David – Credit Scoring and the Equal Credit Opportunity Act. In: Hastings Law Journal, vol. 30, no. 2., pp. 372-375.

34 See FERRETI, Federico - *The Never-Ending European Credit Data Mess*, BEUC Position Paper, Brunel University London, 2017, pp. 15-16; and STANTON, Thomas – Credit and Loan Scoring. Tools for Improved Management of Federal Credit Programs, Center for the Study of American Government, Baltimore: John Hopkins University, p. 8.

35 See ANDERSON, Raymond – op. cit., 2007, p. 5; FERRETTI, Federico; VANDONE, Daniela - *Personal debt in Europe: The EU financial market and consumer insolvency*, Cambridge University Press, UK, 2019, p. 114.

36 See *ibidem*.

37 See KNUTSON, Melissa – *Credit Scoring Approaches Guidelines … supra*, p. 3.

38 See *ibidem,* p. 5.

39 See XIAO, Guorong - Data Processing Model of Bank Credit Evaluation System. In *J. Softw.*, vol. 6, no 7, 2011, pp. 1241-1247.

40 See ANDERSON, Raymond – op. cit., 2007, p. 280.

41 See HSIA, David – Credit Scoring and the Equal Credit Opportunity Act … *supra,* p. 376.

their loans instalment on time. Instead, these sets of individuals share similar values, which reduces credit risks[42]. Onwards, in 2002, Thomas, Elderman and Crook defined credit scoring beyond its more naiver assessment standpoint. They uphold those operations in consumer credit should reflect some additional considerations about risk, profit, and the use of different models. Hence, for them, scoring techniques do much more than CWA. Models attached to this kind of task can determine who and how much consumers will get credit and what operational strategies will raise profitability levels of the borrowers to the lenders[43]. Cut-off scores depict a more detailed credit report which suggests whether lenders in credit must reject the candidate, stress the application to an officer for further review, or accept it immediately[44]. From theory to practice, extracting knowledge of the exact repayment probability allows managers to select rationally the degree of risk the institution wishes to accept when extending credit[45].

All told, in the actual state of the art, scoring in banking 4.0. outlines customers' creditworthiness review, a helpful tool for assessing and preventing default risk, an essential step in credit risk evaluation, or rather, last (but not least), an active research field in financial risk management[46].

Before proceeding with a description of the AI means currently assigned to CWA tasks and the constraints concerning its usage, three are the scientific principles of scoring systems. First, scoring essence in credit merely tries to clarify the identification of personal features link with historical experience with a satisfactory credit risk evaluation. Scoring practices predict (not cause) clients' creditworthiness. This assumption, in turn, does not require that customers tell the truth in a clear-cut manner. Individual applicants should, instead, respond consistently[47]. Secondly, theories of probability depend almost upon the occurrence of many similar events to make efficient analyses. One occurrence has little impact on data scientists. Today, only the large volume of new applications assures frequent future-proof comparisons to the profile automatically drawn from massive databases. Scoring systems set customers just as any human judgmental system. Both procedures to CWA analysis measure an individual application to the mass of past similars. Technological approaches, in here, too, end up showing through treating the user (or individual) as a standardized statistical sample member[48]. In credit scoring, a set of measurements distinguish between two non-overlapping subpopulations: the third scientific principle. It allows a split of creditworthy and noncreditworthy applicants. Creditors prefer to use of the available traits that maximize the cut among the two subpopulations. As the width of non-overlapping increases, clients' profiles are prearranged under more reliable conditions. Consequently, the predictive accuracy achieved much better reliability[49].

The pioneer of the scientific background to modern statistics was Ronald Fisher, who introduced the discriminant analysis technique in 1936. This technique discriminates between two groups in a population through measurable attributes when shared features of both member types are unobservable[50]. Nevertheless, only in 1941, Durand recognised that this methodology could be adapted to distinguish between good and bad borrowers[51]. Linear programming was the first credit scoring algorithm implemented on the financial market. Initially, both variables and scores assigned were deemed mainly judgmental. Nonetheless, the systematic scoring contributed to some consistency in CWA[52]. It also led to the establishment of more organized and transparent credit cycles. Credit cycle traduces the expansion and contraction of loan, differing in

42 See *ibidem*.

43 See THOMAS, Lyn; EDELMAR, David; CROOK, Jonathan – *Credit scoring and its applications*, SIAM, Monographs on Mathematical Modeling and Computation, Philadelphia, 2017 p. 1.

44 See HSIA, David – Credit Scoring and the Equal Credit Opportunity Act … *supra,* p. 377.

45 See *ibidem,* p. 379.

46 See LOUZADA, Francisco; ARA, Anderson; FERNANDES, Guilherme, Classification methods applied to credit scoring: Systematic review and overall comparison. In: *Surveys in Operations Research and Management Science*, 2016, vol. 21, no. 2, p. 117.

47 See HSIA, David – Credit Scoring and the Equal Credit Opportunity Act … *supra,* pp. 382-383.

48 See *ibidem,* pp. 383-384.

49 See *ibidem,* pp. 384-387.

50 See FISHER, Ronald - The use of multiple measurements in taxonomic problems. In: Annals of eugenics, vol. 7, no. 2, 1936, pp. 179-188; KNUTSON, Melissa – *Credit Scoring Approaches Guidelines … supra*, pp. 1-2; and HSIA, David – Credit Scoring and the Equal Credit Opportunity Act. … *supra,* pp. 386-387.

51 See DURAND, David - *Risk elements in consumer installment financing*. In. *National Bureau of Economic Research*, New York, 1941, pp. 105-121; and KNUTSON, Melissa – *Credit Scoring Approaches Guidelines … supra*, p. 2.

52 See *ibidem*.

time from the CRMC. At the later, managers may conduct credit scoring in processes dealing with account management cycle, from the day credit is initially assessed until its full repayment. The CRMC, broadly speaking, comprises segmentation, solicitation, acquisition, management, collection, tracing, and rehabilitation stages, those policies this paper's scope[53].

Several AI-based roles are assigned to a credit risk analysis, namely the application scoring, which supports the approval or rejection of the loan request[54]. It usually combines data from the customer, past debts, and the credit bureaux reports. Although the present study focuses on application credit, it is essential to emphasise four other formats. Behavioural score portrays account management (i.e., limit settings, over-limit management, or authorisations) and commonly focuses upon the behaviour of an individual account. While incorporating behavioural, collections, and bureau data, collection score usually drives predictive diallers in outbound call centres. Instead, customer scoring combines mainly behaviour on many accounts. Early warnings usage remains to account management or cross-sales to existing customers. At the end of the list, the bureau or fraud detection score is the one conducted by financial authorities in credit used to predict or detect delinquency or bankruptcy, summarising data held by them[55]. In this paper, accordingly, the academic research at hand particularly has to do with intelligent application taxonomy as a proposal standpoint for credit access grounded on updated parameters of different candidates. Nowadays, some advanced programs can also assign a credit limit or allocate a loan or credit duration term, though they will not be considered here for due purposes[56]. These individual classifiers simultaneously couple with past data from agreed contracts (or with conventional banking policies) upon former clients to decide better whether to grant credit, henceforth, just segregating "good" from "bad" borrowers (i.e., the upcoming payers)[57]. For instance, the following if-then abstract insight may clarify how credit reprovals proceed, either by manual or automatic means. That is:

Figure 1. If-then (fuzzy) reasoning for dummies

"If the data subject X belongs with probability Y (%) to the set F and this set pertains to potential individual solvency profiles, then involved creditors should not conclude or sign the agreement with an individual applicant" .

53 See ANDERSON, Raymond – op. cit., 2007, Module G, I, Intro; and SILVA, Fábio – *Credit scoring as an asset for decision making in intelligent decision support systems*, Master's Thesis on Computer Science, University of Minho, Braga, 2011, pp. 10-11.

54 See SIDDIQUI, Naem - op. cit., 2017, pp. 128-129.

55 See and KNUTSON, Melissa – *Credit Scoring Approaches Guidelines … supra,* p. 4; and SILVA, Fábio – op. cit., 2011, p. 10.

56 See HILDEBRANDT, Mireille; GUTWIRTH, Serge - *Profiling the European citizen*, Springer, Dordrecht, 2008, p. 206.

57 See SILVA, Fábio; ANALIDE, Cesar - Information asset analysis: credit scoring and credit suggestion. In: *International Journal of Electronic Business*, 2011, vol. 9, no. 3, pp. 207-208.

Albeit referred to as one of the most ancient financial intricacies (or consumer law hot topics) since its very beginning, CWA positioned itself as a utilitarian Intelligent Decision Support System (IDSS)[58] to aid lenders' arrangements in banking institutions for about fifty years ago[59]. However, designing suck a kind of task is still far from easy to find out which AI-based (lawful) approach is the best to implement. Sometimes credit approvals work out differently as expected, and, at final, debtors often end up non-performing or defaulting on payments. The inner quest is that no rational course traces the route on predictive analysis in the consumer credit domain.

AI-powered CWA underpins some self-evident advantages over conventional methods in a contemporary FinTech scenario[60]. CSPs who grant (or at least promise) loans in business courses can or may evaluate quicker and better investment risks from multiple approaches - using broader, dynamic, or even refreshed datasets - also ensuring a maximum operational profit while readjusting management policies. At its best and worst, AI procedures in credit can automatically monitor assets in real-time, reduce maintenance expenses and improvr the quality of the services provided. With AI, banks can now deal more carefully with the unknown and unpredictable behaviour of consumers [61]. Based on AI techniques, CWA undeniably reduces the risks and number of false positives and false negatives. Anyhow, it ensures the demand for the most suitable plan for customers, which is essential for their financial stability[62].

As Servigny and Renault foresaw in 2006, banks have already mainly in the last two decades caught up "*with the integration of nonparametric techniques and Machine Learning*" (ML)[63]-[64]. That is why, nowadays, financial institutions nearly automatically choose to lend money to clients through intelligent and disruptive technologies. Data Mining (DM)[65] and ML tools applied to scoring speed up lending decisions while potentially reducing incremental risks[66]. Innovative credit scoring modelling reports to process that may be split further into multiple subphases at a high level. At first, moneylenders access raw data and then combine, join, and aggregate input data. After that, they employ feature engineering, either manually using expert input or automated approaches, to select the most significant attributes. IT intermediaries interpret and assess results after applying supervised, unsupervised or reinforcement learning ML techniques to the training set at the end of this process, [67]. These techniques include a feedback loop where the algorithm learns from experience: trial and error[68].

---

58 IDSSs are computer-based programs that manage database systems, expert knowledge, and organisations' models to help decision-makers (DMs) solve semi-structured tasks, especially throughout embed AI methods. Intelligent applications within the Business Intelligence spectrum aid a set of recommendations imparting domain expertise. In particular, the central purpose of a DSS applied to financial institutions is to improve operations' quality, speed, and effectiveness, especially regarding decision-making on acceptances or denials in what concerns the credit scoring negotiation stage. See KAKLAUSKAS, Arturas - Introduction to Intelligent Decision Support Systems. In: *Biometric and Intelligent Decision-Making Support*, Springer, Cham, 2015. p. 2.

59 See THOMAS, Lyn; CROOK, Jonathan; EDELMAN, David, op. cit., p. 9.

60 FinTech terminology, meaning Financial Technology, encompasses the group of Big Giants, SMEs or Start-up business models that induce financial breakthroughs for granting credit to consumers. This phenomenon enables the creation of novel enterprise paradigms, applications, or products that materially impact financial markets or provide innovative credit-related services. See BOUYALA, Régis. *La révolution FinTech*, RB édition, Paris, 2016, pp. 71-81.

61 See BPI; Covington & Burling LLP - *Artificial Intelligence Discussion Draft: The future of credit underwriting – Artificial Intelligence and its role in Consumer Credit*, 2019, pp. 4-5.

62 See European Banking Federation, EBF position paper on AI in banking industry, 2019, p. 8.

63 Cit. DE SERVIGNY, Arnaud; RENAULT, Olivier - *Measuring and managing credit risk*, McGraw-Hill, New York, 2004, p. 64.

64 ML evolves subtypes within the IA circumscription, whose autonomous supervised, unsupervised or reinforcement models automate comm plex descriptions, predictions, or prescriptions in real-life in software systems not expressly programmed for that purpose. See ALPAYDIN, Ethem - *Machine learning: the new AI*, The MIT press Knowledge Series, Cambridge, MA, 2016, pp. 16-20.

65 Data Mining refers generally to the process of extracting knowledge from databases, hence, selecting and processing data to identify new patterns and give greater precision to previously known regularities. See SUMATHI, Sai; SIVANANDAM, S. N - *Introduction to data mining and its applications*. Springer, Berlin, Heidelberg, 2006, pp. 1-20.

66 See SILVA, Fábio – *Credit scoring as an asset for decision making in intelligent decision support systems*, op. cit., p. 1.

67 See KNUTSON, Melissa – *Credit Scoring Approaches Guidelines,* The World Bank, 2021, pp. 17-21; GÉRON, Aurélien - *Hands-on Machine Learning with Scikit-Learn, Keras, and Tensorflow,: Concepts, Tools, and Techniques to Build Intelligent Systems*, O'Reilly, 2019, pp. 8-14. ISBN:007-0-428-077.

68 See *ibidem*, p. 17.

Nowadays, unlimited volumes of structured data on transaction and payment history, traditionally implemented in methods such as discriminant analyses, no longer fit with the actual FinTech state of the art Big Data[69]. Nowadays, financial institutions increasingly turn to unstructured and semi-structured data, mostly coming from alternative sources[70]. Some online mobile apps integrate merged data with AI to support financial estimations. Non-traditional sources like these are interwoven with processing updated data through online targeting, using metadata from cookies, services, and money transfers to increase accuracy and identify hidden patterns (see Table 2, concerning traditional and alternative sources of data solvency, below)[71]. For instance, consider that an unemployed or student X can be clustered in the creditworthy profile according to the outcomes traced in a more redefined analysis, contrary to what one would expect[72]. Thus, utility data steaming from on-time payments, transactions, social media activity, mobile tracing, rents, and other types of psychometrics data depict more accurate creditworthiness scoring[73]. Fintech lenders, such as Alibaba, increasingly use of data on phone bills and short-term loans, often not included in credit files, to create alternative data[74].

Table 2. Sources of Big Data for CWA

Data Types		**Data Category**
Bank data	Loan purpose	Traditional
	Loan amounts	
	Late payments	
Credit bureau checks	Public Records (Number of credit inquiries)	Traditional
Commercial data SME		Traditional
Utilities data	On-time payments	Alternative
Social media		Alternative
Mobile apps		Alternative
Behavioural data	Psychometrics	Alternative
Macroeconomic Data		Alternative

As mentioned above, the exchange of clients' financial information and the usage of centralised databases are now more than ever regarded as risk management tools in the interest of CSP. Data and advanced algorithms figure a. potent form nowadays for CWA. It is certainly an excellent tool to prevent over-indebtedness. More than that, let not forget that, nowadays, solvency data marts are one possible - though non-exclusive - source to make such an assessment[75]. Regulatory frameworks are still unclear whether the big data are proportionate to the policy aims intended to achieve. Moreover, big data may not address the most frequent causes of over-indebtedness, potentially and possibly penalizing consumers even further. Lifetime hazard events or poor market conditions may emerge later and impede customers from paying back thoroughly and regularly. AI-based scoring systems may not detect the occurrence of outgoing events that are not predictable at the time of contracting a loan, such as poor macroeconomic

69 "*The term 'big data' refers to large amounts of different types of data produced with high velocity from a high number of various types of sources. Handling today's highly variable and real-time datasets requires new tools and methods, such as powerful processors, software and algorithms*". Cit. Communication from the Commission to the European Parliament, the Council, The European Economic and Social Committee and the Committee of the Regions, Towards a thriving data-driven economy (COM(2014)442), of 2 June 2014, p. 4. See WP29- Opinion 03/2013 on purpose limitation (WP203), adopted on 2 April 2013, p. 45 (Annex 2); and MORGADO REBELO, Diogo; ANALIDE, Cesar; COVELO DE ABREU, Joana – O Mercado Único Digital e a '(Leigo)ritmia' da Pontuação de Crédito na era da Inteligência Artificial, vol. 2, no. 1, 2020, p. 14 (footnote no. 25).

70 See KNUTSON, Melissa – *Credit Scoring Approaches Guidelines … supra,* p. 10; SIDDIQUI, Naem -, op. cit., 2017, p. 16.

71 See EDPS- Opinion 11/2021, on the Proposal for a Directive on consumer credits, of 26 August 2021, p. 5

72 See SILVA, Fábio; ANALIDE, Cesar – op. cit., pp. 214-215.

73 See KNUTSON, Melissa – *Credit Scoring Approaches Guidelines … supra,* p. 10.

74 See GILLIS, Talia – False dreams of algorithmic fairness: the case of credit pricing, Harvard Law School, 2019, p. 35.

75 See FERRETTI, Federico; VANDONE, Daniela – op. cit., p. 172.

indicators, job losses, divorces, illness, or family deaths[76]. In here, too, behavioural factors concerning poor financial choices, resources mismanagement or irresponsible practices seem to have limited bearing. Nevertheless, this listing of the causes allows to denote or link debt issues on consumer credit with external events where consumers cannot adjust or conveniently manage their budgets[77]. As it is now clear, over-indebtedness confirms its multi-causal nature, which combines, in varying proportions, several factors, such as elements of fragility linked to the personal and professional situations of the people concerned, behavioural factors on how they manage household resources and expenses, and the use of credit[78]. At the convergence of budgetary, banking, social and behavioural issues, the phenomena of over-indebtedness, which have multiple dimensions, are thus the result of circumstances whose coexistence and interactions do not shape a straightforward explanatory nature of the different paths[79]. Notwithstanding the non-linearity of the correlations established among the factors that influence the classification of a person as creditworthy, Vojtek and Koenda suggest in 2006 some demographic, financial, employment and behavioural set of attributes which may be pertinent for the analysis of a loan application[80]. On 29 May 2020, the European Banking Authority Guidelines on loan origination and monitoring of (EBA/GL72020/06) provide us with a more extensive list of what categories to use for the processing of personal data regarding consumers' CWA assessment[81] (as briefly summarised in table 3, below):

Table 3. Input attributes on CWA for Customers

Lending to Consumers				
Identification	Residence	Purpose of the Loan	Evidence of Eligibility	Evidence of Employment
Evidence of income or other sources of repayment	Financial Assets and Liabilities	Financial Commitments	Household Composition and Dependants	Tax Status
Life Insurance	Credit Registers or Credit Information Bureaux	Collateral Information	Guarantees	Rental Agreement

So, CSPs applying ML models to big data obtain better qualitative insights regarding consumers' behaviour and their willingness to pay[82]. On the one hand, such autonomous procedures allow for more expansive, faster, and cheaper segmentation of borrower profiles. It ultimately leads to quicker decision-making on credit acceptability. For instance, the application of big data in credit scoring includes evaluating non-credit utility bills, such as those of cell phone payments and recurring payments (i.e., rents, for example), among many other online activities, such

76 See *ibidem,* pp. 172-173; RAMSAY, Ian – *Consumer Law and Policy: Text and Materials on Regulating Consumer Markets*, 2nd ed., Hart Publishing, 2007, pp. 578-580; and BALMER, Nigel [et al] - Worried sick: the experience of debt problems and their relationship with health, illness, and disability, In: *Social Policy and Society*, vol. 5, no. 1, 2006, pp. 39-51.

77 "*Sans remettre en cause la pertinence d'un cadre d'analyse multicausal des parcours menant au surendettement, l'impact de chocs externes (au nombre de trois en moyenne) liés à des accidents de la vie (perte d'emploi du surendetté ou de son conjoint, divorce ou décès du conjoint, maladie ou accident du surendetté ou d'une personne de son entourage) doit être souligné. En effet, dans un contexte caractérisé par ailleurs par le caractère souvent contraint du budget des ménages surendettés, de tels évènements imprévisibles contribuent à précipiter la dégradation de situations initiales fragiles*", cit. Banque de France – Étude des Parcours Menant au Surendettement, Direction générale des Activités fiduciaires et de Place Direction des Particuliers, Étude de la Banque de France, 2014, p. 11.

78 See FERRETTI, Federico; VANDONE, Daniela – op. cit., 2019, pp. 59-62.,

79 See Banque de France – Étude des Parcours Menant au Surendettement … *supra*, p. 11.

80 See VOJTEK, Martin; KOÂENDA, Evïen – Credit-Scoring Methods. In: *Czech Journal of Economics and Finance* (*Finance a uver*), Prague, vol. 56, no. 3-4, 2006, p. 164 (table no. 1), *ex vi* SILVA, Fábio – *Credit scoring as an asset for decision making in intelligent decision support systems*, op. cit., p. 13.

81 See EBA – Guidelines on loan origination and monitoring [EBA/GL/2020/06], 2020, p. 66.

82 See HURLEY, Mikella; ADEBAYO, Julius - Credit scoring in the era of big data. In: *Yale journal of law and technology*, vol. 18, 2017, pp. 157-159; European Commission – *Evaluation of Directive 2008/48/EC on credit agreements for consumers, … supra,* p. 133; and BAESENS, Bart, et al. - Benchmarking state-of-the-art classification algorithms for credit scoring. In. *Journal of the operational research society*, 2003, vol. 54, no. 6, p. 627.

as social network tracking[83]. Moreover, besides easing precise and segmented CWA, ML scoring in consumer credit may allow greater access. To be considered scorable, a potential payer must have enough historical experience with quality for the learning algorithm to produce almost exact evaluations. Otherwise, the lack of information spoils this process because the model does not spawn with the levels of correctness suitable to that specific context.

On the other perspective, from the consumer viewpoint, not everything in these new real-time and online intelligent retail banking turns out to wonder. If working with alternative data may help economies where access to credit is not constant, conversely, it may foster an unaffordable demand for consumer credit in more robust changing markets, sometimes leading to the growth in irresponsible agreements conceded. Reciprocally, these are reciprocally reasons for (or instead, why) AI-based CWA is of general significance for contemporary digital economies[84].

One can deduce that the more extensive transparency, quantity, and quality of borrowers' datasets, the better CWAs' accuracy[85]. Scoring systems with sufficient information do satisfactory risk assessments. Tools for scoring will be claimed as transparent as whether loan seekers tend to be creditworthy. Without history on credit activity, nobody can assure the output[86]. Hence, transparency, on matter of knowledge in credit, is deemed as more significant for the credit-active population, mainly where such an operation includes one or more credit bureaux. Inevitably, sociotechnical issues in (i.) cultures whose members avert loan agreements; (ii.) rural peripheral areas with few service opportunities; (iii.) youth and immigrants who may appeal to credit for the first time; (iv.) inner-city, emerging markets, and other groups with little access to credit, may appear. Given these situations, creditors or intermediaries should mitigate additional risks, designing renewal credit cycles. To do so, lenders shall either charge products with higher rates to offset other hazards, or - this being the preferable option-, make an extra effort to determine which class of information can add positive value, as well as how to obtain and assess it[87]. Especially in the retail credit course, where volumes are high, values are low, and data is plentiful, accessible personal sets (by ways of collection, communication, privacy, and anti-discrimination dictates) must be slightly homogenous and sufficient, both regarding the number of cases (depth) and the amount available (breadth)[88]. Lastly, perhaps the crucial point to decision-making on the credit choices is the quality of the datasets processed. Thus, the input must be meaningful to the decision course. Information processed shall reflect its completeness and consistency[89].

Today, credit data drives the entire lending operation, especially whereabout automated IDSS outputs almost exclusively concede or influence consumer credit approvals or denials. It is no longer the programmers anymore who take on the main characters' status. On the contrary, personal (often sensitive) data, jointly with the learning models, are responsible for predicting or prescribing whom to accept next. The more outstanding quality, volume, and diversity of the attributes at the input layers of a given model will enhance borrower's CWA accuracy[90]. Already Henry Kissinger, Eric Schmidt and Daniel Huttenlocher express, in their most recent co-authored publication dated 2021 that, in finance, AI has the most expeditious means to make high-volume processes, such as loan approval or refusals[91]. Even so, the Annex III (5)(b) of the Artificial Intelligence Act establish that AI-based systems used to CWA are of high-stake risk nature since these tools influence persons' access to financial resources or essential services, such as housing, electricity, and telecommunication services. Consequently, its lawful use on the market depends on whether its functioning complies with specific mandatory requirements and an ex-ante third-party conformity

83 See BIATAT, Viani et al. - Enhancing credit scoring with alternative data. In: *Expert Systems with Applications*, 2021, vol. 163, no. 113766, p. 3.

84 See *idem,* pp. 23-31.

85 See ANDERSON, Raymond – op. cit., 2007, pp. 257-274.

86 See *ibidem,* p. 257.

87 . See. *Ibidem,* pp. 257-258.

88 See *ibidem,* pp. 259-262.

89 See *ibidem,* pp. 262-268.

90 See MORGADO REBELO, Diogo; ANALIDE, Cesar; COVELO DE ABREU, Joana – O Mercado Único Digital e a '(Leigo)ritmia' da Pontuu ação de Crédito ... *supra*, pp. 17-18.

91 See KISSINGER, Henry; SCHMIDT, Eric & HUTTENLOCHER, Daniel – *A Era da Inteligência Artificial: E o nosso futuro humano*, D. Quixote, 2021, p. 73.

assessment[92]. Let us now look at ADM procedures, particularly to what esteems the distinction between explanation vis-à-vis- interpretation by Law in Action.

4. Intelligent-based profiling for CWA and ADM

Banking 4.0. is about *"the ability to access the utility of banking wherever and whenever you need a money solution, in real-time, tailored to your unique behaviour"* [93]. Nowadays, clients' history constitutes valuable assets to banking institutions, spotlighting AI governance on credit scoring, and thus, the growth of the human-machine interface in Banking 4.0. Once again, Article 18(1) and Recitals 45 and 46 of the PCCD, highlights the general interest in preventing irresponsible lending and costumers' over-indebtedness[94]. Nowadays, more and more platforms ease the granting of consumer credit. It is worth emphasising the updated concern that this proposal for a directive on consumer credit has had in adding crowdfunding services in its Article 3(4), as provided for in Article 2(1), within its material scope of application.

According to Article 18(2) of the PCCD, credit-related assessments shall only consider relevant and accurate information on the consumers' income, their expenses, among other additional financial and economic circumstances[95]. To that its non-exhaustive extent, some other multiple kinds of alternative predictors[96] could still portray excellent sources for AI-based systems to perform predictive analysis, more even at the scale of "Know-your-costumer" (KYC)[97]. Banks shall also adopt policies to protect themselves against deviant conducts, eventually of criminal nature. KYC regulations, preventing racketeering, are catered for by data protection clauses, which require entities gathering personal data to provide suspicious maneuvers to public authorities, wherever demanded by law. Also, mathematical, and statistical pattern identification contributes significantly to identifying abnormal transactions in the overall credit cycle. Poor controls in credit scoring may result, for instance, in fraudulent activities[98].

Up until some time ago, running AI tools for scoring in retail banking often entailed outlining privacy-invasive, non-intuitive and unverifiable inductions[99]. Inferences of individuals on solvency usually depicted profiling clients too profoundly, especially in what concerns to their five C's, meaning, character, capacity, capital, or collateral traits (see Articles 4(4), 9(1), 22 and Recitals 71,72,73 of the GDPR)[100]. Character measures client's willingness to repay loans according to their characteristics, such as credit history and job stability. Capacity traduces, on the other hand, client's aptitude to pay back, considering, for instance, sets portraying income and expenses. Clients' savings may also secure unpredictable and unfavourable events, this being the capital stronghold. Also, the report of their heritage, like buildings, houses, and terrains, may assume collateral guarantees when customers fail to pay instalments regularly and thoroughly. Macroeconomic conditions cannot be disregarded in this circumstance, so the job nature, taxation and inflation rates are variables that must be computed in the CWA equation, as noted above[101].

---

92 See Recital 48 of the PCCD; European Commission- Annexes to the Proposal for a Regulation of the European Parliament and of the Council Laying down harmonized rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain Union Legislative Acts (COM(2021) 206 final), of 21 April 2021, p. 4; and European Commission - Proposal for a Regulation of the European Parliament and of the Council, laying down harmonised rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts (COM(2021 206 final), of 21 April 2021, pp. 45-68 (Articles 6 to 51, in particular, Chapter 2, whose prescriptions ascertain requirements of mandatory nature).

93 Cit. KING, Brett - *Bank 4.0: Banking everywhere, never at a bank*, John Wiley & Sons, New Jersey, 2018, p. 40.

94 See Proposal for a Directive of the European Parliament and of the Council on consumer credits … *supra*, p. 23.

95 See *ibidem,* p. 24.

96 See SARTOR, Giovanni – *The impact of the General Data Protection Regulation* (GDPR) on artificial intelligence, EPRS Study, June 2020, p. 15.

97 See CHEN, Ting-Hsuan - Do you know your customer? Bank risk assessment based on machine learning. In: *Applied Soft Computing*, vol. 86, no. 105779, 2020, p. 1 and ff.

98 See ANDERSON, Raymond – op. cit., 2007, pp. 649-652.

99 See WACHTER, Sandra; MITTELSTADT, Brent - A right to reasonable inferences: re-thinking data protection law in the age of big data and AI. In: Columbia Business Law Review, vol. 2012, no. 2, 2019, p. 497, in general, and p. 516, concerning credit scoring.

100 See SILVA, Fábio, *Credit scoring as an asset for decision making in intelligent decision support systems*, op. cit., p. 14; BEARS, Paul; BECK, Richard; SIEGEL, Susan – *Consumer Lending,* 7th ed, American Bankers Association, 2013, p. 260; and ALCARVA, Paulo – op. cit., 2018, p. 106.

101 See *ibidem.*

Nowadays, as far as Recital 47 of the PCCD regards, "*personal data, such as personal data found on social media platforms or health data, including cancer data, should not be used when conducting a creditworthiness assessment*"[102]. The European Data Protection Supervisor (EDPS) recommended explicitly extending this prohibition to all special categories of data under Article 9 GDPR, not just health data. EDPS considered CWA inferences from data such as queries or online browsing cannot fulfil the principles of purpose limitation, fairness, and transparency (see Article 5(1)(a)(c) of the GDPR)[103]. Nevertheless, from now on, potential borrowers should not be so afraid about how all sorts of alternative and personal data (e.g., social media background, purchase history, web browsing, medical history, among many others of sensitive nature) might impact their ability to be granted a loan (see Article 4(1) of the GDPR)[104]. There is a structural flaw in the data protection regime that deserves to be emphasised here for all due purposes. According to the regime in force, both inputs and outputs shall be deemed sensitive data (following the prohibition laid down in Article 9(1) of the GDPR, accordingly). However, as Sandra Wachter and Brent Mittelstadt pointed out in 2019, European policymaking and jurisprudence on personal data protection should be grounded primarily "*on its usage and impact, and secondarily on its source*"[105].

In any case, during the pre-contractual (or negotiation) stage - or when reassessing creditworthiness, by changing the total amount of the claim, as established in Article 18(8) of the PCCD - the usage of AI software to prospect CWA represents more than ever the dynamics of IDSS underlying exclusive ADM. In a generic way, algos rithmic decision systems on credit scoring stress somewhat machine-made decision-making, which evolves systems parameters, the context of use, whether relying solely upon or not on self-learning analysis. The literature often assigns the term algorithmic decision to represent partial and fully automata, hence, keeping the label ADM solely to the outcomes produced by a certain ML procedure[106].

As mentioned above, in today's digital era, computer-based programs self-manage multidimensional databases, expert knowledge and learning models to assist semi-structured problem-solving in finance, thus improving the underwriting operations' quality, speed, and effectiveness in credit. At its best and its worst, consumers acceptances or denials can be assumed to be exclusively automated directly through the usage of online platforms or by the formal intermediation of a middleman who, in practice, is still obliged to fulfil banking policies and do not possess any (or rather, sufficient) control on the outcomes autonomously derived[107]. On what shall be deemed to be an exclusive automated procedure, the German Federal Court of Justice stated in Schufa 2014 that, throughout the credit decision course, when automation circumscribes solely to the collection of evidence, and it is the banking officer who generates or deals with the outputs of a CWA, the system will fall outside the scope of the prohibition layed down in Article 22 of the GDPR[108]. Indeed, from a psychological viewpoint, although even eventually stamped by human supervision, front-officers most probably exhort the tendency to become too complacent, over-reliant, or unduly diffident when faced with a system's outputs accurate and, hence, trustworthy as a performance measure[109].

Thus, too, AI-based credit scoring opens a world in which decisions are made through three basic approaches: humans (which is familiar to us), machines, and genuine human-machine collaboration[110]. Nevertheless, it is prer cisely in the man-machine interface that the human being seeks at all costs to preserve his anthropopathic control.

---

102 See Proposal for a Directive of the European Parliament and of the Council on consumer credits … *supra*, p. 23.

103 See EDPS- Opinion 11/2021, on the Proposal for a Directive on consumer credits … *supra*, p. 7, no. 17.

104 See SARTOR, Giovanni – *The impact of the General Data Protection Regulation … supra,* p. 15.

105 Cit. WACHTER, Sandra; MITTELSTADT, Brent - A right to reasonable inferences … *supra,* p. 616.

106 See CASTELLUCCIA, Claude; LE MÉTAYE, Daniel – *Understanding algorithmic decision-making: Opportunities and challenges,* EPRS, 2019, pp. 3-4.

107 See DA SILVA, Frederico Oliveira; DRAZEWSKI, Kasper – Regulating AI to protect the consumer, BEUC Position Paper, 2021, p. 13; SANN CHO, Diana – Automated Decision-Making and Article 22 GDPR, Towards a more substantial regime for solely automatic decision-making. In: *Algorithms and Law* (Martins Ebers & Susana Navas Eds.), 2020, p. 145; FERRETTI, Federico; VANDONE, Daniela – op. cit., 2019, pp. 168-170; and WP29 – Guidelines on Automated decision-making and Profiling for the purpose of Regulation 2016/679 (WP25rev.01), adopted on 6 February 2018, p. 8.

108 See BGH, Case Schufa, VI ZR 156713, paragraph 34, *ex vi* BAYAMLIOGLU, Emre – Transparency of Automated Decisions in the GDPR: An Attempt for systemisation, PLSC Draft Paper, Tilburg University, 2018, p. 7.

109 See ZERILLI, John et. al. – Algorithmic decision-making and the control problem. In: *Minds and Machines,* vol. 29, no. 4, pp. 556.

110 See KISSINGER, Henry; SCHMIDT, Eric & HUTTENLOCHER, Daniel – op. cit., 2021, p. 26, adapted.

To point out: it is doubtful whether human's control on ADM will mitigate possible adverse effects. Some are the terminology already used regarding human oversight, envisaged in a utopian manner in Article 14 of the AI Regulation Proposal. Firstly, Human-In-the-loop (HITL) refers to the humans' capacity in playing an integral role through the entire credit cycle, thus, influencing every decision. This interface standard is undesirable and pragmatically unfeasible, as humans will most likely introduce bottlenecks. Secondly, Human-On-the-Loop (HOTL) depicts interfaces in which officers assume a supervisory role during both designing and operational stages. In situations like these, front-officers influence the decision course by monitoring scoring operations and interjecting as needed. At this point, coordination becomes increasingly tricky as the more complex business environment is, such as credit, which has multiple agents involved in the decision course. Consequently, HOTL raises trust issues, potentially even leading to safety concerns. Human operators will rarely intervene when over trust machines or, on the contrary, they may distrust and meddle too often when distrust systems' outputs. Few will be the circumstances where a human being externalizes the ability to oversee the entire CWA development and implementation cycle (including its broader economic, societal, legal, and ethical impact), hence, leading almost perfect systems on credit to decide about when and how to use AI for a specific situation. Human-In-Control (HIC) approach seems to be an overlooked utopian scenario for most applications that run at a big data scale because humans lack real-time attention and working memory. Lastly, since in many occurrences the human being will be faced with scenarios where the lack of knowledge, expertise and reaction time is notorious, it is better to outsource the credit performance to the machine. Often, granting autonomy to the operation of these applications, placing the human being in an Out-of-Control position (HOC), is more a topic of necessity than axiological-normative convenience portrayed by Law in Books[111].

Moreover, it is worth recalling, for all due purposes, that following the Article 18(4) of the PCCD, "*the creditor (…) only makes the credit available to the consumer where the result of the creditworthiness assessment indicates that the obligations resulting from the credit agreement (…) are likely to be met in the manner required under that agreement*"[112]. On the one hand, the automated denial of a credit application, regarding AI systems, can significantly affect the user's legal sphere, as envisaged by the prohibition prescribed in Article 22(1)(4) of the GDPR. It can often entail excluding end-users from granting loans, thus, impacting their consumption habits and life satisfaction indexes. That is the reason why AI systems used to access creditworthiness of individuals are classified as high-risk. Ultimately, they decide those persons' access to financial resources or essential services such as housing, electricity, and telecommunication services"[113]. On the other, even a decision favouring granting credit produces "legal" effects on borrowers' status, bounding them to a set of obligations arising from the final agreement[114].

Besides, since an AI-based credit scoring system is premised on the fast collection, storage, and untraceable analysis of vast amounts of personal data, some privacy concerns have been raised upon discrimination risks[115]. In 2015, Frank Pasquale asserted data-driven lending *praxis* bit minority communities hard "*far from liberating individuals to be judged on their character rather than their color. (…) Credit scores (…) launder past practices of discrimination into a black-boxed score, immune from scrutiny*"[116]. Recently, the New York State Department of Financial Services investigated Apple and Goldman Sachs as many applicants voiced suspected issues that trigger gender bias in ADM Apple Card credit-lending[117]. In fact, ADM reflect, at a larger scale, the biased world as it is, sometimes even indirectly founding inferences on factors such as race, sex, age, sexual orientation, or even new unknown forms[118]. As Giovanni Sartor highlighted in his 2020 Study for European Parliament concerning the impact of the GDPR on AI, "*the alternative to automated decision-making is not perfect decisions but human decisions with all their flaws: a biased*

111 See AI HLEG – Ethics Guidelines for Trustworthy AI, European Commission, of 8 April 2019, p. 19; and METHNANI, Leila [et al.] - Let Me Take Over: Variable Autonomy for Meaningful Human Control. In: *Frontiers in Artificial Intelligence*, vol. 4, no. 737072, 2021, pp. 2-3.

112 See Proposal for a Directive of the European Parliament and of the Council on consumer credits … *supra*, p. 24.

113 See Recital 37 of the AI Regulation Proposal; and Recital 48 of the PCCD.

114 See MORGADO REBELO, Diogo; ANALIDE, Cesar; COVELO DE ABREU, Joana – O Mercado Único Digital ... *supra*, pp. 37-38;

115 See HURLEY, Mikella; ADEBAYO, Julius - Credit scoring in the era of big data … *supra*, p. 159; Financial Stability Board – *Artificial intelligence and machine learning in financial services: Market developments and financial stability implications*, 2017, p. 13.

116 Cit. PASQUALE, Frank – *The Black Box Society, The Secret of Algorithms That Control Money and Information,* Harvard College, Cambridge, MA, 2015, p. 41.

117 See METHNANI, Leila, et al. - Let Me Take Over … *supra*, p. 6.

118 See FERRETTI, Federico; VANDONE, Daniela – op. cit., p. 171.

algorithmic system can still be fairer than an even more biased human decision-maker" [119]. At this point, it is essential to remember that fairness does constitute mainly a socio-ethical concept, not a statistical one. Most of the ideas carrying bias discrimination do not consider the underlying correlational mechanism that generated output data. Models on credit scoring used to 'predict the world as it is' shall not be deemed as problem. Reasonable estimations should also model biased decisions made by the bank. From a different angle, the one pretraining banks superior interests, IDSS usually intends to mimic the world as it should be profitable. From these approaches, biased tendencies are highly relevant to detect and, sometimes, avoid.

All of us need some form of prejudice to comprehend and learn the surrounding environment. An IDSS does not operate abnormally: loan approvals often entail treating certain groups differently. Tools for scoring borrowers in credit are configured to accept some customers and reject others. Generally, it can reasonably be a bank's policy not to approve loan applications by people with a meagre income. On the other side, although technically it is conceivable to reject people based on sex or ethnicity, such segmentation shall be referred to as unwanted, racial, or discriminatory from the law viewpoint. Human annotator bias, possibly leveraged during the manual labelling procedures, is deemed inadequate because annotators may transfer their prejudice to the data and further to DM or ML models, hence, discriminating applicants of a particular demographic group. Nevertheless, humans may, consciously or unconsciously, insert kindness when approved loan applications for vulnerable members too often. After all, this is a matter of perspective, so assessing the discrimination subject must be assumed on a case-by-case basis[120]. In its 2019 paper, Talia Gillis tried to demonstrate that policymakers' direction to solve the tension between the old law and technological advancements is not a promising one. Like traditional fair lending methods, scrutinizing input sets is no longer feasible or practical in big data scenarios. In any case, discriminatory trends will be inherent to information from other classes. According to her theory, regulators should, instead, apply tests for examining when the outcomes algorithm produce are impermissible, for instance, in the case of scoring in credit, by verifying whether similarly situated borrowers are treated differently[121].

5. Interpretation for High-stake scoring in credit vis-à-vis Data Protection Jigsaw

AI-based models for scoring in credit (and, most importantly, each dataset attached to the training, testing and implementation periods) execute fuzzy reasoning 'from winter to spring'[122]. For this reason, from a self-determination perspective[123], it is conceivable to doubt the existence, scope, and feasibility of a tailored right to "explanation", hereinafter deemed as the fictional '(EU)-friendly' or suitable safeguard allegedly enacted thereof in Articles 13(2)(f), 14(2)(g), 15(1)(h), and 22(3), all of which enshrined in the GDPR. The AI-engineering community clarifies that explanation does not rely on the formal definition spread among law experts that varies depending on author and context. On the contrary, an approach deemed more feasible, accordingly shall rely on the "*idea of providing elements to explain the results to a human in an understandable manner* (…)"[124]. Tiago Sérgio Cabral, Lilian Edwards and Michael Veale go far beyond the letter of the Regulation and the Recital 71. However, arguments upheld to a more dynamic linkage between existing data subjects' rights of access, erasure, rectification, information, among others, are unsuccessful from the very beginning. Firstly, the nature of the rule is, by *fictio iuris*, prohibitive, as evidenced by the exceptions set out in Article 22(2) of the GDPR. Secondly, the right to information (see Articles 13(2)(f) and 14(2)(g) of the GDPR) or the right to access (see Article 15(1)(h) of the GDPR) do not support in any way the necessity of giving technological explanations for specific ADM-related automata. These provisions do not ensure that the data

119 See SARTOR, Giovanni – *The impact of the General Data Protection Regulation* (GDPR) … *supra,* p. 22.

120 See HELLSTRÖM, Thomas; DIGNUM, Virginia; BENSCH, Suna - Bias in Machine Learning- What is it Good for?. In: *arXiv preprint arXiv:2004.00686*, 2020.

121 See GILLIS, Talia – False dreams of algorithmic fairness … *supra,* p. 86.

122 See DERNONCOURT, Franck - Introduction to fuzzy logic, Massachusetts Institute of Technology, 2013, pp. 1-4.

123 The right to self-determination, established under the *avant-gard* German Federal Constitutional Court in December 1983, circumscribes "*the capacity of an individual to determine in principle the disclosure and use of (...) personal data*", cit. ROUVROY, Antoinette; POULLET, Yves - The right to informational self-determination and the value of self-development: Reassessing the importance of privacy for democracy. In: *Reinventing data protection?*. Springer, Dordrecht, 2009. p 45.

124 Cit. HAMON, Ronan; JUNKLEWITZ, Henrik; SANCHEZ, Ignacio – Robustness and Explanation of Artificial Intelligence, From technical to policy solutions, JRC Technical Report, Publications Office of the European Union, Luxembourg, 2020, p. 12.

subjects' - in here, too consumers' - understand, by design or by default, the logic behind the technique implemented, and the consequences that this type of processing may have[125].

Particularly in what esteem CWA, Article 18(6)(b) and Recital 48 of the PRCC strengthen the monodisciplinary technophobic bias of the European normative acts on Law and Technology. The EC proposal establishes consumers must be granted the right to "meaningful explanation". Hence, clients in AI-based credit scoring can, prior to the agreement, "*request and obtain from the creditor a clear explanation of the assessment of creditworthiness, including on the logic and risks involved in the automated processing of personal data and its significance and effects on the decision*"[126]. In this regard, Recital 39 - vis-à-vis whatever shall be considered an "adequate explanation" entitled in Article 12 – also asserts that creditors and, where applicable, intermediary joint controllers[127], should adapt how such explanations are given to the circumstances and the consumers' need for assistance, considering their know-how, accordingly. Furthermore, it asserts, *in fine*, such explanations should not in itself constitute a personal recommendation[128].

First and foremost, "*the GDPR requires the controller to provide meaningful information about the logic involved, not necessarily a complex explanation of the algorithms used or disclosure of the full algorithm*"[129]. If entered into force, it is still not clear how such an explanation can be compliant with the dictates of an interpretation proposed by Article 13(1) of the Artificial Intelligence Act[130]. From technical to policy solutions, JRC clarified in its 2020 Report that a second interpretability approach, either steamed as a positive or a negative explanation, would emphasise the most prominent attributes that come into play in credit-related ADM or by generating counterfactual explanations[131]. The interpretation approach on counterfactual explanations would better suggest which sets should be minimally changed or added to modify the individual decision-making[132]. Explanations serve, among self-informative and contestation grounds, "*to understand what could be changed to receive a desired result in the future, based on the current decision-making model*"[133]. Interpretative rule-proof "*describes a minimal change to the input that would result in the opposite prediction*"[134]. A counterfactual explanation on scoring shall describe the generic causal situation, as follows:

125 See, arguments of solely legal nature, put forward by CABRAL, Tiago Sérgio – AI and the Right to Explanation, Three Legal Bases under the GDPR. In. *Data Protection and Privacy: Data Protection and Artificial Intelligence* (Dara Hallinan, Ronald Leenes & Paul De Hert Eds.), vol. 13, 2021, pp. 43-50; and EDWARDS, Lilian; VEALE, Michael – Slave to the algorithm? Why a 'right to an explanation' is probably not the remedy you are looking for. In: *Duke Law and Technology,* vol. 16, no. 1, p. 80-82.

126 Cit. WP29 – Guidelines on Automated decision-making and Profiling … *supra,* p. 7.

127 See European Union FRA – *Handbook on European data protection law*, Luxembourg: Publications Office of the European Union, 2018, p. 106.

128 See European Commission- Proposal for a Directive of the European Parliament and of the Council on consumer credits … *supra*, p. 21.

129 See European Commission - Proposal for a Regulation of the European Parliament and of the Council, laying down harmonised rules on Artificial Intelligence (Artificial Intelligence Act) …, p. 50.

130 "*The information provided should, however, be sufficiently comprehensive for the data subject to understand the reasons for the decision*". Cit. WP29 – Guidelines on Automated decision-making and Profiling … *supra,* p. 7.

131 See WATCHER, Sandra; MITTELSTADT, Brent; RUSSEL, Chris – Counterfactual Explanations without opening the Black Box, Automated Decisions and the GDPR. In: *Harvard Law Review,* vol. 31, no. 2, p. 843.

132 Cit. GRATH, Rory Mc [et al.] - Interpretable credit application predictions with counterfactual explanations. In: *arXiv preprint arXiv:1811.05245,* 2018, pp. 3-5; ARRIETA, Alejandro Barredo [et al.] - Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. In: *Information Fusion*, vol. 58, 2020, pp. 84-85; HAMON, Ronan; JUNKLEWITZ, Henrik; SANCHEZ, Ignacio – Robustness and Explanation of Artificial Intelligence … *supra,* p. 13; CARNEIRO, Davide, [et al.] - Explainable intelligent environments. In: *International Symposium on Ambient Intelligence*. Springer, Cham, 2020, p. 36.

133 See WATCHER, Sandra; MITTELSTADT, Brent; RUSSEL, Chris – Counterfactual Explanations without opening the Black Box, … *supra,* p. 843.

134 Cit. RUDIN, Cynthia. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. In: Nature Machine Intelligence, vol. 1, no. 5, 2019, p. 210

Figure 2. Counterfactual Interpretation

> *"Score y was returned because variables X had values (x1, x2…) associated with them. If X instead had valued (x'1, x'2, …), and all other variables had remained constant, score y' would have been returned". On the contrary, from a positive viewpoint, "if instead you had the following values (x, y, z, …), your application would have been rejected"*

Secondly, as Recital 63 of the GDPR pointed out, the way AI operates at the scale of credit-related scoring, using DM approaches through ML modelling, is also sheltered by an 'umbrella' of IP rights, being part of protecting Trade Secrets Directive[135]. In this regard, on 28th January 2014, the German Federal Court of Justice (Bundesgerichtshof, BGH) ruled that information remits regarding personal data protection only compel controllers to provide consumers information underlying the general functioning of the software[136]. For instance, disclosing formulas, practices, processes, designs, instruments, patterns, or compilations of financial information is still under the protection of banking institutions' trade secrets[137]. Consequently, although interpretation and explainability have become critical concerns in governing AI-bases CWA, it is not yet clear for all to perceive what this would mean in terms of legal requirements.

Moreover, last, but not least, the AI HLEG recognises that an increase in the system's explainability may decrease its accuracy. It would then be assumed that the implementation of XAI techniques supposes a trade-off with the accuracy principle provided for in Article 5(1)(d) of the GDPR[138]. However, these losses in systems' accuracy would not occur if the mechanisms employed, instead of determining the data point that led to a particular decision, presupposed additional tools that provide simple counterfactuals. In the last resort, it would only make sense to prescribe the application of XAI techniques in situations where the Technology Readiness Level (TRD) level of the AI system is low. In stages such as training and testing, it would be beneficial to allocate XAI resourses for the optimisation of the corresponding computational tasks.

Amid all the upcoming legal framework dead-end, broadly speaking, the existing 'law-by-books' literature demands that such a right might be accomplished either (or both) *ex-ante* – i.e., offering simple or general information about the system functionality prior to processing – or *ex-post* – i.e., providing a legible full description of the concrete decision by means of full traceability[139]. "*The controller should find simple ways to tell the data subject about the rationale behind, or the criteria relied on in reaching the decision. The GDPR requires the controller to provide meaningful information about the logic involved, not necessarily a complex explanation of the algorithms used or disclosure of the full algorithm*"[140]. A tailored-based explanation would represent a particular logic underpinning individual ADM credit-related scoring practices, differing from the transparency principle to that extent. Explanatory approaches may assume different typologies (whether operational, logical or causal); they may deal with the decision-making

135 See Article 2(1) of the Directive (EU) 2016/943, of the European Parliament and of the Council, of 8 June 2016, on the protection of undiss closed know-how and business information (trade secrets) against unlawful acquisition, use and disclosure, *ex vi* IGLESIAS, Maria; SHAMUILIA, Sheron; ANDERBERG, Amanda – Intellectual Property and Artificial Intelligence, A literature review, JRC Technical Report, Publications Office of the European Union, Luxembourg, 2019, p. 20.

136 See Judgment of BGH, Case Schufa, of 28 January 2014, VI ZR 156/13, paragraph 10.

137 See Judgment of BGH, Case Schufa, of 28 January 2014, VI ZR 156/13, paragraph c), summary; IGLESIAS, Maria; SHAMUILIA, Sheron; ANDERBERG, Amanda – Intellectual Property and Artificial Intelligence, A literature review, JRC Technical Report, Publications Office of the European Union, Luxembourg, 2019, pp. 20-21; and FERRETTI, Federico; VANDONE, Daniela – op. cit., p. 169.

138 See AI HLEG – Ethics Guidelines for Trustworthy AI, European Commission, … *supra,* p. 18.

139 See WACHTER, Sandra; MITTELSTADT, Brent; FLORIDI, Luciano - Why a right to explanation of automated decision-making does not exist in the general data protection regulation. In: *International Data Privacy Law*, vol. 7, no. 2, 2017, p. 81.

140 Cit. WP29 – Guidelines on Automated decision-making and Profiling for the purpose of Regulation 2016/679 … *supra,* p. 25.

process as a whole (i.e., the whole algorithm) or locally (i.e., outcomes); and they may take different forms (Decision Trees, histograms, among many others)[141].

Given the debate triggered by the Recital 71[142], some legal experts argue the word "explanation" attempt to encompass the internal state of models, operating at the scale of applications[143]. However, the average level of digital illiteracy does not let data subjects fully understand the logic involved - i.e., how the machine follows the rules - regardless of how unaware they might be of the importance and the consequences of such processing. Until now, neither data subjects have sufficient know-how, nor do they realize the GDPR legal criteria to decide when and within what limits sensitive information about credit applications should be committed to the lack of transparency. Consequently, candidates or borrowers in the actual state of the AI-based consumer credit art still provide undeniably uninformed consents (see Article 22(2) (c) of the GDPR).[144].

The solution seems clear—modern-day CWA based on ML shall sometimes model reality on its own. While researchers can analyse the results produced by an AI system, the later cannot explain how and what 'it' has learned about the reality (of credit). Nor should researchers ever ask an AI system to characterise what it has learned, as one might do with a human learner[145]. Some artilects figure now as the new mechanical Dolly for CWA, something our specie cannot control similarly. We, human beings, will possibly not be able to order them to explain, at least, as we intend to.

6. Right to suggestive-commoditization of an IDSS MAS-based classifier

From theory to practice, Fábio Silva's 2011 IDSS case study, concerning Distributed AI, already stressed tod-day's imbroglio of a right to explanation *ex-post* at the agent's business level. His work focused on how the MAS-based system[146] works out while realigning "interpretability" with the proposal of a right to suggestive counterfactuals[147]. It exhorts a kind of agonistic practice that brings data-driven MAS solutions into lending legal environment while simultaneously bringing it under future-proof Rule of Law[148].

Firstly, ANN starts training and testing updated classifiers, performing tasks such as DM. Consumers' profile autonomously drawn up by the Model-based Agents categorizes potential clients in their future creditworthiness condition. When put into practice, the Multilayer Perceptron with a Decision Tree for feature selection strengthens the lawful distinction to the 20 predictors of a given dataset, those that may be more relevant and not too sensitive for the Decision Agent model[149]. With a brief overview of the technicity undergone ANN classifications, we conclude

141 See CASTELLUCCIA, Claude; LE MÉTAYE, Daniel – *Understanding algorithmic decision-making … supra,* p. III. WP

142 As a matter of principle, the Court of Justice of the European Union (CJEU) states that recitals have not any direct binding effect. See *Casa Fleischhandels-GmbH v Bundesanstalt für landwirtschaftliche Marktordnung*, Case 215/88, ECLI:EU:C:1989:331, of 31 July 1989, paragraph 31, p. 2808. Even decisions from the WP29, representing the shared opinion of data protection supervisory authorities, shall not be considered by the CJEU since it has an intrinsically issue of having solely normative backgrounds.

143 "*It is reasonable to suppose that any adequate explanation would, at a minimum, provide an account of how input features relate to predictions, allowing one to answer questions such as: Is the model more or less likely to recommend a loan if the applicant is a minority? Which features play the largest role in prediction?*". See GOODMAN, Bryce; FLAXMAN, Seth – EU Regulations on Algorithmic Decision Making and a Right to an Explanation"'. In: *ICML Workshop on Human Interpretability in ML,* 2016, p. 55. However, such a remark assumes that the ML models are clear and understandable enough to human beings from the early soft computing stages, which is not the case in practice.

144 See DA SILVA, Frederico Oliveira; DRAZEWSKI, Kasper – Regulating AI to protect the consumer ... *supra,* p. 5; FERRETTI, Federico; VANDONE, Daniela - op. cit., p. 168; and BURRELL, Jenna - How the machine 'thinks', Understanding opacity in machine learning algorithms. In: *Big Data & Society*, vol. 3, no. 1, 2016, p. 4.

145 See KISSINGER, Henry; SCHMIDT, Eric & HUTTENLOCHER, Daniel – op. cit., 2021, pp. 81-82.

146 A software agent has more robust and more particular significance than the autonomy trait commonly identified in Article 3(1) of the AI Act Proposal. It refers to an autonomous system that exhibits mentalistic notions of knowledge, beliefs, intention or obligations and has the social ability, reactivity and pro-activeness attributes. See, on the weak and strong notion of agents, WOOLDRIDGE, Michael; JENNINGS, Nicholas – Intelligent agents: theory and practice. In: The Knowledge Engineering Review, 1995, pp. 116-117.

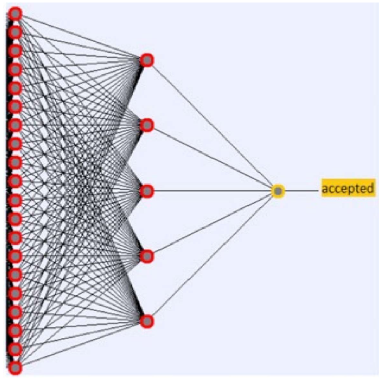
147 See SILVA, Fábio – *Credit scoring as an asset for decision making in intelligent decision support systems*, op. cit. pp. 38-40; and SILVA, Fábio; ANALIDE, Cesar – op. cit., pp. 214-215.

148 See HILDEBRANDT, Mireille - Privacy as protection of the incomputable self: From agnostic to agonistic machine learning. In: *Theoretical Inquiries in Law*, vol. 20, no. 1, 2019, p. 107.

149 See SILVA, Fábio; ANALIDE, Cesar – op. cit. p. 210.

that exposing the relations between pieces of information (or knowledge) from inputs to outputs do not have to be explicitly specified. Data subjects will not, in any case, realize what is: (1) a feedforward neural net with depth that equals 1; (2) a fully 3 inter-layered architecture running through a topology of 20-5-1 nodes in each level; and (3) the importance of training, testing and applying the Backpropagation algorithm on inputs to perform predictions with 97.2% accuracy[150].

Figure 3. Fábio Silva's 2011 Neural Net for scoring applicants in credit



When a customer has its credit denied, the ModelBuilder applies evolutionary computation, revealing Silva's constructive approach to the current 'black box dilemma' as it is not tangible to the average human being[151]. By design, this genetic scheme, relying upon Charles Darwin theory on "The Origin of Species" provides counterfactual interpretations of which parameters were individually lacking, allowing "*consultants from financial institutions to better advise their clients or perform cross selling operations recommending (…) products which improve a client's credit score*"[152]. To its extent, favourable elucidations are added to the nominal solvency profiles drawn up in classification and learning stages[153]. Thus, especially in the case of a credit refusal, the Suggestion Agent grades a list of possibilities for the missing features to reach more practical and alternative solutions. This trait proves to be an advantageous mechanism to meet today's legal requirements of Article 13(2)(f), Article 14(2)(g), and Article 22, all the GDPR. Furthermore, since no client's attributes must be disclosed, understanding missing features through counterfactual interpretation is less likely to infringe on trade secrets or other data subject's rights and freedoms.

More than ever, to avoid the disclosure of knowledge about customers without exact awareness about the effects, thus making consent ineffective, national legislators must once and for all perceive data as a real asset. Data is the new 'golden buzzer' to be granted loans; data is the new oil for better CWA. It should, therefore, be deemed a tradable good[154]. For SMEs or Giant Techs, data provided by the user in exchange for an asset are in many cases much more valuable than financial payments. Such value, at the very least, balances the borrowers' benefits. The result is that we cannot consider negotiation on credit agreements - in which in the act of assessment, no price is paid, but data is provided - as free contracts[155]. Therefore, in line with Jorge Morais Carvalho, an up-to-date interpretation of the current rules is justified to consider as onerous those credit agreements whereby credit is granted as an effect of the provision of alternative data[156]. The relative matrix of personal data, according to Recital 4 of the GDPR, cannot

150 See *idem,* p. 211.

151 See RUDIN, Cynthia - Stop explaining black box machine learning models … *supra*, p. 206.

152 Cit. SILVA, Fábio – op. cit., p. 51.

153 See SILVA, Fábio; ANALIDE, Cesar – op. cit., pp. 212-214; and SILVA, Fábio –op. cit. pp. 45-51.

154 See ZECH, Herbert - Data as a tradeable commodity–implications for contract law. In: *Proceedings of the 18th EIPIN Congress: The New Data Economy between Data Ownership, Privacy and Safeguarding Competition, Edward Elgar Publishing,* 2017, p. 53.

155 See NARCISO, Madalena – "Gratuitous" Digital Content Contracts in EU Consumer Law". In: *Journal of European Consume and Market Law,* no. 5, 2017, p. 200.

156 See MORAIS CARVALHO, Jorge- *Manual de Direito do Consumo,* 7th ed., Coimbra, Almedina, 2021, p. 64.

perpetuate forever its fundamental nature as a right to avoid its commoditisation[157]. The possible qualification of the data as counter-performance has raised discussion, and the following three criticisms can be identified: (i.) non-compatibility with the GDPR; (ii.) the nature of data protection as a fundamental right is affected; (iii.) the legitimization of a new business model - a data market - hostile to data protection principles[158]. This idea is incredibly vivid in EDPS Opinion 4/2017. In this Opinion, many doubts are raised about using the notion of counter-performance for data. It criticizes the comparison of data with money, drawing attention to the lack of awareness on the part of consumers as to what they are giving when they provide their data and the difficulty in assessing the data value[159].

Data is the new 'oil' of creditors. It is the data itself, not the programmers anymore, that classifies what happens next in credit. Consequently, banking institutions shall be obliged to ascertain the duty by which clients would achieve specific transactional and personal advantages for providing missing data or adjust input information. Implicitly, GDPR announces the shift in strength it outlines from production control to commercially data-driven analytics and the relative role ML-based techniques play in DM inferences portrayed within the Big Data Analytics spectrum[160].

7. Conclusion

Today's CWA have not received due attention from the European legislator. There is an urgent necessity for more and better consumer protection when processing solvency profile of customers in retail credit-based agreements. After all, the European regulatory landscape of fragmentated nature, regarding CWA, reveals its difficult effectiveness.

Undeniably, in the current state-of-the-art client's history, portraying processing personal data – which shall also follow the general and abstract GDPR dictates - constitutes valuable assets to banking institutions. The time to change the conventional paradigm has come. Data-driven solutions shall be deemed the new "golden-buzzer" of customers, spotlighting Artificial Intelligence (AI) client-centred tools on credit scoring, and thus, the natural growth of the consumers-machine interface in Banking 4.0. From spring to winter, using AI for scoring still entails outline exclusive automation at its best and worst. That is, evaluate customers in (cyber)-credit often exhorts privacy-invasive, non-intuitive and unverifiable inductive recommendations concerning exclusive automated decision-making, including profiling clients too deeply. These procedures are subsumed to the prohibition laid down in Article 22(1) of the GDPR. Moreover, as these systems perform fast collection, storage, and untraceable analysis of massive input sets of sensitive nature, some major privacy concerns have emerged upon macro-segmentation risks, henceforward, leading to the discrimination of vulnerable groups. In accordance, since the data protection regime focuses solely on the sources or the typology of data collected rather than on the intended purposes, all inferences from credit-related data, using high-stake AI systems, will inevitably be qualified as sensitive from the very beginning, applying Article 22(4) of the GDPR independently of the goal.

Moreover, DM approaches, applying ML models, often hide black box correlations within multiple fuzzy inferences. In here, apart from lenders' trade secrets, the average level of digital literacy does not let data subjects to fully understand the logic involved - i.e., how the machine follows the rules -, regardless of how aware they might be of the importance and the consequences of such processing. Consequently, consents provided will in no way be deemed as valid, hence, affecting the lawfulness of evaluations (see Article 22(2)(c) of the GDPR). Those opacity traits make it possible to doubt the existence, scope, and feasibility of a right to a detailed *ex-post* explanation, likewise enshrined in Article 22(3) of the GDPR and whereabout envisaged just as a theoretical suitable safeguard.

To sum up, our assumptions try to get AI-based credit scoring in Banking 4.0 back on its feet, monetizing missing attributes high pointed by suggestion agent. Despite all the European legislator's attempts to uniformize suf-

157 See DATOO, Akber - Data in the post-GDPR world. In: *Computer Fraud & Security*, vol. 2018, no. 9, 2018, pp. 17-18.

158 See DRECHSLER, Laura – Data as Counter-Performance: A New Way Forward or a Step Back for the Fundamental Right of Data Protection?, A Data Protection Analysis of the Proposed Directive on Certain Aspects for the Supply of Digital Content, 2018, pp. 1-8.

159 See EDPS – Opinion 4/2017 on the Proposal for a Directive on certain aspects concerning contracts for the supply of digital content, of 14 March 2017, pp. 7 ff.

160 See AHO, Brett; DUFFIELD, Roberta - Beyond surveillance capitalism, Privacy, regulation and big data in Europe and China. In: *Economy and Society*, vol. 49, no. 2, 2020, p. 102.

ficient grounds of privacy-preserving ADM, data subjects still do not understand autonomous processing and have little control over how personal data is used to exhort fuzzy predictions. With the establishment of a right to Automated Suggestion in credit scoring, we aim to provide SMEs or FinTech Giants a straightforward privacy-friendly compliance solution through Law in Action. Once again, we conclude that EU Law in books on Data Protection is not yet *prius*, nor *posterius*. It is entirely away for AI workflows, prompting unreasonable hindrances in what is the fascinating era of tech breakthroughs. GDPR, and generally, the EU policymaking are far from being considered the world standard-setter for AI Regulation. Rather, pitfall provisions such as the "meaning explanations" examined above exhorts solely a political *black boxing* prescriptive legal framework that cannot be put into practice, at least, with the desired effectiveness. The solution is plain for all to perceive: Engineering Law of AI shall trigger the next pathway that helps out reveal rules, not just apply them. Engineers are the best source of *iuris cognoscendi*. They, too, will have a word to say in the upcoming pathway applied to credit-related scoring. Unfortunately, the AI governing landscape as it stands today in Europe is still a myriad of an unfeasible regulatory jigsaw. This is the time to change paradigms.

REFERENCES

AHO, Brett; DUFFIELD, Roberta - Beyond surveillance capitalism, Privacy, regulation and big data in Europe and China. In: *Economy and Society*, vol. 49, no. 2, 2020, pp. 187-212. DOI: https://doi.org/10.1080/03085147.2019.1690275.

AI HLEG – Ethics Guidelines for Trustworthy AI, European Commission, of 8 April 2019. [Accessed 2021-11-28]. Available at https://op.europa.eu/en/publication-detail/-/publication/d3988569-0434-11ea-8c1f-01aa75ed71a1/language-pt/format-PDF.

ALCARVA, Paulo – *Banca 4.0: Revolução Digital: Fintechs, blockchain, criptomoedas, robotadvisers e crowdfunding,* Lisboa: Actual Editora, 2018. ISBN: 9789896943011.

ALIYEV, Farid – Review of the Consumer Credit Directive, BEUC Position Paper 2019. [Accessed 2021-11-24]. Available at https://www.beuc.eu/publications/review-consumer-credit-directive/html.

ALPAYDIN, Ethem - *Machine learning: the new AI*, The MIT press Knowledge Series, Cambridge, MA, 2016. ISBN: 9780262529518.

ANDERSON, Raymond - *The credit scoring toolkit: theory and practice for retail credit risk management and decision automation*. Oxford University Press, 2007. ISBN: 9780199226405.

ARRIETA, Alejandro Barredo [et al.] - Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. In: *Information Fusion*, vol. 58, 2020, pp. 82-115. DOI: https://doi.org/10.1016/j.inffus.2019.12.012.

BAESENS, Bart, et al. - Benchmarking state-of-the-art classification algorithms for credit scoring. In. *Journal of the operational research society*, 2003, vol. 54, no. 6, pp. 627-635. DOI: https://doi.org/10.1057/palgrave.jors.2601545.

BALMER, Nigel [et al] - Worried sick: the experience of debt problems and their relationship with health, illness, and disability, In: *Social Policy and Society*, vol. 5, no. 1, 2006, pp. 39-51. DOI: https://doi.org/10.1017/S147474640500271X.

BAYAMLIOGLU, Emre – Transparency of Automated Decisions in the GDPR: An Attempt for systemisation, PLSC Draft Paper, Tilburg University, 2018. [Accessed 2021-11-28]. Available at https://dx.doi.org/10.2139/ssrn.3097653.

BEARS, Paul; BECK, Richard; SIEGEL, Susan – *Consumer Lending,* 7th ed, American Bankers Association, 2013. ISBN: 0899826679.

BIATAT, Viani A. Djeundje, et al. - Enhancing credit scoring with alternative data. In: *Expert Systems with Applications*, vol. 63, no. 113766, 2021. DOI: https://doi.org/10.1016 /j.eswa.2020.113766.

BOUYALA, Régis. *La révolution FinTech*, RB édition, Paris, 2016. ISBN: 9782863257579.

BPI; Covington & Burling LLP - *Artificial Intelligence Discussion Draft: The future of credit underwriting – Artificial Intelligence and its role in Consumer Credit*, 2019. [Accessed 2021-10-02]. Available at

https://bpi.com/artificial-intelligence-discussion-draft/.

BURRELL, Jenna - How the machine 'thinks', Understanding opacity in machine learning algorithms. In: *Big Data & Society*, vol. 3, no. 1, 2016, pp. 1-12. DOI: https: //doi.org/10.1177%2F2053951715622512.

CABRAL, Tiago Sérgio – AI and the Right to Explanation, Three Legal Bases under the GDPR. In. *Data Protection and Privacy: Data Protection and Artificial Intelligence* (Dara Hallinan, Ronald Leenes & Paul De Hert Eds.), vol. 13, 2021, pp. 29-55. ISBN: 9781509941759.

CARNEIRO, Davide, [et al.] - Explainable intelligent environments. In: *International Symposium on Ambient Intelligence*. Springer, Cham, 2020, pp. 34-43. DOI: https://doi.org/10.1007/978-3-030-58356-9_4.

CASTELLUCCIA, Claude; LE MÉTAYE, Daniel – *Understanding algorithmic decision-making: Opportunities and challenges,* EPRS, 2019, pp. 1-86. [Accessed 2021-10-02]. Available at

https://www.europarl.europa.eu/thinktank/en/document.html?reference=EPRS_STU(2019)624261.

CHEN, Ting-Hsuan - Do you know your customer? Bank risk assessment based on machine learning. In: *Applied Soft Computing*, vol. 86, no. 105779, 2020, pp. 1-20. DOI: https://doi.org /10.1016/j.asoc.2019.105779.

CHEREDNYCHENKO, Olha; MEINDERTSMA, Jesse - Irresponsible lending in the post-crisis era: Is the EU consumer credit directive fit for its purpose?. In: *Journal of Consumer Policy*, vol. 42, no 4, 2019, pp. 483-519. DOI: https://doi.org/10.1007 /s10603-019-09421-4.

Communication from the Commission to the European Parliament, the Council, the European Central Bank, The European Economic and Social Committee and the Committee of the Regions, Consumer Financial Services Action Plan: Better Products, More Choice, of 23 March 2017 (COM(2017) 139 final). [Accessed 2021-11-24].

Available at https://op.europa.eu/en/publication-detail/-/publication/055353bd-0fba-11e7-8a35-01aa75ed71a1/language-en.

Communication from the Commission to the European Parliament, the European Council, The Council, and the European Central Bank, Second Progress Report on the Reduction of Non-Performing Loans in Europe, of 14 March 2018, (COM(2018) 133 final). [Accessed 2021-11-24]. Available at

https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52018DC0133&from=PT.

Communication from the Commission to the European Parliament, the Council, The European Economic and Social Committee and the Committee of the Regions, Towards a thriving data-driven economy (COM(2014)442), of 2 June 2014. [Accessed 2021-11-26]. Available at

https://eur-lex.europa.eu/legal-content/pt/TXT/?uri=CELEX%3A52014DC0442.

CRISTOFARO, Giovanni de– La Nuova Disciplina Comunitaria del credit al Consumo: La Diretiva 2008/48/CE E 1' Armonizzazione completa delle disposizioni nazionali concernenti "taluni aspetti" dei "contratti di credit ai consumatori. In: *Rivista di Diritto Civile,* vol. 54, no. 3, 2008. ISSN: 0035-6093.

DA SILVA, Frederico Oliveira; DRAZEWSKI, Kasper – Regulating AI to protect the consumer, BEUC Position Paper, 2021. [Accessed 2021-10-09]. Available at https://www.beuc.eu/publications/beuc-x-2018-058_automated_decision_making_and_artificial_intelligence.pdf.

DATOO, Akber - Data in the post-GDPR world. In: *Computer Fraud & Security*, vol. 2018, no. 9, 2018, pp. 17-18. DOI: https://doi.org/10.1016/S1361-3723(18)30088-5.

DE SERVIGNY, Arnaud; RENAULT, Olivier - *Measuring and managing credit risk*, McGraw-Hill, New York, 2004. ISBN: 9780071417556.

DERNONCOURT, Franck - Introduction to fuzzy logic, Massachusetts Institute of Technology, 2013, pp. 1-4. [Accessed 2021-10-09]. Available at

http://aisii.azc.uam.mx/mcbc/Cursos/IntCompt/Lectura15.pdf

DRECHSLER, Laura – Data as Counter-Performance: A New Way Forward or a Step Back for the Fundamental Right of Data Protection?, A Data Protection Analysis of the Proposed Directive on Certain Aspects for the Supply of Digital Content, 2018, pp. 1-8. [Accessed 2021-11-29].

Available at https://ssrn.com/abstract=3329345.

DURAND, David - *Risk elements in consumer installment financing*. In. *National Bureau of Economic Research*, New York, 1941.

DOI: https://doi.org/10.1177/000271624121800172.

EDWARDS, Lilian; VEALE, Michael – Slave to the algorithm? Why a 'right to an explanation' is probably not the remedy you are looking for. In: *Duke Law and Technology,* vol. 16, no. 1, p. 1-84. [Accessed 2021-10-09]. Available at

https://pureportal.strath.ac.uk/en/publications/slave-to-the-algorithm-why-a-right-to-an-explanation-is-probably-.

European Commission- Proposal for a Directive of the European Parliament and of the Council on consumer credits, of 30 June (COM(2021) 347 final). [Accessed 2021-10-10]. Available at

https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2021:347:FIN.

European Commission - Proposal for a Regulation of the European Parliament and of the Council, laying down harmonised rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts (COM(2021 206 final), of 21 April 2021. [Accessed 2021-10-10]. Available at

https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206.

European Commission- Annexes to the Proposal for a Regulation of the European Parliament and of the Council Laying down harmonized rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain Union Legislative Acts (COM(2021) 206 final), of 21 April 2021. [Accessed 2021-11-28]. Available at

https://eur-lex.europa.eu/resource.html?uri=cellar:e0649735-a372-11eb-9585-01aa75ed71a1.0001.02/DOC_2&format=PDF.

European Commission – *Evaluation of Directive 2008/48/EC on credit agreements for consumers*, Directorate-General for Justice and Consumers, 2020. [Accessed 2021-10-02]. Available at

https://op.europa.eu/en/publication-detail/-/publication/e2a5882a-7d65-11eb-9ac9-01aa75ed71a1.

European Commission – Mapping of national approaches in relation to creditworthiness assessment under Directive 2008/48/CE on credit agreements for consumers, Consumer Protection in Financial Services, 2018. [Accessed 2021-11-25]. Available at https://ec.europa.eu/info/sites/default/files/mapping_national_approaches_creditworthiness_assessment.pdf.

European Commission – Study on the role of digitalisation and innovation in creating a true single market European Commission, for retail financial services and insurance, Final Report (FISMA/2015/075D), 2016. [Accessed 2021-11-25]. Available at

https://www.ceps.eu/wp-content/uploads/2016/12/DigitalisationFinSvcs.pdf.

European Parliament - A governance framework for algorithmic accountability and transparency, EPRS Study, 2019. [Accessed 2021-11-25]. Available at https://op.europa.eu/pt/publication-detail/-/publication/8ed84cfe-8e62-11e9-9369-01aa75ed71a1/language-en.

European Union FRA – *Handbook on European data protection law*, Luxembourg: Publications Office of the European Union, 2018. [Accessed 2021-10-10]. Available at https://fra.europa.eu/en/publication/2018/handbook-european-data-protection-law-2018-edition.

EDPS- Opinion 11/2021, on the Proposal for a Directive on consumer credits, of 26 August 2021. [Accessed 2021-11-29]. Available at

https://edps.europa.eu/system/files/2021-08/opinion_consumercredit-final_en.pdf.

EDPS – Opinion 4/2017 on the Proposal for a Directive on certain aspects concerning contracts for the supply of digital content, of 14 March 2017. [Accessed 2021-12-07]. Available at

https://edps.europa.eu/sites/edp/files/publication/17-03-14_opinion_digital_content_en_0.pdf.

FERRETI, Federico - *The Never-Ending European Credit Data Mess*, BEUC Position Paper, 2017. [Accessed em 2021-09-30]. Available at https://www.beuc.eu/press-media/news-events/never-ending-credit-data-mess-new-study-out.

FERRETTI, Federico; VANDONE, Daniela - *Personal debt in Europe: The EU financial market and consumer insolvency*, Uk: Cambridge University Press, 2019. ISBN: 9781108426732.

Financial Stability Board - *Artificial intelligence and machine learning in financial services: Market developments and financial stability implications*, 2017. [Accessed 2021-10-02] Available at https://www.fsb.org/2017/11/artificial-intelligence-and-machine-learning-in-financial-service/.

FISHER, Ronald - The use of multiple measurements in taxonomic problems. In: Annals of eugenics, vol. 7, no. 2, 1936, pp. 179-188. DOI: https://doi.org/10.1111/j.1469-1809.1936.tb02137.x.

FRADE, Catarina – Um perfil dos sobreendividados em Portugal. In: Observatório do Endividamento dos Consumidores do Centro de Estudos Sociais da Universidade de Coimbra (POCTI/JUR/40069/2001), 2008. [Accessed 2021-11-25]. Available at https://oec.ces.uc.pt/pdf/relatorio_proj_regulacao_consumo.pdf.

FRADE, Catarina – Desemprego e Sobreendividamento dos Consumidores: Contornos de uma ligação perigosa, Projeto Desemprego e Endividamento das Famílias, Relatório Final, Centro de Estudos Sociais da Faculdade de Economia da Universidade de Coimbra (PIQS/ECO/50119), 2003. [Accessed 2021-11-25]. Available at https://oec.ces.uc.pt/biblioteca/pdf/relatorio_desemprego_sobreendividamento.pdf

FSUG – Responsible consumer credit lending, FSUG opinion and recommendations for the review of the Consumer Credit Directive, 2019. [Accessed 2021-11-24]. Available at https://ec.europa.eu/info/publications/fsug-opinions-2019_en.

GÉRON, Aurélien - *Hands-on Machine Learning with Scikit-Learn, Keras, and Tensorflow,: Concepts, Tools, and Techniques to Build Intelligent Systems*, O'Reilly, 2019. ISBN:0070428077.

GILLIS, Talia – False dreams of algorithmic fairness: the case of credit pricing, Harvard Law School, 2019. [Accessed 2021-11-26]. Available at

https://projects.iq.harvard.edu/fintechlaw/publications/false-dreams-algorithmic-fairness-case-credit-pricing.

GOODMAN, Bryce; FLAXMAN, Seth – EU Regulations on Algorithmic Decision Making and a Right to an Explanation"". In: *ICML Workshop on Human Interpretability in ML,* 2016, pp. 50-57.

DOI: https://doi.org/10.1609/aimag.v38i3.2741.

GOURIO, Alain – La reforme du crédit à la consommation. In: *La Semaine Juridique – Édition Enterprise et Affairs,* vol. 29, 2010. ISSN: 1290-5199.

GPFI – Use of Alternative Data to Enhance Credit Reporting to Enable Access to Digital GPFI, 2018 Financial Services by Individuals and SMEs operating in the Informal Economy, 2018. [Accessed 2021-11-25]. Available at

https://www.gpfi.org/sites/gpfi/files/documents/Use_of_Alternative_Data_to_Enhance_Credit_Reporting_to_Enable_Access_to_Digital_Financial_Services_ICCR.pdf

GRATH, Rory Mc [et al.] - Interpretable credit application predictions with counterfactual explanations. In: *arXiv preprint arXiv:1811.05245*, 2018, pp. 1-9. [Accessed 2021-11-29]. Available at https://arxiv.org/pdf/1811.05245.pdf.

HAMON, Ronan; JUNKLEWITZ, Henrik; SANCHEZ, Ignacio – Robustness and Explanation of Artificial Intelligence, From technical to policy solutions, JRC Technical Report, Publications Office of the European Union, Luxembourg, 2020. ISBN: 9789279146605.

HELLSTRÖM, Thomas; DIGNUM, Virginia; BENSCH, Suna - Bias in Machine Learning--What is it Good for?. In: *arXiv preprint arXiv:2004.00686*, 2020. [Accessed 2021-11-29]. Available at https://arxiv.org/abs/2004.00686.

HILDEBRANDT, Mireille - Privacy as protection of the incomputable self: From agnostic to agonistic machine learning. In: *Theoretical Inquiries in Law*, vol. 20, no. 1, 2019, pp. 83-121. DOI: https://doi.org/10.1515/til-2019-0004.

HILDEBRANDT, Mireille; GUTWIRTH, Serge - *Profiling the European citizen*, Springer, Dordrecht, 2008. ISBN: 9781402069130.

HURLEY, Mikella; ADEBAYO, Julius - Credit scoring in the era of big data. In: *Yale journal of law and technology*, vol. 18, 2017, pp. 148-216. [Accessed 2021-10-02]. Available at https: //digitalcommons.law.yale.edu/yjolt/vol18/iss1/5.

HSIA, David – Credit Scoring and the Equal Credit Opportunity Act. In: Hastings Law Journal, vol. 30, no. 2., pp. 371-448 [Accessed 2021-11-23]. Available at: https://repository.uchastings.edu/hastings_law_journal/vol30/iss2/5/.

IGLESIAS, Maria; SHAMUILIA, Sheron; ANDERBERG, Amanda – Intellectual Property and Artificial Intelligence, A literature review, JRC Technical Report, Publications Office of the European Union, Luxembourg, 2019. ISBN 978-92-76-14178- 5.

KAKLAUSKAS, Arturas - Introduction to Intelligent Decision Support Systems. In: *Biometric and Intelligent Decision-Making Support*, Springer, Cham, 2015, pp. 2-29. DOI: https://doi.org/10.1007/978-3-319-13659-2_1.

KISSINGER, Henry; SCHMIDT, Eric & HUTTENLOCHER, Daniel – *A Era da Inteligência Artificial: E o nosso futuro humano*, D. Quixote, 2021 [Portuguese version]. ISBN: 9789722073400.

KNUTSON, Melissa – *Credit Scoring Approaches Guidelines,* The World Bank, 2021, pp. 1-46. [Accessed 2021-11-15]. Available at https://thedocs.worldbank.org/en/doc/935891585869698451-0130022020/CREDIT-SCORING-APPROACHES-GUIDELINES-FINAL-WEB.

LOUZADA, Francisco; ARA, Anderson; FERNANDES, Guilherme, Classification methods applied to credit scoring: Systematic review and overall comparison. In: *Surveys in Operations Research and Management Science*, 2016, vol. 21, no. 2, pp. 117-134. DOI: https://doi.org/10.1016/j.sorms.2016.10.001.

MADJOUR, Oualid – *La responsabilité civile du banquier dispensatur de credit: Étude de droit compare français-algérien,* Thése de doctorate en droit prive, 2009. [Accessed 2021-11-25]. Available at http://www.theses.fr/2009LYO31061.

METHNANI, Leila, et al. - Let Me Take Over: Variable Autonomy for Meaningful Human Control. In: *Frontiers in Artificial Intelligence*, vol. 4, no. 737072, 2021, pp. 1-10. DOI: https://doi.org /10.3389/frai.2021.737072.

MORAIS CARVALHO, Jorge- *Manual de Direito do Consumo,* 7th ed., Coimbra, Almedina, 2021. ISBN: 9789724083407.

MORGADO REBELO, Diogo; ANALIDE, Cesar; COVELO DE ABREU, Joana – O Mercado Único Digital e a '(Leigo)ritmia' da Pontuação de Crédito na era da Inteligência Artificial, vol. 2, no. 1, 2020, pp. 1-69. [Accessed 2021-10-02]. Available at https://blook.pt /publications/publication/66689aed966b/.

MORGADO REBELO, Diogo; ANALIDE, Cesar – Inteligência Artificial na era *data-driven*: a lógica *fuzzy* das aproximações *soft computing* e a proibição de sujeição a decisões tomadas exclusivamente com base na exploração e prospeção de dados pessoais. In: *Forum de Proteção de Dados,* CNPD, Lisboa, noo. 6, 2019, pp. 60-91. [Accessed 2021-10-02]. Available at

https://www.cnpd.pt/media/y1nosvyp/forum6_af_web_low.pdf.

NARCISO, Madalena – "Gratuitous" Digital Content Contracts in EU Consumer Law". In: *Journal of European Consume and Market Law,* n.º5, 2017, pp. 198-206.

NOVA SBE & ASFAC – Impacto do Crédito ao Consumo na Economia Portuguesa, Relatório Final, 2019. [AcA cessed 2021-12-04]. Available at https://www.asfac.pt/documentos/impacto_do_credito_ao_consumo_na_economia_portuguesa.pdf.

RAMSAY, Ian – *Consumer Law and Policy: Text and Materials on Regulating Consumer Markets*, 2nd ed., Hart Publishing, 2007. ISBN: 9781841135052.

ROUVROY, Antoinette; POULLET, Yves - The right to informational self-determination and the value of self-development: Reassessing the importance of privacy for democracy. In: *Reinventing data protection?*. Springer, Dordrecht, 2009. pp. 45-76. DOI: https: //doi.org/10.1007/978-1-4020-9498-9_2.

RUDIN, Cynthia. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. In: *Nature Machine Intelligence*, vol. 1, no. 5, 2019, pp. 206-215. DOI: https://doi.org/10.1038/s42256-019-0048-x.

SANCHO, Diana – Automated Decision-Making and Article 22 GDPR, Towards a more substantial regime for solely automatic decision-making. In: *Algorithms and Law* (Martins Ebers & Susana Navas Eds.), 2020, pp. 136-156. ISBN: 97811083424820.

SARTOR, Giovanni – *The impact of the General Data Protection Regulation (GDPR) on artificial intelligence*, EPRS Study, June 2020, pp. 1-84. [Accessed 2021-10-02]. Available at

https://www.europarl.europa.eu/thinktank/en/document.html?reference=EPRS_STU(2020)641530.

SIDDIQUI, Naem – *Intelligent Credit Scoring: Building and Implementing Better Credit Risk Scorecards,* 2nd ed, New York, Willey & Sons, 2017. ISBN: 9781119279150.

SILVA, Fábio – *Credit scoring as an asset for decision making in intelligent decision support systems*, Master's Thesis on Computer Science, University of Minho, Braga, 2011, pp. 1-86. [Accessed 2021-10-02]. Available at

http://hdl.handle.net/1822/27891.

SILVA, Fábio; ANALIDE, Cesar - Information asset analysis: credit scoring and credit suggestion. In: *International Journal of Electronic Business*, 2011, vol. 9, no. 3, 203-2018. DOI: https://doi.org/10.1504/IJEB.2011.042542.

STANTON, Thomas – Credit and Loan Scoring. Tools for Improved Management of Federal Credit Programs, Center for the Study of American Government, Baltimore: John Hopkins University. [Accessed 2021-11-27]. Available at

https://www.businessofgovernment.org/sites/default/files/Credit.pdf.

SUMATHI, Sai; SIVANANDAM, S. N - *Introduction to data mining and its applications*. Springer, Berlin, Heidelberg, 2006. DOI: https://doi.org/10.1007/978-3-540-34351-6.

THOMAS, Lyn; CROOK, Jonathan; EDELMAN, David - *Credit scoring and its applications*, SIAM, Monographs on Mathematical Modeling and Computation, Philadelphia, 2017. ISBN: 9781611974553.

VOJTEK, Martin; KOÂENDA, Evïen – Credit-Scoring Methods. In: *Czech Journal of Economics and Finance* (*Finance a uver*), Prague, vol. 56, no. 3-4, 2006, pp. 103-167. [Accessed 2021-10-02]. Available at

http://journal.fsv.cuni.cz/storage/1050_s_152_167.pdf.

XIAO, Guorong - Data Processing Model of Bank Credit Evaluation System. In *J. Softw.*, vol. 6, no 7, 2011, pp. 1241-1247. DOI: 10.4304/jsw.6.7.1241-1247.

WACHTER, Sandra; MITTELSTADT, Brent - A right to reasonable inferences: re-thinking data protection law in the age of big data and AI. In: *Columbia Business Law Review*, vol. 2012, no. 2, 2019, pp. 494-620. DOI: https://doi.org/10.7916/cblr.v2019i2.3424.

WATCHER, Sandra; MITTELSTADT, Brent; RUSSEL, Chris – Counterfactual Explanations without opening the Black Box, Automated Decisions and the GDPR. In: *Harvard Law Review,* vol. 31, no. 2, pp. 841-886. [Accessed 2021-10-10]. Available at

https://jolt.law.harvard.edu/assets/articlePDFs/v31/Counterfactual-Explanations-without-Opening-the-Black-Box-Sandra-Wachter-et-al.pdf.

WACHTER, Sandra; MITTELSTADT, Brent; FLORIDI, Luciano - Why a right to explanation of automated decision-making does not exist in the general data protection regulation. In: *International Data Privacy Law*, vol. 7, no. 2, 2017, pp. 76-99. DOI: https://doi.org/10.1093/idpl/ipx005.

WOOLDRIDGE, Michael; JENNINGS, Nicholas – Intelligent agents: theory and practice. In: The Knowledge Engineering Review, 1995, pp. 115-152. DOI: 10.1017 /S0269888900008122.

WP29 – Guidelines on Automated decision-making and Profiling for the purpose of Regulation 2016/679 (WP25rev.01), adopted on 6 February 2018, pp. 1-37. [Accessed 2021-10-09]. Available at

https://ec.europa.eu/newsroom/article29/items/612053.

WP29- Opinion 03/2013 on purpose limitation (WP203), adopted on 2 April 2013. [Accessed 2021-11-26]. Available at https://ec.europa.eu/justice/article-29/documentation/opinion-recommendation/files/2013/wp203_en.pdf.

ZECH, Herbert - Data as a tradeable commodity–implications for contract law. In: *Proceedings of the 18th EIPIN Congress: The New Data Economy between Data Ownership, Privacy and Safeguarding Competition, Edward Elgar Publishing,* 2017, pp. 51-80. DOI: https://doi.org/10.1017/9781780685212.004.

ZERILLI, John et. al. – Algorithmic decision-making and the control problem. In: *Minds and Machines,* vol. 29, no. 4, pp. 555-578. DOI: https://doi.org/10.1007/s11023-019-09513-7.

JURISPRUDENCE

ECJ, of 6 June 2019, *Michel Schyns vs Belfius Bank SA,* Case C-58/18 ECLI:EU:C:2019:467, paragraphs 37-49.

ECJ, of 18 December 2014, *CA Consumer Finance vs. Ingrid Bakkaus, Charline Savary, Florian Bonato,* Case C-449/13 ECLI:EU:C:2014:2464,

ECJ, of 27 March 2014, *LCL Le Crédit Lyonnais SA v Fesih Kalhan*, Case C-565/12 ECLI:EU:C:2014:190

ECJ, of 13 July 1989, *Casa Fleischhandels-GmbH v Bundesanstalt für landwirtschaftliche Marktordnung*, Case 215/88, ECLI:EU:C:1989:331.

BGH*,* of 28 January 2014*,* Case Schufa, *VI ZR 156/13,*