Revisiting the promise:
A feasibility boundary for digital procurement governance

Albert Sanchez-Graells*

To be included in A Sanchez-Graells, *Digital Technologies and Public Procurement. Gatekeeping and experimentation in digital public governance* (OUP, forthcoming).

ABSTRACT

This Chapter builds on the argument that mitigating the allure and policy irresistibility of digital technologies requires reassessing the true potential benefits of digital technologies and, more importantly, the necessary enabling mechanisms, likely roadblocks, and new risks that come with them (which is fully developed at https://ssrn.com/abstract=4216825). Taking a closer functional look at the technologies will allow for a better understanding of the constraints on their likely contribution to improving (digital) procurement governance. Such constraints should not only serve as a counterpoint to the hype that follows superficial or techno optimistic assessments, but also help recentre policy agendas towards establishing proper foundations for digital adaptation in the long term. The Chapter will evidence the importance of data availability and quality across technologies. This will lead to an analysis of the difficulties in generating an enabling big data architecture despite efforts led by eg the European Commission, or the Open Contracting Partnership. Such big data architecture will remain the main constraint on the implementation of digital technologies for a while. Thinking further into the future, the Chapter will highlight the displacement, rather than avoidance or resolution, of governance risks that the adoption of digital technologies can generate (which will then be explored in more detail elsewhere). The Chapter closes with a recapitulation of the feasibility boundary for digital procurement governance.

KEYWORDS

Public procurement, information intensity, information complexity, policymaking, digital technologies, artificial intelligence, machine learning, recommender systems, chatbots, algorithmic screens, blockchain, distributed ledger technology, smart contracts, robotic process automation, oracles, internet of things, data architecture, data integrity.

JEL CODES

D73, H57, K23, K24, K49, O33.

* Professor of Economic Law and Co-Director of the Centre for Global Law and Innovation, University of Bristol Law School. Mid-Career Fellow of the British Academy 2022/23 (MCFSS22\220033). Comments welcome: a.sanchez-graells@bristol.ac.uk.

1. Understanding Digital Technologies in the Procurement Governance Context

The aim of this Chapter is to facilitate an understanding of the workings of digital technologies beyond the superficial overview provided in Chapter 6. This Chapter will concentrate on the function that the different technologies can serve and, perhaps more importantly, the functions that they cannot serve, or could only serve in very specific (and unlikely) circumstances. The barriers to some of those potential functions can be legal as well as technical, and both aspects will be considered. The Chapter will also concentrate on the (data) inputs that the different technologies require. Put together, the potential functionalities and the required inputs will plot a feasibility boundary for the adoption of digital technologies for procurement governance purposes.

The importance of embedding a proper understanding of the different technologies—in other words, a distillation of how they work (or could work)—in legal and policy analysis can hardly be overstated,[1] as 'there is a danger that scholarship not rooted in a technical understanding of [Artificial Intelligence] may be too speculative to be useful'.[2] This is not at all a novel insight or approach.[3] However, some recent scholarship in digital procurement governance has tended to brush aside the need to move past an intuitive understanding of the technologies, especially in relation to blockchain. This can generate conceptual confusion,[4] or technology optimism biases rooted in too general speculation.[5] At the other end of the scale, legal scholarship can seek to over-theorise the interaction between law and technology,[6] which can also obfuscate the analysis. This Chapter seeks to travel a middle path and to engage with the technologies in functional detail sufficient for the analysis of their governance-related deployment.[7]

The Chapter will concentrate on a selection of digital technologies, including robotic process automation (RPA) (Section 2); Machine Learning (ML) implementations, such as recommender systems, chatbots, and automated screens, as specific types of Artificial Intelligence (AI) (Section 3); Distributed Ledger Technology (DLT) systems, including smart contracts (Section 4); and the Internet of Things (IoT) and oracles (Section 5). It is submitted

[1] See eg David Lehr and Paul Ohm, 'Playing with the Data: What Legal Scholars Should Learn About Machine Learning' (2017) 51 UC Davis Law Review 653 (hereafter Lehr and Ohm, 'Machine Learning for Legal Scholars'); Rembrandt Deville, Nico Sergeyssels and Catherine Middag, 'Basic Concepts of AI for Legal Scholars' in Jan De Bruyne and Cedric Vanleenhove (eds), *Artificial Intelligence and the Law* (Intersentia 2021) 1 (hereafter Deville, Sergeyssels and Middag, 'Basic AI Concepts').

[2] Ryan McCarl, 'The Limits of Law and AI' (2022) 90 University of Cincinnati Law Review 923, 924.

[3] It differs, however, from approaches to law and technology that seek to establish the interaction between both and their respective social constructs. For discussion, see eg Mireille Hildebrandt, *Smart Technologies and the End(s) of Law* (Edward Elgar 2015) 159 ff.

[4] Eg Raquel Carvalho, 'Blockchain and Public Procurement' (2019) 6 European Journal of Comparative Law and Governance 187; or Nadia-Ariadna Sava and Dacian Dragos, 'The Legal Regime of Smart Contracts in Public Procurement' (2022) 66 Transylvanian Review of Administrative Sciences 99.

[5] Eg Pawel Nowicki, 'Deus Ex Machina? Some Remarks on Public Procurement in the Second Machine Age' (2020) 15 European Procurement & Public Private Partnership Law Review 53; Sope Williams-Elegbe, 'Public Procurement, Corruption and Blockchain Technology: A Preliminary (Legal) Inquiry' (2018) Iaugural Lecture at Stellenbosh University < https://www.sun.ac.za/english/Documents/newsclips/InauguralLecture_ProfSopeWilliamsElegbe_23Oct2018.pdf > accessed 8 September 2022.

[6] Eg Thibault Schrepel, 'Law + Technology' (2022) VU University Amsterdam Legal Studies Research Paper Series < https://ssrn.com/abstract=4115666 > accessed 13 September 2022.

[7] Of course, this could be challenged on grounds of subjectivity. For a similar approach, see Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1).

that this is the set of digital technologies most likely to be suited to the digitalisation of procurement governance. Although some policy reports also address cloud computing as a separate digital technology, this Chapter takes the position that cloud technology does not have the potential to significantly alter the governance of procurement, although it can alter (and has been altering) the technological infrastructure used in procurement procedures.[8] The Chapter also does not cover 3D printing. Although this technology is also considered in policy reports,[9] it can be useful as a mode of delivery of procurement contracts but can hardly raise issues specific to procurement governance.[10]

2. Robotic Process Automation (RPA)

As advanced in Chapter 6, Section 3.1, RPA facilitates the automation of repetitive, information intensive, back-office processes based on clearly defined rules that do not require complex logic. This means that there are at least three specific requirements for process automation: (i) the process has to be rigid and susceptible of entirely detailed description, so that it can be coded into software (ie the 'bot' that carries out the RPA); (ii) the process has to solely involve the retrieval, transfer and cross-check of information (or some of these tasks) and, implicitly, this information needs to be in machine readable form—or else the automation needs to include a phase of computer vision or natural language processing (NLP) that thus requires integration with ML (see Section 3); and (iii) the output of the RPA can generally be of a descriptive or reporting nature, and can only imply a 'decision' where the latter is subject to a straightforward and simple rule. Automating the consequences of such 'decision' can only be done through RPA if they involve the inclusion of information on a specific ledger or database. Most often, though, the RPA outcome will require human review or implementation.

Emerging evidence on experimentation with RPA for procurement governance shows that it is mainly being deployed at stages of the procurement procedure that require retrieving and cross-checking information from a disparate range of databases (eg for the purposes of assessing whether a tenderer is included within a list of authorised or pre-screened tenderers, or a specific reference is included in a database of previous contracts, to check past performance reports on the tenderer and/or to check that the tenderer is not included in a list of debarred, excluded or sanctioned tenderers);[11] or for back-office purposes requiring a comparison between templates and documents, or between contracts and other documents (eg to automate invoice processing), or processes allowing for automated updates of

---

[8] For discussion of the specific challenges in procuring cloud computing services, see Kevin McGillivray, *Government Cloud Procurement. Contracts, Data Protection, and the Quest for Compliance* (CUP 2022).
[9] Such as Deloitte, 'Study on up-take of emerging technologies in public procurement. Final report' (2020) < https://ec.europa.eu/docsroom/documents/40102 > accessed 7 September 2022 (hereafter Deloitte, 'Emerging technologies in public procurement'); and World Bank, 'Disruptive Technologies in Public Procurement' (2021) < http://documents.worldbank.org/curated/en/522181612428427520/Disruptive-Technologies-in-Public-Procurement> accessed 8 September 2022 (hereafter, WB, 'Disruptive technologies').
[10] Most of those issues relate to intellectual property law and are excluded from the analysis in this Chapter. See eg Time.lex et al, 'Legal review on industrial design protection in Europe', Annex 3 '3D printing' (2016) < https://ec.europa.eu/docsroom/documents/18921/ > accessed 15 September 2022.
[11] Eg the US Truman and the IRS Procurement Office case studies; Deloitte, 'Emerging technologies in public procurement' (n 9) 152 ff and 167 ff, respectively. Broadly the same case is used in WB, 'Disruptive technologies' (n 9) 85. For discussion, see Jessica Tillipman, 'Using AI to Reduce Performance Risk in U.S. Procurement' (*Regulatory Review*, 29 June 2022) < https://www.theregreview.org/2022/06/29/tillipman-using-ai-to-reduce-performance-risk-in-u-s-procurement/ > accessed 15 September 2022.

information in specific databases (eg vendor details in an invoicing database).[12] It is also possible to use RPA to automate some basic screens (eg on compliance with pre-specified deadlines or value ranges), although this type of application can easily require some element of 'intelligent automation',[13] and will thus be discussed in Section 3.3.

The fact that RPA is being deployed in these areas is probably reflective of the three requirements for viable automation through RPA. First, RPA is being deployed to substitute identical manual checks that can be described in full detail. Second, RPA is deployed to overcome an information cost derived from the need to carry out specific, non-discretionary checks, but the automation mostly does not assign consequences to those checks. It rather reports the outcome of the checks, gathering information for human review. Where the automation implies specific consequences, they are primarily limited to the modification of information on a database—the fully automated payment of invoices being the potential exception. Third, RPA is being deployed in areas where procurement information is already digitised through its inclusion in electronic databases and/or an e-invoicing system, and in relation to information that not only is highly standardised and structured, but also follows or is pegged to specific (corporate) identifiers that allow for the relevant cross-checks.

In this type of application, it should be stressed that RPA tends to (completely) discharge the administrative burden and generate time savings in unproblematic cases only, as problematic cases will require human intervention and, potentially, a manual (second) review of the relevant information. RPA will not be able to source information not otherwise available (unless RPA is used to gather information not previously considered due to eg resource limitations), and it will not be able to carry out any analysis of that information. RPA will not be able to deal with open-ended requirements (eg the obligation to accept 'equivalent' documentation or certificates), will not spot errors in the sources of information (it will simply carry them across databases or domains), and will not be able to balance competing pieces of information (eg in relation to self-cleaning claims, or in relation to information that has not yet been included in the databases from which the 'bot' draws it). RPA will also not change or improve the processes themselves; it will simply replicate them and accelerate them.[14]

The main advantages of RPA thus boil down to time savings and the possibility to improve the regularity, consistency, and completeness of the automated checks. However, the outcome of the RPA will only be as good as the sources of information it uses, and only be truly useful if it is generated in a timely and user-friendly manner. However, RPA is essentially limited to high-volume, non-discretionary and entirely standardised checks and processes. This comes to reduce the potential for deployment in areas of the procurement process that are not entirely standardised to the ultimate detail across a large volume of procurement procedures. For example, it would be highly implausible to automate technical or economic evaluations without incurring significant costs to tailor the automation to the specific procedure, or without using forms of 'intelligent automation' capable of generating that customisation.

Moreover, RPA should not necessarily be seen as a fix for some of the dysfunctionalities or unnecessary complexities resulting from broken up processes or the scattering of sources of information. RPA could generate technical debt to the extent that creating the RPA fix required significant maintenance and/or generated the risk of becoming the basis for the

[12] Eg the Finnish Palkeet case study; Deloitte, 'Emerging technologies in public procurement' (n 9) 162 ff.
[13] Along those lines, RPA and several forms of AI are bundled together eg in WB, 'Disruptive technologies' (n 9).
[14] WB, 'Disruptive technologies' (n 9) 86.

implementation of further layers of technological solutions, which would then build on a sub-optimal underlying data architecture. Moreover, RPA can come with significant cybersecurity risks and the possibility of unplanned actions by bots needs to be carefully considered (see Section 7).[15] There can also be legal constraints on the deployment of RPA, such as issues with permissioned access to information or the need to ensure that a public official is involved in the relevant verifications—which could be overcome by eg only deploying 'attended' or 'supervised bots',[16] which would in turn reduce the potential benefits of some RPA applications. RPA can thus seem like the low hanging fruit for the adoption of digital technologies for procurement governance, but its suitability, viability, and desirability in the medium and long term need to be assessed carefully.

3. Machine Learning Implementations

As advanced in Chapter 6, Section 4, ML aims to 'develop systems that learn models from data'[17] or, in other words, 'to acquire skills or knowledge from experience'.[18] ML is the most widely used form of 'narrow' or 'weak' AI. That is, AI that can perform specific tasks, as opposed to ML capable of switching through (very) different tasks, which would require 'general' or 'strong' intelligence.[19] Current ML applications are more advanced than earlier types of narrow AI, such as expert systems,[20] and have the main advantage of avoiding the need to pre-define the rules applicable by a system. ML is a technology that can execute a task without explicitly being programmed to do so,[21] and thus allows moving from input to output without making the rules explicit—and, in some cases, without those rules being susceptible of human comprehension.[22] This opens possibilities to digitalise tasks that cannot be performed through other means, such as RPA (as discussed in the previous Section). ML implementations can classify data on the basis of a trained model (that is categorical classification); generate a prediction or estimate in relation to a data point in a continuous series on the basis of a trained model (through regression); or cluster data points by fitting as close a model as possible to the data (which can functionally be seen as a broader type of classification).[23] In the context of procurement, potential applications could concern classification of tenderers as at risk of insolvency (or not), or as potentially suitable for a contract (or not);[24] prediction of prices to be used for budget-making purposes, or as a

---

[15] WB, 'Disruptive technologies' (n 9) 86.
[16] Deloitte, 'Emerging technologies in public procurement' (n 9) 152 ff.
[17] Deville, Sergeyssels and Middag, 'Basic AI Concepts' (n 1) 6.
[18] Tirath Virdee, 'Understanding AI' in Charles Kerrigan (ed), *Artificial Intelligence. Law and Regulation* (Edward Elgar 2022) 37, 40 (hereafter, Virdee, 'Understanding AI'). See also.
[19] Consideration of 'general' or 'strong' AI is excluded from this Chapter. For discussion, see eg Ragnar Fjelland, 'Why general artificial intelligence will not be realized' (2020) 10 Nature Humanities and Social Sciences Communications 7.
[20] See eg Kevin D Ashley, *Artificial Intelligence and Legal Analytics. New Tools for Law Practice in the Digital Age* (CUP 2017) 8.
[21] Tirath Virdee et al, 'Taxonomy of AI' in Charles Kerrigan (ed), *Artificial Intelligence. Law and Regulation* (Edward Elgar 2022) 474, 479 (hereafter Virdee et al, 'Taxonomy of AI').
[22] This raises fundamental issues of explainability, as discussed in Chapter XXX.
[23] Virdee et al, 'Taxonomy of AI' (n 21) 479. The functionality of skill acquisition is not covered in this Chapter.
[24] Manuel J Garcia Rodriguez et al, 'Bidders Recommender for Public Procurement Auctions Using Machine Learning: Data Analysis, Algorithm, and Case Study with Tenders from Spain' (2020) Complexity 8858258 (hereafter Garcia Rodriguez et al, 'Bidders Recommender').

baseline to control for excessive or abnormally low pricing;[25] or clustering of tenderers for the purposes of analysing market trends and screening eg for anticompetitive effects.[26]

These are all data-intensive functionalities. It follows that, without data, there are no viable ML implementations, and it has been stressed that '[t]he dominant problem in most projects is still the amount of time that is needed to get data ready for ML'.[27] Therefore, data availability and quality are a huge constraint on the viability of ML implementations. This is not an easily solvable problem in many potential implementations for procurement governance and it can well be that ML projects require several years or even decades of data collection before they can even be piloted, as discussed in more detail in Section 6 below.

When data is available, algorithms can be developed and trained in three stylised ways—though these can be combined. Supervised learning requires the data to be 'labelled'. That means that the data used to train the algorithm needs to have been provided with the correct classification so that labelled examples can enable the algorithm to associate the correct input (data) with the correct output (classification). For example, if ML was to be applied to detect corrupt tenders, the training data should contain a clear classification of whether each of the previous tenders was corrupt or not. This raises challenges beyond the mere existence of the data, as mislabelled data (eg corrupt transactions that went undetected and are labelled as not corrupt in the database) will undermine the accuracy of the algorithm. Where the data used to train the algorithm is not labelled, the training is unsupervised and, in these applications, the algorithm must discover patterns and structures on its own to cluster the data. In this case, the 'problem definition entails deciding on a particular mathematical measure of similarity'.[28] This will create significant challenges, especially in relation to the interpretability of the results, which could significantly reduce the functionality of the ML solution in practical terms. A third type is reinforcement training, where the data is primarily generated through a feedback loop that indicates to the algorithm whether it had performed the given task in the intended way. For procurement governance purposes, supervised and unsupervised training seem the most relevant techniques, as there is limited scope for meaningful trial and error (and the related feedback or reinforcement) in a setting where the rules are open-ended.[29]

Regardless of the specific training technique used, developing and deploying ML implementations involves a sequence of steps that require iteration and repetition.[30] Decisions made at each of those stages can have significant legal and governance implications. Training the algorithm will imply using mathematical methods seeking to minimise or maximise a pre-established goal in relation to an also pre-established variable (eg in/accuracy of classification or prediction of a specific attribute of the data).[31] This means that deploying ML does not only require the existence of (training, big) data, but also a clear view

[25] Jong-Min Kim and Hojin Jung, 'Predicting bid prices by using machine learning methods' (2019) 51 Applied Economics 2011.
[26] Manuel J Garcia Rodriguez et al, 'Collusion detection in public procurement auctions with machine learning algorithms' (2022) 133 Automation in Construction 104047 (hereafter Garcia Rodriguez et al, 'Collusion detection with ML').
[27] Virdee, 'Understanding AI' (n 18) 44.
[28] Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1) 676.
[29] There can, however, be scope for mixed approaches where reinforcement is combined with eg unsupervised learning.
[30] Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1) 655.
[31] Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1) 672.

of which variable/s are useful to classify or predict for a specific governance outcome, as well as how the algorithmic goal should be specified—eg in relation to the type of errors that can be tolerated. For example, developing a ML implementation to screen tenderers for corruption will look different if the algorithm is designed to have equal tolerance for false positive and false negative classifications, or if the algorithm is geared towards minimising false negatives over false positives (to catch as many potential instances of corruption as possible).[32] This will in turn have knock-on effects on the workload required to act upon the ML insights, as an overly comprehensive screening tool would generate more work and more complicated due process considerations than a more lenient screening tool. Conversely, deploying an algorithm seeking to minimise false positives to avoid those issues would implicitly require accepting a higher underlying risk of undetected corruption.

Moreover, as mentioned, the development and deployment of ML solutions can be further complicated by difficulties in identifying relevant variables or features in the data. This is important in the context of procurement governance because it can be difficult to identify suitable variables or proxies for complex governance issues,[33] as variables necessarily relate to measurable aspects and some variables can be relatively easier to specify but also generate 'greater risk of mismatch between the predictive goal and the variable's specification'.[34] Moreover, there is generally a difficulty in establishing links between inputs and outputs in relation to contract execution compared to the characteristics of a specific procurement process, which can make implementations very procedure-focused, rather than outcomes-focused. This can weigh heavily in implementation design as constrained by the data. Where no contract execution or procurement outcome data exists, ML can be (inadvertently) trained to operate on the basis of governance proxies that are purely procedural (eg ML that assesses the desirability of a specific criterion or process in relation to whether it is likely to lead to a legal challenge) rather than substantive or operational proxies. This can skew procurement governance towards processes rather than outcomes, which is not necessarily desirable.[35]

The further difficulty from a governance perspective is that determining the right variables and features is largely a technical question that can bear little resemblance to choosing a specific variable from a conceptual or intuitive standpoint. It is also important to acknowledge that most ML implementations can establish associations or correlations, but not necessarily causation.[36] This can obviously make ML inadequate in settings where the interpretive problems generated by correlation cannot be technically dealt with. Moreover, there will almost always be unavoidable trade-offs between the available (viable) choices and the effectiveness and knock-on effects of the chosen ML solutions. Similarly, a choice needs to be made on which type of algorithm to deploy, and choices can be constrained in specific settings of relevance for procurement governance purposes, eg 'if the outcome variable contains multiple classes [ie it is not binary] or ordinal classes, an analyst may have fewer algorithms from which to choose'.[37]

[32] Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1) 692.
[33] Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1) 672-677.
[34] Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1) 675.
[35] See eg Oxford Government Outcomes Law, How to Guide Procurement (2017) < https://golab.bsg.ox.ac.uk/documents/GO_Lab_-_Procurement_Guide_ROe4bJn.pdf > accessed 23 September 2022.
[36] Momiao Xiong, *Artificial Intelligence and Causal Inference* (CRC Press 2022).
[37] Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1) 690.

Some of these issues will only emerge (to potentially be resolved) through the iterative process of developing a ML implementation. This means that, even where data is available, the likelihood of developing a sufficiently good (ie governance adequate) ML implementation will depend on a number of factors that will only be observable down the line—and establishing the threshold of what is a 'sufficiently good' implementation will also be contentious. This generates a further governance risk in the face of failing or inadequate ML projects, as there can be pressures to deploy suboptimal systems due to the costs already incurred in their development,[38] or the expectations raised.

This overview of the complexities of developing a ML solution should already point out that the scope for successful deployment is likely to be relatively limited and that ML should not be perceived as an easy fix to deal with procurement complexity. It will of course be possible for the public sector to adopt or adapt ML based solutions developed in relation to issues that are common to the private sector, eg in relation to category management or financial spending analysis,[39] or to develop ML applications for highly-structured (classification) tasks closely related to RPA automation.[40] However, the development of other solutions specifically tailored to the governance needs of the public procurement function will carry its own complications, some of which derive from legal requirements not applicable to the private sector or which create needs for specific information processing. The complexity of developing ML based solutions in the procurement setting can be further explored in relation to specific 'promising' implementations, such as recommender systems, chatbots, and automated screens (or red flags).

3.1 Recommender systems

Recommender systems are a specific ML-based solution that seeks to predict user responses to options[41]—for example, they could be used to predict whether a public buyer is interested in engaging a specific tenderer or sourcing a specific product in relation to a specific tender. There are two main types of recommender systems: content-based systems and collaborative filtering systems. Content-based systems examine properties of the objects recommended and make recommendations based on specific properties, whereas collaborative filtering systems recommend to a user objects preferred by similar users.[42] There could be ways of implementing collaborative filtering recommenders in public procurement, eg in relation to specific products offered within online platforms used only by public buyers.[43] However, it seems that content-based recommenders are better suited for most aspects of procurement governance, not least because of constraints on the exercise of discretion, objectivity and

[38] Which would be a textbook example of the sunk costs fallacy; for discussion, see Charles A Miller, 'Sunk Costs and Political Decision Making' (2019) Oxford Research Encyclopaedia of Politics < https://doi.org/10.1093/acrefore/9780190228637.013.1022 > accessed 23 September 2022.

[39] These are, to date, the majority of ML implementations in public procurement, at least on the basis of public information; Deloitte, 'Emerging technologies in public procurement' (n 9) 40.

[40] Eg the prediction of CPV or other procurement classification codes; Deloitte, 'Emerging technologies in public procurement' (n 9) 52.

[41] Jure Leskovec, Anand Rajaraman and Jeffrey David Ullman, *Mining of Massive Datasets* (3rd edn, CUP 2020) 307 (hereafter Leskovec, Rajaraman and Ullman, 'Recommendation Systems').

[42] Leskovec, Rajaraman and Ullman, 'Recommendation Systems' (n 41) 307.

[43] This would however not be necessarily straightforward, as it would need to be coordinated with legal requirements on the rules controlling call-offs within the framework agreements or dynamic purchasing systems that would likely underpin such online platform. A detailed analysis exceeds the possibilities of this Chapter.

case-by-case analysis requirements of procurement decision-making. Most of the private sector recommender systems are consumer-facing and, as such, they do not concern decisions comparable to those of the public buyer as consumers can make entirely subjective decisions without being (legally) accountable to others.

Developing a content-based procurement recommender poses significant challenges,[44] starting by ensuring that the system draws from data that includes all possible options available in the market. This requirement is different from that applicable to the private sector. While there will usually be a business case for private sector (online) recommenders to be as comprehensive as possible,[45] the public sector is under a legal mandate not to exclude potential tenderers or potential (equivalent) solutions and any recommender must thus meet this requirement.[46] This can be problematic where there is no database encompassing eg all potential suppliers active in the market in real time, or all products and services capable of satisfying the same need. In that case, using static databases would at the very least exclude new entrants or companies not included in the database where this is built on an opt-in basis. Moreover, using databases only collecting data from past procurements would raise additional barriers to participation and exacerbate incumbency advantages. This type of recommender system could thus be developed within legally compliant closed lists of participants in procurement opportunities, but this may be the exception rather than the norm in the procurement context, and likely limit the scope of the recommender system to very narrow implementations within dynamic purchasing systems or framework agreements, or even, within those, only in relation with lists underpinned by electronic catalogues—which could also potentially serve for the deployment of collective screening recommender systems instead.[47]

Beyond that, choosing which features of the potential suppliers to consider in designing and training the algorithm is also challenging, especially as different markets may function very differently in relation to any given feature—eg distance between contractor and public buyer, which can be relevant for (some) goods and irrelevant for some (digital or remote) services. This creates a significant challenge in establishing the remit of the recommender system,[48] as it could be that different recommenders need to be developed for different types of objects, which would then create issues for procurement needs that could be satisfied in different ways, or mixed contracts, for example. It is also challenging to establish which level of

[44] See eg Stefan Bensch, 'Recommender Systems for Strategic Procurement in Value Networks' (2012). AMCIS 2012 Proceedings. 13 < https://aisel.aisnet.org/amcis2012/proceedings/StrategicUseIT/13 > accessed 23 September 2022.

[45] This is usually referred to as the long-tail issue; Leskovec, Rajaraman and Ullman, 'Recommendation Systems' (n 41) 307.

[46] This is caveated by the fact that some economic operators will not have a legal right to participate in specific tenders, depending on the applicability of international trade rules, in particular the World Trade Organisation Government Procurement Agreement. However, as a general statement, the requirement for universality of the sources of information in this context holds.

[47] But see above (n 43).

[48] These difficulties are clearly exemplified in Garcia Rodriguez et al, 'Bidders Recommender' (n 24), which develops a general recommender system where the best performance creates about one in ten chances of correctly identifying the most suitable provider, or one in five chances of having it included in a basket of five recommendations. For discussion, see Albert Sanchez-Graells, 'Procurement Recommender Systems: How Much Better Before We Trust Them?' (*howtocrackanut.com*, 10 June 2022) < https://www.howtocrackanut.com/blog/2022/6/10/procurement-recommender-systems-how-much-better-before-we-trust-them > accessed 23 September 2022.

accuracy a recommender system should have before it is deployed, which can in turn be dependent on the specific intended use of the recommender system. For example, if the recommender system was solely to be used to target otherwise generally available information (eg a recommender system of potential public tender opportunities addressed to potential tenderers), the requirements, constraints, and practical advantages would be analysed differently than if the recommender system was to be used to determine the scope of the competition for a given contract (eg a recommender system used to select which potential suppliers to invite to a negotiated procedure).

Similar issues would arise in relation to the development of recommender systems for products or services, with the added complexity that the parameters of the recommendation would potentially be either much narrower or much more variable than those concerning a recommender of tenderers or potential providers. The issue of the narrowness and variability of the relevant parameters in product recommendation would stem from the fact that almost each product or service category is likely to have distinguishing features that deviate from those of other products or services—whereas the features that are relevant in comparing tenderers are likely to be more exportable, or at least of relevance at a higher level (eg sector of activity). Products and services are also more likely to generate new features through innovation, while ML models can have very limited accuracy in assessing features that were not included in their training data. All of this has an impact on eg the volume of data that can be available to train the algorithm, or the need to retrain or adjust algorithms on an ongoing basis, which can be crucial in relation to the viability of the intended recommender system. On this point, it seems worth stressing that most popular private sector recommender systems operate as collaborative filtering systems, and that content-based recommender systems tend to concern single product or single service use cases (eg news or video recommendations). As such, both types of approaches seem rather far removed from applications for complex aspects of procurement governance, which would require a significant development effort. This could only be justified or viable in highly centralised procurement settings, as further discussed in Section 8.

3.2 Chatbots

Virtual assistants, or chatbots, are computer programmes that use NLP to understand user questions and automate responses to them. This necessarily brings all constraints of NLP implementations, although this is an area of ML that is quickly evolving towards higher levels of performance,[49] at least in relation to widely used languages.[50] Given that the private sector has a major interest in the further development of NLP, further advances can be expected, although there is significant controversy as to the limits of NLP. However, we do not need to explore those for the purposes of our analysis.

At their simplest, chatbots can be seen as interactive frequently asked question (FAQ) solutions. Advanced AI chatbots can incorporate ML elements to improve their performance over time. It is also possible to integrate chatbots with RPA, so that either the chatbot can

[49] See eg Diksha Khurana et al, 'Natural language processing: state of the art, current trends and challenges' (2022) Multimedia Tools and Applications < https://doi.org/10.1007/s11042-022-13428-4 > accessed 23 September 2022.

[50] This necessarily implies difficulties in developing NLP-based solutions in other languages, and it seems like all languages but English will pragmatically lag behind or be constrained by the workings of automated translation.

activate an RPA process, or an RPA can activate the chatbot.[51] Chatbots are mainly deployed as a way of simplifying access to information and, as such, chatbots can only be as useful or accurate as the information they can retrieve. They are primarily tools to enhance the experience of accessing information for the user, while reducing the cost of providing that information for the implementer.

In that regard, chatbots cannot provide any more clarification or guidance than the knowledge base from which they draw. They can pinpoint to information, but not process it. And in the procurement governance setting chatbots cannot be plugged to open-ended information sources (ie the internet) because the public buyer will hold liability for the information it provides (through the chatbot). In other words, the implementation in procurement governance is likely to be limited to closed domain chatbots.[52] Structurally, then, deploying chatbots for procurement governance will require garden-fencing the information to which the chatbot has access to ensure its reliability, accuracy, etc. In the context of procurement governance, chatbots can thus give access to specific types of information in ways that would save users formulating (more structured) queries in a different manner. This can help reduce initial hurdles to access procurement information, but it would not reduce the difficulties and costs of digesting that information, unless the specific type of analysis was pre-produced and the chatbot had access to it. This would thus not serve to automate the generation of answers or clarifications.

Tenderer-facing chatbots could deal with some queries on administrative processes, such as how to register as a potential supplier, who to contact about a specific issue, or finding out which contract opportunities are currently open in relation to specific goods or services.[53] However, they would not be able to eg provide clarification on the meaning of a specific tender document unless that clarification had already been generated and uploaded into the knowledge database. They could also serve to facilitate interactions in relation to eg the submission of tenders, where a chatbot could use a pre-defined set of questions to prompt tenderers to check for common errors in tender submission. However, the chatbot would not be able to eg answer whether something has been correctly done unless an automated (RPA) check was plugged to it and, in that case, the check would need to be strictly formalised and rules-based. Other sorts of qualitative analysis or discretionary elements would not be suitable for this type of automated check. This shows how tenderer-facing chatbots are likely to be useful mostly in relation to types of information-based queries that are high-volume and as such justify the preparation of specific answers, or in relation to clearly pre-established processes. While this can reduce administrative burdens, it would not go much further.

Public buyer-facing chatbots would have similar constraints and would not really serve to reduce the need to understand the complexity of procurement rules or to be able to process complex information in relation to the tenders received, as chatbots would mainly be able to

---

[51] See eg Christian Daase et al, 'Automation of Customer Initiated Back Office Processes: A Design Science Research Approach to link Robotic Process Automation and Chatbots' (2020) ACIS 2020 Proceedings 15 < https://aisel.aisnet.org/acis2020/15 > accessed 23 September 2022.

[52] For further classification, see Eleni Adamopoulou and Lefteris Moussiades, 'An Overview of Chatbot Technology' in Ilias Maglogiannis, Lazaros Iliadis and Elias Pimenidis (eds) *AIAI 2020, IFIP AICT 584* (Springer 2020) 373, 378.

[53] The case YPO study was even more limited than that and showed significant difficulties in attaining levels of performance justifying the deployment of the chatbot even within the limited domain of the organisation's own website; see Deloitte, 'Emerging technologies in public procurement' (n 9) 65 ff.

help retrieve factual data or pre-prepared (or at the very least pre-existing) knowledge and data. Chatbots could be combined with advanced NLP techniques to eg extract information from specific sources and structure it (eg in summaries). However, for most purposes, it will not be possible to (solely) assess the relevant documents (eg tender documentation) by reference to automated summaries, so the practical gains may be limited. Similarly, a chatbot would be able for example to point a public buyer to the legal provision, or specific piece of guidance, or case law (if it existed) on which criteria control access to a specific type of procedure or which type of criteria are allowed for a specific type of assessment. However, the chatbot would not be able to engage in any assessment of the rationale given for the use of a specific procedure or a specific criterion in the context of a specific tender procedure. In simple terms, chatbots would very quickly reach the limits of their functionality unless they were plugged to a knowledge base created as an expert system. Such a possibility would still have rather limited functionality, particularly in relation to aspects of procurement governance involving value judgements, which are the ones where professional public buyers are more likely to face information burdens.

It thus seems that the practical space for the deployment of chatbots in procurement governance is limited to rather low added value information access tasks. While this could generate administrative savings where the volume of work justified the development, deployment, and maintenance of the chatbot, this technology hardly seems to offer great promise in terms of altering procurement processes or outcomes.

3.3 Automated Screens (or Red Flags)

Red flags can be used to screen procurement procedures from different governance angles. Red flags are quantitative indicators or algorithmic checks based on available procurement data that seek to identify procurement decisions in violation of an identified rule or value.[54] To the extent that the relevant rule or value encapsulates a focus point for suspicious activities, red flags can be useful mechanisms in screening for corruption,[55] anticompetitive behaviour,[56] or other (policy) deviations in procurement practice. For example, a red flag could seek to identify procurement processes where the deadline for the submission of tenders has been very short, which may indicate that the contracting authority had a pre-selected awardee before officially publishing the contract opportunity. In such an

[54] Francesco Decarolis and Cristina Giorgiantonio, 'Corruption red flags in public procurement: new evidence from Italian calls for tenders' (2020) Bank of Italy Economic Research and International Relations Area Occasional Papers No 544 < https://econpapers.repec.org/RePEc:bdi:opques:qef_544_20 > accessed 26 September 2022; Mihaly Fazekas and Gabor Kocsis, 'Uncovering High-Level Corruption: Cross-National Objective Corruption Risk Indicators Using Public Procurement Data' (2017) 50 British Journal of Political Science 155; Elizabeth David-Barrett Mihaly and Fazekas, 'Anti-corruption in aid-funded procurement: Is corruption reduced or merely displaced?' (2020) 132 World Development 105000 < https://doi.org/10.1016/j.worlddev.2020.105000 > accessed 26 September 2022. For discussion, see Albert Sanchez-Graells, 'Procurement Corruption and Artificial Intelligence: between the potential of enabling data architectures and the constraints of due process requirements' in Sope Williams-Elegbe and Jessica Tillipman (eds), *Routledge Handbook of Public Procurement Corruption* (Routledge forthcoming) XXX (hereafter Sanchez-Graells, 'Procurement Corruption and Artificial Intelligence').

[55] Open Contracting Partnership 'RED FLAGS for integrity: Giving the green light to open data solutions' (2016) < https://www.open-contracting.org/resources/red-flags-integrity-giving-green-light-open-data-solutions/ > accessed 26 September 2022.

[56] See eg Martin Huber and David Imhof, 'Machine learning with screens for detecting bid-rigging cartels' (2019) 65 International Journal of Industrial Organization 277; Garcia Rodriguez et al, 'Collusion detection with ML' (n 26).

implementation, the algorithm could simply require a comparison between the deadline given in the specific procurement documentation and a pre-established benchmark of what is considered 'too short' (e.g. three working days, or less than half the standard duration of a 'best practice' period for the receipt of tenders), or be trained to identify suspicious cases on the basis of independently established rules and parameters. ML could follow the latter approach and allow for the development of screens without the need to pre-specify abnormality rules. Different approaches reflect different levels of ambition (or complexity, which raises issues of technical feasibility).

3.3.1 Levels of ambition (and complexity) in the use of red flags

At a 'basic level', red flag checks can be deployed 'manually', eg by having a civil servant carry out comparisons between the data derived from a specific procurement exercise against the pre-specified rule or threshold. This could be part of a routine compliance assessment, either in the context of a pre-market approval of eg tender documentation, or as a post-award check of legal compliance, either in the context of a procurement challenge, or as a matter of general audit of the procurement function.

At an 'intermediate level', if the adequate procurement data architecture exists, red flags can be automated, so that software carries them out. RPA can be used to cross-check published tender notices against the applicable rules (eg on duration of tender submission periods). This can increase the volume and speed at which the screening takes place. However, by itself, this automation does not alter the inputs of the screening, and thus has no more potential to identify deviations than manual checks (except for the potential reduction in manual check error rates or, conversely, a risk of error increase if the software is faulty). It generally can simply reduce gaps in screening where manual checks were either not being carried out, or where it was not possible to screen all procurement exercises due to capacity constraints. Additionally, if there are questions about the integrity of the checks themselves, the automation can also contribute to reducing that corruption risk linked to any discretion (eg not to carry out the check as a result of a corrupt practice). The main advantages of these intermediate level screens are thus their comprehensiveness, objectivity (in the sense of automaticity) and potential repetitiveness of the checks (eg if the parameters of the check are susceptible of modification throughout a procedure). But not their 'analytical power', in the sense that they do not offer insights that would not be attainable by a human decision-maker, given sufficient time.

A more 'advanced approach' to red flags would be to use ML to establish the rules (or the underlying benchmarks and parameters) determining the standard of abnormality to be investigated in the checks. In that case, there would be no set rule (eg number of days), but the ML algorithm would rather be trained to independently calibrate an 'abnormality threshold' that would then allow it to classify procurement exercises as either suspect, or not. This approach would create the potential for a more nuanced (and effective) screening system *if (and only if)* the algorithm was better at setting the relevant benchmarks and/or thresholds than human decision-makers—which would primarily require good access to data, as well as an adequate design of the algorithm itself. Given that most benchmarks and thresholds for manual or RPA checks are established with a relative degree of arbitrariness, even if that reflects previous expert knowledge on suitable values, the deployment of ML could outperform existing approaches if there was enough big data to allow it to generate truly evidence-based thresholds for the required parameter or benchmark—or even to identify parameters or benchmarks not currently used that could however be effective in identifying problematic (potentially corrupt) procurement exercises. The process could be progressively refined through feedback channels that allowed the ML to improve the parameters. However, it is difficult to find such enabling databases in practice (see also Section 6), and the creation of feedback mechanisms can be difficult. All of this indicates that the most advanced approach can be out of reach for a relevant proportion of potential implementations of (theoretical) red flag indicators.

Moreover, depending on the specific type of ML used, this more advanced approach would also generate significant barriers to the explainability of a decision to flag a specific procurement exercise. While intermediate approaches ensure the ease of interpretability of the red flags (as they are the same that could be deployed manually), the more advanced the approach, the less likely that a human decision-maker will be able to interpret why the flag was triggered, or even what the flag precisely means and how to action the relevant insight. Consequently, the more advanced the approach the more likely to breach legal constraints, such as those related to duties of good administration and rights to due process—at least where the algorithms were used for governance functions related to the detection, investigation and eventual sanction of illegal behaviour.[57] In that regard, the closer the relationship between the red flag and the triggering of procedures potentially leading to the imposition of sanctions (or criminal convictions), the higher the demands in terms of procedural rights—including the explanation of the ML underpinning the red flag.

3.3.2 Breadth and depth of the data underpinning the red flags

In addition to those different levels of technological ambition, there are also variations resulting from the breadth and depth of the information used by the red flags at all levels of sophistication. The narrowest approach to red flags concerns the verification of a single variable (eg duration of the tendering period) against a single rule (eg pre-specified 'too short duration' threshold). A slightly broader approach includes a dynamic element, which implies verifying a single variable (eg contract price) through the development of the procurement process (eg initially against a pre-specified 'expected value' or 'reservation price', or against some market-based benchmark, or, later on, against eg payments effectively made under the contract). Similarly, a slightly broader approach would involve crossing information relating to different stages of the procurement process (eg length of the period to receive tenders and procurement challenges, or length of the period to receive tenders and number of tenders received). A more ambitious approach concerns the development of red flags that extract insights from a cross-section or a time series of data (eg to identify entities that are repeatedly awarded contracts by the same contracting authority, or entities that are assigned contracts by different contracting authorities in ways that reflect specific (suspicious) patterns). Finally, perhaps the most ambitious approach concerns developing red flags that also cross information spanning different databases or sources of information (eg to cross-check procurement awards against beneficial ownership information of the awardee, and then against a database on eg donations to political parties).

The availability and quality of the (procurement and other) data in the required formats will determine the feasibility of the implementations of any level of ambition in the deployment of red flags. The most plausible implementations of early detection mechanisms under the current state of the art (or, rather, the current state of the data) concern 'intermediate approaches' to the automation of the screens, primarily based on a narrow scope, but

[57] Sanchez-Graells, 'Procurement Corruption and Artificial Intelligence' (n 54).

progressively including dynamic and systemic checks where the data infrastructure so allows. Importantly, these approaches can either seek to automate checks previously carried out manually or enable checks that were not being carried out at all due to lack of capacity or other operational reasons. In this intermediate approach, it is also likely that the red flags emerge from a bottom-up approach, in the sense of being guided by existing practice and user-centric considerations (eg on who should action the insights generated by the red flag), whereas more advanced red flags could follow a top-down approach due to their more limited connection with existing operations (and could require the creation of new job roles in order to action the related insights).

Ultimately, the difficulties in developing this type of ML solutions can primarily concern data availability and data quality, with some recent projects having been abandoned,[58] or significantly pared down,[59] due to data issues. This is a particularly important constraint in this type of ML implementation because it tends to rely on supervised training and there are notorious difficulties in ensuring that the labelling of the training data is accurate.[60] This is further discussed in Section 6.

4. Distributed Ledger Technology Systems and Smart Contracts

4.1 Distributed Ledger Technology Systems

As advanced in Chapter 6, Section 3.2, DLT systems allow for new approaches to the storage and exchange of information where 'instead of having one centralised database on which records are stored, this data is stored in a decentralised manner across all of the nodes of the … network'.[61] The advantage of decentralisation is that information management does not depend on the decisions of the owner of a traditional database, which is the entity determining what information is contained in the database, and thus establishing the baseline of 'truth'. What is recorded in the centralised database is true on the authority of the database owner. It is thus necessary to trust the database owner and its management of the information. Conversely, in a decentralised system such as a DLT, there can be a multiplicity of (potentially infinite) agents capable of adding information to the database, which is structured as a ledger. In this context, 'truth' is not established by authority, but results from a consensus mechanism (algorithm)[62] determining whether the agent (network node) seeking to add information is entitled to do so. Once information is added, it will be propagated to all other agents, and it will thus be possible to check whether the information was added following the relevant rules. Once information is added, it cannot be amended or changed (although further transactions can change the state of the 'truth' that results from the ledger). Therefore (some types of) DLTs can be considered trustless mechanisms, in the sense that the

[58] Eg the UK's competition watchdog 2017 'Screening for cartels' tool, which was abandoned in early 2020. For discussion of its shortcomings, see Albert Sanchez-Graells, '"Screening for Cartels" in Public Procurement: Cheating at Solitaire to Sell Fool's Gold?' (2019) 10(4) Journal of European Competition Law & Practice 199.
[59] Albert Sanchez-Graells, IDB publication.
[60] See eg contribution by Mihaly Fazekas to European Parliament, 'Use of big data and AI in fighting corruption and misuse of public funds - good practice, ways forward and how to integrate new technology into contemporary control framework' (Workshop Proceedings) PE 691.722 (2021) < https://www.europarl.europa.eu/RegData/etudes/STUD/2021/691722/IPOL_STU(2021)691722_EN.pdf > accessed 23 September 2022.
[61] Deloitte, 'Emerging technologies in public procurement' (n 9) 8.
[62] For an accessible description of the different consensus algorithms, see T-Labs, 'Consensus Algorithms: the essential forces of the DLT universe' (*Medium*, 24 April 2018) < https://medium.com/@_tlabs/consensus-algorithms-the-essential-forces-of-the-dlt-universe-e1dd8e049534 > accessed 15 September 2022.

‘true state’ of the information is determined in a way that does not require trust in any specific agent or entity. Given that agents operate through cryptographic keys that ensure their anonymity, the network can be expected to operate objectively—ie a decision on whether information should or not be added to the ledger will be made on the basis of pre-defined (rigid) criteria.[63]

However, it should be stressed that the verification that the agent adding information on a DLT can carry out is strictly transactional and formal. This is best understood as checking the origin of the request to add information, as well as (potentially) minimal other checks based on the information already existing in the ledger. For example, in the context of a cryptocurrency transfer, the verification of the transaction requires validating the origin of the order to transfer an amount of cryptocurrency and checking whether the originator of the order holds sufficient cryptocurrency in its wallet to transfer the required amount. There is no other check, which can lead to well-known problems eg in relation to the lawfulness of any related transactions, (cryptographic) identity theft, money laundering, etc.

In the context of procurement governance, the functioning of a DLT requires understanding information exchanges as transactions. And, in that regard, the DLT will usually only be able to ensure that those seeking to add information (whether it is a public buyer publishing a call for tenders, or a tenderer uploading qualification information or a tender, etc) are entitled to do so. However, the DLT will not be able to verify the content or accuracy of the information. The DLT would ensure the provenance of the information and effectively timestamp it and store it (for record permanence). It would also generate a cryptographic mechanism to manage access to the recorded information.

Given the way the DLT operates, it would also generate tamper-proofness. Indeed, the ledger (or chain) is append-only (ie not re-writable) and involves the use of cryptographic keys (hashes) that create a single identifier for every block of information, with any change in the information triggering changes in the key. The DLT chain is created by linking the hashes across data entries (grouped in blocks, whereby the first entry in each block is the hash from the previous block), which means that the addition of new sets of data contributes to ensuring the integrity of data further up the chain.[64] Where already recorded information or data is manipulated (eg modified), the cryptographic linkages down the chain no longer match, the chain of information breaks, and the specific point of discontinuity becomes evident (which makes the system tamper-evident, rather than tamper-proof, strictly speaking).

Ultimately, then, the main advantages of such an approach to information management lie in the permanence and tamper-evidence of the records/data that result from the algorithmically-ruled decentralisation and additivity of the system, so that it is not susceptible

[63] See Michel Rauchs et al, ‘Distributed Ledger Technology Systems. A Conceptual Framework’ (2018) 25-27 < https://www.jbs.cam.ac.uk/wp-content/uploads/2020/08/2018-10-26-conceptualising-dlt-systems.pdf > accessed 7 September 2022 (hereafter Rauchs et al, ‘DLT conceptual framework’); see also Chan Yang, ‘Is there a role for blockchain for enhancing public procurement integrity?’ (2019) Papers of the OECD Global Anti-Corruption & Integrity Forum < https://www.oecd.org/corruption/integrity-forum/academic-papers/Chan-Yang-blockchain-public-procurement-integrity.pdf > accessed 15 September 2022 (hereafter, Yang, ‘Blockchain for enhancing public procurement integrity?’).

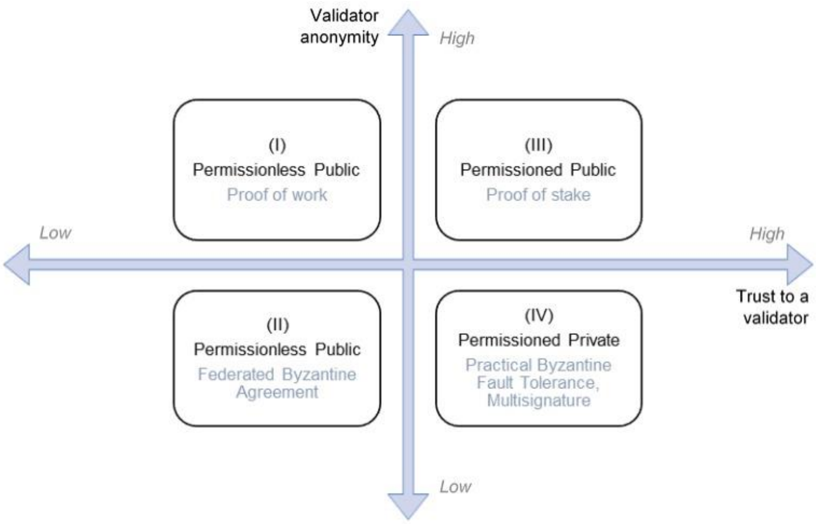
[64] This can be further complicated through techniques allowing for DLT structures other than a (linear) chain; see eg Francisco Luis Benítez-Martínez et al, ‘Neural blockchain technology for a new anticorruption token: towards a novel governance model’ (2022) Journal of Information Technology & Politics, forthcoming < https://doi.org/10.1080/19331681.2022.2027317 > accessed 15 September 2022.

of control or manipulation by any given party—and, crucially, not susceptible of manipulation by the entity owning a (traditional) database.

However, to gather the extent of those advantages and their suitability for procurement governance, it is important to drill down in understanding how such qualities can be achieved through a DLT system, and the variety of DLT systems that exist.[65]

In simple terms, it is possible to classify different DLT solutions according to criteria such as the level of anonymity of transaction validators and the level of trust in validators. Taking these criteria into account, a classification emerges as in Graph 1. 'Blockchain' is popularly used to refer to a DLT that operates like bitcoin (a type I blockchain in Graph 1), with which it is oftentimes confused.[66] In that case, the DLT is permissionless and public, which is understood to mean that anyone can have access to the content of the records (as long as they have access to the required cryptographic keys to meet cybersecurity requirements) and everyone can potentially participate in the system as a validator of transactions, provided it has access to the computing power required to solve increasingly difficult cryptographic puzzles generated by its consensus mechanism. This creates a strictly rules-based system with minimal scope for collusion or corruption between agents (nodes). It is also relevant to note that most of the advantages derived from commonly discussed DLTs are linked to their 'append-only' design—which means that they are tendentially going to grow indefinitely—and the multiplicity of copies that are kept of the ledger—that is, potentially, an infinite number.

Graph 1. Basic classification of DLT technologies



Source: Yang, 'Blockchain for enhancing public procurement integrity?' (n 63) 6, based on further references.

From a procurement governance perspective, the premises on which the permanence and tamper-evidence of records held on a DLT are predicated need revisiting. There seems to be an implicit assumption that the DLTs that would be implemented in the procurement setting would be public and permissionless (like bitcoin's). However, in the public sector, it is very difficult to envisage the adoption of a fully decentralised blockchain solution, not solely due

[65] This section builds on Albert Sanchez-Graells, 'Data-Driven Procurement Governance: Two Well-Known Elephant Tales' (2019) 24 Communications Law 157 (hereafter Sanchez-Graells, 'Data-Driven Procurement Governance').

[66] Rauchs et al, 'DLT conceptual framework' (n 63) 15.

to technical issues of scalability and latency,[67] but also due to the simpler fact that the public sector can hardly be expected to surrender control over the procurement data system. It seems much more plausible that the public sector will consider adopting permissioned DLTs, so that only pre-accredited agents can add information to the ledger. It also seems plausible that, given the need to manage confidential and sensitive information, the DLTs will be private, so that accessing the information also requires pre-accreditation or screening and permissions. It follows that the public sector can plausibly be expected to deploy highly centralised DLTs, where permissions to access and to amend the information are granted by the public sector. It is also possible to think of solutions developed for broad adoption across the public sector, which could keep certain degrees of anonymity and multiplicity of nodes holding records.[68] However, this could create some technical downsides (eg in relation to the network latency of the system, that is, the time it takes for the information to be added) and it is plausible to expect public sector organisations to seek to use smaller, private DLTs. If that comes true, and the public sector mainly deploys private permissioned DLTs (type IV blockchain in Graph 1),[69] the expected advantages of DLT systems will be significantly eroded, in particular in relation to the tamper-evidence, but also record permanence qualities. In that scenario, the technical advantages of a DLT would be very close to those of eg advanced database management including electronic signatures. In some respects, it would also offer limited advantages over systems of automated generation of (open) procurement data.

Emerging evidence on experimentation with blockchain technologies precisely shows this. In some cases, the constraints resulting from the inability of a DLT to hold large volumes of information lead to simply use the DLT as a 'tagging' mechanism seeking to ensure the integrity of the information, which is however stored on off-chain databases,[70] or to only use it in relation to specific types of information related to a specific phase of the procurement process (eg recording evaluation scores).[71] This adds an element of cybersecurity, but one that is probably only marginally different from other types of information security approaches. Emerging implementations are also based on centralised private and permissioned DLTs, initially solely comprising two nodes held by the same public authority[72]—which completely wipes out the expectation of decentralisation of the system. To note, some feasibility studies have concluded that the adoption of a DLT would not be cost effective compared to other approaches.[73] Other cases of larger scale experimentation have not gone beyond pilot phases,[74] or are currently in an uncertain phase of rollout.[75]

[67] As well as cost and the otherwise difficulty of creating adequate incentives for the mining or processing of the transactions, although this will not be discussed in detail.
[68] That underpins the European Blockchain Services Infrastructure (EBSI) project; see < https://ec.europa.eu/digital-building-blocks/wikis/display/EBSI/Home > accessed 15 September 2022.
[69] Along the same lines, Yang, 'Blockchain for enhancing public procurement integrity?' (n 63) 6.
[70] Eg the Digipolis case study; Deloitte, 'Emerging technologies in public procurement' (n 9) 115 ff.
[71] Eg the Glosfer case study; Deloitte, 'Emerging technologies in public procurement' (n 9) 120 ff.
[72] Eg the Digipolis case study; Deloitte, 'Emerging technologies in public procurement' (n 9) 115 ff.
[73] Eg the Japanese MIC case study; Deloitte, 'Emerging technologies in public procurement' (n 9) 135 ff.
[74] Eg the Jalisco case study; Deloitte, 'Emerging technologies in public procurement' (n 9) 126 ff.
[75] Eg the US HHS Accelerate case study; Deloitte, 'Emerging technologies in public procurement' (n 9) 109 ff. See also Alex Zhou, 'Tracing HHS Blockchain Adoption' (*Avascent*, 28 April 2021) < https://www.avascent.com/news-insights/healthcare-pulse/tracing-hhs-blockchain-adoption/ > accessed 15 September 2022.

4.2 Smart Contracts

Beyond the use of DLTs as information management systems, it is also worth considering them as the data infrastructure capable of enabling the deployment of smart contracts.[76] If smart contracts were to have high potential for procurement governance, developing a (private permissioned) DLT would be a required step, which would be justified by the more advanced functionality of smart contracts, rather than the inherent (limited) advantages of the DLT as an information management system. As mentioned in Chapter 6, Section 3.2, in theory, smart contracts could be deployed on a DLT architecture to fully automate (most parts of) the procurement process. However, a detailed analysis of how this would take place will show that the potential for the deployment of smart contracts is rather limited.

Smart contracts are software programs stored on a DLT that are triggered, or run, when predetermined conditions are met. They can be used to automate transactions, as well as workflows, eg triggering the next action when a previous condition is met (such as completion of the previous stage, or the lapse of a pre-specified time period)—and in that regard their functionality can overlap with other forms of automation.

It is generally suggested that it would be possible to use smart contracts to design self-executable tender procedures leading to the automatic award of the contract to the tender that best satisfied the advertised public sector needs. However, it should be stressed that smart contracts follow a rather simple 'if/when … then' logic that requires setting very clear and rigid rules for each of the relevant statements. Translating procurement processes into that logic is a massive challenge,[77] both in terms of the volume of information that needs to be processed and fit into the programme,[78] but also in terms of the impossibility of reducing all but the simplest of procurement processes into rigid rules (eg concerning tenderer qualification, technical specifications, tender evaluation or award formulae).[79] By itself, this poses a large question mark around some potential deployments of smart contracts.[80] Even assuming that those challenges could be overcome, the design of a smart contract would only be justified where it could be used on multiple occasions, which would thus reduce their likely adoption to highly standardised parts of the procurement procedure, likely to overlap with the practical space that RPA could cover.

The second technical reason pointing at limited potential concerns what is generally seen as their main strength: the automatic generation of (legal) effects. As smart contracts are stored on the blockchain, they are deemed irreversible. As soon as the triggering condition is met—usually through the addition of a new transaction to the ledger, or through verification of off-chain information by means of an oracle, potentially an IoT device—the programme automatically executes. However, this irreversibility generates significant legal problems and

[76] Pauline Debono, 'Transforming Public Procurement Contracts into Smart Contracts' (2019) 10 International Journal of Information Technology Project Management 16.

[77] Sanchez-Graells, 'Data-Driven Procurement Governance' (n 65) 165. As is coding smart contracts generally; Eliza Mik, 'Smart contracts: terminology, technical limitations and real world complexity' (2017) 9 Law, Innovation and Technology 269.

[78] A much lauded proof of concept for example stressed that their model could only deal with tenders expressed in up to 700 words; Freya Sheer Hardwick, Raja Naeem Akram, and Konstantinos Markantonakis, 'Fair and Transparent Blockchain based Tendering Framework - A Step Towards Open Governance' (2018) < https://arxiv.org/pdf/1805.05844.pdf > accessed 8 September 2022.

[79] Sanchez-Graells, 'Data-Driven Procurement Governance' (n 65) 164-165.

[80] Kelvin F K Low and Eliza Mik, 'Pause the blockchain legal revolution' (2020) 69 International & Comparative Law Quarterly 135.

would be particularly problematic in the context of procurement governance, where (administrative) decisions are necessarily open to challenge and (judicial) review. It would also generate problems concerning the need to allow for eg clarifications of the published information and requirements, which could require modifications of the previously uploaded information or code.[81] Moreover, the 'automaticity of irreversible effects' is limited to the on-chain environment. Where the (legal effects) need to manifest off-chain, there is nothing automatic or irreversible about the smart contract. Put together, this also constrains the likely uptake of smart contracts to parts of the procurement process that trigger decisions that are recorded on the DLT, but without further (automatic) legal effectiveness. In other words, this can mainly be applied to exchanges of information, as smart contracts follow the same narrow transactional logic as the DLT itself (as discussed in the previous sub-section).

5. Internet of Things and Oracles

As advanced in Chapter 6, Section 3.1, IoT is a technology that automates the collection of information via sensors, as well as facilitating remote interactions by and with the connected things/sensors. It is thus a technology that enables a network of devices or machines to 'exchange information with each other without requiring a human to supervise each action'.[82] IoT can thus be useful in automating the collection of data and this can have benefits in terms of reduction of the data collection burden and the scope of (human) error, as well as potentially speeding up the availability of information to (near) real time. That information can then serve as the prompt for an automated process via RPA or a smart contract. Where an IoT sensor feeds information into an automated process, it is usually called an oracle. Oracles not only comprise (IoT) hardware capturing and exchanging data from the 'real world', but also software oracles delivering data from digital sources such as websites, servers, or databases—which can in turn be fed information either manually or automatically.[83] Oracles can thus be understood as the bridge between the digital and the offline world. However, it should be stressed that this is mostly a one-way bridge, as the oracles can feed 'real world' information into a database or a DLT, but their ability to generate offline effects is limited to the manipulation of environments through adjustments that can be data led, or digitally activated (for example, in the context of a smart heating system, through modifications of a digital thermostat). In other words, oracles are useful to automate the collection of information but, in a procurement governance setting, they can hardly be used to implement any specific environment control mechanisms other than in relation to the execution of public contracts where the mode of delivery is digitally enabled. This largely limits the potential of oracles and IoT implementations to being automated sources of data.

6. The Crucial Relevance of (Big) Data, and the Difficulties in Generating It

Previous sections have stressed the relevance of procurement data across technological solutions. The outcome of RPA can only be as good as its sources of information (Section 2), and adequate ML solutions can only be trained on high-quality big data (Section 3).[84] DLT systems can manage data, but cannot verify its content, accuracy, or reliability (Section 4). IoT and software oracles can automatically capture data, which can alleviate some of the

[81] Sanchez-Graells, 'Data-Driven Procurement Governance' (n 65) 164-165.

[82] Deville, Sergeyssels and Middag, 'Basic AI Concepts' (n 1) 5.

[83] Niall Roche and Alastair Moore, 'Oracles and Internet of Things in the Internet of Value' in Nikhil Vadgama, Jiahua Xu and Paolo Tasca (eds) *Enabling the Internet of Value. How Blockchain Connects Global Businesses* (Springer 2022) 157.

[84] Lehr and Ohm, 'Machine Learning for Legal Scholars' (n 1) 676.

difficulties in generating an adequate data infrastructure. But this is only in relation with the observation of the 'real world' or in relation to digitally available information, which quality raises the same issues as other sources of data (Section 5). These are not solely important technical considerations as, more generally, 'trust in AI is largely based around trust in data'.[85]

Given the crucial relevance of data, it is hard to emphasise how any shortcomings in the enabling data architecture curtail the likelihood of successful adoption of digital technologies for procurement governance. It may simply be impossible to develop digital solutions at all. And the development and adoption of digital solutions developed on poor or inadequate data can generate further problems—eg skewing decision-making on the basis of inadequately derived 'data insights', which can be compounded by the allure of the digital technologies leading to a lack of critical assessment of such insights, as discussed in Chapter 6. Ensuring that adequate data is available to develop digital governance solutions is a challenging but unavoidable requirement.

This Section further explores the difficulties in meeting this requirement, despite significant efforts, eg by the European Commission or the Open Contracting Partnership. The difficulties are two-fold. First, it is proving difficult to generate even a comprehensive system of process-focused (open) procurement (big) data. Second, even if available, such procurement data would be insufficient to enable the deployment of digital technologies, and in particular ML solutions, capable of producing advanced insights beyond the analysis of procurement processes and market interactions explicitly reflected in those processes. A variety of governance-relevant data insights can only be derived from the combination of procurement and other data sources but creating or accessing the latter also raises big challenges.

6.1 (Open) Procurement (Big) Data

In line with the analysis so far, the importance of procurement data is often reflected in high level data strategies, such as the 2020 European strategy for data, which emphasised that

> Public procurement data are essential to improve transparency and accountability of public spending, fighting corruption and improving spending quality. Public procurement data is spread over several systems in the Member States, made available in different formats and is not easily possible to use for policy purposes in real-time. In many cases, the data quality needs to be improved.[86]

This echoes broader policy statements by the Open Contracting Partnership (OCP), which is promoting the adoption of its open contracting data standard (OCDS) across the globe.[87]

To address issues of data quality and to facilitate the creation of a data space for the public administration, the European Union is in the process of implementing a new data standard to control the exchange of information about procurement procedures covered by EU law (eForms).[88] eForms will be mandatory from October 2023. The European Commission has stressed that 'eForms are at the core of the digital transformation of public procurement in

[85] Virdee, 'Understanding AI' (n 18) 50.

[86] European Commission, 'A European strategy for data' (Communication) COM (2020) 66 final, at 32.

[87] See < https://standard.open-contracting.org/latest/en/ > accessed 26 September 2022.

[88] Commission Implementing Regulation (EU) 2019/1780 of 23 September 2019 establishing standard forms for the publication of notices in the field of public procurement and repealing Implementing Regulation (EU) 2015/1986 (eForms) [2019] OJ L 272/7 (hereafter 'eForms Implementing Regulation'). eForms are aligned with OCDS, but not identical to it. A previous OCDS schema for TED publications was developed by OCP < https://standard.open-contracting.org/profiles/eu/latest/en/ > accessed 28 September 2022.

the EU. Through the use of a common standard and terminology, they can significantly improve the quality and analysis of data'.[89] eForms are thus the primary initiative at EU level to build big open procurement data as an enabler for the uptake of digital technologies.

The migration towards eForms requires a complete redesign of information exchanges between public buyers and the central publication platform: Tenders Electronic Daily (TED), a supplement of the Official Journal of the European Union (OJEU). Or, rather, the information exchanges between the providers of e-procurement services (acting as e-senders) and TED.[90] eForms are redesigned around universal business language and involve the use of a much more structured information schema compatible with the EU's eProcurement Ontology.[91] eForms are meant to collect a larger amount of information than current TED forms, especially in relation to sub-units within a tender, such as lots, or in relation to framework agreements. eForms are meant to be flexible and regularly revised, in particular to add new fields to facilitate data capture in relation to specific EU-mandated requirements in procurement, such as in relation with the clean vehicles rules.[92]

The implementation of eForms and the related data standard seeks to achieve two goals: first, to ensure the data quality (eg standardisation, machine-readability) required to facilitate its automated treatment for the purposes of publication of procurement notices mandated by EU law (ie their primary use);[93] and, second, to build a data architecture that can facilitate the accumulation of big data so that advanced data analytics can be deployed by re-users of procurement data. This second(ary) goal is particularly relevant to our discussion.

From an informational point of view, the main constraint that remains despite the adoption of eForms is that their mandatory content is determined by obligations to report and publish tender-specific information under the current EU procurement rules,[94] as well as to meet broader reporting requirements under international and EU law.[95] Ultimately, eForms' main concentration is on disseminating details of contract opportunities and capturing different aspects of decision-making by the contracting authorities.[96] Given the process-orientedness

[89] European Commission, 'eForms' (Website) < https://single-market-economy.ec.europa.eu/single-market/public-procurement/digital-procurement/eforms_en > accessed 26 September 2022.

[90] This distinction is important because in many countries e-procurement services providers compete for the provision of large volume, entirely standardised platform services, which are markets characterised by small operational margins. This creates incentives for a minimal adaptation of current e-sending systems and disincentives for the inclusion of added-value (data) services unlikely to be used by public buyers. Some optional aspects of the eForm implementation are thus likely to remain unused due to this market structure, as discussed in this Section.

[91] European Commission, 'About eProcurement Ontology' (Website) < https://joinup.ec.europa.eu/collection/eprocurement/solution/eprocurement-ontology/about > accessed 27 September 2022.

[92] For details, see European Commission, 'Clean Vehicles Directive' (Website) < https://transport.ec.europa.eu/transport-themes/clean-transport-urban-transport/clean-and-energy-efficient-vehicles/clean-vehicles-directive_en > accessed 27 September 2022.

[93] eForms comprise six standard forms capable of accommodating the over 40 different types of notice required by EU procurement rules: (1) 'Planning'; (2) 'Competition'; (3) 'Direct award prenotification'; (4) 'Result'; (5) 'Contract modification'; and (6) 'Change; Art 1(1) and 2 eForms Implementing Regulation (n 88).

[94] European Commission, 'eForms: policy implementation handbook' (Guidance) (2020) 11 < https://data.europa.eu/doi/10.2873/646999 > accessed 26 September 2022 (hereafter, Commission, 'eForms Handbook').

[95] Commission, 'eForms Handbook' (n 94) 16.

[96] In other words, 'eForms only capture a small portion of the information about public procurement (mainly tender and award notices of large contracts)'; Tenders Guru, 'Recommendations for EU procurement' (2021)

and transactional focus of the procurement rules, most of the information to be mandatorily captured by the eForms concerns the scope and design of the tender procedure, some aspects concerning the award and formal implementation of the contract, as well as some minimal data points concerning its material outcome—primarily limited to the winning tender. While some of that information (especially in relation to the winning tender) will be reflective of broader market conditions, and while the accumulation of information across procurement procedures can progressively generate a broader view of the relevant markets,[97] it is worth stressing that *eForms are not designed as a tool of market intelligence*.

eForms do not capture the entirety of information generated by a procurement process and, as mentioned, their mandatory content is rather limited. eForms do include several voluntary or optional fields, and they could be adapted for some voluntary uses, such as in relation to detection of collusion in procurement,[98] or in relation to the beneficial ownership of tenderers and subcontractors. However, while eForms are flexible and the schema facilitates the development of additional fields, is it unclear that adequate incentives exist for adoption beyond their mandatory minimum content. This will most likely result in two separate tiers of eForms implementation. Tier 1 would solely concern the collection and exchange of information mandated by EU law. Tier 2 would concern the optional collection and exchange of a much larger volume of information concerning eg the entirety of tenders received, as well as qualitative information on eg specific policy goals embedded in a tender process.[99] Of course, in the absence of coordination, a (large) degree of variation within Tier 2 implementations can be expected. Tier 2 is potentially very important for (digital) procurement governance, but there is no guarantee that Member States will decide to implement eForms covering it.

One of the major obstacles to the broad adoption of a procurement data model so far, at least in the European Union, relates to the slow uptake of e-procurement discussed in Chapter 6, Section 1. Without an underlying highly automated e-procurement system, the generation and capture of procurement data is a main challenge, as it is a labour-intensive process prone to input error. The entry into force of the eForms rules could serve as a further push for the completion of the transition to e-procurement—at least in relation to procurement covered by EU law. However, it is also possible that low e-procurement uptake and generalised unsophisticated approaches to e-procurement (eg reduced automation) will limit the future functionality of eForms, with Member States that have so far lagged behind restricting the use of eForms to tier 1. It is also possible that the adoption of eForms is uneven within a given jurisdiction, with advanced procurement entities (eg central purchasing bodies) adopting tier 2 eForms, and (most) other public buyers limiting themselves to tier 1. While this would not

---

12 < https://www.access-info.org/wp-content/uploads/2021-06-28-Tenders-Guru-EU-Recommendations.pdf > accessed 27 September 2022.

[97] In markets where procurement represents most or all demand, that is; for discussion, see Albert Sanchez-Graells, *Public Procurement and the EU Competition Rules* (2nd edn, Hart 2015) 37-51.

[98] This would be facilitated by publishing details of all tenders received, rather than just the winning tender; Commission, 'eForms Handbook' (n 94) 24.

[99] There are likely also going to be discrepancies in the level of transparency given to the information collected by the eForms, which allow for an advanced level of tailoring of which data fields to publish and which not to. This can address concerns of excessive transparency, as well as facilitate the adoption across Member States that currently publish widely varying levels of information, as discussed in Kirsi-Maria Halonen, Roberto Caranta and Albert Sanchez-Graells (eds), *Transparency in EU Procurements: Disclosure within Public Procurement and During Contract Execution* (Edward Elgar, 2019).

pose legal challenges, it would have a major effect on the utility of the eForms-generated data for the purposes of eg developing ML solutions, as the data would hardly be representative of important aspects of procurement (markets).

Relatedly, while the data to be captured through eForms could resolve some of the issues with data quality that have been limiting the useability of TED data, and despite the effort to harmonise the underlying data architecture and link it to the Procurement Ontology, 'eForms are not an "off the shelf" product that can be implemented only by IT developers. Instead, before developers start working, procurement policy decision-makers have to make a wide range of policy decisions on how eForms should be implemented'[100] in the different Member States. This poses an additional challenge from the perspective of data quality (and consistency), as there are many fields to be tailored in the eForms implementation process that can result in significant discrepancies in the underlying understanding or methodology to determine them, in addition to the risk of potential further divergence stemming from the domestic interpretation of very similar requirements. This simply extends to the digital data world the current situation, eg in relation to diverging understandings of what is 'recyclable' or what is 'social value' and how to measure them. Whenever open-ended concepts are used, the data may be a poor source for comparative and aggregate analysis. Where there are other sources of standardisation or methodology, this issue may be minimised—eg in relation to the green public procurement criteria developed in the EU,[101] if they are properly used. However, where there are no outside or additional sources of harmonisation, it seems that there is scope for quite a few difficult issues in trying to develop digital solutions on top of eForms data, except in relation to quantitative issues or in relation to information structured in clearly defined categories—which will mainly link back to the design of the procurement.

Overall, while the implementation of eForms could in theory build a big data architecture and facilitate the development of ML solutions, there are many challenges ahead and the generalised adoption of tier 2 eForms implementations seems unlikely, unless Member States make a positive decision in the process of national adoption. In that regard, it can well be that most of the added functionalities that tier 2 data could enable will only be developed in specific jurisdictions or domains, such as that of centralised procurement. This would not only constrain the broader (re)usability of eForms data, but also generate other governance knock-on effects linked to eg further procurement centralisation pressures, as discussed in Section 8. More generally, that would perpetuate constraints resulting from limited procurement data, which would have a negative effect on the likelihood of successful adoption of digital technologies for procurement governance.

6.2 Other (Big) Data Required to Extract Advanced Insights

A further difficulty in creating an enabling (big) data architecture for digital procurement governance is that a multiplicity of governance-relevant data is not generated within procurement processes, but rather relates to broader market and institutional issues. This includes from sources of information on beneficial ownership or other sources of potential conflict of interest (eg family relations, or financial circumstances of individuals involved in decision-making), to information on corporate activities and offerings, including detailed information on products, services and means of production, to information on levels of

[100] Commission, 'eForms Handbook' (n 94) 19.

[101] European Commission, 'EU GPP criteria' < https://ec.europa.eu/environment/gpp/eu_gpp_criteria_en.htm > accessed 28 September 2022.

utilisation of public contracts and satisfaction with the outcomes by those meant to benefit from their implementation, whether they are within the public administration or not.

This is an important and difficult to tackle issue, as the collection of specific procurement process related data can have very little value (other than for narrow applications, such as category management) unless it can be cross-checked with those other sources of information. To the extent that the outside sources of information are not digitised, or not in a way that is (easily) compatible or linkable with procurement information, some data-based procurement governance solutions will remain undeliverable. In that regard, some developments in procurement governance will be determined by progress in other policy areas (eg tax data, or data on licensing and standardisation of products and services). While these are also receiving increasing attention, for example in the European Union, most data sharing measures are of a voluntary nature,[102] and some recent initiatives fall short of placing procurement-relevant information at the core of the respective regimes.[103]

A final issue to consider is that current initiatives only regulate the capture of data for the future. This means that it will take time for big data to accumulate and accessing historical data would be a way of speeding up the development of digital solutions. Moreover, in some contexts, such as in relation with very infrequent types of procurement, or in relation to decisions concerning previous investments and acquisitions, historical data will be particularly relevant (eg to deploy green policies seeking to extend the use life of current assets through programmes of enhanced maintenance or refurbishment). However, there are also significant challenges linked to the creation of backward-looking digital databases, not only relating to the cost of digitisation of the information, but also to technical difficulties in ensuring the representativity and adequate labelling of pre-existing information.[104] The lack of availability of such data can continue to constrain developments in data-led procurement governance in the short and medium term, or at least for as long as new measures for the generation of data, such as the eForms discussed above, are fully embedded and facilitate the accumulation of sufficient data.

6.3 Recapitulation of Data Issues

The development of an enabling data architecture for the development of digital solutions for procurement governance faces significant challenges. Despite the policy efforts of the European Commission, given the voluntary nature of their most innovative informational

---

[102] Eg initiatives concerning access to and the re-use of data held by public sector bodies Regulation (EU) 2022/868 of the European Parliament and of the Council of 30 May 2022 on European data governance and amending Regulation (EU) 2018/1724 (Data Governance Act) [2022] OJ L 152/1. The latter is likely to be complemented by the Data Act; Proposal for a Regulation of the European Parliament and of the Council on harmonised rules on fair access to and use of data (Data Act), COM (2022) 68 final. The revised guidance on business to government (B2G) data sharing are also of relevance; see High-Level Expert Group on Business-to-Government Data Sharing, 'Towards a European strategy on business-to-government data sharing for the public interest' (2020) < https://op.europa.eu/s/w363 > accessed 28 September 2022. For discussion of the latter, see Albert Sanchez-Graells, 'Some public procurement challenges in supporting and delivering smart urban mobility: procurement data, discretion and expertise' in Michele Finck et al (eds), *Smart Urban Mobility – Law, Regulation, and Policy* (Springer, 2020) 99, 111-113.

[103] Eg in relation to the Directive (EU) 2019/1024 of the European Parliament and of the Council of 20 June 2019 on open data and the re-use of public sector information (recast) (Open Data Directive) [2019] OJ L 172/56, the lack of inclusion of procurement data as a high-value dataset in the draft Implementing Regulation put to public consultation in the Summer of 2022.

[104] Albert Sanchez-Graells, IDB publication.

aspects, it seems unlikely that the new rules on eForms will generate data other than in relation with limited aspects of the procurement procedure. While this can enable the development of some tools aimed at monitoring and improving decision-making in a narrow sense, it seems unlikely that market intelligence will be significantly boosted, other than under specific circumstances, such as in countries with advanced (automated) e-procurement systems, in relation to the activities of central purchasing bodies, or in sector where the public buyer is the sole or dominant buyer. This will limit the uses of the data outside those fields and can generate knock-on governance effects, such as pressures for further centralisation. Similarly, given the voluntary nature of most measures relating to non-procurement data of relevance for procurement governance, it is also unclear that sufficient data will be available to develop digital solutions providing advanced data insights beyond the narrow confines of the procurement processes. The implication of these trends in data generation is that the adoption of digital procurement governance tools will likely either remain slow or not be possible for some applications. This needs to be taken into account as a foundational part of the feasibility boundary discussed in more detail in Section 8 below.

7. The Crucial Relevance of Data and Systems Integrity: A Displacement of Governance Risks?

It should also be stressed that big data comes with additional governance risks in relation to the integrity of data and data systems. Once (or to the extent that) procurement governance is data-driven, protecting the integrity of the data becomes an essential part of ensuring adequate governance.[105] Cyber security thus becomes a crucial aspect of procurement governance, as discussed in more detail in Chapter 8. Moreover, some solutions can generate risks for the integrity of data systems—eg if the deployed digital solutions can rewrite or delete parts of the underlying data architecture, perhaps as a result of their malfunctioning. This requires careful consideration from a technical perspective, and this analysis may be complicated in particular in settings where the new solution is built on top of legacy or inadequate (parts of the) data architecture or requires interoperability with other systems.[106]

The functional point to be stressed here is that the feasibility and desirability of the deployment of digital solutions should be assessed not only in relation to their technical characteristics and the existence of adequate data, but also encompassing an analysis of the new governance risks that the digital solution brings. Moreover, in many cases, the digital solution will not resolve, but rather solely displace, the relevant governance risk. For example, a digital solution seeking to reduce corruption through the implementation of a permissioned DLT to control access to information could simply displace the governance risk to those with adequate permissions. A solution based on an oracle would displace the risk from the potential manipulation of the original information to the manipulation of the oracle. In such cases, the displacement of the original governance risk and the addition of technical governance risks could worsen rather than improve the effectiveness of the procurement governance tools. This should raise questions about the desirability of a potential digital solution compared to current, or alternative (less sophisticated) options. It will thus be

[105] See eg UK National Audit Office, Cyber and information security. Good practice guide (2021) < https://www.nao.org.uk/wp-content/uploads/2021/10/Good-practice-guide-Cyber-and-information-security.pdf > accessed 28 September 2022.

[106] This is stressed in the vast majority of studies in the field; see Aristotelis Mavidis and Dimitris Folinas, 'From Public E-Procurement 3.0 to E-Procurement 4.0; A Critical Literature Review' (2022) 14 Sustainability 11252 < https://doi.org/10.3390/su141811252 > accessed 28 September 2022.

necessary for the risk assessment to be carried out in relation to the deployment of a digital solution not only to cover new risks, but also (displaced) existing risks (see Chapter 8).

8. A Feasibility Boundary for Digital Procurement Governance

As shown above, the major constraint for progression towards digital procurement governance is, and will for some time remain, the underlying (big) data architecture (see Section 6). The absence of adequate data jeopardises the feasibility of digital procurement governance. To facilitate unlocking the potential improvements to be generated by the adoption of digital technologies, the priority should be to invest in such enabling data architecture. In the EU context, it would also require for Member States to consider mandating eg the adoption of Tier 2 eForms implementation, as well as being very proactive in generating useable data regarding other aspects of procurement governance-relevant information, as well as fostering the voluntary compliance with data sharing measures by the private sector. In other jurisdictions, similarly proactive measures should be pursued under the relevant regulatory framework.

Once (or rather, if) that major data hurdle is cleared, the possibilities realistically brought by the functionality of digital technologies need to be embedded in the procurement governance context, which results in a feasibility boundary for the adoption of those technologies that can be summarised as follows.

RPA can reduce the administrative costs of managing pre-existing digitised and highly structured information in the context of entirely standardised and repetitive phases of the procurement process. RPA can reduce the time invested in gathering and cross-checking information and can thus serve as a basic element of decision-making support. However, RPA cannot increase the volume and type of information being considered (other than in cases where some available information was not being taken into consideration due to eg administrative capacity constraints), and it can hardly be successfully deployed in relation to open-ended or potentially contradictory information points. RPA will also not change or improve the processes themselves (unless they are redesigned with a view to deploying RPA). This generates a clear feasibility boundary for RPA deployment, which will generally have as its purpose the optimisation of the time available to the procurement workforce to engage in information analysis rather than information sourcing and basic checks. While this can clearly bring operational advantages, it will hardly transform procurement governance.

Developing ML solutions will pose major challenges, not only in relation to the underlying data architecture (as above), but also in relation to specific regulatory and governance requirements specific to public procurement. Where the operational management of procurement does not diverge from the equivalent function in the (less regulated) private sector, it will be possible to see the adoption or adaptation of similar ML solutions (eg in relation to category spend management). However, where there are regulatory constraints on the conduct of procurement, the development of ML solutions will be challenging.

For example, the need to ensure the openness and technical neutrality of procurement procedures will limit the possibilities of developing recommender systems other than in pre-procured closed lists or environments based on framework agreements or dynamic purchasing systems underpinned by electronic catalogues. Similarly, the intended use of the recommender system may raise significant legal issues concerning eg the exercise of discretion, which can limit their deployment to areas of information exchange or to merely suggestion-based tasks that could hardly replace current processes and procedures. Given the limited utility (or acceptability) of collective filtering recommender solutions, there are also constraints on the generality of recommender systems for procurement applications, both at tenderer and at product/service level. This raises a further feasibility issue, as the functional need to develop a multiplicity of different recommenders not only reopens the issue of data sufficiency and adequacy, but also raises questions of (economic and technical) viability. Recommender systems would mostly only be susceptible of feasible adoption in highly centralised procurement settings. This could create a push for further procurement centralisation that is not neutral from a governance perspective, and that can certainly generate significant competition issues of a similar nature, but perhaps a different order of magnitude, than procurement centralisation in a less digitally advanced setting.[107] This should be carefully considered, as the knock-on effects of the implementation of some ML solutions may only emerge down the line.

Similarly, the development and deployment of chatbots is constrained by specific regulatory issues, such as the need to deploy closed domain chatbots so that the information they draw from can be controlled and quality assured in line with duties of good administration and other legal requirements concerning the provision of information within tender procedures. Chatbots are suited to types of high-volume information-based queries only. They would have limited applicability in relation to the specific characteristics of any given procurement procedure, as preparing the specific information to be used by the chatbot would be a challenge—with the added functionality of the chatbot being marginal. Chatbots could facilitate access to pre-existing and curated simple information, but their functionality would quickly hit a ceiling as the complexity of the information progressed. Chatbots would only be able to perform at a higher level if they were plugged to a knowledge base created as an expert system. But then, again, in that case their added functionality would be marginal. Ultimately, the practical space for the development of chatbots is limited to low added value information access tasks. Again, while this can clearly bring operational advantages, it will hardly transform procurement governance.

ML could facilitate the development and deployment of 'advanced' automated screens, or red flags, which could identify patterns of suspicious behaviour to then be assessed against the applicable rules (eg administrative and criminal law in case of corruption, or competition law, potentially including criminal law, in case of bid rigging) or policies (eg in relation to policy requirements to comply with specific targets in relation to a broad variety of goals). The trade off in this type of implementation is between the potential (accuracy) of the algorithmic screening and legal requirements on the explainability of decision-making. Where the screens were not used solely for policy analysis, but acting on the red flag carried legal consequences, the suitability of specific types of ML solutions (eg unsupervised learning solutions tantamount to a 'black box') would be doubtful, challenging, or altogether excluded. In any case, the development of ML screens capable of significantly improving over RPA-based automation of current screens is particularly dependent on the existence of adequate data, which is still proving an insurmountable hurdle in many an intended implementation.

[107] For discussion, see Albert Sanchez-Graells, 'Public Procurement by Central Purchasing Bodies, Competition and SMEs: towards a more dynamic model?' in Carina Risvig Hamer and Mario Comba (eds), *Centralising Public Procurement – The Approach of EU Member States* (Edward Elgar 2021) 71; Albert Sanchez-Graells and Ignacio Herrera Anchustegui, 'Impact of Public Procurement Aggregation on Competition: Risks, Rationale and Justification for the Rules in Directive 2014/24' in R Fernandez and P Valcarcel (eds), *Centralizacion de compras publicas* (Civitas 2016) 129.

Other procurement governance constraints limit the prospects of wholesale adoption of DLT (or blockchain) technologies, other than for relatively limited information management purposes. The public sector can hardly be expected to adopt DLT solutions that are not heavily permissioned, and that do not include significant safeguards to protect sensitive, commercially valuable, and other types of information that cannot be simply put in the public domain. This means that the public sector is only likely to implement highly centralised DLT solutions, with the public sector granting permissions to access and amend the relevant information. While this can still generate some (degrees of) tamper-evidence and permanence of the information management system, the net advantage is likely to be modest when compared to other types of secure information management systems. This can have an important bearing on decisions whether DLT solutions meet cost effectiveness or similar criteria of value for money controlling their piloting and deployment. The value proposition of DLT solutions could increase if they enabled significant procurement automation through smart contracts. However, there are massive challenges in translating procurement procedures to a strict 'if/when ... then' programmable logic, smart contracts have limited capability that is not commensurate with the volumes and complexity of procurement information, and their development would only be justified in contexts where a given smart contract (ie specific programme) could be used in a high number of procurement procedures. This limits its scope of applicability to standardised and simple procurement exercises, which creates a functional overlap with some RPA solutions. Even in those settings, smart contracts would pose structural problems in terms of their irrevocability or automaticity. Moreover, they would be unable to generate off-chain effects, and this would not be easily sorted out even with the inclusion of IoT solutions or software oracles. This comes to largely restrict smart contracts to an information exchange mechanism, which does not significantly increase the value added by DLT plus smart contract solutions for procurement governance.

To conclude, and to link back to the discussion in Chapter 6, the analysis here shows that a feasibility boundary emerges whereby the adoption of digital technologies for procurement governance can make contributions in relation to its information intensity, but not easily in relation to its information complexity, at least not in the short to medium term and not in the absence of a significant improvement of the required enabling data architecture. This should be taken into account in considering potential use cases, as well as serve to moderate the expectations that come with the technologies and that can fuel 'policy irresistibility'. Further, those advantages do not come without their own additional complexities in terms of new governance risks and requirements for their mitigation. These will be explored in Chapter 8.