A taxonomy of explanations to support Explainability-by-Design

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Abstract
As automated decision-making solutions are increasingly applied to all aspects of everyday life, capabilities to generate meaningful explanations for a variety of stakeholders (i.e., decision-makers, recipients of decisions, auditors, regulators…) become crucial. In this paper, we present a taxonomy of explanations that was developed as part of a holistic ‘Explainability-by-Design’ approach for the purposes of the project PLEAD. The taxonomy was built with a view to produce explanations for a wide range of requirements stemming from a variety of regulatory frameworks or policies set at the organizational level either to translate high-level compliance requirements or to meet business needs. The taxonomy comprises nine dimensions. It is used as a stand-alone classifier of explanations conceived as detective controls, in order to aid supportive automated compliance strategies. A machine-readable format of the taxonomy is provided in the form of a light ontology and the benefits of starting the Explainability-by-Design journey with such a taxonomy are demonstrated through a series of examples.
1 Introduction

Automated decisions and the ways in which they can be interpreted by humans have been at the forefront of Artificial Intelligence (AI) research for a while now. Understanding especially how automated decision-making systems process personal data of individuals became important with the introduction of the General Data Protection Regulation (GDPR) in the European Union. Its Article 22 on ‘Automated individual decision-making, including profiling’ gave rise to a debate about the existence of a right to explanation. Regardless of whether such a right exists or not, the debate provided an opportunity to shift the focus from the inner workings of the ‘black box’, which has been the primary focus of XAI, to information that centres around the individual and is meaningful for the exercise of their rights (Cobbe & Singh, 2020; Selbst & Powles, 2017). Importantly, the recent discussions around explanations have highlighted the limits of current approaches in generating meaningful explanations, i.e. explanations that allow the recipient to reasonably place trust (Pieters, 2010). Solutions have often focused on a ‘one-size-fits-all’ approach that overlooks individuals’ different levels of understanding (Malgieri & Comandé, 2017), attempted to interpret the model and its processing while overlooking the impact of factors external to the black-box (Cobbe & Singh, 2020; Edwards & Veale, 2017), and failed to account for events that have influenced the outcome before and after the application of the algorithmic models (Cobbe, 2019).

The need to develop a systematic approach to explanations for GDPR compliance has been discussed extensively in the literature as a high-level compliance goal or strategy. Discussing the characteristics of explanations through the prisms of philosophy and data science, Pieters (2010) maps the levels of detail of an explanation to different results in the recipient’s trust. Explanations that include very little detail fail, as they do not contain enough information to build recipients’ confidence or trust. Similarly, explanations that contain too much detail fail because they escape the recipient’s level of understanding. Instead, explanations that contain a low level of detail can build confidence, answering questions of ‘why’, and explanations that contain a high level of detail can build trust, by answering questions of ‘how’. Kim and Routledge (2022), arguing for a right to ‘meaningful and intelligible explanation’, distinguish between ex ante generic explanations for informed consent and ex post generic and specific explanations either for remedial actions or for greater, individualised, details about the algorithmic processing. Castets-Renard (2021), discussing the different explanation requirements depending on four levels of impact of predictive policing decisions, distinguishes between triggering events:

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1 See e.g. for the evolution of interpretable tools and the emergence of Explainable AI (XAI) Arrieta et al. (2020); Preece (2018).
2 See e.g. Edwards and Veale (2017); Selbst and Powles (2017); Wachter, Mittelstadt, and Floridi (2017).
3 See for example Labadie and Legner (2019); Martin and Kung (2018).
4 See for example Deng, Wuys, Scandariato, Preneel, and Joosen (2010); Notario et al. (2015).
5 Ranging from Level I ‘no impact’ to Level IV ‘very high impact’ according to the Impact Assessment Levels of the Canadian Directive on Automated Decision Making.
for decisions with no impact on the individual, a publicly available (generic) explanation should suffice; moderate impacts would require the provision of explanations after a request from the user; whereas high and very high impacts would demand specific explanations at the point of disclosure of the decision. Considering general privacy concepts, there have been previous attempts at classification taxonomies. For example, Solove (2006) designed a taxonomy for privacy violations to be adaptable to new developments in privacy law, which however has limited scope in the field of EU data protection law. The GDPR, and the introduction of data protection by design, saw growth in efforts to design solutions that would make GDPR obligations machine readable, from GDPR-specific description languages like Fides, the creation of a vocabulary of GDPR terminology for use in ontologies by Bartolini, Muthuri, and Santos (2015), to an ongoing effort by W3C to extend a Data Privacy Vocabulary with GDPR concepts. However, these efforts have largely remained high-level, with no specific focus on explanation requirements, and with decisions on how to operationalise compliance have been largely left to the industry.

Against this background, the Provenance-driven and Legally-grounded Explanations for Automated Decisions (PLEAD) project proposes a holistic approach by leveraging automated computable explanations to aid supportive automated compliance strategies: Strategies that rely on automation to support the monitoring and auditing performed by humans. PLEAD has developed a methodology characterised by proactive measures to include explanations in the design rather than reactive measures attempting to bolt-on explanation capability after the fact, as an add-on, termed Explainability-by-Design. In PLEAD’s Explainability-by-Design methodology, explanations are integral to the system as detective and corrective controls. Detective controls aim to detect incidents that occur during the runtime of a process, whereas corrective controls aim to reduce the consequences of an incident once it has occurred. Explanations as detective and corrective controls add capabilities to evidence characteristics of the processing activities and detect violations of regulatory and business requirements.

The methodology, depicted in Fig. 1, follows a socio-technical process where explanation requirements are matched to audit trails of decisions to produce explanations. Explanation requirements are the essential conditions that determine or otherwise influence the generation of an explanation, as specified by applicable legal, governance and technical frameworks and other user-driven requirements. An explanation is considered a statement that provides details or reasons relating to or underlying a decision. The ultimate goal of an explanation is to enable the recipient of the statement: (i) to better understand the decision or (aspects of) the decision-making process, e.g. its fairness, accuracy etc.; and, (ii) where necessary, to take action, e.g. to contest a decision or correct the decision-making process etc. A decision can be any output of a data

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6https://ethyca.com/fides/
7http://www.w3id.org/dpv/dpv-gdpr#
8https://plead-project.org
9They can be distinguished from preventive controls, see Majdalawi and Hamad (2019).
processing pipeline, produced after consideration of one or more data points. The output is often followed by an action to bring upon a resolution to a situation. The Explainability-by-Design methodology comprises three phases: 1. An Explanation Requirement Analysis phase, depicted inside rectangle A, where legal engineers determine the explanation requirements of the processing in question; 2. an Explanation Technical Design phase, depicted inside rectangle B, consisting of a set of technological steps, initiated by data engineers, to instantiate a service, the ‘Explanation Assistant’, that generates explanations according to phase 1.; and, 3. a Validation phase, depicted inside rectangle C, where the generated explanations are evaluated by the stakeholders for their suitability and effectiveness.

The essential characteristics of meaningful explanations and the benefits of an Explainability-by-Design approach in overcoming current drawbacks of explanation practices have been previously presented in Tsakalakis et al. (2022), along with an overview of the three phases of the methodology. The technical steps that comprise the Technical Design (rectangle B in Fig. 1) will be the focus of Huynh, Tsakalakis, Helal, Stalla-Bourdillon, and Moreau (2022). This paper focuses instead on the Requirement Analysis phase seen in Fig. 1 and specifically on the ‘Analysing Requirements’ step – A.2 in Fig. 1. It
A taxonomy for Explainability-by-Design presents a taxonomy developed to enable an implementing organisation the systematic generation of explanations according to set explanation requirements. The taxonomy answers necessary questions about a meaningful explanation strategy, such as when explanations will need to be generated, what are their key components and how a meaningful explanation must look like. Within PLEAD’s Explainability-by-Design methodology, this taxonomy is used to match explanation requirements to data points in the audit trails of the processing operations so that the Explanation Assistant can generate explanations that incorporate all the necessary components to meaningfully address an explanation requirement. However, the taxonomy can also stand on its own: It comprises classification rules that take as input applicable explanation requirements and output explanation specifications, so it can be used in any setting where classification of explanations is needed. Further, the taxonomy can be represented in machine-readable formats, with an example representation as a light ontology included in the appendix of this paper. As a result, the taxonomy can be combined with pre-existing compliance strategies of an organisation.

The paper is organised into five sections. Following the introduction in Section 1, Section 2 presents the methodology that was followed in developing the taxonomy for explanations. Section 3 introduces PLEAD’s taxonomy for explanations and specifies its various dimensions and criteria. Section 4 then discusses the implications of the taxonomy and evaluates its application in an example of explanation requirements derived from the GDPR. Finally, Section 5 summarises the contribution of the taxonomy as a classifier of explanations and discusses its limitations.

2 Methodology

This taxonomy was built using the method by Nickerson, Varshney, and Muntermann (2013). At first, the goals of the taxonomy were set, as depicted in Table 1 ‘1. Meta-Characteristics’. The basis for the taxonomy is to classify the information necessary to meet the explanation requirements of law, policy and business needs. The taxonomy is expected to assist in creating compliant explanations by organisations or system vendors that are expected to meet explanation requirements.

Having set the characteristics of the taxonomy, a double approach was followed to build it. At first, in an empirical-to-conceptual approach, the process was grounded in specific use cases. This approach was intentionally selected because it allowed evaluating that the resulting taxonomy can successfully translate high level rules from law and policy to practical explanation requirements. Two use cases were the starting position: An automated credit scoring process factored in assessing loan applications in the finance sector; and, a semi-automated process of allocating school places to UK students in the annual school admissions rounds. The use cases were sampled to identify explanation requirements, which were then analysed to reveal common themes. The themes, or ‘bases’, of the explanation requirements were then grouped under headings
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| Methodology Components | Application |
|------------------------|-------------|
| 1. Meta-Characteristics | **Bases:** Information to meet the explanation requirements arising out of applicable regulatory obligations, business needs or other policies  |
|                        | **Expected User:** Organisations determining their processing methods / System vendors designing processing systems for third-parties |
|                        | **Expected Use:** The proactive production of explanations as part of a supportive automated compliance strategy and the design of ‘Explainable by Design’ systems |
|                        | **Purpose:** The categorisation of information to produce comprehensive explanations for the applicable explanation requirements of the Organisation |

2. Ending Conditions

**Objective Conditions:**
1. A representative sample of objects has been examined
2. No new dimensions or characteristics were added in the last iteration
3. No dimensions or characteristics were merged or split in the last iteration
4. Every dimension is unique and not repeated (i.e., there is no dimension duplication)
5. Every characteristic is unique within its dimension (i.e., there is no characteristic duplication within a dimension)

**Subjective Conditions:** Conciseness, Robustness, Comprehensiveness, Extensibility, and Explainability

3. Empirical to Conceptual Approach

3.1. The sampling of two practical use cases of (semi-)automated decision making (credit scoring and school allocations) and their applicable rules
3.2. The analysis and coding of ‘bases’ from the applicable rules using desk research
3.3. The categorisation of the ‘bases’ into characteristics and dimensions

4. Conceptual to Empirical Approach

4.1. The identification of explainability characteristics in the literature
4.2. Comparing the explainability characteristics to own analysis
4.3. The reorganisation of the Taxonomy taking into account the findings of step 4.2.

Table 1: Nickerson et al. (2013) methodology, as applied

which formed the taxonomy dimensions. Subsequently, in a conceptual-to-empirical approach, the characteristics and dimensions of the previous analysis were compared to explainability characteristics that have been identified in the literature. The findings were used to reorganise the taxonomy to ensure compatibility with literature analyses and to make it more concise.

These processes were followed iteratively, gradually adding new characteristics until both objective and subjective termination conditions were met. The objective conditions were fulfilled when new iterations no longer split or merged dimensions or characteristics; when each dimension was unique and did not repeat; and, when each characteristic was unique within a specific dimension. The subjective criteria were also met by the last iteration. The taxonomy dimensions were within the $7 \pm 2$ limit, as set by Miller (1956), therefore fulfilling the criterion of conciseness. Each of the dimensions points to the elementary characteristics that explanations must have in order to produce comprehensive individualised results, meeting the criterion of robustness to allow meaningful application and differentiation of the object under investigation. The comprehensiveness of the taxonomy, which verifies that all dimensions are included and that new objects can be classified, was tested through the production of examples based on the explanation requirements of the GDPR. The extensibility criterion is satisfied because the resulting taxonomy has been designed to be extensible and able to be combined with other taxonomies. Finally, the explainability criterion, which evaluates how well the dimensions
explain the object of the taxonomy, was met since the taxonomy combines the building blocks of an explanation with rules for its creation and delivery.

The explanation requirements of the GDPR were selected to evaluate the effectiveness of the taxonomy because of feasibility, relevance and popularity reasons. The explainability needs stemming from the GDPR were in both use cases the main drivers behind our partners' interest. Besides, the resulting explanations were certain to apply to most cases, since the GDPR has wide applicability where personal data are systematically processed.

3 Building a taxonomy for explanations

The overall goal of this taxonomy is to create a broad categorisation system that will allow us to address in a systematic way all the different aspects of explanations that were encountered within the scope of the PLEAD project, but the taxonomy itself can be extended to accommodate additional needs. Careful and systematic analysis of their characteristics is essential since a successful explanation must fulfil case-specific requirements, for example when it addresses a data subject as opposed to when it addresses a regulator. Even though the format of a taxonomy was selected, it can still be easily transformed into a light ontology which can be combined with other data models to assist in demonstrating compliance.

Our taxonomy follows a dimensional approach, where each dimension describes a different perspective in the creation of a comprehensive explanation. Where needed, the dimensions are themselves broken down into sub-properties to provide sufficient granularity. Each dimension corresponds to the root of a property. Each sub-property provides increasing details to the properties of its corresponding dimension. Sub-properties divided into further properties are depicted in green.

Fig. 2 shows the dimensions:

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10 See e.g. a legal ontology to express GDPR concepts in Palmirani, Martoni, Rossi, Bartolini, and Robaldo (2018); a semantic model for registers of processing activities in Ryan, Pandit, and Brennan (2020).
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Source defines the origin of the explanation requirement.
Perspective describes the time of generation in relation to a triggering event.
Autonomy distinguishes between explanations that are generated upfront and explanations that rely on input for the generation.
Trigger defines the events that trigger the generation of an explanation.
Content captures the details about the formulation of an explanation.
Scope assesses whether an explanation can be applied only to selected cases or has extended applicability.
Explainability goal defines the functioning purpose of the generated explanation.
Intended recipient defines the target audiences of the generated explanations.
Priority specifies whether the explanation is mandatory or discretionary.

The benefit of using the taxonomy is twofold: First and foremost, the taxonomy aims to assist in designing explanations that fully address each explanation requirement to which the implementing organisation is subject. Combining all applicable properties for a particular explanation requirement reveals the building blocks required to produce a comprehensive explanation. Secondly, the taxonomy allows for an effective organisation of explanation requirements. During the application of the taxonomy, an organisation may find that multiple explanation requirements correspond to the same combination of properties. These requirements can, therefore, be addressed by the same explanation(s), allowing the organisation to streamline their approach and reduce the overhead.

3.1 Source

The dimension Source defines the origin of the explanation requirement (Fig. 3). An explanation requirement may arise out of three main areas: (i) applicable laws; (ii) related authoritative guidance and standards devised by reputable expert groups and bodies; and, (iii) internal compliance functions.

Depending on the nature of processing, an explanation requirement might derive from law. We call these requirements, that may be set out in either legislation or case law (i.e. hard law instruments), primary requirements. The legal obligation might be explicit, binding the responsible entity to provide an explanation in relation to the processing. Such obligations arise from a

![Source Diagram]

Fig. 3: The Source dimension
multitude of legal areas, e.g. public administrative law, consumer law, data protection law. Non-compliance to explicit explanation requirements might result in severe consequences on occasion, such as reputational damage, fines and litigation. Therefore, there are strong incentives for responsible entities to attain compliance for explicit primary explanation requirements. In other circumstances, compliance with other obligations under applicable legal and governance frameworks may be facilitated by the generation of an explanation. In other words, the generation of an explanation would be seen as good practice for achieving compliance with such frameworks. In these cases, the regulatory requirement to provide an explanation is implicit.

**Primary explanation requirements**

**Explicit:** School admission authorities in the UK must explain the reasons behind the refusal of a school place to a child when informing the parent (applicant) of the decision, under paragraph 2.5 of Department of Education (2012).

**Implicit:** Data controllers, who must be able to demonstrate compliance under Article 5(2) of the GDPR, are under an implicit regulatory requirement to detect whether processing is performed according to internal policies, which may be achieved through the generation of explanations.

Because primary requirements for explanations derive from legal instruments, which tend to be high-level, the entities that are called to comply with explanation requirements might be left with a margin of appreciation on how best to comply – which can be substantial on occasion. The translation of high-level rules to practical implementation is assisted by sources of authoritative guidance and standards from reputable, expert groups and organisations, such as national supervisory authorities and (supra-)national standard bodies. These secondary explanation requirements help to better interpret primary requirements and, typically, go beyond minimum legal standards to achieve best practices.

**Secondary explanation requirements**

The Information Commissioner’s Office, the national supervisory authority for data protection in the UK, has released authoritative guidance on explaining AI decisions in practice, in collaboration with the Alan Turing Institute. Information Commissioner’s Office (2021b) provides different tasks that organisations need to consider when deciding how to explain their AI systems.

In practice, the need to remain compliant with applicable laws has led organisations to establish internal compliance functions. The complexity of these functions usually depends on the nature and size of the organisation. It is highly likely that as part of their internal function, organisation will establish their own internal requirements for explanations to address the day-to-day practicalities of generating legally-compliant explanations. Such tertiary requirements can be more granular than primary and secondary requirements, surpassing the minimum standards to e.g. enrich public perception or provide better customer service.
3.2 Perspective

The Perspective dimension describes the point of the generation of an explanation in relation to the event explained by the explanation (Fig. 4). An explanation can be generated either ex ante, i.e. before the event(s) explained within the explanation take place, or ex post, i.e. after the event(s) materialise.

3.3 Autonomy

The Autonomy dimension distinguishes between explanations that are generated without any input from the recipient or explanations that are generated only as a response to specific input from the recipient, depicted in Fig. 5. A Reactive explanation is responsive. Reactive explanations will typically be triggered by a direct request from an individual or organisation for information about a process, event or decision.

On the other hand, Proactive explanations anticipate the need of the intended recipient for an explanation. Proactive explanations will be triggered as soon as the processing, event, or (a part of the) decision-making process is fulfilled.
Proactive explanations

An individual receives an unexpected or undesired decision (e.g. a lower credit score than expected). The decision is accompanied by an explanation, providing the reasons this decision has been taken, the data sources that were taken under consideration during the decision-making process, a brief overview of the decision-making process and the possible effects the decision might have on the individual.

3.4 Trigger

The Trigger dimension (Fig. 6) explores the events that trigger the generation of an explanation. In reactive explanations, the triggering event will typically be an action performed by the recipient of the explanation. However, explanations can also be triggered without any input from the recipient of the explanation, like in the example of an automated decision above. Such triggering events can be the processing of data, i.e. as the input of a decision pipeline, or a decision, i.e. the output of a decision pipeline.

| Triggering conditions |
|-----------------------|
| **Action**: a request by a customer to switch telephone providers, triggering an explanation about the necessary time to fulfil the request. |
| **Processing**: the processing of personal data, triggering the production of explanations to the data subject(s) about the details of processing. |
| **Decision**: the rejection of a loan application, triggering the production of an explanation about the factors that disqualified the applicant. |

3.5 Content

The Content dimension (Fig. 7) aims to capture details about the formulation of the explanation. The Sensitivity sub-property defines the sensitivity of disclosure depending on the contents of the explanation. Aggregated values denotes explanations where personal data have been omitted or anonymised. Content classified under Aggregated values escapes the scope of data protection legislation. In contrast, explanations that contain personal or pseudonymised data will be classified under Identifiable data. The content of these explanations falls within the scope of data protection legislation and, as a result, their use will be subject to data protection obligations.

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Sensitivity

**Aggregated values:** An explanation providing information about the types of data that will be processed only contains the general categories of data that will be collected, i.e. 'location data', without containing actual values.

**Identifiable data:** An explanation about the data that has been processed after the exercise from a data subject of their right to access will contain all the personal data that have been processed by a particular organisation.

The Confidentiality sub-property marks explanations as **Disclosable** or **Confidential**. The purpose of the marker is to indicate whether an explanation can or should be disclosed to the public, as there might exist various restrictions depending on the specific circumstances, e.g. because of trade secrets or national security. The levels **Disclosable** and **Confidential** have been selected for simplicity, although further granularity is possible. The requirement **Disclosable** applies to all explanations that can be accessed by external actors and **Confidential** applies to all explanations for internal use only.

Confidentiality

**Disclosable explanation:** An explanation about a decision to reject an application for a loan because of a low credit score.

**Confidential explanation:** The weights that were used in the applicants’ data to calculate the specific credit score that led to the rejection of the application.

Minimum content denotes which types of information are necessary to comprehensively address the explanation requirement. It is obvious that the contents of this sub-property are not absolute to the system but rely on the specific purpose of the explanation requirement. As a result, no further breakdown into sub-properties is possible at a high-level. It is possible that, in applications of the taxonomy, it may make sense for the particularities of a specific scenario to create further categories, e.g. ‘personal data’ and ‘non-personal data’. However, this will be case specific and will not apply when the same taxonomy is applied to a scenario with different characteristics.

Explanations must contain information to cover all the necessary bases for the underlying obligation they intend to address. The necessary minimum content is determined by the legal source of the obligation for the explicit legally-grounded explanations. For implicit legally-grounded explanations the minimum content will be determined by the relevant business needs and best practices. However, the minimum content is in direct relation to the **Sensitivity** and **Confidentiality** sub-trees, and the implementing organisations might assign different minimum content depending on the settings of **Sensitivity** and **Confidentiality**. For example, an explanation containing intellectual property data classified as confidential might need to undergo processing to obfuscate the data in question before being disclosed to the public.

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11 For example, by breaking down access levels in an ISO:27001 inspired format to confidential for senior management access; restricted for access by most employees; internal for access by all employees; and public information where everyone has access. See ISO/IEC 27001:2013(E) (2013) for more details about the levels.
3.6 Scope

The Scope dimension (Fig. 8) assesses whether the explanation applies only to a particular case or whether it can be reused in different contexts. Local explanations are contingent on specific circumstances of the underlying processes. The conditions that determine or influences its generation are variable; as a result the explanation is context-specific and different scenarios would either not trigger the conditions for its generation or render the explanation meaningless. In contrast, a Universal explanation remains the same for any number of processes. Universal-ality can result either because the determining conditions between different processing scenarios remain the same, or because the different determining conditions result in explanations of similar content.

Minimum content

An organisation making automated decisions without human intervention about individuals under Article 22 of the GDPR must provide an explanation about the decision to the subject of the decision. According to (Information Commissioner’s Office, 2018, pp. 18–19) the explanation shall contain at minimum:

1. which information were taken into account;
2. the rationale behind the decision;
3. the key decision points that formed the basis for the decision;
4. any alternative decisions that were considered and why they were not preferred;
5. how to ask for a review;
6. how to make an appeal, and the available appeal grounds.

Fig. 8: The Scope dimension

Fig. 9: The Explainability goal dimension
3.7 Explainability goal

The Explainability goal dimension (Fig. 9) defines the functional purpose(s) that the generation of a particular explanation intends to achieve. The different goals aim to highlight that, contrary to what is often assumed, explanations are not uniform. The usefulness and meaningfulness of an explanation, i.e. its specific wording and format, will be intrinsically interlinked with the specific goal it pursues.

This dimension builds on the various goal frameworks that have been identified in the literature. Each individual explanation is required to meet one or more pre-determined explainability goals. The explainability goals relate either to the compliance or to the effectiveness (or both) of the explanation. To be compliant and effective, an explanation must enable the recipient to better understand a decision and/or a particular aspect of the decision-making process, and, where necessary to take action. So explainability goals can be divided into two families: Understandability goals and Intervenability goals. The two families reflect the main “cognitive effects” of explanations on recipients, outlined in Maybury (1992) and Chander and Srinivasan (2018).

Goals in the Understandability family (Fig. 10) aim at providing further knowledge for the entities, events, states and know-how involved in a process and to assist evaluating the performance of an explanation by educating about its design and building trust. Overall there are eleven goals that an explanation could belong to:

- **Accountability**, with information on the compliance of the processing;
- **Accuracy**, about the correctness and validity of data and processes;
- **Consequences**, about the possible impact on the recipient;
- **Data minimisation**, on the limitation of personal information;
- **Fairness**, about lawful processing and protection from abuse;
- **Information**, educating on who and how was involved in the process;
- **Reassurance**, showing that the systems are effectively monitored;
- **Satisfaction**, to increase the ease of usability or enjoyment;
- **Persuasiveness**, encouraging recipients to try a feature or option;
- **Transparency**, explaining how the system works;
- **Trust**, increasing recipients’ confidence in the system.

Goals in the Intervenability family (Fig. 11) target the possible actions for a recipient of an explanation, from regulatory-specific actions (e.g. allowing the data subjects of personal data processing to exercise their rights) to monitoring of the performance of the system (e.g. trouble-shooting). The Intervenability family comprises twelve goals:

- **Access**, on how the recipient can request access to their data;
- **Contesting a decision**, on how to challenge an undesirable decision;

12 Often referred to as ‘purposes of an explanation’ Information Commissioner’s Office (2021a), ‘goals’ Huynh, Stalla-Bourdillon, and Moreau (2019), or ‘aims’ Tintarev and Masthoff (2007).

13 Maybury identifies “entity knowledge”, “event and state knowledge” and “know-how knowledge” relating to understandability and “change beliefs/evoke action” relating to intervenability, whereas Chander and Srinivasan identify “education” and “trust” on the one hand and “design”, “action” and “trouble-shooting” on the other.
Efficiency, helping recipient to make decisions faster;
Erasure, explaining how recipients can request the deletion of their data;
Making a complaint, on the processes to formally lodge a complaint;
Modifying a behaviour, educating how different behaviours could result in alternative outcomes;
Human intervention, instructing how to request human review;
Portability, explaining the process to move data to a third party;
Rectification, on how to correct incorrect or incomplete information;
Further information, about how to enquire for more information;
Restriction, on how to request the restriction of processing;
Scrutability, allowing recipients to flag up errors.

Explainability goals aim to highlight the purpose of the generated explanation, so that its effectiveness and compliance can be assessed against the explainability requirements. An explanation may serve multiple goals at once. For example, an explanation about the use of automated decision-making aims at informing the recipient about the operation of the system (the Transparency goal) but also holding the decision-maker accountable (the Accountability goal). Explanations from different goals can also be combined together into larger explanatory statements: The explanation under Article 22 of the GDPR must explain the reasons and impact of an automated decision (Fairness, Transparency and Consequences goals), but can also provide instruction on how to request a
human review of the decision or appeal it (Human intervention and Making a complaint goals).

3.8 Intended recipient

![Intended recipient diagram]

The Intended recipient dimension defines the various categories of recipients for the generated explanations (Fig. 12). The target audience of an explanation is an integral part towards its comprehensiveness, as different groups will have diverse comprehension skills. The dimension makes a distinction between explanations targeting the public and explanations for internal consumption. Outward-facing explanations can target the public, supervisory authorities responsible to oversee the organisation’s processing or other third parties that interface with the organisation. Explanations can also be Internal-facing though, aiming to assist the employees of an organisation to monitor and troubleshoot the processes and their compliance with applicable rules. At first glance, four broad categories can be distinguished: Administrative staff in charge of monitoring internal compliance; business analysts responsible for the various business needs of the organisation; legal engineers who determine the primary and secondary requirements; and, data engineers who are responsible for the implementation and operation of the information systems. However, this dimension will be highly dependent on the nature of the implementing organisation. An organisation could assess that, e.g. based on its business needs, it will need to produce explanations for other stakeholders. The list of recipients should be expanded or reduced accordingly.
3.9 Priority

In practice, there are cases where an obligation to provide an explanation for an action or an omission will arise out of the rules that apply to the specific scenario. However, there are cases where an organisation will opine that providing an explanation will be of benefit and will choose to do so. The final dimension, Priority, depicted in Fig. 13, captures exactly this distinction between a mandatory and a discretionary explanation requirement.

An explanation requirement is Mandatory where an applicable law and/or a governance framework specify that there is an obligation to provide an explanation that will contain certain types of information. On the contrary, there is a Discretionary explanation requirement where it is not compulsory to generate an explanation to fulfil an obligation specified by legal and/or governance frameworks. These obligations may be fulfilled by other means, and explanations are performing a complimentary function in explaining these means, or they can be fulfilled by an array of means and the responsible organisation selects the explanations as suitable means to fulfil them.

**Different priority**

**Mandatory:** Under the School Admissions Appeal Code, admission authorities who inform parents of a decision to refuse their child a place at a school for which they have applied, they are obliged to include an explanation about the reasons for the refusal.

**Discretionary:** Under the GDPR, data controllers must take appropriate measures to provide data subjects with all information necessary to ensure fair and transparent processing. A data controller might include this information in its privacy policy that is publicly accessible. It can then also provide explanations about the details of processing directly to the data subject at the time of data collection.

4 Evaluation of the taxonomy and discussion

In this section, we apply the taxonomy to a sample of explanation requirements to demonstrate its value in eliciting components for targetted explanations. The sample is a sub-set of explanation requirements out of our work for the project PLEAD, and it derives from one of the case studies on an automated
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decision-making system for loan applications based on credit scoring. The examples shown here are primary requirements that arise out of the GDPR, as well as secondary requirements coming from relevant authoritative guidance for the finance industry.\textsuperscript{14}

We will focus on Article 22 of the GDPR on “Automated individual decision-making”. Article 22 imposes a prohibition of solely automated decision-making ingesting personal data of individuals if the decision produces legal or similarly significant effects for them. Exceptionally, solely automated decision-making can take place if

\emph{the data controller [implements] suitable measures to safeguard the data subject’s rights and freedoms and legitimate interests, at least the right to obtain human intervention on the part of the controller, to express his or her point of view and to contest the decision.}

Recital 71, which is not legally binding in itself but clarifies Article 22, imposes an additional obligation that suitable measures “should include specific information to the data subject and the right [...] to obtain an explanation of the decision reached”. Although some have argued that there is no explicit right to explanation because of its non-legally binding nature,\textsuperscript{15} the Courts use Recitals to interpret the provisions of the GDPR.\textsuperscript{16}

Analysing the formulation of the Article and the Recital, we can already begin to distinguish five separate explanation requirements. Organisations using solely automated decision-making to produce significant effects must:

1. provide information about the automated decision-making to the subjects of the decisions;
2. provide an explanation about the decision reached;
3. allow the subject of the decision to express their point of view;
4. provide a way for the subject of the decision to obtain human intervention;
and,
5. advise how they can challenge the decision.

Requirement 1. derives from Articles 13 & 14 on information to the data subjects and Article 15 about the right to data access. The information provided to the data subject, i.e. the future subject of the automated decision, must go beyond the mere existence of automated decision-making. Data controllers must also supply “meaningful information about the logic involved” as well as the “significance” and “envisaged consequences” of any automated decision.\textsuperscript{17}

Explaining how the automated decision-making system works and its consequences come on top of the obligation to provide information about the nature and purpose of processing, the identity of the data controller and the

\textsuperscript{14}arising out of the Information Commissioner’s guidance for the GDPR, for AI and for credit scoring.
\textsuperscript{15}See for example Wachter et al. (2017).
\textsuperscript{16}See the recent Rb. Amsterdam (2021) at para. 4.39 “In that case, the controller must still take appropriate measures, including at least the right to human intervention, the right of the data subject to make his point of view known and the right to challenge the decision (Article 22 (3) GDPR and recital 71 GDPR ).”
\textsuperscript{17}GDPR articles 13(2)(f), 14(2)(g) and 15(1)(h).
The GDPR stays silent as to the necessary components to make any information about the system “meaningful”, but it should be meaningful enough to facilitate the exercise of data subjects’ rights (Selbst & Powles, 2017). To further clarify how to explain a decision-making system and its produced explanations, one should look at the authoritative guidance published by national Data Protection Authorities and the advice of sector-specific groups. In Information Commissioner’s Office (2018), the UK Information Commissioner specifies additional requirements that are necessary to satisfy Article 22. The meaningful information about the logic must also include the types of information that will be used in making the decisions and the reasons that this information is relevant. In explaining a specific decision to a data subject, the organisation should explain how the decision was reached and the rationale behind it. To assist organisations in generating comprehensive explanations, the Information Commissioner recommends that they keep records of the key decision points, the verification methods of the result, the business rules that apply to the decision and whether any alternatives existed. If there were alternatives, organisations should record why they were not preferred over the outcome of the decision.

A form of explanation will also be required in order to facilitate a subject of an automated decision to exercise their rights. Article 22 requests clear communications of the right to review, human intervention, expression of objections, and contesting the decision. The Information Commissioner advises that it would make business sense to also provide an explanation at the point of delivery about how to request a review or appeal of the decision. Organisations will have to demonstrate that the review is carried out by a qualified reviewer who is authorised to assess the decision-making process. At the end of the review, they will have to issue a formal response explaining the outcome of the review process.

Overall, a systematic approach to Article 22 of the GDPR can be broken down into 19 explanation requirements. These have been classified in Table 2. The classification allows the identification of all necessary components to construct a targeted explanation for each of the 19 requirements. In addition, it assists in determining the relationship between the applicable requirements. For example, in this classification the explanation requirements from a primary and from a secondary source form ‘parent – child’ relationship. I.e., the impact of the decision on the recipients and the ways it might affect them aim to further clarify the parent requirement about the significance of the decision. This is specific to this use case, i.e. there will be cases where requirements from secondary or tertiary sources will not relate to a requirement from a primary source.

The taxonomy can form the basis for a proactive explainable-by-design system when coupled with a technology that can monitor the progress of processing operations within an organisation. In PLEAD, we used this taxonomy in a scenario of loan applications, to allow us to generate explanations based
| Source | Perspective | Autonomy | Decision | Action | Sensitivity | Confidence | Minimum content | Explainability goal | Intended recipient | Priority |
|--------|-------------|----------|----------|--------|------------|------------|-----------------|---------------------|---------------------|---------|
|        | Ex ante     | Ex post  | Reactive | Process | Aggregated | Identifiable data | Disclosable confidential | Understanding | Intervenability | Outward-facing | Inward-facing | Mandatory | Discretionary |
|        |             |          |          |         |            |             |                  | Transparency | Fairness |                    |                |            |              |            |

**Table 2:** Classification of explanation requirements from GDPR Article 22
| Source | Perspective | Autonomy | Trigger | Content | Minimum content | Explainability goal | Intended recipient | Priority | Mandatory | Discretionary |
|--------|-------------|----------|---------|---------|-----------------|---------------------|-------------------|----------|-----------|--------------|
| Verification of the results | Secondary | • | • | • | • | • | • | • | • | Data engineer | • |
| Why this decision was reached | Secondary | • | • | • | • | • | • | • | • | Data subject | • |
| Theromale behind the decision | Secondary | • | • | • | • | • | • | • | • | Data subject | • |
| Which business rules applied to the decision | Secondary | • | • | • | • | • | • | • | • | Administrator | Business analyst | • |
| Were there alternatives & why they weren’t preferred | Secondary | • | • | • | • | • | • | • | • | Administrator | Business analyst | • |

**Table 2**: Classification of explanation requirements from GDPR Article 22 (continued)
on the provenance of automated decisions. Provenance data models allow us to traverse and query audit trails of the processing, records that describe the people, institutions, entities, and activities involved in producing, influencing, or delivering the outcome of a processing operation (Moreau & Missier, 2013). Our classification of explanation requirements, of which the subset for Article 22 is presented here, formed the blueprint to design a provenance data model capable of inspecting the data flows within the loan application scenario and extracting the required provenance. In brief, the Minimum content dimension is translated into a provenance pattern that will retrieve the necessary data from the audit trail, while the intended recipient and explainability goal are used by a Natural Language Generation engine to construct the explanation after a linguistic syntax tree. The remaining dimensions determine the delivery rules that dictate when and to whom the explanation will be presented.

We will evaluate the contribution of the taxonomy when creating explanations for a credit application scenario. In the scenario, a prospective applicant, Alex, wishes to apply for a loan through the website of a bank, the Bank. The bank requests some information for the income and living habits of the applicant. It then uses this information together with a credit score for Alex, received by a collaborating credit reference agency – the CRA, to calculate the creditworthiness of Alex. If Alex’s creditworthiness is above a certain threshold the application is automatically approved. Below a certain threshold, the application is automatically rejected, whereas if it falls in between thresholds it is redirected to a manual assessment by an officer. Because the Bank uses solely automated decision-making for all applications that do not go to manual, Article 22 will apply. A system following Explainability-by-Design using the PLEAD taxonomy can construct explanations for the explanation requirements of Article 22 like the samples below, with the minimum content highlighted.

To provide information about automated decision-making before the processing (ex ante):

| R1: The existence of automated decision-making |
|-----------------------------------------------|
| E1: To be able to process applications quickly and accurately, the Bank uses a solely automated system. |

| R2: Meaningful information about the logic |
|------------------------------------------|

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19 The contribution of this provenance-based approach was acknowledged by the Information Commissioner in Information Commissioner’s Office (2021b).
20 The details about the technical design and implementation are beyond the scope of this paper. A thorough explanation of the technical steps can be found in Huynh et al. (2022).
E2.1: The system will screen your application based on the information you provide in the application form, information we hold on file about you and information we receive about you from our partner the CRA. Your information will be assessed against an affordability threshold, to determine whether you can satisfy the affordability criteria for your requested credit. If a decision is made, we will inform you about the relevant information that has impacted the outcome.

E2.2: The system is calculating the probability of meeting our affordability criteria based on information about your financial standing that you provide in your application, that we already hold on file about you, or that we receive from our partner the CRA.

You can experiment with how different financial information can impact our confidence that credit repayment is viable using the slider below.

| Projected loan variations for responsible lending |
|-----------------------------------------------|
| Annual Income: | £10,000.00 | £100,000.00 |
| Monthly instalment payment: | £100.00 | £50,000.00 |
| Previous Credit: | £100.00 | £50,000.00 |
| Permanent residency in the UK: | < 1 year | > 5+ years |
| APR: | Fixed | Variable |

For a requested credit amount £2,500.00 – £4,500.00 a fixed interest rate is projected to be 3.8%.

Note: This tool is provided for illustration purposes only and does not constitute a decision or a promise of a decision of an actual application.

R3: The types of information used in making the decisions

E3: The information that will be processed can be personal identifiers, such as name, date of birth, and current and previous addresses; information about your financial standing, such as the number of credit and current accounts you hold and their repayment histories, salary data or insolvency-related events; information about your credit rating, such as scores about your credit, your affordability, or the possibility of insolvency or fraud.

R4: Why this information is relevant

E4: The personal identifiers are used for matching, so that we know that any processed data are actually about you. Information about your finances and any produced scores are used to determine the likelihood that you will be able to repay your credit commitments.

R5: The significance of envisaged consequences

E5: The screening process will determine whether your application is successful.
R6: What the likely impact is going to be

R7: How it is going to affect the recipient

E6,7: If your application is successful, the Bank will sign a loan agreement with you and credit you a loan of the amount specified in your application. You will have to repay this loan following the repayment conditions agreed in the loan agreement. Following our screening, the Bank may consider that a loan of a different amount is financially viable to your specific circumstances. You will have the opportunity to accept or decline the Bank’s offer. The Bank will provide you with an explanation in case your application is unsuccessful, explaining the reasons why. You will have the chance to challenge that decision if you consider that your application was not processed correctly.

Note that the taxonomy can be used to create various types of explanations. For example, E2.2 uses a counterfactual explanation to illustrate the consequences of the underlying logic. Counterfactual explanations can demonstrate how different behaviour impacts the outcome of a process. However, their usefulness in placing the recipient in a position to challenge a financial decision that has already been made is limited, since one is unlikely to be able to alter their financial assets (e.g. their income) at will.

Information after a decision has been made (ex post) can be given to the subject of a decision by explanations like the following:

R1: How this decision was reached

E1: The Bank made this decision with an automated scoring system that takes into account the information provided in the borrower application as well as a credit score produced by credit referencing agency the CRA. You can access the personal data about you that were processed for this decision by following this link.

R2: Why this decision was reached

E2: We regret to inform you that the loan application (applications no/437) was declined. This is because of negative credit history.

R3: The rationale behind this decision

E3: The borrower credit score indicates the following negative information. The late payment (records/70551), late payment (records/70552) and late payment (records/70553). The assessment indicated that the commitment of the credit agreement would have an adverse impact on the borrower financial situation. Hence the company decision (applications no/437/decision) is to refuse the borrower application.

R4: How to exercise data subject rights

Continued on next page...
To assist the Bank’s staff in monitoring and reviewing the decision-making process:

### R1: Key decision points

E1: The applicant credit score is below the acceptance threshold of 750. The applicant credit score was impacted by late payment (records/70552), missed payment (records/70553) and late payment (records/70551). The source of this information was credit history report credit history/437 provided by credit agency 3.

### R2: Verification of the results

E2: Identity matching was performed using electoral register data received on 2021-01-03T02:00:00. The credit report and credit score from CRA were calculated on 2020-10-03T04:00:00. Late payment (records/70552) of 2020-10-01T01:00:00 was matched to late payment in credit report credit history/437.

### R3: Which business rules applied to the decision

E3: The threshold of acceptance for credit product/322 is 750. The decision was balanced against the FCA rule about the Bank’s commitment to responsible lending. The decision took into account the protection of characteristics under the Equality Act 2010.

### R4: Were there alternatives & why they weren’t preferred

E4: To overturn the decision a score above 750 was necessary. The current score of 715 could justify a loan of up to €10,000 with a fixed interest rate of 3/1 with an initial APR of 3.7%. This option was rejected because the amount surpasses the acceptable difference of ±20%.

### R5: Review is carried out by qualified & authorised reviewer

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5 Conclusions, limitations and future steps

In this paper, we presented a taxonomy to classify explanation requirements. The taxonomy comprises nine dimensions, with each dimension containing necessary elements for the generation of an explanation to address the explanation requirement in question. This taxonomy is the product of conceptual and empirical research and has been tested on real-world practical use cases.

We detailed, in Section 3, the components of the taxonomy and provided examples of how these components would apply to different elements of explanation requirements. The classification of explanation requirements’ elements will assist implementing organisations in identifying their explanation obligations and as part of PLEAD’s Explainability-by-Design methodology it can result in a supportive automated compliance strategy. The taxonomy, however, has value even as a stand-alone in designing systematic explanation generation. This was demonstrated by an example application.

We used as an example an explanation requirement derived from Article 22 of the GDPR to demonstrate how to apply the taxonomy to derive meaningful explanations. As shown in Section 4, meaningfulness is a concept assessed on a case by case basis, and it will rely on a combination of the Content, Explainability goal and Intended recipient dimensions. In our example, we have demonstrated how to construct explanations that enable the recipient of a financial decision to understand it and take action, and the officers of the financial institution to verify its accuracy and collect compliance evidence for their supervisory authority.

We have also developed a light vocabulary based on the taxonomy, included here in the appendix. The light vocabulary provides a machine-readable format of classifying explanation requirements. It can be combined, alongside PLEAD’s Explainability-by-Design methodology or on its own, with existing compliance or auditing ontologies, such as for example the consent ontology developed by Pandit, Debruyne, O’Sullivan, and Lewis (2019).

Some limitations of the taxonomy should be noted though. The purpose of the taxonomy is to classify explanation requirements that apply to particular operations of an organisation. As a result, the quality of the classification will at large depend on the thorough analysis of the data governance framework applicable to the operation(s) in question. In other words, the taxonomy is not exempt from information quality challenges and a rich input will be required to provide actionable output (Solano, 2019). In the case of the taxonomy the information quality will relate to knowledge of applicable rules, albeit legal frameworks, policies, codes of conduct or business needs. When the taxonomy
is used as part of a holistic Explainability-by-Design methodology, information quality will also extend to data quality of the decision-making pipelines.

Further, the taxonomy and the Explainability-by-Design methodology rely on the applicable policies to determine when disclosures are permissible or desirable. The taxonomy allows an implementer to mark explanations as confidential, so they can be filtered by the system. However, the distinction of when an explanation can or should be disclosed to the public is a decision for the implementer, based on the applicable policies. There are cases, for example, where certain information should not be disclosed, for example because of intellectual property or trade secret considerations. In fact, in the example analysed in Section 4 the GDPR allows data controllers to balance the amount of information they will disclose to individuals against their commercial interests.

It should be noted that the evaluation of this taxonomy and the produced classification was based on the limited user studies run in the context of the PLEAD project. The user studies, with participants from the industry partners of the project, confirmed the suitability and effectiveness of PLEAD generated explanations in the domains of the finance industry and e-governance for education. Although the taxonomy has been designed to be domain-agnostic, additional evaluations tests in different settings may uncover that improvements are needed to fully cover specific domains.

Finally, a known limitation of our approach in PLEAD is that the algorithmic processing inside the ‘black-box’ remains. This is intended functionality. PLEAD does not attempt to open the ‘black-box’ and, in fact, one of its aims is to demonstrate how to generate meaningful explanations without a need to unravel the processes of AI and Machine Learning (ML) models. Although this approach should not preclude organisations from providing meaningful explanations to individuals, there are cases where it would make sense to include details about the processing inside the ‘black-box’. These could be cases, for example, for data engineers to troubleshoot the output of a model, or for discovering biases in ML-based processing. In such cases, it should be possible to combine PLEAD’s Explainability-by-Design approach with existing explanation techniques of ML models. In fact, our plan for future research includes incorporating the output produced by LIME\textsuperscript{22} or SHAP\textsuperscript{23} into the Content dimension of the taxonomy to test explanations that also address questions of interpretability of the algorithmic processing.

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\textsuperscript{21} See GDPR Article 15(4).
\textsuperscript{22} See Ribeiro, Singh, and Guestrin (2016).
\textsuperscript{23} See Nohara, Matsumoto, Soejima, and Nakashima (2019).
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The PLEAD Explainability-by-Design Taxonomy is encoded as a lightweight vocabulary encoded as an OWL2 ontology. Its namespace is https://openprovenance.org/ns/plead.

It is designed to be as simple as possible, consisting of 10 top-level classes and 9 object properties. The 10 classes model the concept of Explanation and its associated 9 dimensions (Fig. 14). The 9 object properties have Explanation as their domain and the corresponding dimension class as their range (Fig. 15).

An instance of explanation (such as Existence of automated decision-making in Table 2) can be expressed as set of RDF statements, as in Listing 1.
Listing 1: Explanation instance in RDF

```turtle
# https://openprovenance.org/ns/plead#xplain1
plead:xplain1 rdf:type owl:NamedIndividual ,
    plead:ExistenceAutomatedDecisionMaking ;
    plead:hasAutonomy plead:proactive ;
    plead:hasContent plead:aggregated ,
        plead:disclosable ,
        plead:minimum1 ;
    plead:hasGoal plead:fairness1 ,
        plead:information1 ,
        plead:transparency1 ;
    plead:hasIntendedRecipient plead:consumer1 ;
    plead:hasPerspective plead:ex_ante ;
    plead:hasPriority plead:mandatory ;
    plead:hasScope plead:universal ;
    plead:hasSource plead:implicit_art_22 ;
    plead:hasTrigger plead:loan_application ;
    plead:example "To be able to process applications quickly and accurately, the Bank uses an automated system." .
```