Application-Oriented Selection of Privacy Enhancing Technologies*

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Abstract. To create privacy-friendly software designs, architects need comprehensive knowledge of existing privacy-enhancing technologies (PETs) and their properties. Existing works that systemize PETs, however, are outdated or focus on comparison criteria rather than providing guidance for their practical selection. In this short paper we present an enhanced classification of PETs that is more application-oriented than previous proposals. It integrates existing criteria like the privacy protection goal, and also considers practical criteria like the functional context, a technology’s maturity, and its impact on various non-functional requirements. We expect that our classification simplifies the selection of PETs for experts and non-experts.

Keywords: Privacy Engineering · Privacy Enhancing Technologies · Privacy By Design.

1 Introduction

A decisive activity in privacy engineering is the selection of appropriate Privacy Enhancing Technologies (PETs), for example to fulfill requirements or mitigate risks in goal-based or risk-based engineering methods respectively. While this step is highly application-specific, it can be approached systematically, since common decision criteria for PET-selection exist. For example, one criterion that can guide engineers in their design decisions is the privacy goal that is targeted by a PET, such as anonymity or undetectability.

Existing works have proposed different systematizations of PETs in the past. The LINDDUN methodology [11], for instance, categorizes PETs using their privacy protection goal, and differentiates between PETs that target transactional and contextual data [11]. Heurix et al. [22] categorize PETs, e.g., regarding the trust scenario they target and their involvement of a trusted third party. Yet, these systematizations do not sufficiently take into account the practical context in which PETs are selected: they often omit the PET’s functional context it can be applied in, as well as other practical criteria. Also, they are partly outdated.

In this short paper, we develop a new PET classification that is more application-oriented. Our classification builds upon previous proposals, integrating some of

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their criteria like the technology’s targeted privacy protection goal and its impact on other non-functional requirements. It furthermore includes the PET’s functional context, as well as prioritization criteria, like the maturity of the technology. We present a classification of 30 PETs that we have done according to the proposed criteria.

To demonstrate the effectiveness of our classification, we compare it to the one proposed by LINDDUN based on a use case. We expect that our work can support engineers in selecting appropriate PETs, and motivate PET developers to evaluate their technologies according to our criteria, making them more comparable and usable for architects and engineers.

2 Classification

Various approaches to selecting appropriate PETs have been proposed in the past, but the adequate application of PETs can be even more challenging than their selection, for example due to the development effort involved in applying a PET in a certain environment. Our goal is therefore to develop an application-centered classification of PETs that anticipates the challenges that a PET can cause when it is applied. In the following, we describe and motivate the criteria we have included in our classification.

2.1 Motivating Example

To motivate the choice of criteria, we lay out the following scenario of an engineer developing an architecture for a generic privacy-friendly cloud service, assuming that it is representative for the decisions architects and developers have to make when implementing privacy requirements. This generic service allows users to register, authenticate, provide personal data to the service (e.g. names, addresses), interact with other users of the service (e.g. sending messages), and to retrieve data that is stored in the service’s storages.

An engineer creates a threat model for an initial design of the service which reveals a detectability threat for the service’s users: since their messages to other users are observable by the service and possibly external attackers, their relationships can be identified. A requirement is therefore elicited which states that users’ messages should be undetectable. A PET that mitigates this threat has to match several criteria:

First, it has to fit the functional context of the service. This includes the targeted privacy protection goal, such as anonymity or undetectability. To ensure suitability for the scenario, however, the targeted privacy protection goal is not sufficient; also, the PET has to fit the functional requirements of the application. In a messaging scenario, for example, different PETs are applicable than in an information retrieval or computing scenario. Ideally, the PET should furthermore not only target the correct privacy goal, but should also be measurable in the achieved privacy gain. This way, a more comparable and reproducible selection is facilitated.
Second, various non-functional properties can play a role. For example, the PET should be mature enough to be applied and maintained by the development team: applying a certain technology can otherwise imply large efforts for configuration and further development of the technology. To be able to weigh different usable PETs against each other, also further properties are of interest: PETs can have an impact on the overall architecture, on the utility of transactional data, and the performance of the respective interaction.

In the following we describe the criteria we use to cover these considerations, and classify a list of PETs accordingly.

2.2 Criteria

Privacy Protection Goal One of the most meaningful criteria for selection is the targeted privacy protection goal. To that end we use the goals proposed by the LINDDUN methodology [11], most of which have originally been proposed by Pfitzmann and Hansen [32]: Unlinkability, anonymity, plausible deniability, undetectability, confidentiality, awareness, and policy compliance.

Every PET targets one or more of these goals. Often, it is the case that several goals are targeted by one PET, since they partly overlap or imply each other. For example, it is hardly possible to achieve undetectability without anonymity. In our classification, however, we usually only present one privacy protection goal which we consider to be primarily targeted.

Privacy Metric A technology’s suitability and effectiveness need to be measurable to evaluate its added privacy gain and monitor the system over time. Note that the broader problem of creating a metric suite that comprehensively covers the notion of privacy is a research problem out of scope for this paper (see for example Wagner and Yevseyeva [43]). A number of privacy metrics are reviewed in [42].

Functional Scenario The functional context the PET shall be applied in is highly application-specific. Still, some categories of functional scenarios can be identified and can be used as a selection filter. We identify the following generic interactions: Computation, Messaging, Retrieval, Release, Authentication, as well as Authorization. We use the motivating scenario above to clarify these values: a computation means that data is processed, e.g. a virtual machine processes user data to create recommendations for users; Release is the release of data to another party, e.g. a user sends location data to the social network; Messaging, is a point-to-point interaction between two users via n other parties, e.g. two users of the same social network communicate with each other via the service; Authentication is the process of determining the identity of a user, while Authorization is the process of determining the rights of an identified user.

Maturity When selecting a PET, cost factors play an important role, e.g. in the set-up of the PET and in its continuous maintenance. In this paper we use the
technology’s maturity as an indicator for set-up and maintenance costs, since a technology that is less mature will likely have more defects and will likely imply a more laborious set-up.

For this criterion we loosely base the possible values on the Technology Readiness Level (TRL) which describes a technology’s maturity on a scale from 1 to 9. We generalize this scale to 3 levels as follows: level 1 is a level often achieved in scientific work, which describes a concept and may already prove feasibility in a proof of concept; level 2 can be seen as the development and testing stage, i.e. adopting such a technology still would require considerable development effort if it is applied to a specific use case; finally, level 3 means that the technology is readily available and field-tested, but may still require some set-up cost for the adaption.

**Performance Impact** The performance of processes and interactions can be impacted by the use of PETs. Evaluating the performance of a certain PET, however, is not trivial, especially in comparison to other technologies. Therefore evaluate a PET’s performance in a simplified manner as follows. We first generically describe the performance requirements in a certain functional scenario, and then assess if the use of a PET is expected to significantly impact the performance requirements or not.

We consider Computation and Retrieval scenarios generally to have high performance requirements: In these scenarios the user waits for the result of the interaction and will probably notice also small delays. In contrast, Authentication, Authorization, and Release scenarios generally have low performance requirements since they are usually one-time actions for which performance impacts are more acceptable. Also, we consider Messaging to be a scenario of asynchronous communication where small increases in latency are not noticed by the users.

**Architectural Impact** An impact on the architecture is given if the PET requires a dedicated architectural component or modifications to the architecture, e.g. setting up a mix net requires a separate mix server. This is an important selection criterion, since the selection of a PET with this property needs to be considered early on in the design process.

**Utility** A utility impact is given if a PET reduces the quality of transactional data, e.g. by distorting or filtering it—and thus decreasing the data’s utility.

### 2.3 Classifying PETs

Table 1 shows our classification proposal according to the criteria defined above. Note that our classification only includes the so-called hard privacy goals, i.e. Anonymity, Unlinkability, Plausible Deniability, and Undetectability. The soft
Table 1. Classification of Privacy Enhancing Technologies. A black square indicates that the PET addresses the respective goal, while a triangle indicates a negative impact on the respective criterion.

| Name                                | Linkability | Identifiability | Non-Repudiation | Disclosure | Unawareness | Non-Compliance | Metrics | Functional Scenario | Maturity | Performance | Utility |
|-------------------------------------|-------------|-----------------|-----------------|------------|-------------|----------------|---------|---------------------|----------|-------------|---------|
| k-anonymity, l-diversity, t-closeness | ■           | ■               | ■               | ■          | ■           | ■              | Release | 3 [35]              | ▼        |             |         |
| Suppression                         | ■           | ■               | ■               | ■          | ■           | ■              | Data similarity | Release | 3 [35]              | ▼        |             |         |
| Recoding                            | ■           | ■               | ■               | ■          | ■           | ■              | Data similarity | Release | 3 [35]              | ▼        |             |         |
| Aggregation                         | ■           | ■               | ■               | ■          | ■           | ■              | Data similarity | Release | 3 [35]              | ▼        |             |         |
| Swapping                            | ■           | ■               | ■               | ■          | ■           | ■              | Data similarity | Release | 3 [35]              | ▼        |             |         |
| Noise masking                       | ■           | ■               | ■               | ■          | ■           | ■              | Data similarity | Release | 3 [35]              | ▼        |             |         |
| PRAM                                | ■           | ■               | ■               | ■          | ■           | ■              | Data similarity | Release | 3 [35]              | ▼        |             |         |
| Synthetic data                      | ■           | ■               | ■               | ■          | ■           | ■              | Data similarity | Release | 3 [35]              | ▼        |             |         |
| Mix Network                         | ■           | ■               | ■               | ■          | ■           | ■              | Message          | Release | 3 [35]              | ▼        |             |         |
| Group Signatures                    | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Release | 3 [35]              | ▼        |             |         |
| Anonymous Credentials               | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | AuthN   | 2 [5]                  |         |             |         |
| Zero Knowledge Proofs               | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | AuthN, AuthZ | 2 [5]              | ▼        |             |         |
| Pseudonymization                    | ■           | ■               | ■               | ■          | ■           | ■              | Entropy           | AuthN, Release | 3 [13]              |         |             |         |
| Deniable Authentication             | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Messaging | 3 [17]              |         |             |         |
| Deniable encryption                 | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Messaging | 3 [17]              |         |             |         |
| Searchable Encryption               | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Retrieval | 3 [6]                  |         |             |         |
| Private Information Retrieval       | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Retrieval | 2 [25]              | ▼        |             |         |
| Oblivious Transfer                  | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Retrieval | 2 [7]                  | ▼        |             |         |
| Proxy Re-Encryption                 | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Messaging | 2 [16]              | ▼        |             |         |
| Homomorphic Encryption              | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Computation | 2 [15]              | ▼        |             |         |
| Trusted Execution Environment       | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Computation | 3 [39]              | ▼        |             |         |
| (A)Symmetric Encryption             | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Messaging, Release | 3 [3]                  |         |             |         |
| Dummy traffic                       | ■           | ■               | ■               | ■          | ■           | ■              | Data similarity | Messaging | 2 [9]                  |         |             |         |
| Steganography                       | ■           | ■               | ■               | ■          | ■           | ■              | Entropy           | Messaging | 2 [9]                  |         |             |         |
| MPC                                 | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | Computation | 3 [4]                  | ▼        |             |         |
| Local Differential Privacy          | ■           | ■               | ■               | ■          | ■           | ■              | Indistinguishability | Release | 2 [11]              | ▼        |             |         |
| Global Differential Privacy         | ■           | ■               | ■               | ■          | ■           | ■              | Indistinguishability | Release | 2 [11]              | ▼        |             |         |
| Attribute-based encr.               | ■           | ■               | ■               | ■          | ■           | ■              | Cryptographic Games | AuthN, AuthZ | 2 [39]              |         |             |         |
| Federated Learning                  | ■           | ■               | ■               | ■          | ■           | ■              | Attacker Success Probability | Release | 2 [37]              | ▼        |             |         |
privacy goals. Awareness and Policy Compliance are usually targeted by more generic design patterns (see e.g. [1]). There can, however, be overlaps between technologies and patterns: For instance, onion routing can be seen both as a design pattern and a PET.

Note that regarding the targeted privacy protection goal, we always assign the goal that is targeted primarily. For example, Zero Knowledge Proofs (ZKP) primarily address the threats linkability and identifiability. While they could theoretically also be used to secretly release information, an engineer would not choose ZKP to achieve confidentiality.

Note also that throughout the paper, we use $k$-anonymity [36] as a placeholder also for other related ones like $l$-diversity [29], $t$-closeness [27], etc.

3 Use Case and Discussion

3.1 Use Case

In this section, we compare our classification to the LINDDUN classification which was first proposed by Deng et al. [11] and has since been updated on the LINDDUN website [44]. Note that the LINDDUN classification also includes a selection methodology. This methodology is based on the LINDDUN threat types which are connected to general mitigation strategies. These strategies in turn are mapped to applicable PETs. For instance, a linkability threat concerning a data flow may be mapped to the mitigation strategy protect transactional data which in turn yields the PETs multi-party computation, encryption, and others.

We use again the motivating example introduced earlier, and extend and detail it as follows: our example cloud service is a social network that allows to add friends, exchange private messages with each other, as well as make public posts. Furthermore, the service offers a location-based feature where users can provide their location data and are then offered possible contacts in their proximity they can message. Note that the example used in the original LINDDUN approach is a social network application as well, making it a well-suited basis for a comparison.

We use three example threats from different LINDDUN categories, i.e. a linkability, an identifiability, and a disclosure threat, to demonstrate the effectiveness of our classification in comparison to the LINDDUN classification. Note that these threats have also been identified (on a more high level) in an example analysis conducted by the LINDDUN authors for their social network running example, see [10]. The threats and results from the PET-selection of both approaches are described in the following. Table 2 summarizes the results.

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1 As soft privacy goals, some works also use the goals Intervenability and Transparency [21].
2 Note that we do not compare our approach to Heurix et al. [22], since they partly use different privacy protection goals and generally provide few selection criteria.
**Identifiability** This threat describes the possibility that the server can identify the user via the transmitted transactional data, e.g. due to identifiers like name or address.

- Applying LINDDUN in this scenario we obtain 7 PETs. With our classification we obtain: Suppression, Recoding, Aggregation, Swapping, Noise Masking, PRAM, Synthetic Data, Mix Network, Group Signatures, Global Differential Privacy.
- This is the only case in which our classification outputs more PETs than the LINDDUN methodology.

**Linkability** This threat concerns potential linkability of different types of transactional data which is released by the user to the server. Applying the LINDDUN method results in a set of 10 PETs as summarized in Table 2. In comparison we can see that our classification correctly omits several PETs since they are not usable to mitigate a linkability threat, i.e. Multi-Party Computation, (A)Symmetric Encryption, and Homomorphic Encryption. Furthermore, it does provide more applicable ones, e.g. Aggregation and Noise Masking which can obfuscate the relation between data.

**Disclosure** This threat concerns the disclosure of transmitted data due to insecure connections. Applying the LINDDUN method results in a set of 12 PETs, see Table 2. Our approach results in 4 PETs: Proxy Re-Encryption, Deniable Encryption, (A)symmetric Encryption, and Steganography.

- On the basis of this comparison, we expect that our classification better supports engineers in the selection of PETs than existing classifications and selection approaches.
- This is achieved mainly by filtering through the functional scenario, but also the more targeted mapping of PETs to protection goals.
- Consider also that using our classification, a user can further prioritize the results using the maturity, utility, and architecture impact criteria. For example, the (a)symmetric encryption may be prioritized in the last example because it has high maturity and no impact on architecture or utility.

### 3.2 Discussion

**Limitations** One limitation of our approach is its coverage: while it is an extensive collection of 32 PETs, it is not complete and should be extended and maintained in the future. Especially the evaluation of the maturity criterion may become outdated soon, e.g. if current research proposals are developed further.

Furthermore, the criteria we propose are deduced from a use case. Therefore, their effectiveness still has to be validated in real-world studies. Some relevant criteria, e.g. regarding other non-functional requirements, could also be missing.
Table 2. Comparison of the results of applying the LINDDUN PET Selection method and our classification. Those PETs that are included in both classifications are written in bold. For example, for the linkability threat LINDDUN suggests Multi-Party Computation as a possible mitigation. This PET is also included in our classification, which, however, has not suggested it for this threat. Verifiable Encryption is also suggested by LINDDUN, but it has not been considered in our classification at all.

| Threat          | LINDDUN Result                                                                 | Our Classification                                      |
|-----------------|--------------------------------------------------------------------------------|----------------------------------------------------------|
| Linkability     | **k-anonymity**<br>Multi-Party Computation<br>(A)symmetric encryption<br>Homomorphic Encryption<br>Deniable Encryption<br>Anonymous Buyerseller Watermarking Prot.<br>Verifiable Encryption | **k-anonymity and l-diversity**<br>Recoding<br>Aggregation<br>Swapping<br>Noise Masking<br>PRAM<br>Synthetic Data<br>Group Signatures<br>Global Differential privacy |
| Disclosure (Release) | **k-Anonymity**<br>(A)symmetric Encryption<br>Homomorphic Encryption<br>Private Information Retrieval<br>Oblivious Transfer<br>Searchable Encryption<br>Deniable Encryption<br>Verifiable Encryption<br>Context-Based Access Control<br>Privacy-Aware Access Control<br>Privacy-Preserving Data Mining<br>Private Search | **(A)Symmetric Encryption**<br>Federated Learning |
| Disclosure (Computation) | **Homomorphic Encryption**<br>k-Anonymity<br>(A)symmetric Encryption<br>Private Information Retrieval<br>Oblivious Transfer<br>Searchable Encryption<br>Deniable Encryption<br>Verifiable Encryption<br>Context-Based Access Control<br>Privacy-Aware Access Control<br>Privacy-Preserving Data Mining<br>Private Search | **Homomorphic encryption**<br>Multi-Party Computation<br>Trusted Execution Environment |
| Identifiability (Release) | **Multi-Party Computation**<br>(A)symmetric encryption<br>Homomorphic encryption<br>Deniable Encryption<br>Anonymous Buyerseller Watermarking Prot.<br>Verifiable Encryption | **k-anonymity and l-diversity**<br>Suppression<br>Pseudonymization<br>Group Signatures<br>Global Differential Privacy |
Still, we expect our classification to improve the systematic selection of PETs, and the evaluation of software architectures. For instance, design decisions in software architectures can be linked to our classifications and systematically evaluated.

Our classification could be biased since the use case and the threats the LINDDUN analysis identifies were known to the authors before the classification was finished. We assume, however, that the bias is low since it was developed in discussion with multiple domain experts who did not know the LINDDUN analysis. Also, we would argue that it is evident from that both the general criteria as well as the classification itself are independently applicable from the social network example.

**Criteria** Evidently, it is not guaranteed that the criteria we propose are comprehensive and that they capture what engineers require as selection criteria in practice. On the basis of the case example above, however, we expect that it works better than existing approaches also in other applications.

In comparison to Al-Momani et al. [1], we do not include criteria that indicate an impact on security and complexity, because we would argue that they are redundant. Complexity is always increased by a PET to some degree, while the actual degree of complexity is too difficult to measure. With regards to the security impact, there is one privacy protection goal that directly contradicts a security goal, i.e. plausible deniability contradicts non-repudiation. Thus, any PET that targets plausible deniability also counteracts said security goal which can therefore directly be derived from our classification.

In the following we also compare our criteria with Heurix et al. [22]:

- The **Aim** dimension is similar to our privacy protection goal.
- The **Scenario** dimension is not in scope for us, since we focus on client-server interactions where the server is untrusted.
- The **Aspect** dimension is similar to the mitigation strategies in the LINDDUN method [44]. We do not consider these because they are implied in the functional scenario: for instance, a PET that targets the authentication scenario addresses protection of ID.
- The **Foundation** and **Data** dimensions not relevant for the selection in practice.
- The **Trusted Third Party** dimension is covered by our criterion of architectural impact.
- The **Reversibility** dimension is largely the same criterion as our utility criterion, since the distortion or deletion of a value is usually non-reversible.

Furthermore, previous selection methodologies do not provide means for prioritizing PETs [11,26]. In a set of potentially applicable PETs, however, we would argue it is important to have prioritization factors, such as their maturity, as we propose in this paper.
4 Related Work

4.1 Privacy By Design

Generally, our classification can be seen as a tool that supports privacy by design. As such, it is complementary to other privacy engineering methods which often assume a PET-selection without further detailing this step [19, 20, 35]. One such approach is proposed by Alshammari and Simpson [2] who develop an engineering process that devises architectural strategies, i.e. combinations of tactics, patterns, and PETs, to fulfill privacy goals. In their approach, the set of usable PETs is determined by the chosen design pattern. The concrete selection of a PET, however, is not specified in their work. As such, our classification could be integrated into their methodology.

4.2 Systematization of PETs

Also, further works have investigated the selection and systematization of PETs. Al-Momani et al. [1] follow a similar approach as we do but focus on privacy patterns rather than concrete technologies. As explained above, patterns rather target soft privacy goals. They use the following criteria to classify patterns: applicability scope, privacy objective, qualities (e.g. performance impact), data focus, and LINDDUN GO hotspot. In this paper, we have partly used similar criteria; many criteria, however, are different since the selection of concrete technologies requires other selection criteria than patterns, e.g. maturity. Note also, that our classification of the targeted privacy objective (called privacy goal in this paper) differs in some cases from theirs. Kunz et al. [26] also propose a selection method for PETs but their approach is limited to PETs that manipulate transactional data, e.g. generalization or filter. A systematization of PETs is proposed by Heurix et al. [22]. They identify the dimensions Scenario, Aspect, Aim, Foundation, Data, trusted third party, and Reversibility. We would argue, however, that these dimensions are not directly helpful for engineers who have to select a concrete PET. Rubio et al. [34] review 10 PETs regarding their efficiency for smart grids. Since their analysis is focused on smart grids, they also use respective classification criteria, like suitability for billing or monitoring purposes. Their work is thus complementary to ours since we do not include smart grids as a functional scenario.

ENISA has previously promoted a prototype of a PET maturity repository [13]; to the best of the authors’ knowledge, however, ENISA has not continued this repository.

There is furthermore an ENISA publication about Privacy and Data Protection by Design which classifies PETs into several categories which, however, are not intended as selection criteria [12].

Another recent ENISA publication [15] proposes a categorization of PETs regarding the categories truth-preserving, intelligibility-preserving, and operable technology.
5 Conclusions

The selection of privacy-enhancing technologies is a task that is difficult to address systematically. In this paper we have proposed application-oriented criteria that allow such a systematic selection, and have classified a number of PETs according to these criteria, e.g., their functional scenario and applicable metrics.

One open issue is the performance evaluation of PETs, since their performances are usually not easily comparable. In future work, we therefore plan to propose an evaluation framework for the measurement of the performance of PETs. We also want to extend our classification with more PETs, and connect them with other concepts, such as design patterns. Unifying these, e.g., a comprehensive ontological description of privacy concepts may represent a valuable support tool for engineers. Furthermore, existing threat modeling tools can be extended with suggestions for mitigation based on our classification. Future work also needs to show the effectiveness of the proposed classification in real-world applications.

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