Exploring privacy-enhancing technologies in the automotive value chain

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Abstract—Privacy-enhancing technologies (PETs) are becoming increasingly crucial for addressing customer needs, security, privacy (e.g., enhancing anonymity and confidentiality), and regulatory requirements. However, applying PETs in organizations requires a precise understanding of use cases, technologies, and limitations. This paper investigates several industrial use cases, their characteristics, and the potential applicability of PETs to these. We conduct expert interviews to identify and classify uses cases, a gray literature review of relevant open-source PET tools, and discuss how the use case characteristics can be addressed using PETs' capabilities. While we focus mainly on automotive use cases, the results also apply to other use case domains.

Index Terms—Privacy-enhancing technologies (PETs), anonymization, confidentiality, automotive, applications

I. INTRODUCTION

Data, analytics, and artificial intelligence (AI) are playing an increasingly important role across the automotive value chain [1]–[4]. The capabilities of AI are catalyzed by the growing deployment and use of Internet-of-Things devices [5]. However, as the number of applications grows, the need to utilize advanced privacy-enhancing technologies (PETs) to improve data privacy, security, trust, and regulatory compliance (e. g., the European General Data Protection Regulation (GDPR [6] and the Consumer Privacy Act), is increasing [7]. Thus, PETs must and will become a foundational pillar of modern data platforms [8].

In addition to mitigating privacy, reputational and financial risks [9], [10], the usage of PETs has many benefits for institutions: a careful deployment of PETs may *increase* not only trust but also data usage and collection as PETs help to overcome customer concerns [11]. By doing so, PETs can accelerate existing processes and enable new business

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models [12], [13]. An example is the ability to support crossorganizational collaboration and data exchanges using PETs that provide the necessary trust and security for widespread adoption.

The term PETs, initially coined in 1995 [14], encapsulates technologies designed to protect personal and sensitive data in-use by minimizing their exposure to potential malicious entities. PETs are complementary to established data security practices, e.g., in-transit and at-rest encryption. To reduce exposure, PETs rely on different mechanisms (e.g., cryptography) to conceal the information (confidentiality) or modify data to perturb the link with the data owner (anonymity). Prominent PETs that enhance anonymity are differential privacy (DP) [15] and k-anonymity [16], while secure multiparty computation (SMC) [17] or homomorphic encryption (HE) [18] focus on confidentiality. While each PET contributes uniquely to enhancing privacy, employing them in combination provides more holistic protection.

Many automotive use cases with complex requirements can benefit from numerous privacy-enhancing technologies [19]– [21]. However, understanding use cases characteristics and requirements and the capabilities of PETs are often challenging [22]. While much research focuses on the capabilities of specific PETs and use cases [23]–[25], there is a gap in surveying and mapping use cases to the PETs landscape.

Contributions. We provide a comprehensive analysis of different application domains and use cases from the automotive value chain and discuss what characteristics and aspects of these use cases that can benefit from PETs. For this purpose, we investigate eight application domains, ranging from recommender systems, computer vision to data analytics. Based on a high-level overview, we provide an in-depth discussion of selected use cases, investigating the suitability of specific PETs. We identify important characteristics and patterns that allow practitioners to categorize new use cases and aid in identifying suitable PETs. The remaining of the paper is structured as follows: We introduce our methodology in section II. We continue with an analysis of use cases and PETs in sections III and IV. We discuss related work in section V, and conclude in section VI.

II. METHODOLOGY

We investigate two research questions (RQs). We interviewed several experts to identify and characterize use cases in the domain of privacy (RQ1). Further, we conducted a gray literature review to identify open-source tools that implement privacy-enhancing technologies (RQ2).

RQ1. What are the relevant use cases for PETs in the automotive industry? To answer this RQ, we provide use cases to motivate practitioners to enhance privacy in their institutions (see section III).

To plan and conduct the interviews to answer this RQ, we followed guidelines from P. Runeson and M. Höst [31]. Specifically, throughout the end of 2020 and during the first half of 2021, we interviewed 17 interested practitioners who worked directly or indirectly in the automotive industry; all the participants focused on data or privacy management. Seven of the interviews were conducted verbally, while the remaining ten were through email correspondence. The confidentiality of their identities and answers were communicated before initiating the interviews, as well as the goal of this study and how their answer will be used. The interviews were semi-structured [31], i.e., while we initiated the conversation with a set of preliminary questions about their background and followed up with RQ1 to collect a list of use cases, we promoted further exploration of their ideas revolving around their use cases list. We countered potential bias by ensuring that the experts came from different organizational units and institutions and summarized the findings before the conclusion of the interview to get feedback and avoid misinterpretation [31].

Afterward, we aggregated application domains and over 20 use cases (see Table I). Based on the identified use cases, we identified characteristics that can be addressed by specific capabilities of available PETs to guide their implementation in a production setting: *privacy*, *function types*, *data volume*, *data authenticity*, *query type*, and *the number of interacting parties*. Furthermore, we designed the framework of Fig. 1 to help us map in Table IV selected reference use cases to privacy-enhancing technologies.

RQ2. What are relevant privacy-enhancing tools available? During June and November 2021, we searched for tools practitioners can use to implement PETs in their use cases (see section IV). We define a *tool* as a reusable implementation of an algorithm that abstracts the deployment of a specific technology, i.e., the user does not need to have expertise in the underlying technology for its use.

We chose PETs included in seminal surveys or implementations in the domain of privacy [19]–[21]. We list the tools in Table II. Furthermore, each tool had to be open-source so that the scientific and engineering community could audit and freely access them. However, systematically collecting peerreviewed publications would not capture all the novel tools available [32]. Thus, for our purposes, S. Hopewell and M. Clarke and S. Mallett [32], and J. Vom Brocke et. al [33] indicated that a gray literature review would be a more optimal strategy. Consequently, we included tools that appeared within the first 100 Google search results for the search string "*PET name* AND *open-source* AND *tool* AND *GitHub*". Two researchers searched independently (one identified 67 tools while the other 63), and merged the results into 76 after removing duplicates (52).

III. APPLICATIONS IN THE AUTOMOTIVE VALUE CHAIN

Table I describes the eight identified application domains and the use cases in these domain. In this section, we discuss selected application domains in detail, focusing on challenges and opportunities for deploying PETs.

Recommender systems (#1 in Table I) can enhance customer experience by suggesting location or automatically activating capabilities, such as the seat heating. However, the data required for such use cases is often highly sensitive. PETs may help reduce the amount of data that needs to be transmitted to centralized clouds while retaining the utility of data-driven recommendations.

Computer vision (#3 in Table I) utilizes complex machine learning (ML) models to extract information from images and video. However, the unstructured nature of the input data increases the risk of unknowingly capturing sensitive information, e. g., people, and drives the need for the usage of PETs, e. g., for anonymization data using blurring techniques and synthetic data. The use of federated learning can reduce the need to centralize data and can thus further reduce risks.

Sensitive data management (#4 in Table I) describes the process of preparing data for secondary purposes. For this purpose, complex and automated data transformation pipelines are required for data anonymization. These pipelines should require only a minimal amount of human intervention. PETs, such as k-anonymity and differential privacy, are essential to provide the required privacy guarantees.

Data analytics describes the process of using data to support decisions in the business (#5 in Table I). For this purpose, it is required to aggregate data and connect various data sources. Analytics can be categorized in exploratory, i. e., the objective and business question of the analysis is not completely defined yet, and operational analytics, i. e., the KPI and business decision is well-specified. As for both types of analytics, it is often unnecessary to expose individual records and all attributes. PETs like k-anonymity and differential privacy can limit the amount of information exposed to analysts. However, there is an important trade-off between utility of the data and privacy to be considered, in particular, for exploratory analytics.

While there is sensitive information that corporations would prefer to maintain private, such as business secrets, performance metrics, or suppliers, cross-organizational data sharing

TABLE I Selected application domains and use cases.

#	Application	Use Case	Description
	Domain		
1	Recommender	Vehicle personalization, eco-friendly driving	Personalizing in-vehicle experiences and features based on data from in-vehicle sensors using
	systems		analytics and machine learning, e.g., recommendations for music and locations, seat heating
			activation and supporting gamification features (such as eco-friendly driving) [26].
2	Geoservices	Charging, traffic prediction, frequent routes, park-	Geoservices enhance the travel experience based on highly-sensitive location data.
		ing, charging, refuelling, points-of-interest	
3	Computer	Attentiveness detection, visual quality inspection	Driver attention monitoring using camera-based systems and other sensor for improving safety.
	vision	during manufacturing [3]	Data collected from cameras in-vehicle and in manufacturing plants is highly sensitive and may
			contain personal data, requiring PETs to ensure privacy.
4	Sensitive data	Automation of anonymization pipelines, prolonga-	Creating, streamlining, or automating anonymization pipelines to implement regulatory com-
	management	tion of data storage/access	plicance, increase data security and reduces human-error.
5	Data analytics	Group statistics include business KPIs, sales statis-	Analytics is essential to understand all aspects of the business, e.g., customer preferences, sales,
		tics, demographics	and manufacturing performance [27]. However, such statistics released publicly or confidentially
			for research or collaborative projects between institutions can lead an adversary to re-identify
			individuals [28].
6	Asset search	Tracking components across value chains	Support tracking, search and reconciliation of assets across organizations, e.g., locating vehicle
			components in a supply chain [29]. To mitigate the risks of sharing data, data needs to be
			carefully curated and secured, preventing the sharing of sensitive information.
7	IoT	Connected vehicles	IoT deployments (vehicle, machines, etc.) produce vast amounts of data from on-board sensors
			and traffic infrastructure [30]. Data can be highly sensitive (e.g., behavioral data). PETs can
			reduce the need to centralize data in clouds.
8	Cross-	Logistics & supply chain data, data markets, KPI	Sharing data across organizations to improve analytics and machine learning models (e.g.,
	organizational	comparisons (industry benchmarks)	supply chain management and automated driving). PETs remove risk of sharing and the
	data sharing		disclosure of sensitive and personal information to non-intended recipients.

TABLE II Technologies and their most relevant open-source tools.

Technology	Description	Tool		
Differential privacy (DP)	Mathematically guarantees that the output of a dataset analysis is "essentially" identical, despite the presence or absence of an individual in the dataset [15], [34].	Google-DP (Python wrapper: PyDP), SmartNoise, diffprivlib, DiffPriv, OpenDP, DPComp Core and Chorus (behind Uber's DP SQL). Focused on DP and deep learning: TensorFlow privacy and PyTorch Opacus.		
K-anonymity	K-anonymity guarantees the indistinguishability of a record with k-1 number of others in a dataset [16]. K-anonymity is useful to anonymize datasets before usage.	ARX, Amnesia, and Anonimatron.		
Synthetic data	Populate a synthetic dataset with the learned distribution of the real data by means of ML [35], [36].	SDV, ZPY, Gretel, Synth, Ydata, DataSynthesizer, Synthea, and Tru- mania.		
Zero-knowledge proof (ZKP)	Enables proof of authenticity of information without revealing or sharing the underlying data [37], [38].	emmy, dizk, zkMega, libsnark, libiop, ZKRollups, ZKRP, ckb-zkp, ginger-lib, OpenZKP, and gnark.		
Secure multi-party computation (SMC)	Parties can jointly compute a function without disclosing their inputs by employing secret sharing or garbled circuits [17].	Multi-Protocol SPDZ, LIBSCAPI, MPyC, CrypTen, EMP-Toolkit, Mul- tiparty, ZoKrates and MPC-SoK.		
Homomorphic encryption (HE)	Allows computing functions on ciphertext without prior decryp- tion [18], [39].	TFHE, fhe-toolkit-linux, Google FHE SEAL, Concrete, eclib, HElib, and PALISADE.		
Trusted execution environments (TEE)	Hardware and software that provide computation security against the unwarranted retrieval of sensitive information [40].	mTower, Open Enclave SDK, Trusty, TrustZone, Mystikos, Open-TEE and Intel's Trusted Execution Technology.		
Federated Learning (FL)	Distributes ML models across data sources for training and averages the weights into one model [41], [42].	Fate, sherpa.ai, PaddleFL, PySft, Xaynet, fedn, FedML-AI, Flower, PyVertical, TensorFlow Federated, and federated-learning-lib.		
Blockchain (no PET)	Tamper-proof, distributed database, whose state is replicated and stored across P2P network nodes using a consensus algorithm [43].	Corda, Hyperledger, Go Ethereum, BigchainDB, Chainlink, Ganache, XRPLF, Graphene, Polygon, Vechain, and Tezos.		

increasingly becomes a necessity to optimize entire value chains and business networks, e.g., to support asset search (#6) and cross-organizational sharing (#8 in Table I). Asset search addresses the need to locate and track components and products across organizations. Cross-organizational data sharing envisions the sharing of more comprehensive data sets. PETs can address the need to expose the minimal amount of data and the ability to verify data and results. Emergent platforms, such as GAIA-X [44], heavily rely on PETs to establish secure data exchange mechanisms and controls.

IV. PRIVACY-ENHANCING TECHNOLOGIES: CAPABILITIES AND APPLICATIONS

PETs comprise technologies designed to protect the privacy of data owners. PETs accomplish this by enhancing *anonymity* with technologies such as differential privacy (DP), k-anonymity, or synthetic data, or *confidentiality* with secure and outsourced computation technologies such as zero-knowledge proof (ZKP), secure multi-party computation (SMC), homomorphic encryption (HE), trusted execution environments (TEE), or federated learning (FL). Furthermore, PETs can provide capabilities for supporting the use cases described in Table I. Table II provides an overview of important PETs and the most relevant open-source tools, which we resulted from our gray literature review.

While blockchain is not strictly a PET, we included it because it is an instrumental building block for establishing trust and support for data verification use cases. Additionally, blockchain can anchor trust of zero-knowledge proof protocols that prove a claim without engaging in sequential messaging [45].

 TABLE III

 TECHNOLOGY CAPABILITIES FULFILLING USE CASE CHARACTERISTICS

Technology	Privacy	Function type	Data volume	Data authenticity	Query type	Number of interacting parties
DP	Anonymity	Noise added to data processing	TB	Noisy outputs	Known / Unknown	One
K-anonymity	Anonymity	Dataset anonymization	GB	Generalized	Known / Unknown	One
Synthetic data	Anonymity	Dataset generation	TB	Noisy	Known / Unknown	One
ZKP	Confidentiality	Authenticity proofs	MB	Yes	Known	Two
SMC	Confidentiality	Arbitrary	MB	Yes	Known	Multiple
HE	Confidentiality	Arbitrary	MB	Yes	Known	Two
TEE	Confidentiality	Arbitrary	GB	Yes	Known / Unknown	Multiple
FL	Confidentiality	ML	TB	Yes	Known	Multiple
Blockchain (no PET)	Not applicable	Arbitrary	MB	Yes	Known	Multiple

Legend: DP = Differential privacy; ZKP = Zero-knowledge proof; SMC = Secure multiparty computation; HE = Homomorphic encryption; TEE = Trusted execution environments; FL = Federated learning

A. Characteristics and Capabilities

Based on an in-depth analysis of the use cases, we define six important characteristics for selecting PETs and architecting privacy-preserving systems.

Privacy. This characteristic describes the sensitivity of the data, e. g., the need to anonymize personally identifiable information (PII) and confidential information. Anonymization removes the link between data and individuals. Confidentiality requirements may also exist for non-personal data, e. g., due to business reasons.

Function type. Use cases may require the use of analytics queries, ML models, or proofs for the authenticity of data. Depending on the function, PETs, such as basic queries to verify the existence of an asset in a dataset (SMC), aggregation queries (DP), or ML (FL), can be chosen.

Data volume. Some technologies are more suitable than others, depending on the data volume the use case is processing. The noise added by DP is independent of the data volume, while SMC cannot process large data volumes given the encryption and communication overhead.

Data authenticity. For high-value data, blockchain-based data verification might be necessary to ensure authenticity. Some PETs reduce the authenticity, e.g., anonymization perturbs the exact value of data points to disjoint attributes from the users who generated the data.

Query type. Some use cases require exploratory queries (unknown), while others repetitively execute well-defined queries and ML models. For example, to train an ML model with FL, one must know what the model will predict or classify. A TEE can execute arbitrary user-defined functions (including ML), and transforming a dataset into k-anonymous or synthetic data does not necessarily require knowing in advance the query types.

Number of interacting parties. Some use cases require data and interactions from more than one entity to interact. For example, FL can train a model distributed across potentially different data owners. SMC jointly computes a function based on the inputs of multiple parties, and DP allows an analyst to query a dataset.



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Fig. 1. Framework to map use cases and privacy-enhancing technologies.

PETs provide different capabilities to address use cases requirements and characteristics. Table III summarizes the capabilities provided by the defined PETs.

B. PETs and automotive use cases

Understanding use case characteristics and the capabilities of PETs is essential to architect privacy-preserving and practical systems. Figure 1 illustrates our framework for mapping use cases to suitable PETs based on the six defining characteristics and capabilities. Table IV investigates eight automotive use cases and illustrates how a specific PET can address the privacy requirements of each use case.

The mapping is intended to be illustrative, not complete. It emphasizes the strengths and weaknesses of the PETs, helping practitioners align PETs and use case requirements. Thus, we have selected reference use cases to highlight the unique benefits of a specific PET. In practice, a combination of PETs is often required to implement a use case end-to-end. We continue with an in-depth discussion of three use cases.

Computer vision: attentiveness detection (#3 in Table IV). Alerting drivers of their lack of attention behind the

 TABLE IV

 Reference automotive use cases mapped to privacy-enhancing technologies

# Domain: Use Case Description Suitable Capabilities PETs 1 Recommender systems: eco-friendly driving Traing of ML models from complex distributed datasets contain- ing numerous vehicle signals to predict what patterns improve eco-friendly driving. Anonymity, ML over anonymous data, TB of data, noisy data, unknown queries, one party Synthe 2 Geoservices: charging Discovering most frequent locations on an aggregated dataset where electric vehicles have low batteries. Anonymity, aggregation query functions over (anonymous) dataset, GB of data, noisy out- puts or generalized data, unknown queries, one party DP, k-anony 3 Computer vision: attentiveness detection Training ML models across multiple vehicles and devices. Confidentiality, ML functions, TB of data, authentic data, known queries, multiple par- tics FL 4 Sensitive data management: A practitioner automates the anonymization of ingested customer Anonymity, approximation, GB of data, gen- tics K-anonymization	Description Traing of ML models from complex distributed datasets contain- ing numerous vehicle signals to predict what patterns improve eco-friendly driving.	PETs Synthetic
1 Recommender systems: eco-friendly driving Traing of ML models from complex distributed datasets contain- ing numerous vehicle signals to predict what patterns improve eco-friendly driving. Anonymity, ML over anonymous data, TB of data, noisy data, unknown queries, one party Synthe data 2 Geoservices: charging Discovering most frequent locations on an aggregated dataset where electric vehicles have low batteries. Anonymity, aggregation query functions over (anonymous) dataset, GB of data, noisy out- puts or generalized data, unknown queries, one party DP, k-anony 3 Computer vision: attentiveness detection Training ML models across multiple vehicles and devices. Confidentiality, ML functions, TB of data, authentic data, known queries, multiple par- ties FL	Traing of ML models from complex distributed datasets contain- ing numerous vehicle signals to predict what patterns improve eco-friendly driving.	Synthetic
eco-friendly driving ing numerous vehicle signals to predict what patterns improve cco-friendly driving. data, noisy data, unknown queries, one party data 2 Geoservices: Discovering most frequent locations on an aggregated dataset where electric vehicles have low batteries. Anonymity, aggregation query functions over (anonymous) dataset, GB of data, noisy outputs or generalized data, unknown queries, one party DP, k-anonymity, one party 3 Computer vision: attentiveness detection Training ML models across multiple vehicles and devices. Confidentiality, ML functions, TB of data, authentic data, known queries, multiple parties FL	ing numerous vehicle signals to predict what patterns improve eco-friendly driving.	Synthetic
2 Geoservices: charging Discovering most frequent locations on an aggregated dataset where electric vehicles have low batteries. Anonymity, aggregation query functions over (anonymous) dataset, GB of data, noisy out- puts or generalized data, unknown queries, one party DP, k-anonymity authentic data, known queries, authentic data, known queries, multiple par- tics DP, k-anonymity 3 Computer vision: attentiveness detection Training ML models across multiple vehicles and devices. Confidentiality, ML functions, TB of data, authentic data, known queries, multiple par- tics FL	eco-friendly driving.	data
2 Geoservices: charging Discovering most frequent locations on an aggregated dataset where electric vehicles have low batteries. Anonymity, aggregation query functions over (anonymous) dataset, GB of data, noisy out- puts or generalized data, unknown queries, one party DP, k-anony 3 Computer vision: attentiveness detection Training ML models across multiple vehicles and devices. Confidentiality, ML functions, TB of data, authentic data, known queries, multiple par- tics FL		
charging where electric vehicles have low batteries. (anonymous) dataset, GB of data, noisy outputs or generalized data, unknown queries, one party k-anonymous 3 Computer vision: attentiveness detection Training ML models across multiple vehicles and devices. Confidentiality, ML functions, TB of data, authentic data, known queries, multiple parties FL	Discovering most frequent locations on an aggregated dataset	DP,
3 Computer vision: attentiveness detection Training ML models across multiple vehicles and devices. Confidentiality, ML functions, TB of data, authentic data, known queries, multiple par- ties FL 4 Sensitive data management: A practitioner automates the anonymization of ingested customer A nonymity, anonymization GB of data, gen- tics K-anonymity, anonymization, GB of data, gen- tics	where electric vehicles have low batteries.	k-anonymity
3 Computer vision: attentiveness detection Training ML models across multiple vehicles and devices. Confidentiality, ML functions, TB of data, authentic data, known queries, multiple par- ties FL 4 Sensitive data management: A practitioner automates the anonymization of ingested customer A nonymity, anonymization GB of data, gen- tics K-anonymization		
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attentiveness detection authentic data, known queries, multiple par- tics 4 Sensitive data management: A practitioner automates the approximation of ingested customer	Training ML models across multiple vehicles and devices.	FL
ties 4 Sensitive data management: A practitioner automates the anonymization of ingested customer Anonymity anonymization GB of data generation		
4 Sensitive data management: A practitioner automates the anonymization of ingested customer Anonymity anonymization GB of data gen- K-anon		
+ Sensitive data management. A practitioner automates the anonymization of ingested customer Anonymity, anonymization, OD of data, gen-	A practitioner automates the anonymization of ingested customer	K-anonymity
automating anonymization vehicle data. eralized data, unknown queries, one party	vehicle data.	
5 Data analytics: Computing aggregate business KPIs for dashboards by querying Anonymity, aggregation query functions, up DP	Computing aggregate business KPIs for dashboards by querying	DP
group statistics various datasets without downloading the underlying data. to TB of data, noisy outputs, unknown	various datasets without downloading the underlying data.	
queries, one party		
6 Asset search: Tracking components and parts across the value chain to optimize Confidentiality, arbitrary function, MB of SMC	Tracking components and parts across the value chain to optimize	SMC
tracking components supply chain management (e.g., management of stock levels). data, authentic data, known query, multiple	supply chain management (e.g., management of stock levels).	
parties		
7 IoT: Management of vast amounts of sensor data from vehicles and Confidentiality, arbitrary functions, MB of HE	Management of vast amounts of sensor data from vehicles and	HE
Connected car traffic infrastructure across the edge and cloud. data, authentic data, known query, two parties	traffic infrastructure across the edge and cloud.	
8 Cross-organizational data Track and share data across organizations to optimize business Confidentiality, arbitrary functions, GB of TEE,	a Track and share data across organizations to optimize business	TEE,
sharing: Logistics & supply processes, e.g., for improved supply chain visibility [29]. data, authentic data, known queries, multiple blockch	y processes, e.g., for improved supply chain visibility [29].	blockchain
chain parties (anchor		(anchors trust)

Legend: DP = Differential privacy; SMC = Secure multiparty computation; ZKP = Zero-knowledge proof; HE = Homomorphic encryption; TEE = Trusted execution environments; FL = Federated learning; ML = Machine learning

wheel can prevent road accidents and save lives. The training of ML models typically requires large volumes of potentially sensitive training data. Thus, an important building block is anonymized and synthetic data, particularly for bootstrapping the ML model. However, due to the safety-critical nature, anonymization approaches are not sufficient alone. Federated learning allows the training of models across multiple vehicles without the need of centralizing data, and thus, preserving confidentiality.

Data analytics: group statistics (#5 in Table IV). Data warehouses and data lakes are essential enablers for analytics. Data anonymization is an important practice for enabling secondary data usage. Once datasets are anonymized, an analyst can execute a potentially manifold set of queries, e. g., joining and exploring many attributes of vehicles. The use of differential privacy (DP) can prevent the de-identification of data while retaining the utility of the analysis. Using a well-calibrated noise mode a good query accuracy is ensured while preserving each individual's anonymity. DP is also an important enabler for more democratized data access and analytics. Differential privacy can also be applied on the fly, e. g., using a DP-aware SQL engine and a privacy budget that controls the number of queries allowed.

Asset search: tracking components (#6 in Table IV). The automotive value chain is highly complex, involving many partners in an international network. As a result, supply chains are highly complex. They often lack visibility and trust, in particular concerning tier-n suppliers, i.e., suppliers that are not directly in contact with an automotive company. A critical capability is the tracking of components and parts in this cross-organizational network. Blockchains provide a mean to orchestrate a decentral business network [29]. However, additional PETs are essential to facilitate secure data exchange, e.g., secure multi-party computation (SMC) enables the secure

computation, e.g., to reconcile stock levels, avoiding the exposure of confidential business information. However, SMC is only suitable for specific, well-defined use cases, small data volumes, and certain types of computation.

An important characteristic of many use cases is data verification and the establishment of trust in distributed and crossorganizational environments. Blockchains and zero-knowledge proofs (ZKP) are an important enablers for these requirements. They allow the sharing of proofs without revealing the underlying data. For example, individuals can reveal identity-related attributes (e. g., the possession of a driver's license [46]) using ZKP.

V. RELATED WORK

Most research focuses on applying or optimizing a single PET to tackle one particular use case, or investigate the use cases that a single PET can address. Examples include applying SMC to privacy-preserving deep learning [23], implementing DP in the context of sensitive health data [24], or identifying applications for which practitioners can employ TEEs [25]. However, these publications do not provide an overview of privacy use cases for different PETs.

Other publications have surveyed how PETs fulfill privacy requirements in general [47] or from a particular context such as data exchanges [48]. Alternatively, publications highlight market opportunities for PETs to solve business problems, e.g., build trust or establish a competitive advantage [9]). However, mapping PETs with requirements or business opportunities does not provide immediate insights regarding privacy use cases. Another set of publications proposes industry use cases without explicitly mapping them to a list of PETs. Examples range from outlining privacy use cases in the supply chain [49], the role of PETs in predictive maintenance in the automotive industry [50], or the use of PETs in the context of IoT [51] or smart cities [52].

We identified a few publications that survey applications of PETs. There is a repository of implemented PET use cases [53] from different sectors (e.g., health, transport, finance) and a list of case studies that used PETs to reach their objectives [54] in the financial sector. However, these surveys do not focus on production and industry use cases.

While the publications covering the domain of privacy and use cases are varied, to the best of our knowledge, they do not (i) identify suitable capabilities required by use cases to map them to PETs, (ii) present actionable use cases in the automotive industry, (iii) include a list of reference use case that succinctly demonstrate the value of each PET.

VI. DISCUSSION AND CONCLUSION

While PETs have matured and are increasingly available, developing privacy-preserving architectures is challenging, requiring an in-depth understanding of PETs and use cases. This paper addresses this challenge and provides guidelines synthesized from expert interviews and a literature review.

PETs provide the ability to increase the protection of data while in-use and can be considered complementary to established security practices, e.g., security monitoring, data encryption at rest and in-transit, data governance. There is no "one-size-fits-all" privacy-enhancing technology (PET). The selection and deployment of PETs require a careful understanding of use cases characteristics, the capabilities of a PET and its limitation. We demonstrated how use case characteristics can be used to assess the suitability for PETs. While this paper focuses on automotive use cases, the identified characteristics and capabilities generalize well to other application domains.

The usage of PETs is associated with increased architectural and operational complexity, and performance-related constraints that must be carefully considered when choosing a PET. Further, the limitations of PETs must be carefully considered. For example, homomorphic encryption and secure multi-party computation cannot handle large volumes of data and do not address anonymization requirements, e.g., for secondary data processing. K-anonymity does not provide a formal guarantee of privacy like differential privacy.

The importance of PETs will increase. In particular, the need to collaborate across organizational boundaries will intensify the need for PETs. In the future, we will refine and extend our classification to other application categories and domains. Further, we implement and experiment with concrete PETs and use cases, e. g., differential privacy and secure multi-party computing.

REFERENCES

H. Ramezani and A. Luckow, *Big data, small data, and getting products right first time*, M. Dastbaz and P. Cochrane, Eds., In Mohammad Dastbaz and Peter Cochrane, Industry 4.0 and Engineering for a Sustainable Future: https://doi.org/10.1007/978-3-030-12953-8_6, 2019.

- [2] A. Luckow, K. Kennedy, F. Manhardt, E. Djerekarov, B. Vorster, and A. Apon, "Automotive big data: Applications, workloads and infrastructures," in 2015 IEEE International Conference on Big Data (Big Data), 2015, pp. 1201–1210. DOI: 10.1109/BigData.2015.7363874.
- [3] A. Luckow, K. Kennedy, M. Ziolkowski, E. Djerekarov, M. Cook, E. Duffy, M. Schleiss, B. Vorster, E. Weill, A. Kulshrestha, and M. C. Smith, "Artificial intelligence and deep learning applications for automotive manufacturing," in 2018 IEEE International Conference on Big Data (Big Data), 2018, pp. 3144–3152. DOI: 10.1109/ BigData.2018.8622357.
- [4] J. Eirich, D. Jäckle, S. Werrlich, and T. Schreck, "Visual analytics in organization knowledge creation: A case study," in *European Conference on Information Systems*, Apr. 2021.
- [5] A. Montazerolghaem and M. H. Yaghmaee, "Load-balanced and QoS-aware software-defined Internet of Things," *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 3323–3337, Apr. 2020, ISSN: 2327-4662, 2372-2541. DOI: 10.1109/JIOT.2020.2967081. [Online]. Available: https://ieeexplore.ieee.org/document/8962313/ (visited on 08/07/2021).
- [6] R. E. 2016/679, Protection of natural persons with regard to the processing of personal data and on the free movement of Such data, and repealing directive 95/46/EC. European Parliament and Council, Luxembourg: Office for Official Publications of the European Communities., Apr. 2016.
- [7] A. Zöll, C. M. Olt, and P. Buxmann, "Privacy-sensitive business models: Barriers of organizational adoption of privacy-enhancing technologies," in *Proceedings of the 29th European Conference on Information Systems*, 2021.
- [8] L. Yuming, "Data sovereignty theory," in *Sovereignty blockchain 1.0: Orderly Internet and community with a shared future for humanity*. Singapore: Springer Singapore, 2021, pp. 37–77. DOI: 10.1007/978-981-16-0757-8 2.
- [9] M. Jaatun, I. A. Tondel, K. Bernsmed, and A. Nyre, "Privacy enhancing technologies for information control," in 2012, pp. 1–31, ISBN: 9781613505021. DOI: 10.4018/978-1-61350-501-4.ch001.
- [10] IBM Security and P. Institue LLC, 2020 cost of a data breach study, 2020. [Online]. Available: https://www. ibm.com/security/data-breach.
- [11] N. Kaaniche and M. Laurent, "Attribute-based signatures for supporting anonymous certification," in *Computer Security – ESORICS 2016*, I. Askoxylakis, S. Ioannidis, S. Katsikas, and C. Meadows, Eds., Cham: Springer International Publishing, 2016, pp. 279–300, ISBN: 978-3-319-45744-4.
- [12] R. Garratt and M. R. v. Oordt, "Privacy as a public good: A case for electronic cash," *Journal of Political Economy*, 2018. DOI: 10.1086/714133.

- [13] McKinsey & Company, Four ways to accelerate the creation of data ecosystems. [Online]. Available: https: //www.mckinsey.com/business-functions/mckinseyanalytics/our-insights/four-ways-to-accelerate-thecreation-of-data-ecosystems (visited on 05/28/2021).
- [14] R. Hes, J. J. Borking, Netherlands, and I. a. P. Commissioner/Ontario, Eds., *Privacy-enhancing technologies: the path to anonymity*, en, Rev. ed, ser. Achtergrondstudies en verkenningen 11. The Hague: Registratiekamer, 1998, ISBN: 978-90-74087-12-4. [Online]. Available: https://www.researchgate.net/publication/243777645_Privacy-Enhancing_Technologies_The_Path_to_Anonymity.
- [15] C Dwork, K Kenthapadi, F McSherry, I Mironov, and M Naor, "Our data, ourselves: Privacy via distributed noise generation," *International Conference on the Theory* and Applications of Cryptographic Techniques (EURO-CRYPT), 2006.
- [16] P. Samarati and L. Sweeney, "Protecting privacy when disclosing information: K-anonymity and its enforcement through generalization and suppression," en, p. 19,
- [17] A. C. Yao, "Protocols for secure computations," in 23rd annual symposium on foundations of computer science (sfcs 1982), 1982, pp. 160–164. DOI: 10.1109/SFCS. 1982.38.
- M. A. Will and R. K. Ko, A guide to homomorphic encryption. Elsevier Inc., 2015, p. 101, ISBN: 9780128017807. DOI: 10.1016/B978-0-12-801595-7.00005-7. [Online]. Available: http://dx.doi.org/10. 1016/B978-0-12-801595-7.00005-7.
- [19] D. López and B. Farooq, "A multi-layered blockchain framework for smart mobility data-markets," *Transportation Research Part C: Emerging Technologies*, vol. 111, no. June 2019, pp. 588–615, 2020, ISSN: 0968090X. DOI: 10.1016/j.trc.2020.01.002.
- [20] G. M. Garrido, J. Sedlmeier, O. Uludag, I. S. Alaoui, A. Luckow, and F. Matthes, *Revealing the landscape of privacy-enhancing technologies in the context of data markets for the iot: A systematic literature review*, 2021. arXiv: 2107.11905 [cs.CR].
- [21] A. Trask, E. Bluemke, B. Garfinkel, C. G. Cuervas-Mons, and A. Dafoe, *Beyond privacy trade-offs with structured transparency*, 2020. arXiv: 2012.08347
 [cs.CR]. [Online]. Available: https://www.researchgate.net/publication/347300876_Beyond_Privacy_Trade-offs_with_Structured_Transparency.
- [22] P. B. Anne Zöll Christian M. Olt, "Privacy-sensitive business models: barriers of organizational adoption of privacy-enhancing technologies," p. 22, 2021. [Online]. Available: https://aisel.aisnet.org/ecis2021_rp/34/.
- [23] K. Bittner, M. D. Cock, and R. Dowsley, Private speech classification with secure multiparty computation, 2021. arXiv: 2007.00253 [cs.CR].
- [24] O. Choudhury, A. Gkoulalas-Divanis, T. Salonidis, I. Sylla, Y. Park, G. Hsu, and A. Das, *Differential privacy-*

enabled federated learning for sensitive health data, 2020. arXiv: 1910.02578 [cs.LG].

- [25] G. Arfaoui, S. Gharout, and J. Traoré, "Trusted execution environments: A look under the hood," in 2014 2nd IEEE International Conference on Mobile Cloud Computing, Services, and Engineering, 2014, pp. 259–266. DOI: 10.1109/MobileCloud.2014.47.
- [26] A. Chin, J. Tian, and J. P. Prenninger, "Toward contextual and personalized interior experience in a vehicle: Predictive preconditioning," in 92nd IEEE Vehicular Technology Conference, VTC Fall 2020, Victoria, BC, Canada, November 18 - December 16, 2020, IEEE, 2020, pp. 1–5. DOI: 10.1109/VTC2020-Fall49728.2020. 9348478. [Online]. Available: https://doi.org/10.1109/ VTC2020-Fall49728.2020.9348478.
- [27] S. Jeereddy, K. Kennedy, E. Duffy, A. Walker, and B. Vorster, "Machine learning use cases for smart manufacturing kpis," in 2019 IEEE International Conference on Big Data (Big Data), Los Angeles, CA, USA, December 9-12, 2019, C. Baru, J. Huan, L. Khan, X. Hu, R. Ak, Y. Tian, R. S. Barga, C. Zaniolo, K. Lee, and Y. F. Ye, Eds., IEEE, 2019, pp. 4375–4380. DOI: 10. 1109/BigData47090.2019.9006539. [Online]. Available: https://doi.org/10.1109/BigData47090.2019.9006539.
- [28] K. El Emam and L. Arbuckle, Anonymizing health data. O'Reilly Media, Inc., 2013.
- [29] D. Miehle, D. Henze, A. Seitz, A. Luckow, and B. Bruegge, "Partchain: A decentralized traceability application for multi-tier supply chain networks in the automotive industry," in *IEEE International Conference on Decentralized Applications and Infrastructures, DAPPCON 2019, Newark, CA, USA, April 4-9, 2019*, IEEE, 2019, pp. 140–145. DOI: 10.1109/DAPPCON. 2019.00027. [Online]. Available: https://doi.org/10. 1109/DAPPCON.2019.00027.
- [30] Y. Du, M. Chowdhury, M. Rahman, K. Dey, A. Apon, A. Luckow, and L. B. Ngo, "A distributed message delivery infrastructure for connected vehicle technology applications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 3, pp. 787–801, 2018. DOI: 10.1109/TITS.2017.2701799.
- [31] P. Runeson and M. Höst, "Guidelines for conducting and reporting case study research in software engineering," *Empirical software engineering*, vol. 14, no. 2, pp. 131–164, 2009.
- [32] S. Hopewell, M. Clarke, and S. Mallett, "Grey literature and systematic reviews," in *Publication bias in metaanalysis*, Chichester, UK: John Wiley & Sons, Ltd, Mar. 2006, pp. 49–72. DOI: 10.1002/0470870168.ch4.
- [33] J. Vom Brocke, A. Simons, B. Niehaves, K. Riemer, R. Plattfaut, and A. Cleven, "Reconstructing the giant: on the importance of rigour in documenting the literature search process," in *Proceedings of the 17th European Conference on Information Systems*, vol. 161, Verona, Italy, 2009, ISBN: 9788861293915.

- [34] C. Dwork and A. Roth, "The algorithmic foundations of differential privacy," en, *Foundations and Trends® in Theoretical Computer Science*, vol. 9, no. 3-4, pp. 211–407, 2013, ISSN: 1551-305X, 1551-3068. DOI: 10. 1561/0400000042. [Online]. Available: http://www.nowpublishers.com/articles/foundations-and-trends-in-theoretical-computer-science/TCS-042 (visited on 04/07/2021).
- [35] E. Dikici, L. M. Prevedello, M. Bigelow, R. D. White, and B. S. Erdal, *Constrained generative adversarial* network ensembles for sharable synthetic data generation, 2020. arXiv: 2003.00086 [eess.IV]. [Online]. Available: https://www.researchgate.net/publication/ 339642358 _ Constrained _ Generative _ Adversarial _ Network _Ensembles _for _Sharable _Synthetic _Data _ Generation.
- [36] J. W. Anderson, K. E. Kennedy, L. B. Ngo, A. Luckow, and A. W. Apon, "Synthetic data generation for the internet of things," in 2014 IEEE International Conference on Big Data (Big Data), 2014, pp. 171–176. DOI: 10.1109/BigData.2014.7004228.
- [37] S. Goldwasser, S. Micali, and C. Rackoff, "The knowledge complexity of interactive proof systems," *SIAM J. Comput.*, vol. 18, no. 1, 186–208, Feb. 1989, ISSN: 0097-5397. DOI: 10.1137/0218012. [Online]. Available: https://doi.org/10.1137/0218012.
- [38] O. Goldreich and Y. Oren, "Definitions and properties of zero-knowledge proof systems," en, *Journal of Cryptology*, vol. 7, no. 1, pp. 1–32, Dec. 1994, ISSN: 0933-2790, 1432-1378. DOI: 10.1007/BF00195207.
 [Online]. Available: http://link.springer.com/10.1007/BF00195207 (visited on 02/11/2021).
- [39] P. Chaudhary, R. Gupta, A. Singh, and P. Majumder, "Analysis and comparison of various Fully homomorphic encryption techniques," 2019 International Conference on Computing, Power and Communication Technologies, GUCON 2019, pp. 58–62, 2019.
- [40] OMTP, Advanced trusted environment: Omtp tr1, May 2009. [Online]. Available: http://www.gsma. com/newsroom/wp-content/uploads/2012/03/ omtpadvancedtrustedenvironmentomtptr1v11.pdf.
- [41] J. Konečný, B. McMahan, and D. Ramage, "Federated optimization:distributed optimization beyond the datacenter," en, arXiv:1511.03575 [cs, math], Nov. 2015, arXiv: 1511.03575. [Online]. Available: http://arxiv. org/abs/1511.03575 (visited on 04/07/2021).
- [42] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated learning: Challenges, methods, and future directions," *IEEE Signal Processing Magazine*, vol. 37, no. 3, pp. 50–60, 2020. DOI: 10.1109/MSP.2020.2975749.
- [43] B.-J. Butijn, D. A. Tamburri, and W.-J. v. d. Heuvel, "Blockchains: A systematic multivocal literature review," ACM Computing Surveys (CSUR), vol. 53, no. 3, pp. 1–37, 2020. [Online]. Available: https://dl.acm.org/ doi/abs/10.1145/3369052.

- [44] G. Eggers, B. Fondermann, B. Maier, K. Ottradovetz, J. Pformmer, R. Reinhardt, H. Rollin, A. Schmieg, S. Steinbuß, P. Trinius, A. Weis, C. Weiss, and S. Wilfling, "GAIA-X: Technical Architecture," en, [Online]. Available: https://www.data-infrastructure.eu/ GAIAX/Redaktion/EN/Publications/gaia-x-technicalarchitecture.pdf?__blob=publicationFile&v=5 (visited on 05/26/2021).
- [45] S. A. Brands, *Rethinking Public Key Infrastructures and Digital Certificates: Building in Privacy*. Cambridge, MA, USA: MIT Press, 2000, ISBN: 0262024918. [On-line]. Available: https://direct.mit.edu/books/book/1912/Rethinking-Public-Key-Infrastructures-and-Digital.
- [46] I. Gudymenko, A. Khalid, H. Siddiqui, M. Idrees, S. Clauß, A. Luckow, M. Bolsinger, and D. Miehle, "Privacy-preserving blockchain-based systems for car sharing leveraging zero-knowledge protocols," in 2020 IEEE International Conference on Decentralized Applications and Infrastructures (DAPPS), 2020, pp. 114– 119. DOI: 10.1109/DAPPS49028.2020.00014.
- [47] J. Heurix, P. Zimmermann, T. Neubauer, and S. Fenz, "A taxonomy for privacy enhancing technologies," *Computers & Security*, vol. 53, pp. 1–17, 2015, ISSN: 0167-4048. DOI: 10.1016/j.cose.2015.05.002.
- [48] J. Pennekamp, M. Henze, S. Schmidt, P. Niemietz, M. Fey, D. Trauth, T. Bergs, C. Brecher, and K. Wehrle, "Dataflow challenges in an internet of production: A aecurity & privacy perspective," in *Proceedings of the ACM Workshop on Cyber-Physical Systems Security & Privacy*, ser. CPS-SPC'19, Association for Computing Machinery, 2019, 27–38, ISBN: 9781450368315. DOI: 10.1145/3338499.3357357.
- [49] P. Gonczol, P. Katsikouli, L. Herskind, and N. Dragoni, "Blockchain implementations and use cases for supply chains – a survey," *IEEE Access*, vol. 8, pp. 11856– 11871, 2020. DOI: 10.1109/ACCESS.2020.2964880.
- [50] A. Theissler, J. Pérez-Velázquez, M. Kettelgerdes, and G. Elger, "Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry," *Reliability Engineering & System Safety*, p. 107 864, 2021, ISSN: 0951-8320. DOI: https://doi. org/10.1016/j.ress.2021.107864.
- [51] J. Pennekamp, M. Henze, S. Schmidt, P. Niemietz, M. Fey, D. Trauth, T. Bergs, C. Brecher, and K. Wehrle, "Dataflow challenges in an internet of production," in ACMWorkshop on Cyber-Physical Systems Security & Privacy (CPS-SPC'19), November 11, 2019, London, United Kingdom. ACM, 2019, pp. 27–38, ISBN: 9781450368315. DOI: 10.1145/3338499.3357357.
- [52] J. Curzon, A. Almehmadi, and K. El-Khatib, "A survey of privacy enhancing technologies for smart cities," *Pervasive and Mobile Computing*, vol. 55, pp. 76–95, 2019, ISSN: 1574-1192. DOI: 10.1016/j.pmcj.2019.03. 001.

- [53] CDEI, "Privacy enhancing technologies adoption guide," 2021. [Online]. Available: https://cdeiuk.github. io/pets-adoption-guide/ (visited on 07/15/2021).
- [54] FFIS, "Case studies of the use of privacy preserving analysis to tackle financial crime," 2020. [Online]. Available: https://www.gcffc.org/wp-content/uploads/ 2020/06/FFIS-Innovation-and-discussion-paper-Casestudies-of-the-use-of-privacy-preserving-analysis.pdf (visited on 11/06/2021).