TechOps: Technical Documentation Templates for the AI Act

Laura Lucaj[1,2], Alex Loosley[3,4], Håkan Jonsson[4], Urs Gasser[2], Patrick van der Smagt[5,6]
[1]Volkswagen Group,
[2]Technical University of Munich,
[3]Capgemini Deutschland GmbH,
[4]Zalando SE,
[5]Foundation Future Industries,
[6]ELTE University Budapest
laura.lucaj@argmax.org

Abstract

Operationalizing the EU AI Act requires clear technical documentation to ensure AI systems are transparent, traceable, and accountable. Existing documentation templates for AI systems do not fully cover the entire AI lifecycle while meeting the technical documentation requirements of the AI Act.

This paper addresses those shortcomings by introducing open-source templates and examples for documenting data, models, and applications to provide sufficient documentation for certifying compliance with the AI Act. These templates track the system's status over the entire AI lifecycle, ensuring traceability, reproducibility, and compliance with the AI Act. They also promote discoverability and collaboration, reduce risks, and align with best practices in AI documentation and governance.

The templates are evaluated and refined based on user feedback to enable insights into their usability and implementability. We then validate the approach on real-world scenarios, providing examples that further guide their implementation: the data template is followed to document a skin tones dataset created to support fairness evaluations of downstream computer vision models and human-centric applications; the model template is followed to document a neural network for segmenting human silhouettes in photos. The application template is tested on a system deployed for construction site safety using real-time video analytics and sensor data. Our results show that TechOps can serve as a practical tool to enable oversight for regulatory compliance and responsible AI development.

Introduction

AI is increasingly used in areas where managing its risks is difficult, especially when protecting people's fundamental rights (Brundage 2019; O'neil 2017; Barocas and Selbst 2016; Critch and Russell 2023; Solow-Niederman 2023). Many AI systems use complex, opaque models that make it hard to explain their predictions and outcomes. This complexity makes it challenging to manage risks throughout design, development, and deployment (Mittelstadt et al. 2016; Smuha 2021).

Policies are emerging worldwide to address the harms and risks associated with the deployment of AI systems. The UK (Nodes 2024) and Switzerland (Digital Society Initiative 2021) have been adapting existing laws to govern AI. In contrast, globally, approaches vary from strict frameworks in China (Project 2022; for Security and CSET) and Brazil (Partnership 2023) to sectoral or executive orders and proposed bills in the US (Register 2020, 2019; Congress 2021; of Science and Policy 2022) with stricter state-level legislations such as Colorado and many other federal states (Assembly 2024). The EU AI Act is the first law in the world to comprehensively regulate AI systems, categorizing them into different risk categories to determine the legal requirements they are subject to (Commission 2024).

Nonetheless, turning such abstract legal requirements into operational solutions remains a challenge. The debate has focused on methods and tools to solve such gaps and the critical need for mechanisms that enable adequate oversight of AI systems, such as robust documentation (Lucaj, van der Smagt, and Benbouzid 2023; Veale and Zuiderveen Borgesius 2021; Alder et al. 2024; Díaz-Rodríguez et al. 2023). Documenting an AI system enables transparency, accountability, as well as proof of adherence to legal requirements (Gebru et al. 2021; Mitchell et al. 2019; Chmielinski et al. 2024; Kroll 2021; Raji et al. 2020; Naja et al. 2021).

Prior work has already provided several artifacts to support the recording of specific lifecycle processes or components, or to provide a high-level mapping of the AI Act's technical documentation requirements. However, none of these tools offers comprehensive coverage of the whole AI system lifecycle in a manner that meets the AI Act's obligations while also enabling a coherent and actionable overview of system functionality. To bridge this gap, we introduce TechOps, a set of open-source automatable templates for documenting data, models, and applications. Our templates are designed to fully align with the AI Act's technical documentation requirements by following all stages of the AI lifecycle. This approach facilitates a clearer understanding of system performance, supports the timely identification and resolution of issues, improves overall quality, and helps to prevent the accumulation of technical debt.

Currently, there is a critical need to develop comprehensive technical documentation templates that account for all the processes throughout the AI lifecycle. This work bridges best-practice AI documentation and the EU AI Act's practical requirements. In the next section, we outline the AI Act's documentation requirements and current best practices. We then introduce TechOps, delineate the structure of each template, and explain how they enable tracking the system's status over the entire AI lifecycle, ensuring traceability, reproducibility, and compliance with the AI Act. We then evaluate the templates on user feedback. This helps us identify implementability and usability issues, as well as opportunities. We illustrate this with real-world datasets, models, and applications, then compare TechOps with current AI documentation practices, summarizing feedback from industry stakeholders. Finally, we outline its limitations and propose future improvements.

Related Work

Documentation is a key practice for AI transparency and accountability. It records decisions across the lifecycle, such as system purpose, design choices, and development steps to enable stakeholders to assess behavior, limitations, and risks (Gebru et al. 2021; Mitchell et al. 2019; Königstorfer and Thalmann 2022; Winecoff and Bogen 2024). Structured documentation also supports audits, enabling regulatory oversight and responsible deployment (Arnold et al. 2019; Birkstedt et al. 2023; Arnold et al. 2024). Here, we position our work within existing literature, underscoring the role of structured documentation for compliance, accountability, and transparency.

Documentation and AI Act Compliance

The EU AI Act sets out detailed technical documentation requirements (Art. 11, 56, Annex IV) to support transparency, accountability, and demonstrable compliance (Commission 2024). These include a description of the system's intended purpose and interactions, along with comprehensive records of its design, data use, testing procedures, performance metrics, risk management strategies, and post-market monitoring plans. The requirements are summarised in Fig. 2.

Studies have identified the necessary information to be included when documenting AI systems for AI compliance (Hupont et al. 2023; Golpayegani et al. 2024). Two methods specifically target AI Act compliance: Use Case Cards (Hupont et al. 2024), which document intended purpose and stakeholders, and AI Cards (Golpayegani et al. 2024), a high-level template covering technical features and risk management. While valuable, these approaches do not capture the full complexity of AI system components or the technical practices across the entire machine learning lifecycle, design, development, deployment, and post-market monitoring. They lack the granularity needed for a complete understanding of such systems. In the next section, we review best practices in AI documentation and show how our work addresses these gaps to operationalize the AI Act's technical documentation requirements while retaining established practices. The European Commission recently published a concise documentation template for general-purpose AI models to provide an overview of the data origin, list main data collections, and explain other sources used (Commission 2025). While the current documentation guidance for GPAI focuses primarily on transparency around training data sources and rights reservations, TechOps extends this scope by incorporating explicit fields for disclosing user data usage, data protection impact assessments, and aligning documentation practices with core GDPR obligations often overlooked in existing guidance.

Existing documentation practices

Early oversight is critical, as inadequate governance can lead to costly retrofitting or fines when regulations take effect (Holland et al. 2020). Data documentation has emerged as a foundational oversight tool. "Datasheets for Datasets" (Gebru et al. 2021) set a de facto standard by outlining questions on purpose, composition, processes, distribution, maintenance, and impact. Other templates, such as Open Datasheets (Roman et al. 2023), Dataset Nutrition Labels (Holland et al. 2020; Chmielinski et al. 2022), and full lifecycle frameworks (Hutchinson et al. 2021) have extended this work to improve usability, transparency, and governance. Drawing from software engineering, some frameworks document the dataset lifecycle from requirements through maintenance (Hutchinson et al. 2021). Tools like Data Cards (Pushkarna, Zaldivar, and Kjartansson 2022), Data Statements (Bender and Friedman 2018), and Data Portraits (Marone and Van Durme 2024) expose decisions affecting model performance, bias, and exclusion. Domain-specific approaches, such as Augmented Datasheets (Papakyriakopoulos et al. 2023), Reflexive Documentation (Miceli et al. 2021), and CrowdWorkSheets (Díaz et al. 2022) target accountability in areas such as speech and vision.

Model documentation practices have evolved alongside system-level approaches to give a full view of a model's design and development. Properly documenting the model lifecycle ensures it is not only functional but also reliable, fair, and aligned with its intended purpose.

Early adoption is key to assessing AI systems and prompting developers to identify, understand, and address product limits before release (Raji et al. 2022). Model Cards (Mitchell et al. 2019) provide a template to document an AI model's intended use, performance, and limitations. They concisely report performance across domains to help prevent unintended uses and unsuitable applications. Inspired by "Supplier's Declarations of Conformity" (SDoCs), Factsheets (Arnold et al. 2019) expand this to include provenance, safety, and security considerations. Related frameworks include Method Cards (Adkins et al. 2022), System Cards (Procope et al. 2022), and Explainability Fact Sheets (Sokol and Flach 2020), each targeting different issues such as detection of functional fallacies, transparency in the architecture, and explainability. Moreover, tools like Value Cards (Shen et al. 2021) and Interactive Model Cards (Crisan et al. 2022) further explore trade-offs and promote the inspection of specific aspects of the ML lifecycle, and understand the functionality and limitations of the systems. While these approaches represent significant contributions, neither fully captures the technical documentation requirements of the AI Act and the intricacies of AI system components or the technical practices applied across the AI lifecycle, including design, development, deployment, and post-market monitor-

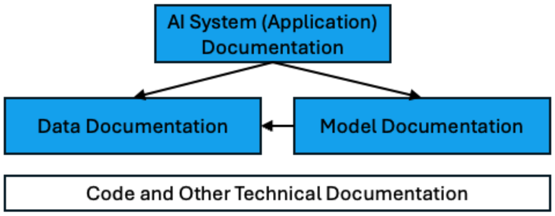

Figure 1: **AI system documentation hierarchy.** Arrows point in the direction of referral. For example, applications that rely on various models and datasets should refer to the corresponding documentation. Going the opposite direction, model and dataset documentation can also refer to known applications but do not have to.

ing. This limitation makes it difficult for large organizations with diverse stakeholders to develop a comprehensive understanding of these systems. Existing studies adopt varying perspectives on documentation. Some propose static documents describing the dataset or model at a specific point in time, while others advocate for evolving documents or interactive dashboards. However, it is important to document the status of the AI System at every point in time separately to make sure that everything can be tracked back, and past results can be easily reconstructed (Gei and Jonsson 2023). Hence, a specific version of the documentation templates should be treated as an immutable artifact at a certain point in time. Therefore, to address such a gap whilst maintaining the existing best practices, we introduce three separate templates for data, models, and applications to enable compliance with the requirements of the AI Act, as well as enabling sustainable maintenance of such practices within organizations and relevant stakeholders.

TechOps Development Methodology

To align with established best practices in AI documentation, this paper introduces three distinct documentation templates: for data, for models, and for applications. This separation acknowledges the distinct roles each component fulfills, letting those responsible for each component focus on providing documentation they are responsible for, while referencing information from the other components, so that information is not duplicated (see Fig. 1). The documentation templates presented in this paper merge the technical documentation requirements of the AI Act with the documentation of the different stages of the ML lifecycle and the practices of machine learning operation (MLOps). MLOps streamline all the practices conducted throughout the lifecycle of AI systems, from design to continuous integration/delivery, data management, model development, testing and validation, deployment (including cloud and edge), post-market monitoring, and continual learning. Therefore, MLOps provide a guide for implementing all documentation requirements throughout the design, development, and deployment lifecycle of AI systems (Billeter et al. 2024).

The templates were developed iteratively, incorporating feedback from diverse stakeholders across the AI lifecycle and from different companies (see Tab. 1). Participants included AI system developers, data and model platform engineers, tech law and governance experts, managers, and non-technical product specialists. A key challenge was balancing the right level of technical, legal, and ethical detail with readability. Because documentation serves multiple audiences, it had to reflect their varied responsibilities and backgrounds. Many existing templates sacrifice technical depth for simplicity; our approach preserves necessary detail on processes that link system performance to legal and ethical considerations. We focused on balancing conciseness with the detail needed to prove compliance and give all relevant stakeholders a clear view of design, development, and deployment. To help maintain both overview and depth, we recommend rendering documentation so users can navigate high-level summaries and easily drill down into specific sections (tested method described below).

These documentation artifacts aim to help all responsible stakeholders for each AI lifecycle component understand what must be documented for AI Act compliance and to assess the system's quality, reliability, and robustness.

By following best practices and dividing the approach into three templates, we created a maintainable solution for organizations. Each stakeholder can focus on the sections relevant to their role: data teams on provenance, collection, preprocessing, labeling, and curation; model teams on training configurations, evaluation metrics, hyperparameters, and performance (while referencing data documentation); and application teams on intended use, limitations, and user interaction (while referencing model and data documentation). This separation lets stakeholders access only relevant details, improving clarity, transparency, accountability, and compliance across the lifecycle while supporting effective oversight and evaluation of each component.

One of the main challenges was the translation of abstract legal and ethical requirements into concrete documentation of the technical measures implemented across the AI system lifecycle—spanning design, development, deployment, and post-market monitoring (Shneiderman 2020). The templates we propose address this issue by blending legal and technical language to enable usability across all stakeholders. To reflect the diversity of roles involved in AI development, the templates accommodate input from multiple stakeholders, each responsible for distinct phases and tools. For example, technical documentation of data management processes is directly linked to broader questions about their ethical and regulatory implications. This traceability enables stakeholders to assess both the localized and systemic impact of each process, offering granular insight as well as a holistic view of compliance. Another challenge was making the templates generalizable across organizational functions with different terminology, tools, and data formats. We addressed this by unifying role-specific documentation requirements into a single structure, enabling contributors to add relevant information without losing completeness. For highly technical phases, the templates provide clear definitions and step-by-step guidance so governance stakeholders—including auditors, AI testers, and regulators—can access and understand the content, promoting transparency and accountability across the lifecycle.

TechOps

We introduce TechOps documentation templates, divided into data, model, and application templates, for all processes along the AI lifecycle that must be documented to enable the necessary oversight for compliance with the AI Act (see Fig. 2). TechOps can enable organizations to delineate design choices and development processes, as well as monitoring the performance after market deployment, and document roles and responsibilities along the AI lifecycle. [1]

Data Documentation Template

This template builds on existing data documentation literature (Gebru et al. 2021; Roman et al. 2023; Pushkarna, Zaldivar, and Kjartansson 2022; Chmielinski et al. 2022; Holland et al. 2020; Bender and Friedman 2018). It also complements existing efforts in data documentation, fostering transparency regarding the origin, quality, and potential biases of the data (Hutchinson et al. 2021). Moreover, this section builds on the work assessing the quality dimensions of data that must be documented for transparency and explainability (Afzal et al. 2021; Castelijns, Maas, and Vanschoren 2020; Hiniduma et al. 2024). That includes greater transparency about data and accountability for decisions made when developing it (Kale et al. 2023; Kroll 2021). In this paper, we introduce a framework to enable compliance as well as transparency and accountability throughout dataset development. This allows organizations to systematically record all critical stages of the data governance lifecycle, facilitating the evaluation of data quality metrics, assessment of model performance, and adherence to the legal requirements of the AI Act (Bhardwaj et al. 2024a,b; Micheli et al. 2023; Díaz-Rodríguez et al. 2023). We based the design of this artifact on the studies that guide the design of templates based on ML practitioners' needs, such as integration into existing tools and workflows (Heger et al. 2022).

This template focuses on the requirements for data governance laid out in Article 10 and Article 11 paragraph 2(d) (Commission 2024) for documenting datasets, including data types and characteristics, origin and source, preprocessing steps, transformation steps that enable inferences about the quality as well as the annotation and validation steps to detect implicit data biases and limitations. (i.e. what biases existed in the data generating process?) This approach enables the overview of the composition of the dataset, ensures transparency by helping downstream dataset users (e.g. developing an AI Model or evaluating an AI System), understand the potential limitations of the data selected, and whether it is appropriate for the intended use.

It is important to note that datasets, though often curated with a particular AI Model or AI System in mind, are not necessarily associated with any one AI Model or AI System. Thus, the data documentation template is designed to be filled without complete knowledge of all downstream AI models and systems. The focus is on enabling data owners to make clear statements about the intended and unintended downstream usages of the dataset, potentially also with hypothetical examples of appropriate and inappropriate AI models and systems. As usages become known, downstream developers that use the dataset are encouraged to contribute information to a "Known Usages" section.

As a generic example portraying the version-controlled, distributed approach to contributing to dataset documentation, consider a dataset of high-resolution human faces and corresponding genders. A downstream model developer wants to develop an AI model that estimates skin health parameters and performs reliably irrespective of gender, skin tone, skin oiliness, and facial shape. As a result, the model developer would like to train and evaluate their model on data that are representative of these four attributes. The model developer works to curate a dataset of the three missing attributes given the faces, say by means of subject interviews and crowd-sourced data annotation. The model developer now has two choices. They can either partner with the original dataset owner to merge their new results with the original dataset, creating a new version of that dataset with updated dataset documentation, or create a new separate dataset with its own documentation that focuses on the new dataset while referencing the existing dataset documentation. In both cases, the existing data documentation update or new data documentation would mainly focus on providing representation statistics of the three new attributes, information about the data-generating / collection process (including known annotation/annotator biases, etc.), and information about the intended and unintended usages of these data. In the latter case, in which a new dataset and data documentation is created by the model developer, the model developer would also ideally be encouraged to contribute a "Known Usage" entry to the original data documentation.

Dataset Status, Characteristics, Origin and Source The first section enables capturing the dataset's maintenance status, core characteristics (e.g., data types, volume, number of instances), and intended AI use cases, including any associated systems. It also includes details on features, annotations, and target variables to support broad applicability. Provenance and sourcing are documented through descriptions of data origin, collection methods, platform, update frequency, and associated risks. This ensures transparency and reliability in understanding the dataset's composition and lifecycle context.

Data Pre-Processing; Versioning, Access, Retention and Deletion This section outlines key practices in data collection, pre-processing, and post-processing, including cleaning, transformation, feature engineering, dimensionality reduction, and augmentation. It documents annotation procedures and quality assurance to ensure labeling accuracy. Dataset licensing, distribution, and versioning are addressed to support transparency, traceability, and usability. Guidance on access, retention, and deletion is included to promote secure and accountable data management within research workflows. It is important to log this information to promote clarity, accountability, and secure data handling in research workflows.

[1] More details on the iterative design and the guidance for the implementation of the the templates can be found on the extended version of the paper at https://arxiv.org/abs/2508.08804.

AI Act Technical Documentation Requirements	TechOps Data Documentation Template	TechOps Model Documentation Template	TechOps Application Template
1. General Description of the AI System **(I)** (a) Intended purpose and version **(II)** (b) System interaction with software and hardware **(III)** (c) Software Versions and Updates **(IV)** (d) Deployment format (built-in software, download, APIs) **(V)** (e) Hardware requirements description **(VI)** (f) Visuals explaining product design and integration (**VII)** (g) User-interface description **(VIII)** (h) Instructions for the deployer **(IX)** 2. Detailed description of the elements and development of the system **(X)** (a) Development methods **(XI)** (b) Design specifications **(XII)** (c) System architecture **(XIII)** (d) Data requirements and datasheet **(XIV)** (e) Human-oversight measures **(XV)** (f) Pre-determined changes and solutions for compliance **(XVI)** (g) Validation, testing and performance metrics, logs **(XVII)** (h) Cybersecurity measures **(XVIII)** 3. Monitoring, functioning and control **(XIX)** 4. Performance metrics **(XX)** 5. Risk-management system **(XXI)** 6. Lifecycle changes **(XXII)** 7. Standards applied **(XXIII)** 8. EU declaration of conformity **(XXIV)** 9. Post-market monitoring **(XV)**	1. Dataset Overview **(I) (XIV)** (a) Dataset Description **(II)** (b) Version and status **(II, V)** (c) Relevant links **(V)** (d) Developers (e) Owners (f) Instructions and user interface description **(VIII, IX)** 2. Data Versioning **(IV)** 3. Known Usages **(XII)** (a) Model(s) (b) Application(s) 4. Dataset Characteristics **(XIV)** 5. Data Origins and Source **(X, XI)** 6. Provenance (Collection Method(s) and Source Description) **(XIV)** 7. Data pre-processing **(XI, XIV)** (a) Data Cleaning (b) Data Transformation (c) Feature Engineering (d) Data Augmentation 8. Data Annotation **(XV)** 9. Dataset distribution **(XIV, XXII)** 10. Access, Retention, Deletion**(XIX)** 11. Data Risk Assessment **(XVIII, XXI)** 12. Cybersecurity Measures (Storage, Transfer, Processing) **(XVIII)** 13. Documentation Metadata **(XXII)** 14. Standards applied **(XXIII)** 15. Data Monitoring **(XV)**	1. Model Overview **(I, II, IV)** (a) Model Type **(I)** (b) Model Description **(I, II)** (c) Relevant links **(V)** (d) Developers (e) Owners (f) Version Details ans Artefacts 2. Intended and Known Usage (In and Out of Scope Use) **(VII, IX)** 3. Model Architecture **(X, XI, XII, XIII)** (a) Datasheet **(XIV)** (b) Model Training (c) Model Validation**(XVII)** 4. Model Testing and Evaluation **(XIX, XX, XVII)** (a) Accuracy, precision, recall, F1 score for classification. - MSE, RMSE, MAE for regression. (b) ROC Curve and AOC 5. Model Bias and Fairness Analysis **(XV, XXI)** (a) Bias detection methods used (b) Mitigation Measures **(XIX)** (c) Retraining**(XXII)** (d) Post-Processing **(XV)** 6. Model Interpretability and Explainability **(XV)** 7. Documentation Metadata 8. Standards Applied **(XXIII)**	1. General Information **(I)** (a) Intended Purpose **(II)** (b) Status (c) Relevant links **(V)** (d) Developers (e) Owners 2. Intended/Known Usage **(VII, IX, XII)** 2. AI Act Risk Classification **(XXI)** 3. Data Documentation **(XIV)** 4. Model Documentation **(XII, XIII)** 5. Deployment (a) Infrastructure and Environment Details **(III, V, VI)** 6. Integration with External Systems **(III, V)** 7. Deployment Plan **(XIX)** (a) Risk Management System **(XXI)** (b) Risk Mitigation Measures **(XIX)** 8. Testing and Validation **(XVII)** 9. Human Oversight **(XV)** 10. Monitoring **(XIX, XV)** 11. Incident Management (**XV)** 12. Standards applied **(XXIII)** 13. EU declaration of conformity

Figure 2: **AI Act Requirements and Template Mapping.**

Data Risks and Security The cybersecurity section of the documentation template outlines protocols for safeguarding data. Key measures include documenting methods for secure storage through encryption, role-based access, and integrity monitoring; secure transfer and data masking; and secure processing using trusted execution environments, audit logging, and data minimization. These steps ensure data confidentiality, integrity, and compliance across its lifecycle.

Model Documentation Template

This template operationalizes the AI Act's model documentation requirements by building on best practices for enabling structured reporting of intended and unintended uses, model architecture, training processes, hyperparameters, and evaluation metrics to enable deeper insight into model behavior (Chudasama et al. 2023; Kreuzberger, Kühl, and Hirschl 2023; Gong et al. 2023; Tagliabue et al. 2021; Arboretti et al. 2022; Kim, Comuzzi, and Di Francescomarino 2024; Sovrano et al. 2022). It builds on foundational work such as Model Cards (Mitchell et al. 2019), Factsheets (Arnold et al. 2019), and other key frameworks (Richards et al. 2020; Crisan et al. 2022; Golpayegani et al. 2024; Hupont et al. 2024).

As with the data documentation template, it is important to note that AI models, though designed for a particular AI system, are not necessarily associated with any one AI System. Thus, the model documentation template is designed to be filled without complete knowledge of all downstream AI Systems. Instead, the focus is on enabling model owners to make clear statements about the intended and unintended downstream usages of the model, potentially also with hypothetical examples of appropriate and inappropriate AI Systems. As known usages become known, downstream developers that use the model are encouraged to contribute information to a "Known Usages" section.

As a generic example portraying the version-controlled, distributed approach to contributing to model documentation, consider again an AI model that estimates skin health parameters for dermatologists based on high-resolution face images (henceforth skin parameter model). A downstream AI System developer wants to develop an AI System that provides Skincare advice based on the skin parameter model, as well as other models and logic, and wishes to fine-tune the existing skin parameter model to output a particular type of score. The downstream system developer would then create the appropriate downstream AI system documentation based on the application documentation template, as well as model documentation for the new fine-tuned AI model. In both cases, the new application and model documentation would refer to the existing model documentation, and the downstream AI System developer would also ideally be encouraged to contribute to a "Known Usages" section of the skin parameter model documentation. The following sections describe key sections of the model documentation in more detail.

Model Overview, Intended Purpose, Architecture This section provides an overview of the model, including its architecture, key components, parameters, and selected training method, as well as duration and compute resources. It also documents input and output formats. The Model Purpose subsection defines the model's intended and known applications, operational domains, and specific tasks, to support ethical and regulatory assessment. It includes known use cases and their associated risk levels under the AI Act, and it clearly identifies unsuitable applications to promote responsible and safe deployment.

Model Validation The Model Validation section provides a structured approach for documenting model performance. It focuses on assessing predictions using a validation dataset, monitoring metrics like accuracy, F1 score, and RMSE, and tracking validation loss to detect overfitting that compromises generalization. It also includes benchmarking results, stress testing, and real-world performance assessments across diverse environments to ensure an overview of robustness. Key optimization strategies, such as hyperparameter tuning, regularization, and early stopping, can be documented to demonstrate efforts to enhance generalization and prevent overfitting. This part ensures a transparent, reproducible, and comprehensive validation process.

Model Evaluation The Model Evaluation section in the template enables a comprehensive assessment of the model's performance using a variety of metrics and techniques. It begins with the computation of performance metrics on the test set, such as accuracy, precision, recall, and F1 score for classification tasks, or MSE, RMSE, and MAE for regression tasks. Moreover, the documentation of confusion matrices provides detailed insights into classification outcomes, while ROC curves and AUC scores offer a deeper evaluation of binary classifiers. Feature importance analysis enhances interpretability by highlighting key contributors to predictions. Robustness testing can be documented to assess performance on edge cases or adversarial examples, ensuring model reliability under challenging conditions.

Model Bias and Fairness The Bias Detection and Mitigation section in the template provides a structured framework to document efforts in identifying and addressing biases within a model. This part was particularly challenging to draft as significant research has been conducted on the incompatibility of various fairness criteria in algorithmic decision making (Loosley et al. 2023; Zehlike et al. 2025). Hence, in this section, we build on the methods developed to interpolate between different fairness criteria (Zehlike et al. 2025), and understand what to document along the AI lifecycle, to understand where bias can enter ML models (Barocas and Selbst 2016; Friedman and Nissenbaum 1996; Corbett-Davies et al. 2023; Barocas, Hardt, and Narayanan 2023), for instance, through non-representative training data. This part provides a structured guide on bias detection methods across three stages: pre-processing (resampling, reweighting, relabeling), in-processing (transfer learning, constraint optimization, adversarial learning), and post-processing (calibration, thresholding). Results from bias testing can be recorded to assess the extent of disparities and develop mitigation strategies such as demographic parity and adversarial debiasing. Retraining methods, such as fairness regularization, recalibration, and output perturbation, can be documented to understand the model's performance. A Fairness Impact Statement concludes the documentation, outlining trade-offs made to ensure transparency and accountability.

Model Transparency and Explainability This section documents the methods and tools used to make the model's decision-making process transparent and comprehensible, such as Shapley Values, LIME, or Counterfactual Explanations. This documentation ensures that stakeholders can assess the interpretability of the model and trust its decisions.

Application Documentation Template

This template focuses on documenting how AI models and other logic are integrated to form an application, including APIs, deployment environment, and user interaction. This helps developers and end-users understand operational aspects of systems. AI applications are complex systems that must be documented as they often include multiple components whose interaction significantly affects the overall performance and impact of the system (Smart et al. 2024; Lee 2023; Micheli et al. 2023; Madaio et al. 2020). For this template, we build on the best practices promoting the documentation of systems in their entirety, with each component, such as factsheets (Arnold et al. 2019; Adkins et al. 2022), system cards (Procope et al. 2022). Moreover, this section builds on the research analyzing the provision of evidence about the safety and security (Brundage et al. 2020), fairness, accuracy, accountability, reliability, and privacy protection of AI systems (Brundage et al. 2020; Li et al. 2023; Schoenherr et al. 2023; Dobbe 2022).

AI Systems General Information, Risk Assessment, Functionality This section outlines the AI system's purpose, target users, deployment context, and key performance goals, while addressing ethical considerations, prohibited uses, and AI Act–based risk classification. It describes system functionality, including capabilities, input requirements, usage scenarios, and limitations, with guidance on interpreting outputs. A high-level architecture overview covers core components and emphasizes integration with documentation, logging, and responsible contacts to support transparency and accountability.

System Deployment The Deployment section provides a concise framework for documenting the infrastructure, integration, and operational requirements of the AI system. It outlines the deployment environment and the integration with external systems is detailed through dependencies, data flow diagrams, and error-handling mechanisms. The section also includes a deployment plan covering infrastructure, steps, and security compliance, alongside a monitoring framework to track performance. Finally, it provides user documentation to support operators and end-users in effectively using the system.

Lifecycle Management The Lifecycle Management section documents procedures for monitoring performance to comply with the post-market monitoring requirement of the AI Act, ethical compliance, and versioning throughout the system's lifecycle. It outlines metrics for application performance (e.g., response time, error rate), model accuracy, and infrastructure usage. Key activities to be described include real-world monitoring, addressing drifts or failures, and periodic model updates. Monitoring logs, incident reports, retraining logs, and audit trails can be inserted here to ensure transparency, compliance, and continuous improvement.

Risk and Incident Management The Risk Management can be documented according to the Article 9 requirements, by outlining measures to ensure safe and ethical operation along frameworks like ISO 31000 or NIST (Force 2018). It enables documenting identified risks and potential harmful outcomes (e.g., bias, privacy breaches) and assessing their likelihood and severity. Preventive measures, such as data validation and bias mitigation, can be documented alongside protective measures, including contingency plans to minimize impact. It covers the documentation of all possible incidents, such as infrastructure challenges alongside integration problems. Strategies for ensuring data quality, handling model issues like drift, and addressing safety or security risks can be delineated.

Testing and Validation (Accuracy, Robustness, Cybersecurity) The Testing and Validation section ensures the AI system's reliability is documented through rigorous evaluation of accuracy, robustness, and cybersecurity. It outlines performance metrics (e.g., accuracy, F1 score) and validation results against benchmarks, with measures about the data curation, algorithm optimization, and real-time feedback to maintain accuracy. Robustness can be documented through the deployment of adversarial training, stress testing, and fail-safes to handle edge cases and uncertainty. Cybersecurity documentation focuses on threat modeling, secure development, and post-deployment monitoring, with detailed documentation for compliance and accountability.

Human Oversight The Human Oversight section follows the requirements of Articles 13 and 14 of the AI Act (Commission 2024). Details mechanisms for integrating human judgment into the AI system, such as human-in-the-loop decision-making and override options for emergencies, can be documented. It includes information about user training and space for guidelines to ensure safe operation, along with the documentation of clear statements of the system's limitations and potential weaknesses to promote responsible use.

Validation

The templates are tested through their implementation and rendering on real-world example scenarios. Such practical example implementations augment the templates for further guidance to documentation developers. In the data documentation example, a skin tone dataset used in an E-Commerce AI system is documented to highlight potential biases and support fairness evaluations (Loosley et al. 2023). This use case validates the utility of the TechOps approach as it provides an overview of all the necessary information to help downstream stakeholders understand the dataset, providing information about the distribution of skin tones in the customer images dataset. In fact, the documentation readers can easily find out that the dataset is made up primarily of light skin tone users and would potentially underperform for users with underrepresented skin tones. In the model documentation example, the performance and limitations of the ALiSNet segmentation model are documented to guide downstream developers in identifying risks, particularly related to body shape bias. Both examples show how the templates help developers meet regulatory requirements and conduct more informed system evaluations (Seifoddini et al. 2023).

Data Documentation Example

The context of this example is an E-Commerce company developing an AI System to improve size and fit recommendations based on customer images to estimate body measurements (Loosley et al. 2023). In the real example, the E-Commerce company conducted a fairness evaluation to ensure the system did not systematically underperform for customers of certain genders, body shapes, or skin tones. A Skin Tones Dataset based on human annotations of skin tones of real customer images was curated to carry out this fairness evaluation and is the subject of this data documentation example.

The skin tones dataset documentation provides an overview of all the necessary information to help downstream stakeholders understand the dataset. It provides information about the distribution of skin tones in the customer images dataset, the potential biases arising from the data-generating process (in this case, human annotation), and the intended purpose and usage of the dataset. Documentation readers can, for example, easily find that the dataset is made up primarily of light skin tone users. This documentation can be used to help developers of downstream AI Systems identify and assess risks, such as the system potentially underperforming for users with underrepresented skin tones. Ultimately, for providers of high-risk AI Systems based on components trained or tested with the skin tones dataset, the skin tones data documentation can be used to, in part, comply with the technical documentation requirements set forth in Annex IV in order for them to pass a conformity assessment.

Model Documentation Example

The context of this example is again an E-Commerce company developing an AI System to improve size and fit recommendations based on customer images to estimate body measurements. One key component of the AI System is a neural network-based image segmentation model called ALiSNet that outputs silhouette images of customers based on front and side photos the customer takes with their mobile phone (Seifoddini et al. 2023).

The ALiSNet model documentation provides an overview of all the necessary information to help downstream stakeholders understand the model, including its intended use, how well it performs overall, under what circumstances it is prone to systematic underperformance, known caveats, and ethical considerations. Documentation readers can, for example, easily find that the model performs well regardless of gender and skin tone, but there is a statistically significant detectable difference in how the model performs with respect to body shape. Despite this, on an absolute scale, the underperformance for some body shapes is not likely severe because the absolute average length scale of error of silhouettes obtained by the model on images of customers with the weakest performing body shapes was still below the typical body measurement error of a trained human taking measurements. Thus, this documentation helps downstream AI System developers, like those developing an AI System for Size and Fit recommendations, identify and assess potential risks, such as the system potentially underperforming for users of certain body shapes. Even though the underperformance on specific body shapes is minimal from the AI Model itself, even small errors can be amplified as they propagate through the various components making up the AI System. Thus, the AI System developer is informed by this model documentation that they should probably also test their AI System end-to-end to ensure that the system overall does not underperform for certain body shapes.

This model documentation not only guides the downstream AI System on how they may want to design a fairness evaluation, but also documents crucial data sources the AI System developer can use to perform the fairness evaluation. Thus, the AI System developer does not have to reinvent the wheel.

Ultimately, for providers of high-risk AI systems that use ALiSNet as one of their components, the model documentation can be used to, in part, comply with the technical documentation requirements in Annex IV in order to pass a conformity assessment.

Application Documentation Example

The application documentation example is applied to a high-risk AI system developed to enable construction site safety using real-time video analytics and sensor data. Deployed on-site with edge devices and cloud integration, it identifies unsafe behaviors (like lack of PPE or entering danger zones) and hazardous conditions to trigger alerts, reduce accidents, and support regulatory compliance. The documentation process enables gaining insights into whether the application is designed for site supervisors and safety managers or whether the system aligns with GDPR and the EU AI Act, with human oversight built in for alert validation. This process provided critical visibility into its functionality, data flows, model limitations, and associated risks, enabling better governance, regulatory alignment, and continuous system monitoring and improvement.

Rendering of Templates and Examples

To ensure that both documentation developers and users can optimally view complex documentation without getting lost in the details, we provide an mkdocs based open source rendering so that one can always maintain a documentation overview while deep diving into specific sections of interest (https://github.com/aloosley/techops). For convenience, we have also rendered all documentation templates and examples online at https://aloosley.github.io/techops/ (see Fig. 3).

ID	Role	Organization	Background
U1	Researcher	Industry	Mathematics
U2	Senior Researcher	Robotics	Informatics
U3	Researcher	Industry	Informatics
U4	Senior Researcher	Industry	Informatics
U5	Senior Researcher	Industry	Informatics
U6	Manager	Industry	Informatics
U7	Researcher	Industry	Informatics
U8	Senior Developer	Industry	Informatics
U9	Senior Developer	Industry	Informatics
U10	Team Lead	Industry	Informatics
U11	Senior Data Scientist	Finance	Data Science
U12	Project Manager	Banking	Economics
U13	Researcher	Tech	Mathematics
U14	Researcher	Academia	Law
U15	Researcher	Academia	Law

Table 1: User Study Participants

Evaluation and Feedback

This section offers a thematic analysis of the qualitative insights gained from conducting semi-structured interviews with users and practitioners along the AI lifecycle (Clarke and Braun 2017; Terry et al. 2017; Braun and Clarke 2022; Squires 2023). The practitioners were recruited through theoretical sampling, which required participants in the study to work along the AI lifecycle as either an ML engineer, a data scientist, a legal expert, or an auditor. This methodology enabled us to collect feedback from the relevant stakeholders around the AI lifecycle and make sure that the templates enable all information relevant for different stakeholders (see Tab. 1). Due to the novelty of the research topic in best practices for AI governance, the "snowball" technique was applied to expand the network through the connections of the interview candidates (Naderifar, Goli, and Ghaljaie 2017). We used an inductive thematic analysis to organically identify and analyse patterns in the stakeholder feedback data to capture all potential improvement suggestions that would enable us to increase the templates' implementability (Braun and Clarke 2024, 2022).

Theme 1: Avoiding Duplication of Information

One of the main issues that emerged is the duplication of information that can occur when navigating separate templates of intertwined components, which might lead to unsustainable maintenance issues (User 1, 2, 3, 4, 5, 6, 8, 9). In order to avoid duplication of information, we have color-coded in the application template the information that must be retrieved from the data and model documentation in order to enable maintenance in the long term, while keeping a clear oversight on the data and model selection practices that impact the overall quality and impact of the application. Moreover, some users found this approach helpful in documenting beyond compliance needs for business and research purposes (User 5, 13, 14). For instance, the templates could be useful to fill the documentation requirements "when publishing research on AI" (U5) or when "discussing with clients the AI system provided" (U13, U14, U15).

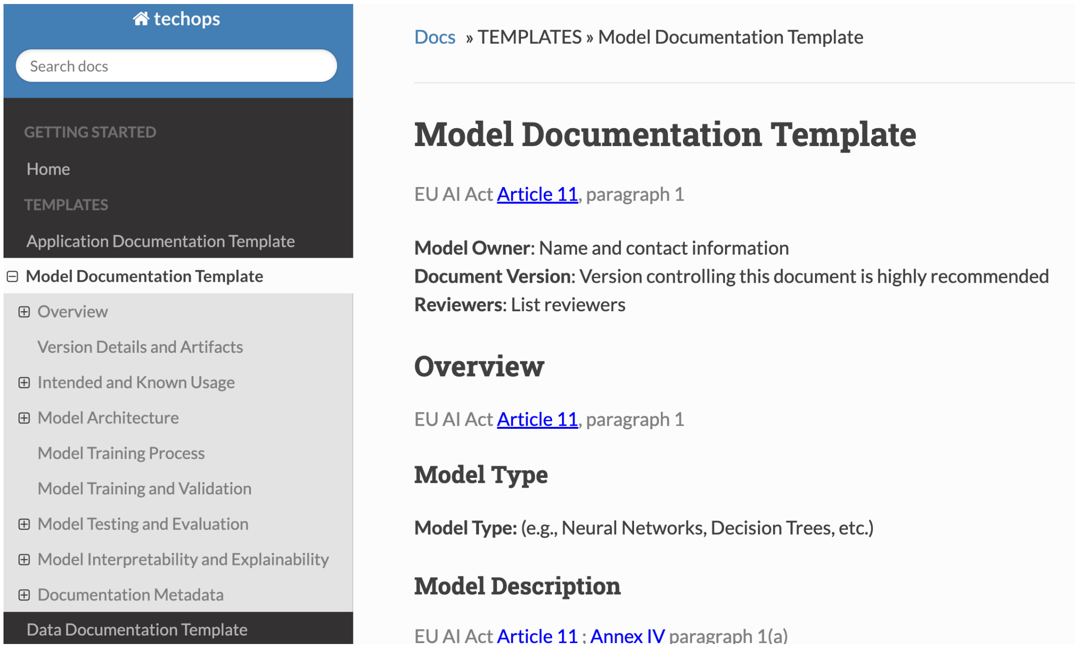

Figure 3: **Template and example rendering snippet.** (See https://aloosley.github.io/techops/)

Theme 2: Implementability Issues

Users were concerned with the comprehensiveness of the templates covering all tasks along the AI lifecycle, which would make the templates too overwhelming for practitioners focusing on a specific task (User 1, 2, 3, 5, 7, 8, 9). Hence, not just a task related but use-case related automation would be necessary for customization (User 1, 5, 7, 8, 9). Practitioners also expressed their concerns about making sure that the templates can be easily implemented within the organizational workflows to optimize their usability and maintenance (User 1, 2, 3). In practice, developers would mainly be able to log relevant information if it is automatically generated whilst coding and send this information directly to a report. Hence, this framework can help developers understand which decisions must be logged and why, and can serve as a guiding framework that collects all relevant information to be documented. A solution could be to adopt methods such as the automatic versioning of Git, like GitHub Actions, where practitioners can check the git repository to see who worked on which part of the templates. We made sure that automating our documentation is fully achievable. Compared to existing templates, certain users (User 1, 5, 7, 8, 9) found Techops to be easier to follow from a technical perspective, which enables them to better document their code, as other templates, such as datasheets, are more abstract and therefore more challenging to fill. Moreover, some users (U12, U13, U14, U15) found the templates approach helpful in navigating interdisciplinary teams' barriers to understanding the translation of abstract concepts into actionable processes along the lifecycle.

Theme 3: Guidance for documentation

A theme that emerged is that many practitioners, especially those without a legal background, are unaware of the documentation requirements of the AI Act (User 1–13). This clearly delineates the need to implement better governance strategies across the companies to clarify what must be documented. However, this is currently challenging due to the lack of standards and open-source solutions. A clear difference we could observe was the awareness of adopting such practices early on between the users in startups and those in highly regulated industries such as banking and finance (U11, U12). This finding suggests that SMEs lack the resources currently on the market to implement such solutions and understand the implications of good governance practices early on. Moreover, a clear gap emerged in the knowledge of the technical and legal implications of certain decisions and the necessity to document them between the users with different backgrounds. Certain users needed more information and examples to understand the implications of deploying certain systems, as well as the necessity to document certain processes along the lifecycle (User 5, 7). For instance, certain developers did not understand the necessity for documenting specific details such as the hyperparameters (User 3, 5). We had to explain that in highly regulated fields like finance, for instance, inspecting hyperparameters enables us to see how potentially biased a model is. Hence, such inspection is necessary to avoid overfitting of sensitive attributes and making models simpler and less likely to memorize biased patterns. User 3 was concerned with the initial sections defining in and out of scope use-cases, as it is hard to predict for developers inappropriate usage. However, this process is fundamental to defining liability and delineating the safe extent of deployment of certain systems by outlining what they were optimised for. We included examples to guide users in delineating the safe extent of deployment. Moreover, certain users (User 4, 5) needed more guidance on the distinction between documenting necessary information for governance purposes, whilst avoiding the documentation of important intellectual property information. We clarified how to keep the balance in the templates, such as how model type and architecture can be described without disclosing business-critical information,such as fine-tuning strategies or optimization methods.

Discussion

In all our tests and feedback sessions, a significant issue raised by the users has been the absence of open-source templates and standards targeting the AI Act's documentation requirements throughout the entire lifecycle. Many companies openly struggle to meet these requirements and remain unsure about documentation standards. Users expressed concern over the perceived gaps in current AI compliance solutions, which often lack guarantees and remain unaffordable for SMEs. We therefore stress the importance of guidance from the open-source community. Existing best practices in AI documentation do not capture the entire AI lifecycle while aligning with the specific legal obligations related to risk management, data governance, human oversight, robustness, and accuracy, as well as a framework for continuous monitoring and lifecycle updates. Moreover, existing practices lack the legally required level of detail to document system interactions, software versions, deployment methods, and human oversight measures. Compared to the existing open-source templates, users found TechOps to help bridge the gap between abstract legal requirements and actual documenting of practices along the AI lifecycle. For instance, compared to questionnaire-based approaches such as datasheets, Techops was found to be better at enabling this overview for different stakeholders and guiding technical practitioners to understand the implications of their choices. The templates provided in this paper capture decision-making processes across the AI lifecycle, from design to post-market monitoring. They do so by tracking performance metrics over time, as everything is under version control so it is easy to identify causes of variation, and benchmark across models. Finally, they improve auditability by providing a central repository of all relevant information, simplifying the audit process for both auditors and auditees. By integrating these structured practices, the proposed documentation templates not only facilitate compliance with the AI Act but also enhance fairness, trust, transparency, and accountability in AI system development.

Our findings show that practitioners still need help applying documentation solutions consistently throughout the AI system lifecycle, as this is not yet a common practice. There is a significant gap between legal and technical experts in understanding why certain elements must be documented and what their legal and technical consequences are. This combined expertise is rare and typically found in auditors. To address this gap, the templates should be reviewed in multidisciplinary meetings at each stage of the lifecycle to ensure effective auditing and oversight.

TechOps can guide stakeholders across the entire AI lifecycle, serving not only as a tool for documenting compliance with the AI Act but also as a framework for fostering the development of safe, robust, fair, and reliable AI systems. By systematically bridging the gap between legal and technical literacy, this approach mitigates the risk of ethics washing, ensuring that the completion of documentation templates involves substantive reflection on both the functional characteristics of the system and its legal implications. Our users said that they could also benefit from using TechOps to submit documentation when publishing AI research or open-sourcing their AI systems, models, and datasets. Therefore, we hope that TechOps provides a standardized and adaptable framework that contributes to emerging best practices. We hope it serves as a building block toward a more consistent and thoughtful approach to AI development—one that not only meets regulatory demands but also fosters trust, accountability, and collaboration within the broader research and developer communities.

Limitations

AI systems are currently used in many domains, which means that these templates are not to be seen as a one-size-fits-all solution but as a contribution to enable relevant stakeholders to understand what to document throughout the AI lifecycle. The aim was to provide guidance through the translation of the legal requirements; however, it is unlikely that these templates can completely capture all components and practices across the different vertical domains in which AI is used. Moreover, we are aware of the complexity vs. applicability dilemma that such thorough documentation is time-consuming and might not be sustainable and maintainable. However, we believe that without thorough guidance and an overview of the components and processes of the AI lifecycle, efficient governance measures cannot be implemented. We thus encourage organizations and stakeholders to adapt these templates to their own context of deployment.

Documenting datasets, models, and applications to comply with the AI Act in the industry still remains a challenge due to the lack of resources and solutions, constant innovation, iterative design and engineering approaches, lack of reliable testing resources, and many other reasons that make documentation a challenge. Here, we provide open-source templates that can be automated, addressing a clear gap in governance and oversight practices to help companies navigate legal uncertainties around AI Act documentation.

Conclusion

We propose TechOps: templates and examples for documenting data, models, and applications to provide sufficient documentation for AI Act certification. TechOps addresses the gaps between the existing documentation templates by enabling a holistic approach to documenting all components and processes across the lifecycle while meeting the technical documentation requirements of the AI Act. We believe this work to be a key input in the ongoing efforts to operationalize the AI Act requirements. Beyond regulatory alignment, the templates serve as practical tools for governing AI systems by helping responsible stakeholders assess quality metrics, identify risks and biases, and prevent the accumulation of technical debt throughout the system lifecycle.

Acknowledgments

We would like to thank Pak-Hang Wong, Rocco Maresca, Scott Small, Daniela Kato, Sobia Naz, Silke Claus, Hosna Sattar, Amrollah Seifoddini, Mathias Deschamps, Ola Wahab, Stanimir Dragiev, and all the other applied scientists, engineers, lawyers, and business leaders that provided valuable feedback. Their insights were instrumental in shaping this work to meet the diverse needs of developers and the many types of users and stakeholders of AI/ML systems. We would like to thank Chiara Gei for her significant contributions on model cards in etami, which played a key role in building this work, and to the etami consortium members for their foundational efforts in translating ethical AI principles into actionable practices.

References

Adkins, D.; Alsallakh, B.; Cheema, A.; Kokhlikyan, N.; McReynolds, E.; Mishra, P.; Procope, C.; Sawruk, J.; Wang, E.; and Zvyagina, P. 2022. Method cards for prescriptive machine-learning transparency. In *Proceedings of the 1st International Conference on AI Engineering: Software Engineering for AI*, 90–100.

Afzal, S.; Rajmohan, C.; Kesarwani, M.; Mehta, S.; and Patel, H. 2021. Data readiness report. In *2021 IEEE international conference on smart data services (SMDS)*, 42–51. IEEE.

Alder, N.; Ebert, K.; Herbrich, R.; and Hacker, P. 2024. Ai, climate, and transparency: Operationalizing and improving the ai act. *arXiv preprint arXiv:2409.07471*.

Arboretti, R.; Ceccato, R.; Pegoraro, L.; and Salmaso, L. 2022. Design choice and machine learning model performances. *Quality and Reliability Engineering International*, 38(7): 3357–3378.

Arnold, M.; Bellamy, R. K.; Hind, M.; Houde, S.; Mehta, S.; Mojsilović, A.; Nair, R.; Ramamurthy, K. N.; Olteanu, A.; Piorkowski, D.; et al. 2019. FactSheets: Increasing trust in AI services through supplier's declarations of conformity. *IBM Journal of Research and Development*, 63(4/5): 6–1.

Arnold, S.; Yesilbas, D.; Gröbner, R.; Riedelbauch, D.; Horn, M.; and Weinzierl, S. 2024. Documentation Practices of Artificial Intelligence. *arXiv preprint arXiv:2406.18620*.

Assembly, C. G. 2024. Senate Bill 24-205: Consumer Protections for Artificial Intelligence. Accessed: 20 January 2025.

Barocas, S.; Hardt, M.; and Narayanan, A. 2023. *Fairness and machine learning: Limitations and opportunities*. MIT press.

Barocas, S.; and Selbst, A. D. 2016. Big data's disparate impact. *Calif. L. Rev.*, 104: 671.

Bender, E. M.; and Friedman, B. 2018. Data statements for natural language processing: Toward mitigating system bias and enabling better science. *Transactions of the Association for Computational Linguistics*, 6: 587–604.

Bhardwaj, E.; Gujral, H.; Wu, S.; Zogheib, C.; Maharaj, T.; and Becker, C. 2024a. Machine learning data practices through a data curation lens: An evaluation framework. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, 1055–1067.

Bhardwaj, E.; Gujral, H.; Wu, S.; Zogheib, C.; Maharaj, T.; and Becker, C. 2024b. The State of Data Curation at NeurIPS: An Assessment of Dataset Development Practices in the Datasets and Benchmarks Track. *arXiv preprint arXiv:2410.22473*.

Billeter, Y.; Denzel, P.; Chavarriaga, R.; Forster, O.; Schilling, F.-P.; Brunner, S.; Frischknecht-Gruber, C.; Reif, M.; and Weng, J. 2024. MLOps as enabler of trustworthy AI. In *2024 11th IEEE Swiss Conference on Data Science (SDS)*, 37–40. IEEE.

Birkstedt, T.; Minkkinen, M.; Tandon, A.; and Mäntymäki, M. 2023. AI governance: themes, knowledge gaps and future agendas. *Internet Research*, 33(7): 133–167.

Braun, V.; and Clarke, V. 2022. Conceptual and design thinking for thematic analysis. *Qualitative psychology*, 9(1): 3.

Braun, V.; and Clarke, V. 2024. Thematic analysis. In *Encyclopedia of quality of life and well-being research*, 7187–7193. Springer.

Brundage, M. 2019. Responsible governance of artificial intelligence: An assessment, theoretical framework, and exploration. Technical report, Arizona State University.

Brundage, M.; Avin, S.; Wang, J.; Belfield, H.; Krueger, G.; Hadfield, G.; Khlaaf, H.; Yang, J.; Toner, H.; Fong, R.; et al. 2020. Toward trustworthy AI development: mechanisms for supporting verifiable claims. *arXiv preprint arXiv:2004.07213*.

Castelijns, L. A.; Maas, Y.; and Vanschoren, J. 2020. The abc of data: A classifying framework for data readiness. In *Machine Learning and Knowledge Discovery in Databases: International Workshops of ECML PKDD 2019, Würzburg, Germany, September 16–20, 2019, Proceedings, Part I*, 3–16. Springer.

Chmielinski, K.; Newman, S.; Kranzinger, C. N.; Hind, M.; Vaughan, J. W.; Mitchell, M.; Stoyanovich, J.; McMillan-Major, A.; McReynolds, E.; Esfahany, K.; et al. 2024. The CLeAR Documentation Framework for AI Transparency.

Chmielinski, K. S.; Newman, S.; Taylor, M.; Joseph, J.; Thomas, K.; Yurkofsky, J.; and Qiu, Y. C. 2022. The dataset nutrition label (2nd gen): Leveraging context to mitigate harms in artificial intelligence. *arXiv preprint arXiv:2201.03954*.

Chudasama, Y.; Purohit, D.; Rohde, P. D.; and Vidal, M.-E. 2023. Enhancing Interpretability of Machine Learning Models over Knowledge Graphs. In *SEMANTiCS (Posters & Demos)*.

Clarke, V.; and Braun, V. 2017. Thematic analysis. *The journal of positive psychology*, 12(3): 297–298.

Commission, E. 2024. Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts. https://eur-lex.europa.eu/eli/reg/2024/1689/oj. Accessed: 28 December 2024.

Commission, E. 2025. GPAI Model Documentation Form. https://digital-strategy.ec.europa.eu/en/policies/contents-code-gpai. Accessed: 29 July 2025.

Congress, U. 2021. S.2551 - A bill to establish guidelines for the use of artificial intelligence in government and to ensure that such use is effective, efficient, ethical, and accountable. Accessed: 20 January 2025.

Corbett-Davies, S.; Gaebler, J. D.; Nilforoshan, H.; Shroff, R.; and Goel, S. 2023. The measure and mismeasure of fairness. *The Journal of Machine Learning Research*, 24(1): 14730–14846.

Crisan, A.; Drouhard, M.; Vig, J.; and Rajani, N. 2022. Interactive model cards: A human-centered approach to model documentation. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, 427–439.

Critch, A.; and Russell, S. 2023. TASRA: a taxonomy and analysis of societal-scale risks from AI. *arXiv preprint arXiv:2306.06924*.

Díaz, M.; Kivlichan, I.; Rosen, R.; Baker, D.; Amironesei, R.; Prabhakaran, V.; and Denton, E. 2022. Crowdworksheets: Accounting for individual and collective identities underlying crowdsourced dataset annotation. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, 2342–2351.

Díaz-Rodríguez, N.; Del Ser, J.; Coeckelbergh, M.; de Prado, M. L.; Herrera-Viedma, E.; and Herrera, F. 2023. Connecting the dots in trustworthy Artificial Intelligence: From AI principles, ethics, and key requirements to responsible AI systems and regulation. *Information Fusion*, 99: 101896.

Digital Society Initiative, U. o. Z. 2021. Position Paper: AI Regulation in Switzerland. Accessed: 20 January 2025.

Dobbe, R. 2022. System safety and artificial intelligence. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, 1584–1584.

for Security, C.; and (CSET), E. T. 2021. Ethical Norms for New Generation Artificial Intelligence Released. Accessed: 20 January 2025.

Force, J. T. 2018. Risk Management Framework for Information Systems and Organizations: A System Life Cycle Approach for Security and Privacy. Technical Report Special Publication (SP) 800-37, Rev. 2, National Institute of Standards and Technology, Gaithersburg, MD.

Friedman, B.; and Nissenbaum, H. 1996. Bias in computer systems. *ACM Transactions on information systems (TOIS)*, 14(3): 330–347.

Gebru, T.; Morgenstern, J.; Vecchione, B.; Vaughan, J. W.; Wallach, H.; Iii, H. D.; and Crawford, K. 2021. Datasheets for datasets. *Communications of the ACM*, 64(12): 86–92.

Gei, C.; and Jonsson, H. 2023. etami: The Open Guidebook on Legal, Trustworthy, and Ethical Artificial Intelligence. https://guidebook.etami.org. Accessed: 8 August 2025.

Golpayegani, D.; Hupont, I.; Panigutti, C.; Pandit, H. J.; Schade, S.; O'Sullivan, D.; and Lewis, D. 2024. AI cards: towards an applied framework for machine-readable AI and risk documentation inspired by the EU AI Act. In *Annual Privacy Forum*, 48–72. Springer.

Gong, L.; Zhang, J.; Wei, M.; Zhang, H.; and Huang, Z. 2023. What is the intended usage context of this model? An exploratory study of pre-trained models on various model repositories. *ACM Transactions on Software Engineering and Methodology*, 32(3): 1–57.

Heger, A. K.; Marquis, L. B.; Vorvoreanu, M.; Wallach, H.; and Wortman Vaughan, J. 2022. Understanding machine learning practitioners' data documentation perceptions, needs, challenges, and desiderata. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW2): 1–29.

Hiniduma, K.; Byna, S.; Bez, J. L.; and Madduri, R. 2024. AI data readiness inspector (AIDRIN) for quantitative assessment of data readiness for AI. In *Proceedings of the 36th International Conference on Scientific and Statistical Database Management*, 1–12.

Holland, S.; Hosny, A.; Newman, S.; Joseph, J.; and Chmielinski, K. 2020. The dataset nutrition label. *Data Protection and Privacy*, 12(12): 1.

Hupont, I.; Fernández-Llorca, D.; Baldassarri, S.; and Gómez, E. 2024. Use case cards: a use case reporting framework inspired by the European AI Act. *Ethics and Information Technology*, 26(2): 19.

Hupont, I.; Micheli, M.; Delipetrev, B.; Gómez, E.; and Garrido, J. S. 2023. Documenting high-risk AI: a European regulatory perspective. *Computer*, 56(5): 18–27.

Hutchinson, B.; Smart, A.; Hanna, A.; Denton, E.; Greer, C.; Kjartansson, O.; Barnes, P.; and Mitchell, M. 2021. Towards accountability for machine learning datasets: Practices from software engineering and infrastructure. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 560–575.

Kale, A.; Nguyen, T.; Harris Jr, F. C.; Li, C.; Zhang, J.; and Ma, X. 2023. Provenance documentation to enable explainable and trustworthy AI: A literature review. *Data Intelligence*, 5(1): 139–162.

Kim, S.; Comuzzi, M.; and Di Francescomarino, C. 2024. Explaining the impact of design choices on model quality in predictive process monitoring. *Journal of Intelligent Information Systems*, 1–26.

Königstorfer, F.; and Thalmann, S. 2022. AI Documentation: A path to accountability. *Journal of Responsible Technology*, 11: 100043.

Kreuzberger, D.; Kühl, N.; and Hirschl, S. 2023. Machine learning operations (mlops): Overview, definition, and architecture. *IEEE access*, 11: 31866–31879.

Kroll, J. A. 2021. Outlining traceability: A principle for operationalizing accountability in computing systems. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 758–771.

Lee, B. C. G. 2023. The "Collections as ML Data" checklist for machine learning and cultural heritage. *Journal of the Association for Information Science and Technology*.

Li, B.; Qi, P.; Liu, B.; Di, S.; Liu, J.; Pei, J.; Yi, J.; and Zhou, B. 2023. Trustworthy AI: From principles to practices. *ACM Computing Surveys*, 55(9): 1–46.

Loosley, A.; Seifoddini, A.; Canopoli, A.; and Zehlike, M. 2023. Body Measurement Prediction Fairness. In *Proceedings of the 2nd European Workshop on Algorithmic Fairness*.

Lucaj, L.; van der Smagt, P.; and Benbouzid, D. 2023. Ai regulation is (not) all you need. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, 1267–1279.

Madaio, M. A.; Stark, L.; Wortman Vaughan, J.; and Wallach, H. 2020. Co-designing checklists to understand organizational challenges and opportunities around fairness in AI. In *Proceedings of the 2020 CHI conference on human factors in computing systems*, 1–14.

Marone, M.; and Van Durme, B. 2024. Data portraits: Recording foundation model training data. *Advances in Neural Information Processing Systems*, 36.

Miceli, M.; Yang, T.; Naudts, L.; Schuessler, M.; Serbanescu, D.; and Hanna, A. 2021. Documenting computer vision datasets: an invitation to reflexive data practices. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 161–172.

Micheli, M.; Hupont, I.; Delipetrev, B.; and Soler-Garrido, J. 2023. The landscape of data and AI documentation approaches in the European policy context. *Ethics and Information Technology*, 25(4): 56.

Mitchell, M.; Wu, S.; Zaldivar, A.; Barnes, P.; Vasserman, L.; Hutchinson, B.; Spitzer, E.; Raji, I. D.; and Gebru, T. 2019. Model Cards for Model Reporting. In *Proceedings of the Conference on Fairness, Accountability, and Transparency*, 220–229. Atlanta GA USA: ACM. ISBN 978-1-4503-6125-5.

Mittelstadt, B. D.; Allo, P.; Taddeo, M.; Wachter, S.; and Floridi, L. 2016. The ethics of algorithms: Mapping the debate. *Big Data & Society*, 3(2): 2053951716679679.

Naderifar, M.; Goli, H.; and Ghaljaie, F. 2017. Snowball sampling: A purposeful method of sampling in qualitative research. *Strides in development of medical education*, 14(3).

Naja, I.; Markovic, M.; Edwards, P.; and Cottrill, C. 2021. A semantic framework to support AI system accountability and audit. In *The Semantic Web: 18th International Conference, ESWC 2021, Virtual Event, June 6–10, 2021, Proceedings 18*, 160–176. Springer.

Nodes, L. 2024. UK AI Regulations: An Overview. Accessed: 20 January 2025.

of Science, T. W. H. O.; and Policy, T. 2022. Blueprint for an AI Bill of Rights: Making Automated Systems Work for the American People. Accessed: 20 January 2025.

O'neil, C. 2017. *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.

Papakyriakopoulos, O.; Choi, A. S. G.; Thong, W.; Zhao, D.; Andrews, J.; Bourke, R.; Xiang, A.; and Koenecke, A. 2023. Augmented datasheets for speech datasets and ethical decision-making. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, 881–904.

Partnership, A. 2023. Access Alert: Brazil's New AI Bill – A Comprehensive Framework for Ethical and Responsible Use of AI Systems. Accessed: 20 January 2025.

Procope, C.; Cheema, A.; Adkins, D.; Alsallakh, B.; Green, N.; McReynolds, E.; Pehl, G.; Wang, E.; and Zvyagina, P. 2022. System-level transparency of machine Learning. *Meta Research. February*, 23.

Project, S. D. 2022. Translation: Internet Information Service Algorithmic Recommendation Management Provisions. Accessed: 20 January 2025.

Pushkarna, M.; Zaldivar, A.; and Kjartansson, O. 2022. Data cards: Purposeful and transparent dataset documentation for responsible ai. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, 1776–1826.

Raji, I. D.; Kumar, I. E.; Horowitz, A.; and Selbst, A. 2022. The fallacy of AI functionality. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, 959–972.

Raji, I. D.; Smart, A.; White, R. N.; Mitchell, M.; Gebru, T.; Hutchinson, B.; Smith-Loud, J.; Theron, D.; and Barnes, P. 2020. Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*, 33–44.

Register, F. 2019. Executive Order on Maintaining American Leadership in Artificial Intelligence. Accessed: 20 January 2025.

Register, F. 2020. Executive Order on Promoting the Use of Trustworthy Artificial Intelligence in the Federal Government. Accessed: 20 January 2025.

Richards, J.; Piorkowski, D.; Hind, M.; Houde, S.; and Mojsilović, A. 2020. A methodology for creating AI FactSheets. *arXiv preprint arXiv:2006.13796*.

Roman, A. C.; Vaughan, J. W.; See, V.; Ballard, S.; Torres, J.; Robinson, C.; and Ferres, J. M. L. 2023. Open datasheets: machine-readable documentation for open datasets and responsible AI assessments. *arXiv preprint arXiv:2312.06153*.

Schoenherr, J. R.; Abbas, R.; Michael, K.; Rivas, P.; and Anderson, T. D. 2023. Designing AI using a human-centered approach: Explainability and accuracy toward trustworthiness. *IEEE Transactions on Technology and Society*, 4(1): 9–23.

Seifoddini, A.; Vernooij, K.; Künzle, T.; Canopoli, A.; Alf, M.; Volokitin, A.; and Shirvany, R. 2023. ALiSNet: Accurate and Lightweight Human Segmentation Network for Fashion E-Commerce. In *Proceedings of the 18th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2023) - Volume 4: VISAPP*, 746–754. INSTICC, SciTePress. ISBN 978-989-758-634-7.

Shen, H.; Deng, W. H.; Chattopadhyay, A.; Wu, Z. S.; Wang, X.; and Zhu, H. 2021. Value cards: An educational toolkit for teaching social impacts of machine learning through deliberation. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, 850–861.

Shneiderman, B. 2020. Bridging the gap between ethics and practice: guidelines for reliable, safe, and trustworthy human-centered AI systems. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 10(4): 1–31.

Smart, A.; Ahmed, S.; Metcalf, J.; Kasirzadeh, A.; Belli, L.; Rismani, S.; Dobbe, R.; et al. 2024. What Is Sociotechnical AI Safety? What Do We Want It To Be? A FAccT Community Workshop. Presented at the FAccT Community Workshop.

Smuha, N. A. 2021. Beyond the individual: governing AI's societal harm. *Internet Policy Review*, 10(3).

Sokol, K.; and Flach, P. 2020. Explainability fact sheets: a framework for systematic assessment of explainable approaches. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*, 56–67.

Solow-Niederman, A. G. 2023. Algorithmic grey holes. *JL & Innovation*, 5: 116.

Sovrano, F.; Sapienza, S.; Palmirani, M.; and Vitali, F. 2022. Metrics, explainability and the European AI act proposal. *J*, 5(1): 126–138.

Squires, V. 2023. Thematic analysis. In *Varieties of qualitative research methods: Selected contextual perspectives*, 463–468. Springer.

Tagliabue, J.; Tuulos, V.; Greco, C.; and Dave, V. 2021. DAG Card is the new Model Card. *arXiv preprint arXiv:2110.13601*.

Terry, G.; Hayfield, N.; Clarke, V.; Braun, V.; et al. 2017. Thematic analysis. *The SAGE handbook of qualitative research in psychology*, 2(17-37): 25.

Veale, M.; and Zuiderveen Borgesius, F. 2021. Demystifying the Draft EU Artificial Intelligence Act—Analysing the good, the bad, and the unclear elements of the proposed approach. *Computer Law Review International*, 22(4): 97–112.

Winecoff, A. A.; and Bogen, M. 2024. Improving governance outcomes through AI documentation: Bridging theory and practice. *arXiv preprint arXiv:2409.08960*.

Zehlike, M.; Loosley, A.; Jonsson, H.; Wiedemann, E.; and Hacker, P. 2025. Beyond incompatibility: Trade-offs between mutually exclusive fairness criteria in machine learning and law. *Artificial Intelligence*, 104280.