TOWARDS A DEFINITION OF A RESPONSIBLE ARTIFICIAL INTELLIGENCE

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Our research aims to contribute to the concept of responsible artificial intelligence (AI), a topic under significant discussion in EU politics, further emphasized by recent EU publications. Primarily, AI, while beneficial, can be a potential weapon, necessitating responsible use and prevention against misuse or misalignment. In recognizing the critical role of AI research in aiding legislators and machine learning practitioners, our work aims to help prepare for future AI advancements. To the best of our knowledge, we establish the first unified definition of responsible AI. As part of a structured literature review, we clarify the current state of the art in the context of responsible AI. Based on the knowledge of the analysis part we also have discussed an approach for developing a future framework for responsible AI. The results demonstrate that responsible AI should be a human-centered approach, encompassing ethical considerations, explainability of models, privacy, security, and trust.

Keywords:
structured literature review,
artificial intelligence,
responsible AI,
privacy-preserving AI,
explainable AI,
ethical AI,
trustworthy AI

University of Maribor Press

DOI https://doi.org/10.18690/um.feri.5.2023.2
ISBN 978-961-286-745-4

1 Introduction

Over the years, significant research has been conducted to enhance Artificial Intelligence (AI), which is already widely used in various life and industry sectors. In 2020 and 2021, the European Commission published a series of papers [1,2,3] outlining their strategy for AI. The white paper "A European Approach to Excellence and Trust" from 2020 outlines political strategies to encourage the use of AI while reducing the potential risks associated with certain applications of this technology. This proposal aims to establish a legal framework for trustworthy AI in Europe so that the second objective of building an ecosystem for trust can be implemented. The framework should fully respect the values and rights of EU citizens. It is repeatedly emphasized that AI should be human-centered and that European values have a high priority. The papers also address challenging issues such as ethical issues, privacy, explainability, safety, and sustainability. It is pointed out how important security is in the context of AI, and they also present a risk framework in five risk groups for AI systems in short form. The document authors recognize that *"[EU] Member States are pointing at the current absence of a common European framework."* This indicates that a common EU framework is missing, and it is an important political issue.

The document "Communication on Fostering a European Approach to AI" represents a plan of the EU Commission, where numerous efforts are presented that are intended to advance AI in the EU or have already been undertaken. In the beginning, it is stated that the EU wants to promote the development of "human-*centric, sustainable, secure, inclusive and trustworthy artificial intelligence (AI) [which] depends on the ability of the European Union"*.

The Commission's goal is to ensure that excellence in the field of AI is promoted. Collaborations with stakeholders, building research capacity, environment for developers, and funding opportunities are talked about as well as bringing AI into the play for climate and environment. Part of the discussion on trust led to the question of how to create innovation. It was pointed out that the EU approach should be *"human-centered, risk-based, proportionate, and dynamic."* The plan also says they want to develop *"cutting-edge, ethical and secure AI, (and) promoting a human-centric approach in the global context"*. At the end of the document, there is an important statement: *"The revised plan, therefore, provides a valuable opportunity to strengthen competitiveness, the capacity for* *innovation, and the responsible use of AI in the EU".* The EC has also published the "Proposal for a Regulation laying down harmonized rules on artificial intelligence" which contains, for example, a list of prohibited AI practices and specific regulations for AI systems that pose a high risk to health and safety as well as some transparency requirements.

It becomes noticeable that terms in the mentioned political documents that are used to describe the goal of trustworthy AI, however, keep changing (are inconsistent), and remain largely undefined. The documents all reflect, on the one hand, the benefits and on the other hand the risks of AI from a political perspective. It becomes clear that AI can improve our lives, solves problems in many ways, and is bringing added value but also can be a deadly weapon. But on the other hand, the papers do not exactly define what trustworthy AI even means in concrete terms. Topics and subtopics are somehow addressed but there is no clear definition of (excellence and) trustworthiness, but more indirectly mentions some aspects which are important, e.g., ethical values, transparency, risks for safety as well as sustainability goals.

Furthermore, we believe that trust as a goal (as defined vaguely in the documents) is also not sufficient to deploy AI. Rather, we need approaches for "responsible AI", which reflect the EU values. This should of course also be trustworthy, but that concept covers just a part of the responsibility. Therefore, in this paper, our goal is to find out the state-of-the-art from the scientific perspective and whether there is a general definition for "trustworthy AI". Furthermore, we want to clarify whether or not there is a definition for "responsible AI". The latter should actually be at the core of the political focus if we want to go towards *"excellence"* in AI.

As a step towards responsible AI, we conduct a structured literature review that aims to provide a clear answer to what it means to develop responsible AI.

During our initial analysis, we found that there is a lot of inconsistency in the terminology overall, not only in the political texts. There is also a lot of overlap in the definitions and principles for responsible AI. In addition, similar/content-wise similar expressions exist that further complicate the understanding of responsible AI as a whole. There are already many approaches in the analyzed fields, namely trustworthy, ethical, explainable, privacy-preserving, and secure AI, but there are still many open problems that need to be addressed in the future. Best to our knowledge this is the first detailed and structured review regarding responsible AI.

The paper is organized as follows: First, we explain our research methodology, including our research aims and objectives, and the databases and research queries we used for searching. Next, we analyze the existing definitions for responsible AI in the literature, along with related expressions and their definitions. We compare these definitions to determine the essence of responsible AI. We then summarize our key findings within the previously defined scopes of responsible AI, conducting both qualitative and quantitative analyses. In the discussion section, we outline the key points and pillars for developing responsible AI. Finally, we conclude by mentioning the limitations of our work and discussing future research.

2 Research Methodology

In order to address the research questions, we conducted a systematic literature review (SLR) using the guidelines outlined in [4]. The process of performing the structured literature review for our study is explained in detail in the following subsections.

2.1 Research Aims and Objectives

Our research focuses on exploring the different aspects of "Responsible AI" including privacy, explainability, trust, and ethics. Our objectives are to define the term "responsible AI", examine the current state of research in this field, and identify areas that require further investigation. Ultimately, we aim to uncover any challenges, opportunities, and open problems that exist in this area.

In summary, we provide the following contributions:

1. Specify a concise Definition of ”Responsible AI”
2. Analyze the state of the art in the field of ”Responsible AI”

2.2 Research Questions Formulation

Based on the aims of the research, we state the following research questions:

- RQ1: What is a general or agreed on definition of ”Responsible AI” and what are the associated terms defining it?
- RQ2: What does ”Responsible AI” encompass?

2.3 Databases

In order to get the best results when searching for the relevant studies, we used the indexing data sources. These sources enabled us a wide search of publications that would otherwise be overlooked. The following databases were searched:

- ACM Digital Library (ACM)
- IEEE Explore (IEEE)
- SpringerLink (SL)
- Elsevier ScienceDirect (SD)

The reason for selecting these databases was to limit our search to peer-reviewed research papers only.

2.4 Studies Selection

To search for documents, the following search query was used in the different databases:

("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning"
OR "Neural Network" OR "AI" OR "ML") AND (Ethic* OR Explain* OR Trust*) AND (Privacy*).

Considering that inconsistent terminology is used for ”Artificial Intelligence”, the terms ”Machine Learning”, ”Deep Learning” and ”Neural Network” were added, which should be considered synonyms. Because there are already many papers using the abbreviations AI and ML, these were included to the set of synonyms.

The phrases ”Ethic”, ”Trust” and ”Explain” as well as ”Privacy” was included with an asterisk (*), for all combinations of the terms following the asterisk, are included in the results (e.g. explain*ability). The search strings were combined using the Boolean operator OR for inclusiveness and the operator AND for the intersection of all sets of search strings. These sets of search strings were put within parentheses.

To ensure that all state-of-the-art papers were included, the search was limited to a three-year period from 2020 to 2022, with the search conducted in December 2022. The search results were sorted by relevance to eliminate non-relevant papers, as some search engines lack advanced options. During the screening stage, the authors followed specific guidelines to exclude irrelevant papers. Papers did not pass the screening if:

1. They mention AI in the context of cyber-security, embedded systems, robotics, autonomous driving or internet of things, or alike.
2. They are not related to the defined terms of responsible AI.
3. They belong to general AI studies.
4. They only consist of an abstract.
5. They are published as posters.

These defined guidelines were used to greatly decrease the number of full-text papers to be evaluated in subsequent stages, allowing the examiners to focus only on potentially relevant papers.

The initial search produced 10.313 papers of which 4.121 were retrieved from ACM, 1064 from IEEE, 1.487 from Elsevier Science Direct, and 3.641 from Springer Link. The screening using the title, abstract, and keywords removed 6.507 papers. During the check of the remaining papers for eligibility, we excluded 77 irrelevant studies and 9 inaccessible papers. We ended up with 254 papers that we included for the qualitative and quantitative analysis (see Figure 1).

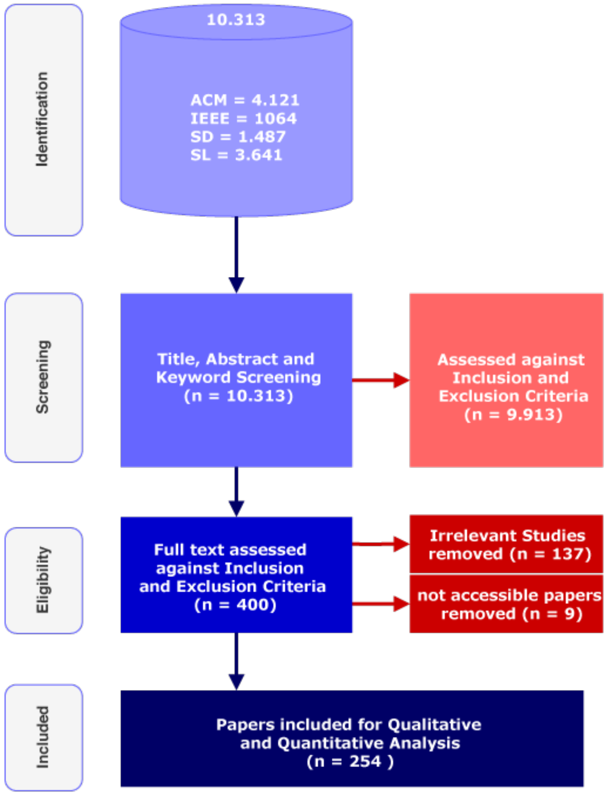


Figure 1: Structured review flow chart: the Preferred Reporting Items for Systematic Reviews and Meta– Analyses (PRISMA) flow chart detailing the records identified and screened, the number of full-text articles retrieved and assessed for eligibility, and the number of studies included in the review.

Source: own.

3 Analysis

In this section, we analyze existing definitions of "responsible AI" in literature. We also examine content-wise-similar expressions and their definitions, comparing and searching for any overlaps. As a result, we extract the essence of the analysis to formulate our definition of responsible AI.

3.1 Responsible AI

In this subsection, we answer the first research question: What is a general or agreed on definition of 'Responsible AI', and what are the associated terms defining it?

3.1.1 Terms defining Responsible AI

Upon careful examination of 254 papers, it was found that a mere 5 of them specifically address the definition of "responsible" AI. The papers use the following terms in connection with ’responsible AI’:

- Fairness, Privacy, Accountability, Transparency and Soundness [5]
- Fairness, Privacy, Accountability, Transparency, Ethics, Security & Safety [6]
- Fairness, Privacy, Accountability, Transparency, Explainability [7]
- Fairness, Accountability, Transparency, and Explainability [8]
- Fairness, Privacy, Sustainability, Inclusiveness, Safety, Social Good, Dignity, Performance, Accountability, Transparency, Human Autonomy, Solidarity [9]

However, after reading all 254 analyzed papers we strongly believe, that the terms that are included in those definitions can be mostly treated as subterms or ambiguous terms.

- ’Fairness’[5] and ’Accountability’ [5,6,7], as well as the terms ’Inclusiveness, Sustainability, Social Good, Dignity, Human Autonomy, Solidarity’ [9] according to our definition, are subterms of Ethics.
- ’Soundness’[5], interpreted as ’Reliability’ or ’Stability’, is included within Security and Safety.
- Transparency [5,6,7] is often used as a synonym for explainability in the whole literature.

Therefore we summarize these terms of the above definitions to: ”Ethics, Trustworthiness, Security, Privacy, and Explainability”. However, only the terms alone are not enough to get a picture of responsible AI. Therefore, we will analyze and discuss what the *meaning* of the five terms ”Ethics, Trustworthiness, Security, Privacy, and Explainability” in the context of AI is, and how they *depend* on each other. During the analysis, we found also content-wise similar expressions to the concept of ”responsible AI” which we want to include in the findings. This topic will be dealt with in the next section.

3.1.2 Content-wise similar expressions for Responsible AI

Our analysis uncovered that the terms "Responsible AI," "Ethical AI," and "Trustworthy AI" are frequently utilized interchangeably. Furthermore, we determined that "Human-Centered AI" holds a similar significance.

Therefore, we treat the terms:

- ”Trustworthy AI”, found in [10,11,12,13,14,15,16], and [17] as cited in [18]
- ”Ethical AI”, found in [19,20,21,22,23], and [24] as cited in [25]
- ”Human-Centered AI”, found in [26] as cited in [23]

as the *content-wise similar expressions* for ”Responsible AI” hereinafter.

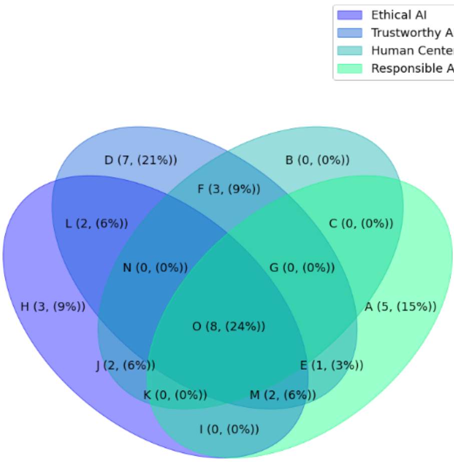
3.2 Collection of definitions

The resulting collection of definitions from ’responsible AI’ and ’content-wise similar expressions for responsible AI’ from the papers results in the following Venn diagram:

We compared the definitions in the Venn diagram and determine the following findings:

- From all four sets there is an overlap of 24% of the terms: Explainability, Safety, Fairness, Accountability, Ethics, Security Privacy, Transparency.
- The terms occurring in the set of the definition for ’trust’ only occurred in these, which is why this makes up the second largest set in the diagram. This is since most of the terms actually come from definitions for trustworthy AI.
- There are also 6 null sets.

To tie in with the summary from the previous section, it should be pointed out once again that the terms ’Explainability, Safety, Fairness, Accountability, Ethics, Security Privacy, Transparency’ can be grouped into generic terms as follows: Ethics, Security, Privacy, and Explainability.



Set	Terms
A	Solidarity, Performance, Sustainability, Soundness, Inclusiveness
B	-
C	-
D	Equality, Usability, Accuracy under Uncertainty, Assessment, Reliability, Data Control, Data Minimization Reproducibility, Generalization User Acceptance
E	Social Good
F	Human-Centered, Human Control, Human Agency
G	-
H	Autonomy, Non-Maleficience, Trust
I	-
J	Human Values, Non-Discrimination
K	-
L	Compliant with Rules and Laws, Social Robustness
M	Human Autonomy, Dignity
N	-
O	Explainability, Safety, Fairness, Accountability, Ethics, Security Privacy, Transparency

Figure 2: Venn diagram

Source: own.

We also strongly claim that 'trust/trustworthiness' should be seen as an outcome of a responsible AI system, and therefore we determine, that it belongs to the set of requirements. And each responsible AI should be built in a 'human-centered' manner, which makes it therefore another important subterm.

On top of these findings, we specify our definition of Responsible AI in order to answer the first research question:

DEFINITION OF RESPONSIBLE AI

Responsible AI is **human-centered** and ensures users' **trust** through **ethical** ways of decision making. The decision-making must be fair, accountable, not biased, with good intentions, non-discriminating, and consistent with societal laws and norms. Responsible AI ensures, that automated decisions are **explainable** to users while always preserving users **privacy** through a **secure** implementation.

Figure 3: Definition of responsible AI

Source: own.

As mentioned in the sections before, the terms defining ”responsible AI” result from the analysis of the terms in sections 3.1.1 and 3.1.2. We presented a figure depicting the overlapping of the terms of content-wise similar expressions of Responsible AI, namely ”Ethical AI, Trustworthy AI, and Human-Centered AI”, and extracted the main terms of it. Also by summarizing the terms Fairness and Accountability into Ethics, and clarifying the synonyms (e.g., explainability instead of transparency), we finally redefined the terms defining ”responsible AI” as **”Human-centered, Trustworthy, Ethical, Explainable, Privacy(-preserving) and Secure AI”**.

3.3 Aspects of Responsible AI

After analyzing the literature, we have identified six categories related to responsible AI in section 3. These categories are Human-centered, Trustworthy, Ethical, Explainable, Privacy-preserving, and Secure AI. Adhering to these categories will ensure the responsible development and use of AI.

To answer the second research question (RQ2), we analyze the state-of-the-art of topics ”Trustworthy, Ethical, Explainable, Privacy-preserving and Secure AI” in the following subsections. We have decided to deal with the topic of ’Human-Centered AI’ in a separate paper so as not to go beyond the scope of this work. To find out the state of the art of the mentioned topics in AI, all 254 papers were assigned to one of the categories ”Trustworthy AI, Ethical AI, Explainable AI, Privacy-preserving AI, and Secure AI”, based on the prevailing content of the paper compared to each of the topics. The detailed analysis of these papers is beyond the scope of the present work and will be presented in our future work. Nevertheless, we highlight their most important features in the following subsections.

3.3.1 Trustworthy AI

A concise statement for trust in AI is as follows:

”Trust is an attitude that an agent will behave as expected and can be relied upon to reach its goal. Trust breaks down after an error or a misunderstanding between the agent and the trusting individual. The psychological state of trust in AI is an emergent property of a complex system, usually involving many cycles of design, training, deployment, measurement of performance, regulation, redesign, and retraining.”[27]

In summary, Trustworthy AI aims to provide the benefits of AI while addressing scenarios that have significant implications for people and society. To be accepted in society, it is crucial for AI applications to prioritize trust as a key goal and make every effort to maintain and measure it throughout all stages of development. Despite this importance, achieving trustworthy AI remains a significant challenge as it has not yet been comprehensively addressed.

3.3.2 Ethical AI

In this section, we will outline the discoveries made in the realm of ethical AI. The most fitting explanation of ethics in relation to AI is the one provided in source [28]:

”*AI ethics is the attempt to guide human conduct in the design and use of artificial automata or artificial machines, aka computers, in particular, by rationally formulating and following principles or rules that reflect our basic individual and social commitments and our leading ideals and values* [28].”

During our analysis, we noticed that Ethical AI deals often with fairness. Fair AI can be understood as

”*AI systems [which] should not lead to any kind of discrimination against individuals or collectives in relation to race, religion, gender, sexual orientation, disability, ethnicity, origin or any other personal condition. Thus, fundamental criteria to consider while optimizing the results of an AI system is not only their outputs in terms of error optimization but also how the system deals with those groups.*”[6]

In any case, the development of ethical artificial intelligence should be also subject to proper oversight within the framework of robust laws and regulations. It is also stated, that transparency is widely considered also as one of the central AI ethical principles [29]. In the state-of-the-art overview of [30] the authors deal with the relations between explanation and AI fairness and examine, that fair decision-making requires extensive contextual understanding, and AI explanations help identify potential variables that are driving the unfair outcomes.

Mostly, transparency and explainability are achieved using so-called explainability (XAI) methods. Therefore, it is discussed separately in the following subsection.

3.3.3 Explainable AI

The choices made by AI systems or humans utilizing AI can greatly affect the welfare, liberties, and prospects of those influenced by those choices. That's why the issue of AI explainability is a crucial ethical concern. This subsection deals with the analysis of the literature in the field of explainable AI (XAI).

We found an interesting definition in [6] which is quite suitable for defining explainable AI:

Given a certain audience, explainability refers to the details and reasons a model gives to make its functioning clear or easy to understand.[6]

Numerous XAI techniques have been extensively discussed in literature. The authors of [6] as well as [31] give a detailed overview of the known techniques and their strengths and weaknesses, therefore we will only cover this topic in short. First, the models can be distinguished into two different approaches to XAI, the intrinsically transparent models and the Post-hoc explainability target models that are not readily interpretable by design. These so-called ”black-box models” are the more problematic ones, because they are way more difficult to understand. The post-hoc explainability methods can then be distinguished further into model-specific and model-agnostic techniques.

We can also distinguish generally between data-dependent and data-independent mechanisms for gaining interpretability as well as global and local interpretability methods.

The general public needs more transparency about how ML/AI systems can fail and what is at stake if they fail. Ideally, they should clearly communicate the outcomes and focus on the downsides to help people think about the trade-offs and risks of different choices (for example, the costs associated with different outcomes). But in addition to the general public also Data Scientists and ML Practitioners represent another key stakeholder group. In the study by [32] the effectiveness and interpretability of two existing tools were investigated; the results indicate that data scientists over-trust and misuse interpretability tools.

There is a "right to explanation" in the context of AI systems that directly affect individuals through their decisions, especially in legal and financial terms, which is one of the themes of the General Data Protection Regulation (GDPR) [33,34]. Therefore, we need to protect data through secure and privacy-preserving AI-methods, which are analyzed in the following section.

3.3.4 Privacy-preserving and Secure AI

As previously mentioned, trust in AI is dependent on privacy and security. However, the success of ML models relies heavily on data, including sensitive information. This has resulted in increasing worries about privacy violations, such as the unlawful use and exposure of private data [35,36]. To ensure complete privacy protection, we require holistic methods that consider the usage of data and user activities and transactions.[37].

Privacy-preserving and Secure AI methods can help mitigate those risks. We define "Secure AI" as protecting data from malicious threats, which means protecting personal data from any unauthorized third-party access or malicious attacks and exploitation of data. It is set up to protect personal data using different methods and techniques to ensure data privacy. Data privacy is about using data responsibly. This means proper handling, processing, storage, and usage of personal information. It is all about the rights of individuals with respect to their personal information. Therefore, data security is a prerequisite for data privacy.

Although the AI field is undergoing extensive research into privacy and security, achieving flawless privacy preservation and security in AI is currently not possible. Nonetheless, several challenges require addressing to further advance in this area.

Table 1: Quantitative Analysis

Feature of a study	Representation	Percentage	Sources
Trustworthy AI (28/254, 11%) *			
Reviews and Surveys	9/28	32%	[11,17,38,13,39,14,40,41,42]
Perceptions of trust	4/28	14%	[43,44,45,27]
Frameworks	9/28	32%	[26,46,47,48,49,15,50,51,52]
Miscellaneous	6/28	28%	[53,54,55,56,16,57]
Ethical AI (85/254,34%) *			
Frameworks	19/85	22%	[35,58,59,7,20,60,29,24,61,62]
			[63,64,65,66,67,68,69,70,71]
Ethical issues	22/85	26%	[72,20,73,74,75,76,77,78]
			[79,80,81,28,82,36,83,84]
			[85,86,87,88,89,90]
Miscellaneous	33/85	39%	[91,19,92,93,94,95,96,22,21,97,98]
			[99,100,101,102,9,103,104]
			[105,106,107,108,109,110,111]
			[112,113,114,115,116,117,118,8]
Reviews and Surveys	10/85	12%	[119,120,121,122,123,124,125,126,127,30]
Tools	1/85	1%	[128]
Explainable AI (46/254 , 18%) *			
Reviews and Surveys	10/46	22%	[6,31,33,12,129,34]
			[130,131,132,133]
Stakeholders	7/46	15%	[134,135,136,137]
			[32,138,139]
XAI Approaches	14/46	30%	[140,5,141,142,143,144]
			[145,146,147,148,149,150,151,152]
Frameworks	4/46	9%	[153,154,155,156]
Miscellaneous	11/46	24%	[157,158,159,160,161]
			[162,163,164,165,166,167]
Privacy-preserving and Secure AI (95/254 , 38%) *			
Reviews and Surveys	10/95	10%	[168,169,170,171,172,37]
			[173,174,175,176]
Differential Privacy	12/95	13%	[177,178,179,180,181,182]
			[183,184,185,186,187,188]
Secure Multi-Party Computation	2/95	2%	[189,190]
Homomorphic Encryption	4/95	4%	[142,191,192,193]
Federated learning	35/95	37%	[194,195,196,197,198,199,200,201]
			[202,203,204,205,206]
			[207,208,209,210,211,212,213,214,215]
			[216,217,218,219,220,221,222]
			[223,224,225,226,227,228,229]
Hybrid Approaches	8/95	xx%	[230,231,232,233,234,235,236,237]
Security Threats	7/95	8%	[238,239,240,241,242,243,244]
Miscellaneous	16/95	17%	[245,246,247,248,249,250,251,252,253,254]
			[255,256,257,258,259,260]

*percentage does not add up to 100 due to rounding.

Within the topic ”Privacy-Preserving and Secure AI”, most papers belong to ”Federated learning”, obviously being a very emerging research field in the time frame.

There were also many different papers that were not assigned to any specific category (see ”Miscellaneous)” since the topic is very multifaceted.

In the topic area of ”Ethical AI”, the most common category was ’Miscellaneous’, since the authors of the ethical AI field handle very different topics. In addition, second most of them could be assigned to the category ’ethical issues’ since this is a hot topic in the field of ethics. The rest of the papers dealt with ethical frameworks that try to integrate ethical AI in the context of a development process.Most studies in the field of XAI deal with coming up with new XAI approaches to solve different explainability problems with new AI models. There were also a few that presented stakeholder analyses specifically in the context of the explainability of AI models. Few of them presented miscellaneous topics that could not be assigned to any specific category or framework to integrate explainable AI.

In Trustworthy AI, we saw that most presented a review or survey on the current state of Trustworthy AI in research. There were also papers that presented frameworks especially for trustworthiness or papers that reported on how Trust is perceived and described by different users.

4 Discussion

Several key points have emerged from the analysis. It has become clear that AI will have an ever-increasing impact on our daily lives, from delivery robots to e-health, smart nutrition and digital assistants, and the list is growing every day. AI should be viewed as a tool, not a system that has infinite control over everything. It should therefore not replace humans or make them useless, nor should it lead to humans no longer using their own intelligence and only letting AI decide. We need a system that we can truly call ”responsible” AI. The analysis has clearly shown that the elements of ethics, privacy, security and explainability are the true pillars of responsible AI, which should lead to a basis of trust.

4.1 Pillars of Responsible AI

Here we highlight the most important criteria that a responsible AI should fulfil. These are also the points that a developer should consider if she wants to develop responsible AI. Therefore, they also form the pillars for the future framework.

Key-requirements for the Ethical AI are as follows:

- fair: non-biased and non-discriminating in every way,
- accountability: justifying the decisions and actions,
- sustainable: built with long-term consequences in mind, satisfying the Sustainable Development Goals,
- compliant: with robust laws and regulations.

Key-requirements for the privacy and security techniques are identified as follows:

- need to comply with regulations: HIPAA, COPPA, and more recently the GDPR (like, for example, the Federated Learning),
- need to be complemented by proper organizational processes,
- must be used depending on tasks to be executed on the data and on specific transactions a user is executing,
- use hybrid PPML-approaches because they can take advantage of each component, providing an optimal trade-off between ML task performance and privacy overhead,
- use techniques that reduce communication and computational cost (especially in distributed approaches).

Key-requirements for Explainable AI are the following:

- Human-Centered: the user interaction plays a important role and how he understands and interacts with the system,
- Explanations must be tailored to the user needs and target group
- Intuitive User interface/experience: the results need to be presented in a understandable visual language,

  - Explainable is also feature to say how well the system does its work (non functional requirement),
  - Impact of explanations on decision making process,

- Key-Perceptions of trustworthy AI are as follows:
  - ensure user data is protected,
  - probabilistic accuracy under uncertainty,
  - provides an understandable, transparent, explainable reasoning process to the user,
  - usability,
  - act ”as intended” when facing a given problem,
  - perception as fair and useful,
  - reliability.

Therefore, we define Responsible AI as an interdisciplinary and dynamic process: it goes beyond technology and includes laws (compliance and regulations) and society standards such as ethics guidelines and the Sustainable Development Goals.

Figure 3 shows that on the one hand there are social/ethical requirements/pillars and on the other hand the technical requirements/pillars. All of them are dependent on each other. If the technical and ethical side is satisfied the user trust is maintained. Trust can be seen as the perception of the users of AI.

Each pillar of ethics includes "sub-modules" such as accountability, fairness, sustainability, and compliance. These are essential to ensure that AI meets ethical standards.

Furthermore, the explainability methods must value privacy, meaning they must not have that much access to a model so that it results in a privacy breach. Privacy is dependent on security because security is a prerequisite for it.

Every "responsible system" requires humans to care for it. These individuals must handle the system responsibly, conducting maintenance work and regularly checking metrics to ensure that their responsibilities are fulfilled. To achieve this, special metrics are used as a continuous check. This makes responsible AI a joint effort between the system-side and the developer-side.

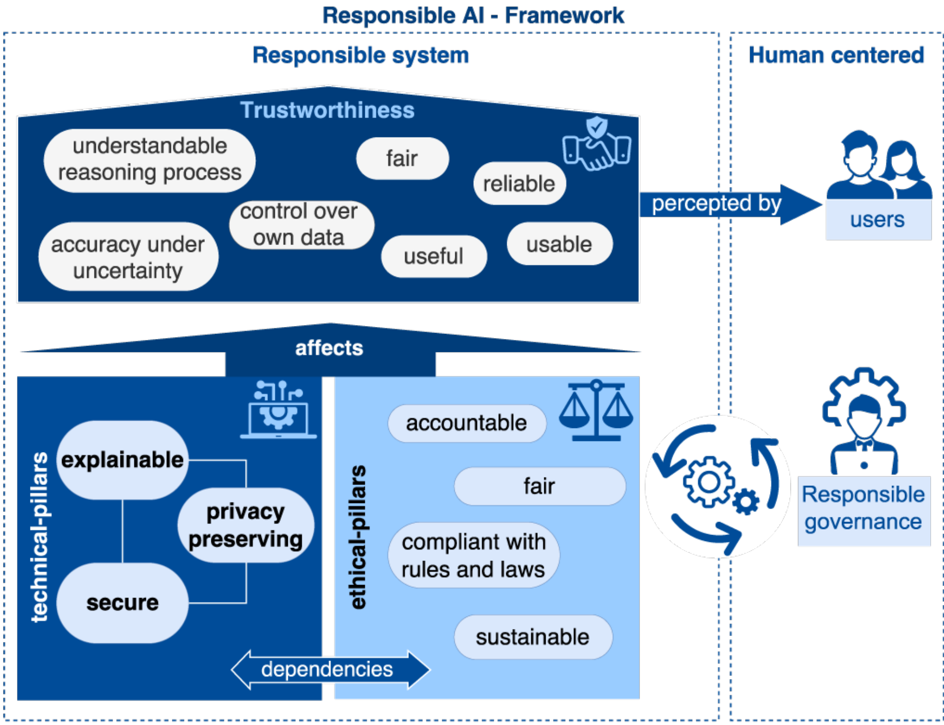


Figure 4: Pillars of the Responsible AI framework
Source: own.

In section 3.3, the concept of Human-Centered AI is highlighted as a crucial aspect of responsible AI. It is closely linked to the "Human-in-the-loop" approach, which emphasizes the importance of human involvement in the development and use of AI. This approach allows for the detection and correction of errors and retraining of the system throughout its lifespan, ensuring that AI is designed and utilized for the benefit of humans.

Therefore, responsible AI is interdisciplinary, and it is not static but it is a dynamic process that needs to be taken care of in the whole system lifecycle.

4.2 Trade-offs

To fulfill all aspects comes with tradeoffs as discussed for example in [16] and comes for example at the cost of data privacy. For example, the methods that make the model more robust against attacks or methods that try to explain a model's behavior and could leak some information. Managing AI systems that are accurate, fair, private, robust, and explainable simultaneously is a challenging task. To begin, we suggest creating a benchmark for each requirement, which will determine the extent to which each requirement is met.

5 Research Limitations

Our study aims to provide a thorough and detailed analysis of the available literature on responsible AI from various journals. However, we encountered limitations in accessing some journals that were not freely available despite extensive access provided by our institutions. Despite our best efforts, accessibility remained an issue. It is also possible that some relevant research publications were not included in the databases we used for our search. Furthermore, our study only included the most recent state-of-the-art research, which may have caused us to miss out on some older but still relevant developments.

Another limitation of the presented work is the missing in-depth analysis of the papers reviewed. Due to paper length constraints, we have omitted a detailed overview of each of the reviewed papers' contributions in each of the subsections of section 3.3.

6 Conclusion

The field of AI is rapidly evolving and a legal framework is necessary to ensure responsible practices. However, the terms "trustworthy AI" and "responsible AI" lack clear definitions, making it difficult to establish efficient regulations. Instead of focusing solely on trust, regulations for responsible AI must be defined. As a leading authority in setting standards, such as the GDPR, the EU should be informed and prepared for upcoming research and legal regulations. This research provides an important contribution to the concept of responsible AI, being the first to address it comprehensively through a structured literature review and presenting an overarching definition. The review analyzed 254 recent high-quality works on the topic, and included a qualitative analysis of the papers covered.

We have defined the concept of "responsible AI" and conducted a thorough analysis of its key components. These components include human-centered design, trustworthy development, ethical considerations, explainability, privacy preservation, and security. By prioritizing these aspects, we can ensure the responsible development and use of AI products, and establish legal frameworks to regulate their use. In the discussion section, we propose a framework for responsible AI based on the insights gained from our analysis. In future research, we plan to analyze individual papers to determine their contributions to responsible AI, and explore topics such as human-centered AI and "human-in-the-loop" approaches. We also aim to develop benchmarking methods for responsible AI and establish a holistic framework to guide responsible AI development.

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A complete list of 260 references is available at https://drive.google.com/file/ d/1Fm-9hKkrY_YAzS02TWec2L3lIqgPSmqm/view?usp=sharing, or by scanning the QR code below.

Figure 4: QR Code with the list of references
Source: own.

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