



A Scoping Review on Analysis of the Barriers and Support Factors of Open Data

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Abstract: *Background:* Using personal data as Open Data is a pervasive topic globally, spanning various sectors and disciplines. Recent technological advancements, particularly in artificial intelligence and algorithm-driven analysis, have significantly expanded the capacity for the automated analysis of vast datasets. There's an expectation that Open Data analysis can drive innovation, enhance services, and streamline administrative processes. However, this necessitates a legally and ethically sound framework alongside intelligent technical tools to comprehensively analyze data for societal benefit. *Methodology:* A systematic review across seven databases (MEDLINE, CINAHL, BASE, LIVIVO, Web of Science, IEEExplore, and ACM) was conducted to assess the current research on barriers, support factors, and options for the anonymized processing of personal data as Open Data. Additionally, a supplementary search was performed in Google Scholar. A total of n = 1192 studies were identified, and n = 55 met the inclusion criteria through a multi-stage selection process for further analysis. *Results:* Fourteen potential supporting factors (n = 14) and thirteen barriers (n = 13) to the provision and anonymization of personal data were identified. These encompassed technical prerequisites as well as institutional, personnel, ethical, and legal considerations. These findings offer insights into existing obstacles and supportive structures within Open Data processes for effective implementation.

Keywords: open data; support factors; barriers; personal data; anonymization; open science

1. Introduction

Releasing anonymized personal data as Open Data sparks intense debate across academic disciplines, fueled by a burgeoning global interest in exploring its diverse applications [1,2]. Recent technological advancements have exponentially increased the possibilities for fully automated data collection and analysis, impacting all aspects of human life [3,4]. However, the comprehensive and cross-disciplinary use of Open Data has not yet been fully implemented [5].

Many opportunities, especially in managing diverse sources of personal health data, remain unexplored [2]. Organizations often struggle to prepare and integrate available datasets for comprehensive analysis, hindering the ability to derive full benefits from the data [6–8].

Hence, it is evident that Open Data offers significant societal potential across various dimensions, but organizations have been reluctant to make data available as Open Data. Moreover, there is an absence of a widespread, cross-sectoral data pool for Open Data. To understand why organizations hesitate to provide data as Open Data, this paper conducts a Scoping Review to analyze the barriers and supporting factors mentioned in the existing scientific literature on Open Data. Therefore, the overarching research question for this article is as follows:

What barriers and supporting factors are described in the scientific literature regarding providing personal data as Open Data within organizations?



Citation: Lichtenauer, N.; Schmidbauer, L.; Wilhelm, S.; Wahl, F. A Scoping Review on Analysis of the Barriers and Support Factors of Open Data. *Information* **2024**, *15*, 5. https:// doi.org/10.3390/info15010005

Academic Editor: Arkaitz Zubiaga

Received: 23 November 2023 Revised: 4 December 2023 Accepted: 18 December 2023 Published: 20 December 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). The article is structured as follows: Section 2 provides background insights into Open Data across diverse organizations, followed by a delineation of the methodology of this Scoping Review in Section 3. Section 4 presents the findings on barriers and facilitators, while conclusions and discussion are expounded in Sections 5 and 6, respectively. Additionally, limitations are addressed in Section 7.

2. Open Data in Authorities, Companies, Research Institutions, and the Healthcare Sector *2.1. Authorities*

The disclosure of government data, known as Open Governance Data (OGD), has become a significant global topic [9–11]. OGD is attributed to transformative value [11]. Over the last decade, the OGD spectrum has gained much attention in research and practice. Governments worldwide strive to build an OGD ecosystem, as many cultural and institutional benefits are expected through OGD [10]. Enhanced data utilization should be integrated into decision-making processes, especially locally [8]. OGD initiatives are emerging as part of a new public governance policy that increasingly includes citizens as co-producers of public policy through access to official information [12]. The data release is expected to drive new service innovations, increase transparency in government agencies [13], and result in societal benefits [12]. For instance, Csányi et al. describe significant efforts within the EU justice system to share and provide online access to court decisions and legal documents. These documents often contain sensitive and rare events that must be protected against re-identification risks [14]. Currently, innovation barriers hinder the value creation for OGD users [12]. Moreover, government data are often trapped in data silos, limiting the public and societal value of the data [11]. Although governments already release substantial amounts of data, many untapped opportunities exist for further use and analysis [11]. Therefore, a strategic approach as a data strategy is considered essential [15].

During these developments, the Organization for Economic Co-operation and Development (OECD) developed an OUR (open, useful, reusable) Data Index to determine and evaluate public data provision. Similarly, the international WWW Foundation created an Open Data Barometer, providing an overview of government data publication [9].

2.2. Companies

Companies across various industries concur that big data plays a pivotal role in shaping the future, necessitating the development of relevant workforce capabilities and knowledge. For instance, big data technologies are seen as promising opportunities for companies in the health and pharmaceutical sectors seeking to secure or establish a competitive advantage [16]. Some studies have identified the impact of using Open Data on economic growth [10]. Therefore, continued data utilization and processing are regarded as crucial drivers for future industrial development and value creation [9]. Enabling these extensive data analyses is viewed as a shared responsibility among all industry stakeholders [2]. For this purpose, a data strategy for businesses is considered indispensable, encompassing internal orientation, such as how data are collected and used to enhance administrative processes and services and external alignment. This involves data management for other stakeholders who utilize the data to create societal value. A data-driven culture is essential [15]. Furthermore, numerous supportive tools are required to collect, analyze, manage, and store data [2].

2.3. Research Institutions

Open Science in the realm of research projects pertains to unrestricted access to scholarly publications and research raw data [17]. The past decade has witnessed significant growth in the Open Science movement, aiming to facilitate the unimpeded dissemination of scientific discourse and broad distribution of research findings [18]. Open Science is seen as instrumental in enhancing data accessibility [17]. In 2018, the International Committee of Medical Journal Editors (ICMJE) introduced data sharing from clinical studies published in

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journals; however, recent studies have revealed considerable disparities between intentions and actual data accessibility [17]. Similarly, clinical research journals increasingly require the disclosure of considerations related to Open Data [1]. In 2021, UNESCO, the United Nations Educational, Scientific and Cultural Organization, emphasized the significance of Open Science in enhancing the quality of scientific outcomes and processes. The value anticipated from extensive data analysis is indisputable in the research domain [19].

Nevertheless, disseminating and institutionalizing Open Science is considered a pivotal moment in shaping rules for data protection and sharing [20]. The European Commission released a strategy specifically for research data called the European Open Science Cloud (EOSC), aimed at facilitating data exchange and further data analysis for publicly funded research [18]. Leveraging the FAIR (findable, accessible, interoperable, reusable) data framework and EOSC initiatives, the entire research lifecycle is set to undergo fundamental changes to become more efficient, transparent, credible, and collaborative. Integrating data with expanded sample sizes have led to significant progress, particularly in rare diseases and genetic disorders. Similar strides are anticipated if health and environmental data are interconnected [18]. However, collecting data anew for each new project and insufficiently incorporating previous studies into meta-analyses are considered wasteful of research resources [21]. Research by Zuiderwijk and Spiers reveals that different academic disciplines currently have varying traditions regarding the application of Open Science. For instance, it is common in oceanography and astrophysics but less prevalent in the social sciences and medicine [22]. As a result, there is a significant need for discipline-specific data repositories [21].

2.4. Healthcare Sector

The global COVID-19 pandemic has underscored significant challenges in collecting, integrating, and sharing medical personal data worldwide [6,23]. Data analysis from various sources can provide vital information for pandemic management [6]. For instance, Horn and Kerasidou emphasize that data on individual behavior can offer crucial insights into virus spread [24]. Furthermore, Feeney et al. [25] stress the importance of collecting and managing personal health data in times of increased mobility and crises. Data flow is becoming increasingly important for ensuring optimal healthcare, especially for vulnerable groups, such as migrants, chronically ill individuals, and children. National borders must not constrain health data [25]. Consequently, there is a demand for cross-border data exchange in electronic health services at the European level [25,26]. The need for international collaboration has grown steadily, and the opportunities presented by artificial intelligence and big data in the medical sector should be fully harnessed [26]. The healthcare sector has long called for more excellent technological orientation and the use of big data [24]. However, patients and healthcare organizations are frustrated by numerous barriers to accessing patient data [19]. Many health data are currently stored in data silos due to privacy concerns and are not yet accessible for shared data utilization [27]. Throal et al. illustrate, using intensive care as an example, that much machine-readable data are generated daily in this discipline. However, they have not been used further due to legal and ethical concerns [28]. Leveraging big data in healthcare promises more accurate prognosis, new diagnostic approaches, and improved and efficient treatment [24,26,29]. The rapid technological advancements driven by artificial intelligence and machine learning techniques have fundamentally expanded the ability to identify patterns and structures in data that can enhance health, diagnosis, and treatment [30]. Access to scientific health data is essential for further scientific progress and innovation [31]. Clinical, evidence-based decision making ideally requires a foundation in big data to support decision making [2,31]. Simultaneously, the optimized use of personal patient data can fundamentally transform healthcare, individual understanding, and disease prevention [29]. Open data availability can provide new and deeper insights into prevention, diagnosis, and therapy, especially in the context of genomic data [32,33]. Its benefits are particularly pronounced in rare diseases. Big data applications enable deep and precise phenotyping of genetic and rare diseases,

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offering invaluable insights [34]. Furthermore, data sharing for comparing genetic and epidemiological risk factors is crucial [26]. Therefore, the collaborative use of personal health data for medical research and practice is considered fundamentally significant [35]. Aspects of general quality assurance in healthcare through shared data usage are critical [31]. However, using data from health-related activities has raised new ethical challenges related to data privacy, integrity, and appropriate use [30]. The ability to link individual data records is considered a central element for medical research while simultaneously being ethically sensitive due to the potential to gain deep insights into very intimate aspects [3]. This has revealed societal and individual contradictions and dilemmas [36]. Househ et al. (2018) also describe in their Scoping Review that the information needs of patients seem to conflict with data protection and confidentiality preferences [36].

3. Methodology

The international state of the art in the utilization of personal data as Open Data across various societal domains is sought to be comprehensively surveyed in this work. Established scholarly practices for conducting systematic reviews are adhered to, with the methodological framework developed by [37] being employed.

3.1. Systematic Research

The literature review used a sensitive search strategy to ensure comprehensive coverage of the subject matter [37]. Consequently, the research question was methodically operationalized into search components based on Booth's adapted PICO-Mnemonic to facilitate focused inquiries within specialized databases [38]. The classification according to PICO is shown in Table 1.

Table 1. PICO elements of the literature review.

Р	Personal data
Ι	Barriers and support factors
С	-
0	Provision of persona data as Open Data

Considering the multidisciplinary facets of the research question, the search was conducted in the following comprehensive databases:

- MEDLINE: One of the most extensive healthcare databases, providing a broad spectrum of content [37].
- CINAHL: Chosen to capture developments in healthcare, nursing, and therapy sciences.
- **BASE**: A meta-search engine encompassing disciplines such as computer science, information science, social sciences, health, medicine, and philosophy.
- Additionally, research encompassed cross-sectional databases, including LIVIVO, an interdisciplinary meta-search engine focused on life sciences, and the **Web of Science Core Collection**, a comprehensive database spanning various fields.
- The search was further augmented by investigating technical, information, and computer science databases: IEEE Xplore Digital Library, specializing in electrical engineering and information technology, and ACM Digital Library, primarily offering a full-text collection in computer science.

Conducting a sensitive search involves identifying various term variations and synonyms for search components [37]. The team initially brainstormed the terms and synonyms and then supplemented them using special keyword directories (e.g., MeSH Terms) and terms from already-known literature. In the search for corresponding synonyms for the operationalized search terms, existing literature and reviews, the keyword index of databases, and freely accessible Theasaurus databases were used. The results of the terms and synonyms classified as relevant are shown in Table 2.

Search Components	Personal Data	Barriers	Support Factors	Providing Data	Open Data
	(Population)	(Intervention)	(Intervention)	(Outcome)	(Outcome)
Synonyms	Personal Data, Personal Information, Person- related Data, Personal Identification Information, Patient Data	Barriers, Challenges, Obstacles, Impediments, Hindrances, Hurdle	Promotion, Support, Enabling, Opportunities, Incentives	Data Sharing, Data Provision, Providing Data, Data Supply, Data Publishing	Open Data, Open Information, Open Science

Table 2. Identification of synonym search components.

3.2. Search Strings

In a subsequent step, the keywords and search terms were transformed into database-specific search strings using Boolean operators as described by [37]. The search strings were based on the database-specific keyword directories and were created according to the respective filter and search options of the databases. The development of the search strings is presented in Table 3.

Table 3. Development of search strings.

Search Component	Search String
1—Personal Data (P)	("personal data" OR "personal information" OR "person-related data" OR "personal identification information" OR "patient data")
2—Barriers (I)	(barriers OR challenges OR obstacles OR impediments OR hindrances OR hurdle)
3—Support factors (I)	(promotion OR support OR enabling OR opportunities OR incentives)
4—Providing Data (O)	("data sharing" OR "data provision" OR "providing data" OR "data supply" OR "data publishing")
5—Open Data (O)	("open data" OR "open information" OR "open science")

The search string was verified using the PRESS-control questions [39] and within the project team. Documentation of the search results can be found in Appendix A.

The search was last executed on 12 June 2023 and constrained to the last five years in all databases. This restriction emanates from the rapid technological advancements within the domain of the research question and the enforcement of the European General Data Protection Regulation (GDPR) on 25 May 2018. The GDPR introduced novel specifications for handling personal data and set a benchmark for the subsequent processing of personal information, hence necessitating this temporal restriction.

Additionally, in conjunction with the systematic search in the databases mentioned above, an exploratory search was conducted in Google Scholar using the search terms listed in Table 2, arranged in various combinations.

3.3. Evaluation of the Studies

A total of n = 1069 records were identified via the sensitive search in the seven databases. In addition, n = 123 records were added to the selection out of the exploratory search within Google Scholar. So, in Summary, n = 1192 records were identified. The detailed results are listed in Appendix B.

In the first step, the titles and abstracts of the studies were analyzed for further relevance to the topic. In some cases, the full text was used for a more detailed relevance

analysis. Furthermore, duplicates were removed, and inclusion and exclusion criteria (Table 4) were implemented.

Criteria	Inclusion	Exclusion
Language	English, German	Other Languages
Date of Publication	Published as of 2018, as 2018 GDPR was used as a benchmark at the European Level	Published before 2018
Type of Publication	Original Papers, Reviews, Systematic Reviews	Case Studies, Opinion Articles

Table 4. Identification of synonym search components.

After the initial title and abstract screening, n = 1107 records were excluded. The remaining n = 85 studies exhibited evident relevance to the research question and underwent comprehensive full-text analysis. All studies were accessible, and after the full-text analysis, n = 55 studies were included in the further analysis.

The PRISMA flow chart for systematic screening is shown in Figure 1.



Figure 1. PRISMA flow chart for systematic screening.

4. Results

A total of n = 55 records were included in the review and were categorized by author, year of publication, mentioned barriers, and mentioned supporting factors as shown in Table 5.

Author		Focus	Barriers	Supporting Factors
Aleixandre- Benavent et al.	[40]	Research Data Shar- ing	ELSI; Personnel barriers; data mis- use; institutional barriers;	education and training; participation
Alorwu et al.	[41]	Ethics and concerns	ELSI; Personnel barriers; data mis- use	ELSI; technical infrastructure; educa- tion and training; personnel aspects; trust; consent procedures;
Alzahrani et al.	[19]	Healthcare/Blockchair	ELSI; data structure; technical barri- ers	technical infrastructure; data access; education and training; data struc- ture; consent procedures;
Broes et al.	[42]	Healthcare/Oncology	data structure	positive outcome; participation
Burgess et al.	[43]	EU—Ethics Advi- sory Group	Stigmatization; commercial inter- ests;	-
Crusoe and Melin	[13]	Open Government Data Barriers	ELSI; Personnel barriers; data struc- ture; technical barriers; institutional barriers; economic barriers;	technical infrastructure; communica- tion;
Csányi et al.	[14]	Open Data in Judi- cial Systems	technical barriers; data privacy;	-
Deist et al.	[31]	Healthcare	ELSI; Personnel barriers; data struc- ture; technical barriers; institutional barriers;	technical infrastructure; data struc- ture; collaborations;
Dos Santos Rocha et al.	[17]	Research/Open Sci- ence	ELSI; Personnel barriers; technical barriers; data misuse; economic bar- riers;	positive outcome;
Dove et al.	[5]	Open Government	Personnel barriers; data structure; communication;	positive outcome; technical infras- tructure; data access; education and training; personnel aspects; collabo- rations;
Feeney et al.	[25]	Healthcare	ELSI; Personnel barriers; data struc- ture; technical barriers; trust;	ELSI; data access; data struc- ture; trust;
Fischer et al.	[44]	Research/Open Sci- ence	data structure; clarification and con- sent; economic barriers;	positive outcome; ELSI; economic as- pects
Fischer-Hübner et al.	[45]	Cybersecurity/Open Data	ELSI; Personnel barriers; technical barriers; data privacy; trust;	ELSI; technical infrastructure; data access; education and training; insti- tutional aspects
Floridi et al.	[46]	Ethics/Healthcare	ELSI	positive outcome; data access; educa- tion and training; personnel aspects; economic aspects
Fylan and Fylan	[29]	Healthcare	Personnel barriers; technical barri- ers; data misuse; clarification and consent; stigmatization; commercial interests; trust;	technical infrastructure; data access; data structure; trust; consent proce- dures; collaborations;
Galdon Clavell	[47]	Open Data for Ur- ban Safety	-	ELSI;
Govarts et al.	[18]	Healthcare/Research	ELSI; Personnel barriers; data struc- ture; technical barriers; clarification and consent; institutional barriers; economic barriers; data privacy;	ELSI; technical infrastructure; data access; personnel aspects; data struc- ture; consent procedures; collabora- tions;

Table 5. Involved studies.

	Suppor	ting Facto	rs	
arriers: data struc-				

Table 5. Cont.

Author		Focus	Barriers	Supporting Factors
Hallock et al. [27]		Healthcare	ELSI; Personnel barriers; data struc- ture; technical barriers; clarification and consent; institutional barriers; data privacy;	positive outcome; education and training; personnel aspects; trust; in- stitutional aspects
Horn and Kerasi- dou	[24]	Healthcare	economic barriers; data privacy; commercial interests; trust; commu- nication;	positive outcome; ELSI; data access; trust; collaborations; economic as- pects; participation
Househ et al.	[36]	Healthcare	ELSI; Personnel barriers; data struc- ture; technical barriers; stigmatiza- tion; trust;	ELSI; education and training; per- sonnel aspects; communication; eco- nomic aspects; participation
Kamikubo et al.	[1]	Healthcare/Research	data misuse; clarification and con- sent; stigmatization; commercial in- terests;	positive outcome; technical infras- tructure; data access; education and training; education and training; data structure; trust; consent proce- dures; participation
Kawashita et al.	[11]	Open Government	ELSI; Personnel barriers; data struc- ture; technical barriers; clarification and consent; institutional barriers; communication;	positive outcome; ELSI; technical infrastructure; education and train- ing; personnel aspects; data struc- ture; collaborations; communication; economic aspects; institutional as- pects
Kuo et al.	[33]	Healthcare/genomic data	ELSI; data misuse; stigmatization	positive outcome;
Kwon and Moto- hashi	[48]	Research/Open Sci- ence	Personnel barriers	positive outcome;
Mahomed and Labuschaigne	[49]	Ethics/Research	ELSI; data structure; technical barri- ers; data misuse; stigmatization; eco- nomic barriers; communication;	ELSI;
McWhirter et al.	[32]	Healthcare	ELSI; economic barriers;	-
Medley et al.	[21]	Healthcare	ELSI; clarification and consent; eco- nomic barriers;	technical infrastructure; data access; trust; collaborations;
Mutambik et al.	[10]	Open Government	ELSI; Personnel barriers; data struc- ture; technical barriers; clarification and consent; stigmatization; insti- tutional barriers; economic barriers; data privacy; trust;	positive outcome; ELSI;
Nellåker et al.	[34]	Healthcare/Research	ELSI; data privacy;	positive outcome; data access; con- sent procedures;
Nunes Vilaza et al.	[50]	Healthcare	ELSI; data misuse; clarification and consent; stigmatization; commercial interests;	positive outcome; data access; ed- ucation and training; personnel as- pects; consent procedures; commu- nication;
Papageorgiou et al.	[51]	Healthcare/Migration	Personnel barriers; stigmatization; trust; communication;	participation
Queralt-Rosinach et al.	[6]	Healthcare/Hospital	data structure; clarification and con- sent; communication;	technical infrastructure; education and training; data structure; consent procedures; collaborations; commu- nication; institutional aspects

Table 5. Cont.

Author		Focus	Barriers	Supporting Factors
Rehman et al.	[2]	Healthcare	ELSI; data structure; technical barriers	positive outcome;
Rempel et al.	[8]	Open Government	Personnel barriers; data misuse; in- stitutional barriers;	positive outcome; ELSI; communica- tion;
Rockhold et al.	[52]	Open Sciences	-	data access; consent procedures;
Roguljić et al.	[7]	Healthcare/Patient images	Personnel barriers; technical barri- ers; clarification and consent	-
Sandoval- Almazan et al.	[53]	Open Government	ELSI; data misuse; institutional bar- riers;	ELSI; data access; trust; institutional aspects
Scheibner et al.	[35]	Healthcare	technical barriers; institutional barriers;	technical infrastructure;
Schwalbe et al.	[23]	Healthcare	ELSI; Personnel barriers; data struc- ture; technical barriers; stigmatiza- tion; economic barriers;	-
Seo et al.	[9]	Open Government Data	-	data structure;
Sleigh	[4]	Healthcare/Data do- nation	data misuse; commercial interests;	positive outcome; personnel aspects;
Smart et al.	[54]	Healthcare	stigmatization	education and training; personnel as- pects; trust; institutional aspects
Smith and Sand- berg	[12]	Open Government	Personnel barriers	positive outcome; personnel aspects; communication;
Tan et al.	[55]	Open Science	Personnel barriers; clarification and consent; data privacy;	-
Thoral et al.	[28]	Healthcare	ELSI; stigmatization; institutional barriers;	ELSI; collaborations;
Tuler de Oliveira et al.	[56]	Healthcare	data structure	technical infrastructure; data access; education and training; personnel as- pects; trust;
van der Burg et al.	[57]	Agriculture	commercial interests; trust;	ELSI; data access;
van Donge et al.	[15]	Open Government	Personnel barriers; data structure; technical barriers; institutional barri- ers; communication;	positive outcome; data access; eco- nomic aspects
Vianen et al.	[58]	Healthcare/Pre- Hospital	ELSI; economic barriers; data pri- vacy;	-
Viberg et al.	[30]	Healthcare/Research	ELSI; data misuse; commercial inter- ests;	positive outcome; ELSI; trust;
Wang et al.	[59]	ELSI data misuse;	data privacy;	-
Wieczorkowski	[60]	Open Government	ELSI; data structure	positive outcome;
Wolff et al.	[61]	Open Govern- ment/Research	Personnel barriers; data structure	technical infrastructure; education and training; data structure;
Yerden and F. Luna-Reyes	[62]	Open Government	-	ELSI; technical infrastructure; data structure;
Zuiderwijk and Spiers	[22]	Research/astrophysic	S -	positive outcome; ELSI; technical in- frastructure; personnel aspects; data structure; collaborations;

In the following, the identified barriers in Section 4.1 and the supporting factors of publishing Open Data in Section 4.2 are described in more detail.

4.1. Barriers

A total of n = 50 out of all reviewed records identified barriers in publishing data as Open Data. These barriers encompassed concerns related to data privacy, data structure, and technical constraints. Additionally, there were fears concerning data misuse and the potential risk of stigmatization through data sharing. It is noted that the clarification and consent regarding data utilization are perceived as inadequately regulated. Furthermore, the adherence to the ethical, legal, and social implications (ELSI) aspect is considered challenging. Obstacles and hindrances in utilizing Open Data were also described in institutional, economic, commercial, and personnel contexts. Insufficient trust and communication regarding data usage and application were reported as impeding factors.

A comprehensive breakdown of specific barrier factors can be found in Table 6. The subsequent Sections 4.1.1–4.1.13 provide detailed insights into the backgrounds of these individual factors.

Barriers	#	Authors
ELSI	27	[2,10,11,13,17–19,21,23,25,27,28,30–34,36,40,41,45,46,49,50,53,58,60]
personnel barriers	23	[5,7,8,10–13,15,17,18,23,25,27,29,31,36,40,41,45,48,51,55,61]
data structure	20	[2,5,6,10,11,13,15,18,19,23,25,27,31,36,42,44,49,56,60,61]
technical barriers	19	[2,7,10,11,13–15,17–19,23,25,27,29,31,35,36,45,49]
data misuse	13	[1,4,8,17,29,30,33,40,41,49,50,53,59]
clarification and con- sent	13	[1,6,7,10,11,18,21,27,29,44,50,55]
stigmatization	12	[1,10,23,28,29,33,36,43,49–51,54]
institutional barriers	12	[8,10,11,13,15,18,27,28,31,35,40,53]
economic barriers	12	[10,11,13,17,18,21,23,24,32,44,49,58]
data privacy	10	[10,14,18,24,27,34,45,55,58,59]
commercial interests	8	[1,4,24,29,30,43,50,57]
trust	8	[10,24,25,29,36,45,51,57]
communication	7	[5,6,11,15,24,49,51]

Table 6. Open Data barriers.

4.1.1. ELSI

The ethical, legal, political, and social implications touched upon by the Open Data approach can also be perceived as barriers.

Ethical and Social Implications

Several ethical obstacles for sharing and analyzing data are cited in the studies [18,31,34]. A significant ethical and societal dilemma is that the potentially great benefits of Open Data may not materialize due to data privacy concerns [30]. Normative standards for ethical scrutiny are currently lacking, which can lead to physical and psychological harm in the re-use of data [49]. Individual harmlessness is perceived to be at risk when data are sold, leading to re-identification or extortion, which can result in financial, physical, psychological, and emotional harm [30]. In addition, negative social implications are feared, for example, in aspects of equity and social participation, if, for example, minorities are not represented or are underrepresented in Open Data sets [30].

Risks and benefits of data sharing must, therefore, be carefully weighed [10,23,49], and it is unclear whether specific datasets can be ethically released [10]. There is also

concern about subsequent unethical and inappropriate projects in secondary use with a risk to privacy [30,36,50]. Ethical issues are mainly seen in further health data exchange [46]. Another challenge is the wide range of methodologies and practices within Open Data, each involving specific legal and ethical issues [32]. An essential ethical problem is that Open Data are irrevocable and cannot be retrieved [33]. Alorwu et al. point out that past scandals and negative examples influence the ethical perception, acceptance, and concerns regarding data use [41]. Approval processes by ethics committees and data protection officers often take a long time, which is seen as hindering [27]. These review bodies are sometimes described as somewhat distrustful in the context of data analysis [21].

Legal and Policy Implications

Political decisions can make data sharing and analysis difficult [18,31]. There is often a lack of political priority and action to drive an Open Data culture [10,11,53]. Many barriers are also cited on the legal side [13,18,23,25,30,58,60]. Many legal aspects and standards on Open Data are still unresolved [2,11,25] and vaguely regulated [11,23], especially in the area of data security and consent procedures [23,34], as well as in the further, transparent use of data [23,30,40]. In addition, the traceability of data must be ensured, for example, if consent is revoked [19,49]. Currently, existing legal consent structures tend to restrict data use [23,34]. There is a lack of a solid legal framework that protects all actors involved [10], where Househ et al. point out in this context that the universal protection of confidentiality and privacy seems impossible in the Internet age [36]. Furthermore, it is seen as challenging to apply established legal protections to new data-intensive contexts, and researchers in particular, judge the legal provisions to be too strict [30], especially for health-related personal data [58]. Further, the lack of accountability for Open Data is complained about [10,49]. In this regard, Fischer-Hübner et al. summarize that there are also few rules for data exchange internationally [45]. Legal challenges also exist regarding whether specific datasets should be released [10,13]. For example, over-arching laws may block data release, such as critical infrastructure data, and there are unresolved liability issues for potential damages [13].

The unclear ownership of datasets is also a significant problem [13,18,27,34]. Here, there are concerns about loss of ownership of data [17]. It is also open to whom the findings and inventions made based on Open Data belong [34]. These legal obstacles also exist in Open Science [18], as researchers often view data as personal property with sole rights to determine and keep the data [28]. For example, losing authorship is risky [40].

4.1.2. Personnel

A lack of interest in Open Data structures is generally described as an obstacle [55]. Further, parts of the public are reluctant to increase data collection and fear increasing surveillance [8].

A lack of human resources for implementation is a significant difficulty [11,15,18]. Human resources are needed to use the technology and provide data [13,15,40]. In this regard, a significant hurdle is seen in potential users' lack of skills and abilities [55]. There is a lack of time and resources to acquire the missing skills [61]. There is a lack of background knowledge about Open Data [7,27], and the goals of Open Data use are not understood [5]. Here, the perspective and awareness toward a data-centric culture have yet to develop and benefits to be recognized [5,10,15] even among experts [36] and executives [11]. There is a further lack of awareness about data privacy and sharing opportunities [23,45]. The potential uses of data are not recognized [13]. Similarly, there are insufficient skills in publishing and making data available [13]. Particularly in healthcare settings, this technical expertise is often not available [29,31]. Access to Open Data is also a significant challenge [10,61]. Often, this is too complicated for inexperienced users [61], and knowledge about data platforms' purpose and use is sometimes unavailable [36]. In this context, potential users are described as heterogeneous regarding resources and knowledge [12]. Moreover, it is considered difficult to interpret data, their relevance, and their breakdowns correctly [10,13,29,55,61]. This increases the risk of misinterpretation [17,40]. Personal fears

of cognitive overload with the processes are formulated [5]. In the field of research, there is also a fear of losing academic recognition by slowing the replacement of knowledge with data sharing [48]. The willingness to share data is described as very different in academic disciplines. There is also a lack of definition of required competencies and support options for skill acquisition [11,61]. The lack of incentives to share data also poses motivational barriers [23]. Another significant personnel barrier was revealed in an apparent discrepancy in the assessment of a data release and an actual willingness to share data [55]. Patients may also not appreciate the impact of data sharing [51]. Similarly, there is a contradiction between claims and concerns about data management and personal behavior in private data sharing [41]. Data misuse is assumed to be likely, and a loss of control over one's own data is described, which can lead to carelessness with one's own data [41]. The awareness of data sharing can lead to false information, especially in the case of minorities and existing fears, for example, the fear of deportation in the case of migrants [51]. Here, obstructive cultural differences in the understanding of privacy and the implications of data disclosure are also mentioned [36]. Minorities, in particular, often have a problem understanding how data are shared and used [51], and language barriers also pose an obstacle [25].

4.1.3. Data Structure

Multiple data sources are considered a technical barrier in the data structure, leading to highly heterogeneous data structures [2,23,42]. Not all data are suitable for Open Data [10]. However, ensuring data interoperability for analysis and storage is deemed essential [2,13,18,27,31,56]. Various system architectures and data infrastructures are described as a root cause for the lack of interoperability [15,27,31]. Institutions with specific orientations, such as patient groups, can introduce diverse data formats [31]. The nonconformity of medical applications with web-based standards is also noted [36]. The involvement of numerous stakeholders in data collection and ownership increases the risk of data distortion [31,42,44]. Data collection often neglects data formats and validity [13,25].

Many datasets are fragmented and stored in various data silos, further limiting their subsequent processing and exchange [6,10,11,15,19,25,27,56]. The fragmentation is, in turn, attributed to differing semantics and data formats [6].

Furthermore, the existing data quality is perceived as inadequate for further processing [5,10,11,13,23,60,61], especially in the integration of old data [11,31]. Some data are either not machine-readable or only available in paper format [11,13]. Data validity is sometimes questioned [49] due to inadequate maintenance, updates, and comparability [11]. Valuable metadata for analysis are often insufficiently documented [10,11]. Criticism is also directed at inadequate data preparation before publication [61].

4.1.4. Technical

Data sharing and analysis often require the implementation of administrative and analytical systems, which frequently lack the necessary technical resources [11,18,23,31]. In some cases, the essential technical infrastructure is absent [13,18] with closed system architectures [1,13]. Additionally, many different systems, infrastructures, data formats, and cybersecurity protocols are considered another technological barrier [15,27]. Furthermore, analytical techniques that are currently insufficiently available are required [2,7,10,11,23]. Comprehensive solutions for all data types are still lacking [14,18]. For the further use of unstructured data, anonymization methods are scarce, as many methods were developed for structured data [14]. The existing software solutions often address ethical, legal, and social issues insufficiently [25].

Data management is also described as challenging [15,35]. Data storage is perceived as a hurdle [18,19,27], and there is a lack of established standards for data storage [18] and data processing [10,45], especially when integrating data into third-party applications [10]. Concerns about handling large data volumes and their secure storage are widespread [2,27,29]. Some data storage facilities still employ outdated technical security measures [45], and central storage can pose an elevated security risk [19]. Lack of central exchange portals [11]

and uncertainty about the most suitable repositories [17,27] create obstacles. Limited resources for data provision also hinder progress [13].

Moreover, secure and practical authentication for data access and corresponding control options and access restrictions are often lacking [45]. Preventing unauthorized access to personal health data is considered highly challenging [36]. At the same time, it is problematic when access is restricted to specific users [10]. Additionally, technological reliability [49] and the resilience of such systems [45] are required. Certified processes are lacking [45], and rapid technological advancements also create technical challenges [18].

4.1.5. Data Misuse

Concerns and fears about potential data misuse in the exchange and analysis of anonymized personal data have been described [1,17,30,40,41]. Simultaneously, the public has become more critical and sensitive to data misuse [8]. Even when personal data are collected and used with good intentions, there can be no guarantees for their future use [29]. Possible data breaches, unauthorized data access, malicious attacks, or illegal data sales raise further cybersecurity concerns [29,33,50,59]. Healthcare facilities, in particular, are increasingly identified as attractive targets for hackers [49].

Digital files can be easily shared, either unintentionally by responsible individuals or through illegal practices as exemplified by cases like the Cambridge Analytica scandal or ransomware attacks such as WANNACRY [29,41]. Additionally, there are concerns and apprehensions that when sharing data, information may be misinterpreted or that the accessing party may not meet sufficient confidentiality requirements or lack a duty of confidentiality [29]. Sleigh also postulated a fear of a surveillance state arising from collecting publicly sourced personal data [4]. There is also a general mistrust of data use by public institutions [53].

A loss of control over data can result in physical and psychological harm to individuals and financial burdens on individuals and organizations [49].

4.1.6. Clarification and Consent

Express consent for the re-use of data for other purposes is considered a significant barrier [1,11,18,27,29,55]. Particularly, reusing research data is often not addressed in prior consent [10,18,21]. In research, data are typically linked to the research project, which can be problematic for secondary use [44,55]. For example, with real-time patient data from COVID-19 case records, obtaining consent and sharing data proved to be a significant challenge [6]. Differences in the interpretation of consents according to the GDPR and the Declaration of Helsinki are also cited as obstacles [18]. In medical research, prior informed consent may not always be feasible [18]. These missing terms of use and consent often lead to data isolation in data silos [27]. Dynamic consents as a potential solution pose their own challenges, including the potential under-representation of minorities through this process [18] and the need for ongoing contact with data contributors, which can be highly resource-intensive [1,27]. Another barrier is understanding and assessing consent agreements [6,7,50]. Consent forms are sometimes misunderstood [50], and consents are misinterpreted and evaluated incorrectly [6,7].

4.1.7. Stigmatization

When data are shared, there are significant concerns about potential stigmatization [10,29, 33,49,63]. Stigmatization can lead to extensive and long-lasting problems, especially when data are interconnected [33]. Digital profiling is perceived as increasingly unpredictable [43], and there are fears of possible re-identification [1,29,36]. According to Thoral et al. the risk of re-identification can never be entirely eliminated, especially in cases involving criminal or terrorist motives [28]. In some cases, this involves unknowingly sharing health data [36]. Conversely, there is concern about discrimination if one chooses not to disclose their data [23].

Individuals could be embarrassed by the publication of their data [10]. Discrimination may only loom in the future [50]. There is also fear of financial and professional discrimination, especially when disclosing health data [29]. Concerns exist about the rationing and reduction in services and rising individual costs [29,51]. Furthermore, minorities, such as migrants, have specific fears of discrimination and stigmatization, for instance, the threat of deportation, which can lead to incorrect and missing data [51].

4.1.8. Institutional Barriers

Several administrative barriers and organizational challenges are described that make data sharing and analysis difficult [31]. In some cases, the processes for establishing new administrative systems are described as so slow that they cannot keep up with rapid technological developments [15]. Necessary data access agreements between data repositories and users are estimated to be administratively burdensome and lengthy [18]. Additional contractual mechanisms often need to be created to regulate access in compliance with data protection laws, which requires a lot of time and trust from the parties involved [35]. Further, resistance to the transformation of facilities and institutions is also cited as a barrier [27] and a lack of institutional capacity [53]. This raises the question of whether organizations are interested in collecting and publishing data on an ongoing basis [13]. Releasing data may not be consistent with the organization's goals [13]. For example, there are reservations about publicizing pbD in healthcare organizations when treatment errors or quality of care are publicly exposed, threatening a poor reputation [28]. Another major challenge is a lack of interest and commitment to using Open Data in the organization, especially at higher management levels [10,11]. For example, the main barriers cited for government agencies are organizational [13] and a lack of coordination among departments for the process [10]. Resource allocation is also considered a challenge for government agencies [15]. Similarly, agencies question whether municipal data are used effectively for processes [8]. Standard organizational procedures, routines, and processes for using Open Data are also often lacking [11]. Aleixandre-Benavent et al. found that many respondents did not have a data management plan [40]. In addition, there are challenges in working with the private sector, as they often perceive it as difficult to work with government agencies [15].

4.1.9. Economic Barriers

The introduction and establishment of management and analysis systems for the use of Open Data requires financial and economic resources [18,23,58], which are often lacking [10,11], especially in the health sector [58]. In addition, technical solutions evolve very diversely and rapidly, which requires recurring investments [18]. In addition, external collaborations are described as expensive [11,21]. Investments and deploying resources also require a high intrinsic motivation in dealing with Open Data [44]. In collaboration with technology companies, new or increasing dependencies could also arise [24]. In addition, economic disadvantages are feared as a result of Open Data. For example, the general workload may increase [17], or revenue from Open Data may be reduced, limiting future resources [13]. Licenses for data use may also be lacking, or data may be limited in access through pay-for-use services [13]. In addition, the disclosure of data could lead to displacement of one's business model by competing stakeholders and run counter to one's own interests [13,32]. In addition to embarrassment and stigmatization, data loss can lead to enormous financial burdens [49].

4.1.10. Data Privacy

Preserving data confidentiality and safeguarding the privacy and identity of individuals are widely recognized as significant challenges [45,55,58]. In the era of big data, the potential for privacy breaches has increased [59]. Furthermore, achieving comprehensive compliance with the GDPR is often perceived as demanding, particularly in the context of medical data exchange and reuse [18,27,45,58]. On the other hand, it has been observed that some stakeholders may disregard regulations, which can further undermine trust in data protection [24]. Adhering to stringent data privacy measures can also potentially reduce the overall value and utility of the data by limiting the analytical potential [18]. Additionally, despite data protection and anonymization protocols, the risk of re-identification remains a concern [14]. Furthermore, it remains uncertain whether anonymizing personal data is feasible in all cases [34]. Notably, when data are linked, there is an inherent risk of inadvertently disclosing personal identities [10].

4.1.11. Commercial Interests

Commercial interests through Open Data are viewed critically [43]. Sharing data for commercial purposes is called a red line [24,29]. Furthermore, personal advertising, disease-related health marketing, and unsolicited contact are viewed critically [1,29,57]. Insurance companies, in particular, would have a great interest in health data in this regard, with the risk of economic disadvantage for the individuals [30]. There are also fears of selling data for commercial gain [50], especially against conditions of the general capitalist framework [4]. In addition, fears are expressed about not participating in the benefits and profits with the data or being influenced by the profiling of data [57]. Similarly, consent to use data is withdrawn after new collaborations are announced [24].

4.1.12. Trust

Lack of trust in the processes for sharing and using data is presented as a significant challenge.

Here, trust towards stakeholders varies widely, with healthcare institutions and public authorities being trusted even more than private actors. Especially in large tech corporations [29] and private commercial companies, great distrust is evident in data reuse [29,57]. Househ et al. also noted a lack of trust in healthcare institutions [36]. This issue significantly challenges the trust relationship when government and private stakeholders seek to collaborate [24].

Further, there is mistrust toward the responsible and executing individuals [29,36], including health professionals [36,51]. Lack of trust has been cited as a critical problem in medical data sharing [45]. Further, there may be a loss of trust in the relationship between health professionals and patients when data are shared [29,51]. The difficult balance between risk management and confidentiality when disclosing, for example, data that are hazardous to health is emphasized here and can lead to data withholding [51].

In data publication, data owners also indicate low trust in the processes [10]. Lack of trust in the processes also leads to revocation of consent [24]. Feeney et al. also found a lack of trust in previous data protection regulations from the general public and health professionals [25].

4.1.13. Communication

Communication about the use and purpose or benefit of data sharing is seen as a critical challenge.

Projects have failed in government and private collaborations due to a lack of communication about plans and intentions regarding data use [24]. The lack of transparency and communication can further contribute to mistrust of the government, health workers, patients, and the public [51]. In this regard, all stakeholders involved have requirements for transparency and communication when data are shared [49]. Government institutions, in particular, find it challenging to establish transparency concerning the further use of data and the expected benefits [15]. Lack of transparency in communication leads to different understandings of the benefits and purposes of data sharing [51] and creates problems in the establishment of data standards, such as the FAIRification of data [6]. Further, communication between different disciplines is also described as challenging [51], as is communication with data providers [11]. The complex technical language in data analytics makes communication even more challenging [5].

4.2. Support Factors

Numerous conducive aspects were identified in n = 47 of the studies involved. Aspects of the technical infrastructure, the structure of the data, the use, and the access possibilities can be beneficial. Further beneficial aspects are mentioned in the approval process, in collaborations, in economic and personnel aspects, and in further education and training. Furthermore, the ethical, legal, and social implications (ELSI) are possible enabling aspects. Further, the necessary trust, detailed and transparent communication, and participation in the process are conducive aspects. Likewise, disclosing a positive outcome is crucial for a conducive climate.

A comprehensive breakdown of specific supporting factors can be found in Table 7. The subsequent Sections 4.2.1–4.2.14 provide detailed insights into the backgrounds of these individual factors.

Support Factors	#	Authors
positive outcome	22	[1,2,4,5,8,10–12,15,17,22,24,27,30,33,34,42,44,46,48,50,60]
ELSI	18	[8,10,11,18,22,24,25,28,30,36,41,44,45,47,49,53,57,62]
technical infrastructure	17	[1,5,6,11,13,18,19,21,22,29,31,35,41,45,56,61,62]
data access	17	[1,5,15,18,19,21,24,25,29,34,45,46,50,52,53,56,57]
education and training	15	[1,5,6,11,19,27,36,40,41,45,46,50,54,56,61]
personnel aspects	13	[4,5,11,12,18,22,27,36,41,46,50,54,56]
data structure	12	[1,6,9,11,18,19,22,25,29,31,61,62]
trust	11	[1,21,24,25,27,29,30,41,53,54,56]
consent procedures	10	[1,6,18,19,29,34,41,50,52]
collaborations	10	[5,6,11,18,21,22,24,28,29,31]
communication	7	[6,8,11–13,36,50]
economic aspects	6	[11,15,24,36,44,46]
institutional aspects	6	[6,11,27,44,53,54]
participation	6	[1,24,36,40,42,51]

Table 7. Open Data support factors.

4.2.1. Positive Outcome

Describing the intended general benefits and disclosing the advantages is cited as essential [27,46]. Best practice examples and role models for possible data sharing help [5,11]. Furthermore, the general data quality can be improved by Open Data, and people's motivation to acquire the necessary technical skills can be increased [10].

Public Sector/Public Authorities

Public policy should be improved by using and exploiting OGD [8,10,11]. Open Data are considered an essential resource for public services to understand local needs better [5]. In addition, Open Data are increasingly creating opportunities for participation [11,60]. Transparency and accountability are increased through OGD, and political and social benefits are assumed [10–12,60]. Further, it is hoped that there will be improvement and support in social and political decision-making processes, as any problems can be better identified and problem-solving capacities are improved [8,10–12]. Access to external capacities and resources for problem solving emerges, which improves decision making [11]. The use of collective intelligence to solve public problems can occur [10,11]. This can also strengthen crisis management [10].

Further, Open Data can enable more citizen participation, public engagement, and informed decision making [5,8,10–12]. Kawashita et al. cite increased social control through Open Data in this regard [11]. Open Data are described as a resource for community

activism [5]. The collaboration of stakeholders can be strengthened, and political and social initiatives can be motivated. This can also improve overall trust in the government [10,12]. Citizens' expectations of public services increase [15].

Public administration processes can also become more inclusive [5,10,11]. Similarly, intra-government collaboration is strengthened, and understanding between agencies is enhanced [5,11]. Redundancies within government structures can be reduced, and the public sector has better evaluation capability [10,11].

Entrepreneurship

A positive impact of Open Data on economic growth and the overall economy is described [5,10,12]. Open Data supports the transition to a knowledge-based economy, and a gain in knowledge about the digital transformation for all stakeholders occurs. Through Open Data, the competitiveness of all sectors can be increased, and information for potential investments is better provided [10]. Further, Open Data are considered a resource for innovation [1,5,10] and foster social and commercial value creation [11,60]. New processes, products, or services can be developed, or existing ones can be improved [10,11]. Innovations from the private sector should also support the mechanization of public authorities [15].

Open Data are also expected to lead to greater efficiency in changes in service provision and administration and reduce operating costs [5,10,11].

Research

Open data can be profitable for future research and accelerate innovation and discovery [4,17,33,50]. Open data improve transparency and reproducibility and protect against manipulation, further solidifying the scientific peer review process [17,44]. This strengthens trust in science, which is considered essential for discourse [44]. There are financial savings in access and labor costs to data [17], and disadvantages due to inaccessible research data can be avoided [44,48]. Furthermore, researchers hope that data sharing will enhance the reputation and visibility of their research [17,44,48]. In addition, Open Data provide a resource for educational processes [5]. For example, students can benefit from Open Data in theses, which strengthens the value of research overall [44].

Healthcare Sector

The reuse of personal health data is expected to improve healthcare and quality of life for individuals and the community as a whole [2,4,10,22,24,50]. Also, the care needs of an aging population can be better understood through health data [24]. Further, Open Data supports more individualized precision medicine and quality of care [2,50]. Sharing health data also strengthens personal engagement with one's own data [4]. Similarly, treating rare diseases is hoped to add value to clinical care [34]. Linking lifestyle data with biological samples and clinical information improves the generation of clinical insights [2,42] and enables complex inferences [2,34]. This could result in new prevention approaches [2].

Likewise, it is hoped that Open Data will lead to discoveries, for example, in medicines or the development of new medical devices [30]. In addition, it is hoped to counteract development and cost pressures and improve the efficiency of the healthcare system [2,42].

4.2.2. ELSI

The ethical, legal, and social implications (ELSI) and the associated challenges in data collection should be taken seriously and play a central role in data process decisions [25].

Ethical Implications

Generally, an ethical approval system based on established guidelines and regulations is recommended [30,36]. Mahomed and Labuschaigne also emphasize the necessary data competence that members of an ethics committee need [49]. Full ethical transparency is considered a sustainable and promising way to do this [30]. Viberg et al. emphasize

the importance of how participants are informed [30]. It is essential here that the more powerful partners pass on all information needs to the weaker side so that they can be fully understood [57].

Another critical aspect is data management and use ethics [41]. It is essential to consider the tension between individual needs in use and the desire to maintain privacy and confidentiality [36]. Addressing the information that may promote potential stigma or otherwise be used against the individual's best interest is enormously important [25]. Freedom from harm for the individual must be fully considered [30]. Individual protection from financial, physical, psychological, or emotional harm to a person should be considered [30]. Human dignity should be considered in all data processes, considering that people are behind the data, so respectful and responsible handling is required [30]. Thoral et al. conclude that data use should be enabled when the benefits are perceived as high and the burden low [28].

Researchers mainly presented the positive consequences of the further use of research data and expressed few risks and possible individual harms from secondary use [30]. Here, justice towards vulnerable groups must be maintained [25,30], and possible damage events must be considered from the beginning to prevent discrimination [25].

Social Implications

In addition, the consequences for society and the benefits for science must also be considered [30]. The degree of possible identifiability is of central importance for the public assessment of data sharing [30]. Thus, the benefit of the data, financed by public tax money, should be maximized for society [30].

Here, even an obligation of the re-use is implied, for the research data are usually very expensive in your emergence. In addition, there is a scientific necessity for the use of large and Open Data sets in order to be able to answer specific research questions [30] Fischer et al. point out that Open Data are less burdensome to society in the long run, partly because over-sampling and duplication can be avoided [44].

In this context, collective interest and consideration of the common good significantly influence building trust in data processes [24]. Similarly, broad public debate can offer a way to resolve socio-technical issues, for example, when it comes to data use [8]. This should include public and transparent discourse regarding potential conflicts of interest [24]. The specific interests of data owners may also influence how data are handled [30].

It should also be noted that societal inequalities must be resolved through appropriate representativeness during data management [30]. Data sharing also supports people's need for information and the human right to information. Similarly, knowledge barriers can be reduced because less-well-resourced countries and institutions can gain access to knowledge [44].

Law and Policy

Policy frameworks are described as conducive to establishing and using Open Data [11,18,22,62]. In this context, a discernible political will for Open Data and the support and commitment of political leadership are essential [11,62]. Further, there are external constraints and constellations of pressure from international organizations and standards [11,47]. Professional procedures in data collection and sharing must be followed [30]. Mahomed and Labuschaigne for example, suggest agreeing on additional data transfer agreements that support legal and ethical standards, especially in the case of international data sharing and different data protection bases [49]. Likewise, a broad public debate on Open Data is seen as a political driver for corresponding laws and standards [11]. It is emphasized that corresponding Open Data initiatives should be robust, sustainable, and effectively consider local, regional, and national characteristics [10].

Clearly formulated legal regulations are considered another prerequisite for establishing Open Data [10,22,24,45,53]. These legal frameworks help convince people that their

interests are protected [24,41]. In doing so, it is essential to respect the rights of individuals, especially the rights to privacy, autonomy, freedom, human dignity, and justice [30].

The right to privacy includes the right not to be identified without consent. The right to autonomy includes the right to decide freely whether or not to disclose data and which data to disclose. In this context, the extent of a potential threat to rights must be determined in advance to adapt security measures to the needs of the person at risk [30]. Data producers want to retain full control over the data [41]. Achieving this requires comprehensive information at many levels about the purpose, method, outcome, and data sharing. Protection by external regulatory frameworks is considered particularly important, especially for vulnerable groups. Further, respecting the freedom of research is an essential perspective for the research community [30]. In addition, rules are needed vis à vis data stewards in the sense of "who watches the watchers?" [41]. However, a paradox of the inverse relationship is also described because the more rights and laws there are, the less trustworthy they are perceived to be in studies [24].

4.2.3. Technical Infrastructure

The technical systems and existing infrastructure must be secure and resilient [19,29,45] and are also required at the European level [18]. The security and design of the infrastructure also influence trust and the willingness to share data [1,29]. A data-protection-friendly infrastructure in which the data never leave the institution is advantageous [18,31]. To this end, internal data trustees and a separate data analysis depository are recommended [18].

In addition, the technical infrastructure should harness the benefits of artificial intelligence [45]. For example, the possibility of machine learning makes centralized storage superfluous, making legally and ethically problematic agreements on data transfer unnecessary. Machine learning uses an iterative process to exchange information between databases and not between individual data records. This protects privacy [31]. Alzahrani et al. recommend blockchain technology as a further decentralized storage and analysis option, ensuring data integrity and protection, as transactions remain traceable and the data remain unchangeable. The technology is also efficient and cost-effective [19]. Homomorphic multi-party encryption is also a solution in which the data remain in the original institution, and standardization and shared use by institutions are made possible [35]. Queralt-Rosinach et al. also propose developing an ontological model to integrate existing datasets into the management system [6]. However, Medley et al. also emphasize the need for central data registries as part of such an infrastructure, as these repositories are necessary for meta-analyses with personal data [21].

It is helpful to gain insight into existing technical systems when introducing new systems [6]. Tuler de Oliveira et al. point out that merging existing systems is preferable to entirely new systems [56].

Furthermore, high usability and user-friendly software are recommended for handling data [13,22,31,61], especially when converting raw data according to the FAIR principles [31]. Prepared access is crucial, especially for technically inexperienced users [61]. The available equipment must be supportive and good [62]. The interfaces must enable and support interaction and management with the data [41]. Appropriate platforms and tools for use are considered to be very helpful [5,11]. The data portals should facilitate fast and convenient searches and support data discovery, for example, through automatic visualizations [61]. Open data portals are also seen as beneficial [11].

4.2.4. Data Access

Data sharing should be planned and regulated [5,18,21,29,52]. Planning and all sharing aspects are considered essential to avoid complications in consent, data collection, grant compliance, data format, and data sharing, and should be conducted as early as possible [15,52]. In data use, the highest level of transparency should always be ensured with clarity on the purpose and goal of data sharing [1,25]. The goal should be useful and functional data sharing [56]. Contracts can support a trusting data-sharing relationship in

this regard [57]. Rockhold et al. recommend including patients in this process and point out that such sustainability plans for data use in research are increasingly required by funding agencies for externally funded projects [52].

Access controls to data are described as a significant and beneficial aspect [19,25,29,34,56]. Developing an access model/access procedure for the data is considered necessary [18,24,53]. Adherence to transparency in access is critical in this regard [25]. Thus, trust, acceptance, and willingness to share data depend significantly on access arrangements [29,50]. Data subjects should be able to view and review data sharing [29]. Data donors must be protected against unlawful access [25]. This requires options for simple and secure authentication [45] and the use of controllable access protocols [18].

At the same time, high requirements regarding the availability of datasets are described [19]. In this context, exclusive access is described as dataset-dependent [46]. Tuler de Oliveira et al. point out that access controls may only apply to be-stained professional groups, as in the case of electronic patient records [56]. Further, data access rights and aspects of data protection can change, so it is never a static system [18].

4.2.5. Education and Training

Linguistic, technical, and legal competencies are needed for Open Data processes [46]. This involves understanding how information is stored, managed, and shared [41,63]. Maximum engagement with these processes should be ensured [1,27,50]. Individuals often have special needs in this regard to enable use [61]. For this, the effective training and development of professionals is essential, and learning resources are needed to train individuals with specific skills [5,45,46,56,61]. Increased awareness of the use of Open Data is generally helpful [11]. Therefore, all stakeholders involved in Open Data should be intensively involved and sensitized [40,56]. General knowledge about current developments and possibilities and AI-supported data processing must be conveyed [1,40]. Training on technical backgrounds, personal fears, and possible cognitive overloads related to the use of Open Data is beneficial [5]. In this context, Queralt-Rosinach et al. report on organized workshops, for example, to educate stakeholders about the benefits of introducing FAIR data principles [6]. Further, knowledge of professionals and data donors on cybersecurity and potential threat scenarios is needed, as well as awareness raising on security measures and privacy aspects [1,36,45,56]. There is also a need to increase trust and acceptance of the technology as a whole [1,56]. Trustworthy platform knowledge is needed [36,56]. It must also be possible to assess the data regarding relevance and quality [5,61]. Furthermore, the user friendliness of the technical systems should be demonstrated to the target group [19].

4.2.6. Personnel Aspects

Increased data use requires human resources and experience [18,22]. In this regard, personal judgment, attitude, and understanding are critical to readiness for data sharing [4,22,41,46,56,63]. To this end, Smith and Sandberg emphasized the importance of fostering general engagement in creating appropriate value with data [12].

Especially among executives and management, an awareness of Open Data is conducive [11]. In this regard, Dove et al. speak of intermediaries (individuals or organizations) being critical to the success of using Open Data [5]. Likewise, the will of stakeholders and assertiveness are described as necessary, especially in overcoming challenges [27]. To this end, differences in cross-cultural understanding regarding data processes must be considered [36].

In this regard, it is beneficial to convey data donation as a positive experience to retain potential resources in the long term [4]. Health professionals are generally more likely to rate data sharing as meaningful, useful, and highly relevant to care [56]. For Open Government Data, an interest in government processes is described as beneficial [5]. For example, individual data donation of health-related personal data is often accompanied by an altruistic motive reminiscent of organ donation circumstances [4]. In their study, Nunes Vilaza et al. determined that young individuals with a high educational background are

especially motivated to share data. Transparency of the benefits was found to be a key factor for the acceptance of sharing personal data [50]. Obtaining more in-depth information about oneself and individual benefit recognition, such as more tailored care, were motivating factors [41,50,63]. Furthermore, there was a correlation between the individual's positive attitude toward data storage and sharing and their own interest in health issues [50].

4.2.7. Data Structure

The structure and characteristics of the data represent significant factors that can favor further uses [22]. It is essential to ensure data quality [11,62]. Further, data quality standards according to FAIR principles represent a conducive data structure for Open Data processes [6,18,31]. There are high requirements for datasets in terms of security, integrity, authenticity, access controls, confidentiality, and availability [19]. It is considered crucial that only anonymized data are shared [1]. Datasets following the FAIR principle are considered a prerequisite for distributed analysis and machine learning. Therefore, all stakeholders who want to participate in reusing data must agree on a data model according to the FAIR principles, and institutions need different tools to FAIR-ify the data [31]. Its structure and form influence the FAIR-ification of data. In this regard, FAIR principles improve structure and discoverability, especially for health data and the intent of international exchange [6]. FAIR-ification also offers the opportunity to establish data privacy and data security through anonymization or synthetic case representations and should, therefore, be implemented in a data management plan [6]. Only current and relevant data should be shared [29]. A government-supported system for improving data quality is also seen as beneficial [9].

Further, it is described as essential to consider possible abuses and fears of whether the information contained may be harmful or discriminatory in some way already during the development of datasets [25]. This facilitates subsequent data harmonization [18]. However, the data's level of detail and information content also reveal different views in the studies. Govarts et al. generally recommend the principle of data minimization, even with subsequent anonymization and pseudonymization, to protect privacy as comprehensively as possible [18]. On the other hand, the context of data/meta-data should be preserved as comprehensively as possible to avoid distortions or quality deficiencies in the data [11,61].

4.2.8. Trust

The trust of users and data donors in the various data processes is considered an essential prerequisite for success and must be built and increased [27,56]. During data collection, a trusting relationship is already crucial [63]. Similarly, the importance of existing trust from the users to the data managers is emphasized [41]. Similarly, the data ecosystem and technical infrastructure must be trusted [1,53]. This trust is achieved through strict security measures, transparency of measures, and strict access to data [25,29]. In addition, society trusts different public and economic sectors to different degrees, and the scientific sector, in particular, must be perceived as absolutely trustworthy [30]. Similarly, established international institutions enjoy high trust [21]. There is also trust in governmental health institutions for responsible use [24]. Trust in the government and public authorities is further considered crucial [53]. Particularly in the case of cooperation between government and private institutions, a focus on building trust is essential [24]. However, even between departments within an institution, trust between professionals is critical for data sharing [63]. In general, trust and data sharing also depends on knowledge regarding intended penalties for misuse [29].

4.2.9. Consent Procedures

Consent procedures must adapt to the new realities of personal data sharing and use [1,18,19,34]. An important step can be a data governance policy that clearly regulates how consent is available [6]. Further, free choice and autonomy for data sharing are emphasized as necessary [29,50], especially for accepting possible sharing [50]. In this context, the

new type of consent structures must explicitly integrate, for example, further processing of personal data within research [34]. Data producers want to retain control over personal-related data [41]. Rockhold et al. note that consent documents and protocols should be worded appreciatively, and data contributors should be understood as cooperators and contributors [52].

Alzahrani et al. emphasize the high importance of intelligent consent procedures [19]. Thus, dynamic consent overcomes many ethical obstacles after appropriate re-education. In this regard, dynamic consent requires ongoing engagement and communication between data owners and custodians [1,18]. Here, Kamikubo et al. emphasize the positive perception and estimation of persistent consent for purposes of use despite practical challenges in the necessary long-term relationship [1]. Dynamically informed consent to research projects is also seen as an essential prerequisite for promoting autonomy and decision-making power [18].

Particularly for data that cannot be anonymized, specific agreements are needed between the actors involved [34]. Alorwu et al. recommend a procedure similar to that for organ donation to provide medical personal data [41].

4.2.10. Collaborations

To address complexity, collaboration among institutions, as well as with policymakers and other stakeholders, is described as beneficial and significant [5,18,22,24,28,31]. Fylan and Fylan emphasize that collaboration with trust-based institutions is essential [29]. Thus, the government health system or government institutions should have an important role, for example, in data management [21,29]. The guiding principles of equity, solidarity, and quality in data use should be considered in partnerships between public and private institutions [24]. In this regard, Kawashita et al. emphasize the beneficial synergies in collaborating public and private partnerships [11]. The responsible use of data is enormously important for all participants and the entire process [28]. A multidisciplinary approach is seen as helpful, especially in developing open-access databases [28]. Likewise, support from the Open Data community can be helpful [5], or external stakeholders and user communities can provide resources [18]. In addition, professional societies play an essential role in disseminating standards and guidelines in this field and international cooperation [28]. In this regard, Deist et al. suggest collaboration with research networks [31]. Creating win–win situations for all actors involved can facilitate the further use and reuse of data [18]. Especially for work with personal health data, regular collaboration and iterative meetings between clinicians and data managers who are familiar with the data systems are essential. It is important to know the questions and goals of the stakeholders in advance in order to define and interpret the outcome process [6].

4.2.11. Communication

The increasingly broad communication and dissemination of Open Data to society, for example, by committees and journalists, is described as beneficial [8,11,50]. Raising public awareness of the benefits of sharing personal data is particularly important [50]. In this regard, improving communication with unknowing individuals who have previously had little awareness of the topic is essential [36]. In addition, communication is critical to learning user needs and technical requirements [6,12]. Data sharing must be consistently communicated at all levels and processes [13].

4.2.12. Economic Aspects

An increased demand for efficiency and cost savings can be conducive to supporting the reuse and re-purposing of data in general [15]. Available financial resources and existing digitization capacity are considered particularly conducive, as is a willingness to disclose data internally [11]. Fischer et al. emphasize, in particular, the saving of financial resources for the usually expensive data collection [44]. In addition, it is crucial to consider the commercialization aspects in the further use of personal data [36]. Here, the question of whether data should be offered commercially as for-profit, or non-commercially as non-profit, must be addressed [46]. For example, digital health data have a financial value [24]. Here, the question of possible benefit sharing also needs to be addressed, for example, whether there should be preferential access to goods and services provided by the data donors if these are developed from the available data [24,46]. These potential benefits of data sharing can be motivational [24].

4.2.13. Institutional Aspects

The trend toward increased data sharing among departments and institutions is generally described as a positive and conducive factor [63]. Sandoval-Almazan et al. describe the internal design of rules for data processes as conducive [53]. Kawashita et al. emphasize how conducive a positive and changeable organizational culture is perceived to be for this process [11]. A structured data management plan approach is also crucial for success [6,27,45]. A data management plan allows individual challenges in interoperability, cybersecurity, and existing and necessary infrastructure to be considered [27]. In addition, FAIR data principles should be implemented in a data management plan to produce machine-usable data [6]. In addition, institutions and agencies at different levels need to overcome resistance to transformation, holding agreements on value to the barriers and expectations of responsible data use. Identifying the available resources is equally important [27].

4.2.14. Participation

It is crucial to involve all stakeholders in Open Data processes [42,51]. For example, in future policy developments, diverse stakeholders, minorities, professionals, and ethicists should be involved in creating guidelines for data sharing [51]. Especially for data donation and the development of AI-based systems, the participation of the target group is of high importance, as the participation of the stakeholders involved also raises awareness on the topic of Open Data [1]. Horn and Kerasidou cite an expanded say for data processes in this context [24]. A participatory essential attitude is also crucial in designing corresponding data platforms in this context. Such participatory platforms should focus on empowering data donors [36]. People must also be willing to participate in this process [40].

5. Conclusions

There are currently too few literature reviews that describe the individual perspectives of the actors involved in using and reusing Open Data [10]. At the same time, it is emphasized that specific barriers and support factors may be present, which may also change in the course of ongoing developments [11].

In analyzing and categorizing the topics mentioned in the literature, certain aspects were highlighted as both barriers and facilitators and described across disciplines and sectors.

Various aspects of the data structure and technical infrastructure can be both hindering and conducive to establishing Open Data processes. In particular, aspects of data protection are perceived as a barrier with a fear of data misuse and stigmatization. On the other hand, aspects of controlled data access with transparent access rules are seen as conducive to reducing existing concerns and fears. The process of education and consent is also described as both hindering and beneficial, depending on how many resources are put into these elementary processes and how serious the processes are, leading to satisfied and fully informed individuals. The ethical, legal, and social implications (ELSI), as well as institutional and economic aspects, are also described as hindering and promoting, depending on which priorities are placed on these aspects and how they are pursued and observed. If there are commercial interests, this is generally described as a hindrance, whereas transparent and trustworthy collaborations, primarily with research institutions and state institutions, are considered trustworthy and feasible. Furthermore, personnel aspects can be both a help and a hindrance. On the one hand, many skills and abilities have been reported among people involved in Open Data. In principle, person-centered training and further education focusing on creating more awareness for individual Open Data processes and establishing a data-oriented culture are seen as particularly beneficial here.

Furthermore, the areas of trust and communication can have both a positive and negative effect, whereby the participation of the actors involved is described as particularly beneficial, as is transparent and appreciative communication that includes all actors involved equally. The disclosure of possible positive outcomes and benefits and the integration of best-practice examples are considered particularly conducive to establishing Open Data processes.

Overall, the studies involved show that overcoming the challenges and promoting the use of Open Data requires a holistic approach that focuses on people, data protection, ethics and trust, and a careful examination of the legal and ethical framework conditions. The ELSI aspects, in particular, must be comprehensively integrated so that social science research will continue to play a decisive role in the further development of these topics in the future [20].

6. Summary

Obstacles to Open Data can manifest at various levels, including data generation, publication, discovery, utilization, and user feedback [13]. Mutambik et al. [10] classify potential barriers into six categories in line with existing categorizations. These barriers may be institutional, related to task complexity, use and engagement, legal frameworks, information quality, and technology [10]. Similarly, Kawashita et al. describe obstacles and facilitators concerning legal and policy requirements, institutional, organizational, and cultural aspects, economic and financial considerations, and technological factors [11].

The following main conclusions can be drawn from this work concerning the publication of personal data as Open Data:

1. Data Privacy and Legal Frameworks

In the context of data privacy and legal frameworks, it is evident that the use of Open Data, especially personally identifiable information, relies on a robust legal foundation and a clear ethical framework. The European General Data Protection Regulation (GDPR) has undoubtedly contributed to harmonizing and enhancing data portability across Europe, yet challenges persist in its full implementation [25]. Data privacy, particularly in healthcare, continues to be perceived as one of the most significant barriers [64]. The GDPR, applicable throughout Europe, aims to safeguard personal data comprehensively and establish global standards for managing such data [65]. Furthermore, it has been complemented by the EU Data Governance Act (DGA), designed to promote the broader use of personal data and foster data altruism across Europe [65]. However, due to the ongoing developments in the field of Open Data, existing regulations for personal data protection are increasingly scrutinized [59]. Addressing these challenges necessitates compliance with existing data protection

regulations and the establishment of new legal frameworks capable of adapting to the evolving landscape of Open Data. Given the continuous advancements in the field of Open Data, the existing regulations for personal data protection are increasingly questioned [59]. So far, the EU GDPR and the EU proposals regarding regulations for using artificial intelligence represent some of the few mechanisms that encompass responsible regulation, which may not suffice in all cases [30]. Furthermore, developing specific data usage policies, particularly in health research data, is essential [6].

2. Ethics and Trust

Ensuring society's trust in the handling of personal data and the strict adherence to ethical principles are fundamental requirements for Open Data. Transparency regarding data usage, especially when dealing with sensitive health data, is crucial in establishing this trust.

The European Ethic Advisory Board underscores the need for a new digital ethics framework, given the challenges and disruptions caused by the increasing use of data streams, which are difficult to predict. The inseparable connection between individuals and their personal data is emphasized [43]. This emphasis necessitates a broad discourse on managing health data, considering expectations of security and privacy associated with a wide range of uses and applications [30].

Another focal point of this discussion is the integrity and accountability in data handling, including data loss prevention and the accountability for adding data during processing and utilization [56]. Building trust in data exchange processes and shaping a societal data-sharing contract is pivotal. Both technological solutions and ethical principles must align to create the necessary trust and promote the societal acceptance of Open Data usage [29].

3. Resources

Adequate financial and human resources are essential for the collection, maintenance, and dissemination of Open Data [11,18]. Without sufficient funding and skilled personnel, data quality and accessibility can suffer, hindering the realization of Open Data's full potential [46,61]. Moreover, long-term sustainability strategies are crucial to ensure that Open Data initiatives continue to evolve and meet the changing needs of their stakeholders. By allocating resources effectively, organizations can maximize the benefits of Open Data while addressing the challenges associated with data governance, privacy, and security. Developing a clear roadmap for resource allocation and sustainability is vital for Open Data efforts' continued growth and success [52].

4. Interoperability and Standards

In the realm of Open Data processes, standards, guidelines, and professional associations also have a critical role to play. Examples of freely accessible databases developed using a multidisciplinary approach are presented [28]. Data aggregation into centralized databases, such as the Database of Genotypes and Phenotypes of the US National Institutes of Health and the European Genomic Phenome Archive, can offer solutions to interoperability challenges [27]. Promoting standards and guidelines for Open Data fosters a more unified and efficient data-sharing environment. This, in turn, enhances collaboration among diverse stakeholders and ensures the quality and utility of data for research, industries, and data-driven decision making.

5. **Evaluation and Review**

It is imperative to identify and select appropriate data before release meticulously. Following this selection process, the decision to publish should be made with continuous evaluation of the impact and utility of the data. This process is a cyclical approach [13]. The entire approach to Open Data should be measured by its success, with data-driven applications aimed at enabling improved health outcomes, preventive measures, and forecasts [24].

The comprehensive utilization of data necessitates a thorough evaluation [13] and ongoing audits and reviews of the associated processes [46]. Furthermore, there is an urgent requirement for tools and a step-by-step model to guide stakeholders, such as hospitals, in this process, ensuring that data are structured and organized following the FAIR principles (Findable, Accessible, Interoperable, Reusable) [6].

7. Limitations

This Scoping Review has several limitations to consider when interpreting the results.

- 1. Lack of systematic risk assessment (risk of bias assessment): A systematic risk assessment was not carried out as part of this Scoping Review. Consequently, it is impossible to ascertain the risk of overestimating or underestimating the effects and results of the selected studies.
- 2. Quality of selected studies: Despite carefully selecting and reviewing studies, some studies might have been erroneously considered relevant to Open Data. Including such studies could have implications for the results of Open Data.
- 3. Limited search coverage: The search strategy primarily relied on seven databases supplemented with Google Scholar searches. Using only these sources may have led to the omission of some relevant studies, further emphasizing the limitations of the

search. This study may not encompass all relevant synonyms and terms associated with Open Data.

These limitations are crucial to consider when interpreting the findings and underline the need for further research that can address these limitations to provide a more comprehensive understanding of Open Data.

Author Contributions: Conceptualization, N.L. and S.W.; methodology, N.L.; validation, N.L. and L.S.; formal analysis, N.L.; investigation, N.L.; data curation, N.L.; writing—original draft preparation, N.L.; writing—review and editing, N.L., L.S. and S.W.; visualization, N.L. and S.W.; supervision, S.W. and F.W.; project administration, S.W. and F.W.; funding acquisition, S.W. and F.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the European Union and sponsored by the German Federal Ministry of Education and Research under grant number 16KISA128K. ("Verbundprojekt: Empfehlungs- und Auditsystem zur Anonymisierung—EAsyAnon").

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data utilized for this Scoping Review are drawn from a comprehensive search encompassing various databases and sources. All search terms employed in this review are detailed in the methodology section and are listed in Appendices A and B. The included studies, references, and relevant information extracted are publicly accessible and retrievable through the respective databases or repositories referenced in the bibliography.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

- ELSI Ethical, Legal, and Social Implications
- EOSC European Open Science Cloud
- FAIR Findable, Accessible, Interoperable, Reusable
- OGD Open Governance Data
- OUR Open, Useful, Reusable

Appendix A

Table A1. Search strings used for searching in databases.

Database	Search String
MEDLINE via PubMed	("personal data" OR "personal information" OR "person-related data" OR "personal identification information" OR "patient Data") AND (barriers OR challenges OR obstacles OR impediments OR hindrances OR hurdle) AND (promotion OR support OR enabling OR opportunities OR incentives) AND ("data sharing" OR "data provision" OR "providing data" OR "data supply" OR "data publishing") AND (y_5[Filter])
CINAHL via EBSCOhost	(("personal data" OR "personal information" OR "person-related data" OR "personal identification information" OR "patient Data")) AND (barriers OR challenges OR obstacles OR impediments OR hindrances OR hurdle)) AND ((promotion OR support OR enabling OR opportunities OR incentives)) AND (("data sharing" OR "data provision" OR "providing data" OR "data supply" OR "data publishing"))
BASE	("personal data" OR "personal information" OR "person-related data" OR "personal identification information" OR "patient Data") AND (open data" OR "open information" OR "open science") AND ("data sharing" OR "data provision" OR "providing data" OR "data supply" OR "data publishing") AND (barriers OR challenges OR obstacles OR impediments OR hindrances OR hurdle) AND (promotion OR support OR enabling OR opportunities OR incentives) year: [2018 TO *]

Table A	A1 . Co	ont.
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Database	Search String			
LIVIVO	(((("personal data" OR "personal information" OR "person-related data" " "personal identification information" OR "patient Data")) AND TI = ((barriers OR challenges OR obstacles OR impediments OR hindrances OR hurdle) AND (promotion OR support OR enabling OR opportunities OF incentives))) AND TI = (("data sharing" OR "data provision" OR "provid data" OR "data supply" OR "data publishing") AND ("open data" OR "open information" OR "open science"))) AND PY = 2018:			
Web of Science Core Collection	((((#1) AND ALL = (("personal data" OR "personal information" OR "person-related data" OR "personal identification information" OR "patient Data"))) AND ALL = ((barriers OR challenges OR obstacles OR impediments OR hindrances OR hurdle))) AND ALL = ((promotion OR support OR enabling OR opportunities OR incentives))) AND ALL = (("data sharing" OR "data provision" OR "providing data" OR "data supply" OR "data publishing")) and 2023 or 2022 or 2021 or 2018 or 2019 or 2020 (Publication Years)			
IEEE Xplore Digi- tal Library	((("All Metadata":"personal data" OR "All Metadata":"personal information" OR "All Metadata":"person-related data" OR "All Metadata":"personal identification information" OR "All Metadata": "patient data") AND ("All Metadata": barriers OR "All Metadata": challenges OR "All Metadata": obstacles OR "All Metadata": impediments OR "All Metadata": bindrances OR "All Metadata": hurdle)) AND("All Metadata": promotion OR "All Metadata": support OR "All Metadata": incentives) AND ("All Metadata": opportunities OR "All Metadata": incentives) AND ("All Metadata": "data sharing" OR "All Metadata": "data supply" OR "All Metadata": "incentives) AND ("All Metadata": "incentives) AND ("All Metadata": "incentives) AND ("All Metadata": "incentives) AND ("All Metadata": "incentives) OR "All Metadata": "incentives) AND ("All Metadata": "incentives) OR "All Metadata": "i			
ACM Digital Li- brary	333 Results for: [[All: "personal data"] OR [All: "personal information"] OR [All: "person-related data"] OR [All: "personal identification information"] OR [All: "patient data"]] AND [[All: barriers] OR [All: challenges] OR [All: obstacles] OR [All: impediments] OR [All: hindrances] OR [All: hurdle]] AND [[All: promotion] OR [All: support] OR [All: enabling] OR [All: opportunities] OR [All: incentives]] AND [[All: "data sharing"] OR [All: "data provision"] OR [All: "providing data"] OR [All: "data supply"] OR [All: "data publishing"]] AND [[All: "open data"] OR [All: "open information"] OR [All: "open science"]] AND [E-Publication Date: (01/01/2018 TO 12/31/2023)]			

The search in MEDLINE was performed using the PubMed platform in the advanced search and included a combination of the operationalized search components as shown in Table 3. The search in CINAHL was performed using the EBSCOhost interface in the full-text search. For searches in BASE, LIVIVO, Web of Science, IEEEXplore, and ACM, the integrated advanced search was used. In some cases, individual search components proved to be too limiting in combination, so they were adapted depending on the database. The search was performed in MEDLINE and CINAHL in Title and Abstract, in BASE and LIVIVIO in Title and in Web of Science, IEEEXplore and ACM in All Fields and All meta-data.

Appendix **B**

Search last performed on 12 June 2023.

Table A2. Documentation systematic search results.

Nr.		Search String	MEDLINE	CINAHL	BASE	LIVIVO	Web of Science	IEEE Xplore	ACM
		Date	1 June 2023	5 June 2023	5 June 2023	7 June 2023	7 June 2023	9 June 2023	12 June 2023
1	Personal Data	("personal data" OR "personal informa- tion" OR "person-related data" OR "per- sonal identification information" OR "pa- tient Data")	12,741	4,301	182,713	14,463	19,338	8405	21,662
2	Barriers	(barriers OR challenges OR obstacles OR impediments OR hindrances OR hurdle)	658,970	133,618	1,783,959	1,056,699	1,411,084	217,496	340,022
3	Support factors	(promotion OR support OR enabling OR opportunities OR incentives)	2,752,603	261,118	3,441,003	1,664,052	3,982,684	290,271	488,208
4	Providing Data	("data sharing" OR "data provision" OR "providing data" OR "data supply" OR "data publishing")	5198	10,961	58,194	6813	15,972	433,303	13,625
5	Open Data	("open data" OR "open information" OR "open science")	4428	696	475,197	16,229	15,464	177,906	7187
6	1+2	Personal Data + Barriers	1505	361	15,540	-	-	766	16,433
7	1 + 2 + 3	Personal Data + Barriers + support factors	942	146	-	-	-	250	15,950
8	1 + 2 + 3 + 4	Personal Data + Barriers + support factors + providing Data	66	11	-	47	81	74	2614
9	1 + 2 + 3 + 4 + 5	Personal Data + Barriers + support factors + providing Data + Open Data	5	1	242	8	8	37	338
10	1 + 3	Personal Data + support factors	-	-	-	-	-	-	-
11	1 + 4	Personal Data + providing Data	264	-	-	-	-	-	-
12	1 + 4 + 2	Personal Data + providing Data + Barriers	-	-	-	-	-	-	-
13	1 + 4 + 3	Personal Data + providing Data + support factors	-	-	-	-	-	-	-

Table A2. Cont.

Nr.		Search String	MEDLINE	CINAHL	BASE	LIVIVO	Web of Science	IEEE Xplore	ACM
14	1 + 4 + 5	Personal Data + providing Data + Open Data	22	-	1.937	27	21	-	-
15	1 + 4 + 5 + 2	Personal Data + providing Data + Open Data + Barriers	-	-	440	11	-	-	-
16	1 + 4 + 5 + 3	Personal Data + providing Data + Open Data + support factors	-	-	-	-	-	-	-
17	1 + 5	Personal Data + Open Data	56	17	61.833	-	-	-	-
18	1 + 5 + 2	Personal Data + Open Data + Barriers	15	-	-	-	-	-	-
19	1 + 5 + 3	Personal Data + Open Data + support fac- tors	38	-	-	-	-	-	-
20	1 + 5 + 2 + 3	Personal Data + Open Data + support fac- tors + Barriers	-	-	-	-	-	-	-
	total	studies (n)/Database	146	29	242	93	110	111	338

Legend: - = No search performed in corresponding combination; 38 = Search results included in the evaluation.

References

- Kamikubo, R.; Lee, K.; Kacorri, H. Contributing to Accessibility Datasets: Reflections on Sharing Study Data by Blind People. In Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, Hamburg, Germany, 23–28 April 2023. [CrossRef]
- Rehman, A.; Naz, S.; Razzak, I. Leveraging big data analytics in healthcare enhancement: Trends, challenges and opportunities. *Multimed. Syst.* 2022, 28, 1339–1371. [CrossRef]
- 3. Ethikrat, D. *Big Data und Gesundheit: Datensouveränität als Informationelle Freiheitsgestaltung: Stellungnahme: Kurzfassung;* Bundesministerium für Gesundheit: Bonn, Germany, 2017.
- 4. Sleigh, J. Experiences of Donating Personal Data to Mental Health Research: An Explorative Anthropological Study. *Biomed. Inform. Insights* **2018**, *10*, 1178222618785131. [CrossRef] [PubMed]
- 5. Dove, G.; Shanley, J.; Matuk, C.; Nov, O. Open Data Intermediaries: Motivations, Barriers and Facilitators to Engagement. *Proc. ACM Hum.-Comput. Interact.* 2023, 7, 1–22. [CrossRef]
- 6. Queralt-Rosinach, N.; Kaliyaperumal, R.; Bernabé, C.H.; Long, Q.; Joosten, S.A.; van der Wijk, H.J.; Flikkenschild, E.L.A.; Burger, K.; Jacobsen, A.; Mons, B.; et al. Applying the FAIR principles to data in a hospital: Challenges and opportunities in a pandemic. *J. Biomed. Semant.* **2022**, *13*, 12. [CrossRef] [PubMed]
- Roguljić, M.; Šimunović, D.; Poklepović Peričić, T.; Viđak, M.; Utrobičić, A.; Marušić, M.; Marušić, A. Publishing Identifiable Patient Photographs in Scientific Journals: Scoping Review of Policies and Practices. *J. Med. Internet Res.* 2022, 24, e37594. [CrossRef] [PubMed]
- 8. Rempel, E.; Barnett, J.; Durrant, H. Contrasting views of public engagement on local government data use in the UK. In Proceedings of the 12th International Conference on Theory and Practice of Electronic Governance, Melbourne, Australia, 3–5 April 2019; Ben Dhaou, S., Ed.; ACM Digital Library: New York, NY, USA, 2019; pp. 118–128. [CrossRef]
- Seo, J.; Kim, B.; Kwon, H.Y. Open Data Policies Analysis Disputes Mediation Cases in Korea: Based on OUR Data Index and ODB. In Proceedings of the DG.O2021: The 22nd Annual International Conference on Digital Government Research, Omaha, NE, USA, 9–11 June 2021; ACM Digital Library: New York, NY, USA, 2021; pp. 153–167. [CrossRef]
- 10. Mutambik, I.; Nikiforova, A.; Almuqrin, A.; Liu, Y.D.; Floos, A.Y.M.; Omar, T. Benefits of Open Government Data Initiatives in Saudi Arabia and Barriers to Their Implementation. *J. Glob. Inf. Manag.* **2022**, *29*, 1–22. [CrossRef]
- 11. Kawashita, I.; Baptista, A.A.; Soares, D. Open Government Data Use by the Public Sector—An Overview of its Benefits, Barriers, Drivers, and Enablers. In Proceedings of the 55th Hawaii International Conference on System Sciences, Maui, HI, USA, 4–7 January 2022.
- 12. Smith, G.; Sandberg, J. Barriers to innovating with open government data: Exploring experiences across service phases and user types. *Inf. Polity* **2018**, *23*, 249–265. [CrossRef]
- 13. Crusoe, J.; Melin, U. Investigating Open Government Data Barriers; Springer: Cham, Switerland, 2018; pp. 169–183. [CrossRef]
- 14. Csányi, G.M.; Nagy, D.; Vági, R.; Vadász, J.P.; Orosz, T. Challenges and Open Problems of Legal Document Anonymization. *Symmetry* **2021**, *13*, 1490. [CrossRef]
- van Donge, W.; Bharosa, N.; Janssen, M.F.W.H.A. Future government data strategies: Data-driven enterprise or data steward? In Proceedings of the 21st Annual International Conference on Digital Government Research, Seoul, Republic of Korea, 15–19 June 2020; Eom, S.J., Ed.; ACM Digital Library: New York, NY, USA, 2020; pp. 196–204. [CrossRef]
- Pesqueira, A.; Sousa, M.J.; Rocha, Á. Big Data Skills Sustainable Development in Healthcare and Pharmaceuticals. *J. Med. Syst.* 2020, 44, 197. [CrossRef]
- 17. Dos Santos Rocha, A.; Albrecht, E.; El-Boghdadly, K. Open science should be a pleonasm. Anaesthesia 2023, 78, 551–556. [CrossRef]
- Eva, G.; Liese, G.; Stephanie, B.; Petr, H.; Leslie, M.; Roel, V.; Martine, V.; Sergi, B.; Mette, H.; Sarah, J.; et al. Position paper on management of personal data in environment and health research in Europe. *Environ. Int.* 2022, *165*, 107334. [CrossRef] [PubMed]
- 19. Alzahrani, A.G.; Alhomoud, A.; Wills, G. A Framework of the Critical Factors for Healthcare Providers to Share Data Securely Using Blockchain. *IEEE Access* 2022, *10*, 41064–41077. [CrossRef]
- 20. Phillips, M.; Knoppers, B.M. Whose Commons? Data Protection as a Legal Limit of Open Science. J. Law Med. Ethics 2019, 47, 106–111. [CrossRef]
- 21. Medley, N.; Cuthbert, A.; Crew, R.; Stewart, L.; Smith, C.T.; Alfirevic, Z. Developing a topic-based repository of clinical trial individual patient data: Experiences and lessons learned from a pilot project. *Syst. Rev.* **2021**, *10*, 162. [CrossRef]
- 22. Zuiderwijk, A.; Spiers, H. Sharing and re-using open data: A case study of motivations in astrophysics. *Int. J. Inf. Manag.* 2019, 49, 228–241. [CrossRef]
- 23. Schwalbe, N.; Wahl, B.; Song, J.; Lehtimaki, S. Data Sharing and Global Public Health: Defining What We Mean by Data. *Front. Digit. Health* **2020**, *2*, 612339. [CrossRef] [PubMed]
- 24. Horn, R.; Kerasidou, A. Sharing whilst caring: Solidarity and public trust in a data-driven healthcare system. *BMC Med. Ethics* **2020**, *21*, 110. [CrossRef]
- Feeney, O.; Werner-Felmayer, G.; Siipi, H.; Frischhut, M.; Zullo, S.; Barteczko, U.; Øystein Ursin, L.; Linn, S.; Felzmann, H.; Krajnović, D.; et al. European Electronic Personal Health Records initiatives and vulnerable migrants: A need for greater ethical, legal and social safeguards. *Dev. World Bioeth.* 2020, 20, 27–37. [CrossRef]

- 26. Bentzen, H.B.; Castro, R.; Fears, R.; Griffin, G.; ter Meulen, V.; Ursin, G. Remove obstacles to sharing health data with researchers outside of the European Union. *Nat. Med.* **2021**, *27*, 1329–1333. [CrossRef]
- 27. Hallock, H.; Marshall, S.E.; 't Hoen, P.A.C.; Nygård, J.F.; Hoorne, B.; Fox, C.; Alagaratnam, S. Federated Networks for Distributed Analysis of Health Data. *Front. Public Health* **2021**, *9*, 712569. [CrossRef]
- Thoral, P.J.; Peppink, J.M.; Driessen, R.H.; Sijbrands, E.J.G.; Kompanje, E.J.O.; Kaplan, L.; Bailey, H.; Kesecioglu, J.; Cecconi, M.; Churpek, M.; et al. Sharing ICU Patient Data Responsibly Under the Society of Critical Care Medicine/European Society of Intensive Care Medicine Joint Data Science Collaboration: The Amsterdam University Medical Centers Database (AmsterdamUMCdb) Example. *Crit. Care Med.* 2021, 49, e563–e577. [CrossRef]
- Fylan, F.; Fylan, B. Co-creating social licence for sharing health and care data. *Int. J. Med. Inform.* 2021, 149, 104439. [CrossRef]
 [PubMed]
- Johansson, J.V.; Bentzen, H.B.; Mascalzoni, D. What ethical approaches are used by scientists when sharing health data? An interview study. BMC Med. Ethics 2022, 23, 41. [CrossRef]
- Deist, T.M.; Dankers, F.J.W.M.; Ojha, P.; Scott Marshall, M.; Janssen, T.; Faivre-Finn, C.; Masciocchi, C.; Valentini, V.; Wang, J.; Chen, J.; et al. Distributed learning on 20,000+ lung cancer patients—The Personal Health Train. *Radiother. Oncol. J. Eur. Soc. Ther. Radiol. Oncol.* 2020, 144, 189–200. [CrossRef] [PubMed]
- McWhirter, R.; Eckstein, L.; Chalmers, D.; Critchley, C.; Nielsen, J.; Otlowski, M.; Nicol, D. A Scenario-Based Methodology for Analyzing the Ethical, Legal, and Social Issues in Genomic Data Sharing. *J. Empir. Res. Hum. Res. Ethics JERHRE* 2020, 15, 355–364. [CrossRef] [PubMed]
- 33. Kuo, T.T.; Jiang, X.; Tang, H.; Wang, X.; Harmanci, A.; Kim, M.; Post, K.; Bu, D.; Bath, T.; Kim, J.; et al. The evolving privacy and security concerns for genomic data analysis and sharing as observed from the iDASH competition. *J. Am. Med. Inform. Assoc. JAMIA* **2022**, *29*, 2182–2190. [CrossRef]
- Nellåker, C.; Alkuraya, F.S.; Baynam, G.; Bernier, R.A.; Bernier, F.P.J.; Boulanger, V.; Brudno, M.; Brunner, H.G.; Clayton-Smith, J.; Cogné, B.; et al. Enabling Global Clinical Collaborations on Identifiable Patient Data: The Minerva Initiative. *Front. Genet.* 2019, 10, 611. [CrossRef]
- Scheibner, J.; Raisaro, J.L.; Troncoso-Pastoriza, J.R.; Ienca, M.; Fellay, J.; Vayena, E.; Hubaux, J.P. Revolutionizing Medical Data Sharing Using Advanced Privacy-Enhancing Technologies: Technical, Legal, and Ethical Synthesis. *J. Med. Internet Res.* 2021, 23, e25120. [CrossRef]
- Househ, M.; Grainger, R.; Petersen, C.; Bamidis, P.; Merolli, M. Balancing between Privacy and Patient Needs for Health Information in the Age of Participatory Health and Social Media: A Scoping Review. *Yearb. Med. Inform.* 2018, 27, 29–36. [CrossRef]
- 37. Nordhausen und Hirt. 10 Schritte zur systematischen Literaturrecherche. RefHunter—Systematische Literaturrecherche. 2022. Available online: https://refhunter.org/research_support/rechercheschritte/ (accessed on 22 November 2023).
- Davies, K.S. Formulating the Evidence Based Practice Question: A Review of the Frameworks. *Evid. Based Libr. Inf. Pract.* 2011, 6, 75–80. [CrossRef]
- McGowan, J.; Sampson, M.; Salzwedel, D.M.; Cogo, E.; Foerster, V.; Lefebvre, C. PRESS Peer Review of Electronic Search Strategies: 2015 Guideline Statement. J. Clin. Epidemiol. 2016, 75, 40–46. [CrossRef] [PubMed]
- 40. Aleixandre-Benavent, R.; Vidal-Infer, A.; Alonso-Arroyo, A.; Peset, F.; Ferrer Sapena, A. Research Data Sharing in Spain: Exploring Determinants, Practices, and Perceptions. *Data* **2020**, *5*, 29. [CrossRef]
- 41. Alorwu, A.; Kheirinejad, S.; van Berkel, N.; Kinnula, M.; Ferreira, D.; Visuri, A.; Hosio, S. Assessing MyData Scenarios: Ethics, Concerns, and the Promise. In Proceedings of the CHI'21, 2021 CHI Conference on Human Factors in Computing Systems, Yokohama, Japan, 8–13 May 2021; Kitamura, Y., Quigley, A., Isbister, K., Igarashi, T., Bjørn, P., Drucker, S., Eds.; Association for Computing Machinery: New York, NY, USA, 2021; pp. 1–11. [CrossRef]
- 42. Broes, S.; Lacombe, D.; Verlinden, M.; Huys, I. Toward a Tiered Model to Share Clinical Trial Data and Samples in Precision Oncology. *Front. Med.* **2018**, *5*, 6. [CrossRef] [PubMed]
- 43. Burgess, J.P.; Floridi, L.; Pols, A.; van den Hoven, J. Towards a Digital Ethics: EDPS Ethics Advisory Group. 2018. Available online: https://philpapers.org/rec/BURTAD-3 (accessed on 22 November 2023).
- 44. Fischer, C.; Hirsbrunner, S.D.; Teckentrup, V. *Producing Open Data*; Pensoft Publishers: Sofia, Bulgaria, 2022; Volume 8, p. e86384. [CrossRef]
- 45. Fischer-Hübner, S.; Alcaraz, C.; Ferreira, A.; Fernandez-Gago, C.; Lopez, J.; Markatos, E.; Islami, L.; Akil, M. Stakeholder perspectives and requirements on cybersecurity in Europe. *J. Inf. Secur. Appl.* **2021**, *61*, 102916. [CrossRef]
- 46. Floridi, L.; Luetge, C.; Pagallo, U.; Schafer, B.; Valcke, P.; Vayena, E.; Addison, J.; Hughes, N.; Lea, N.; Sage, C.; et al. Key Ethical Challenges in the European Medical Information Framework. *Minds Mach.* **2019**, *29*, 355–371. [CrossRef]
- 47. Galdon Clavell, G. Exploring the ethical, organisational and technological challenges of crime mapping: A critical approach to urban safety technologies. *Ethics Inf. Technol.* **2018**, *20*, 265–277. [CrossRef]
- 48. Kwon, S.; Motohashi, K. Incentive or disincentive for research data disclosure? A large-scale empirical analysis and implications for open science policy. *Int. J. Inf. Manag.* 2021, *60*, 102371. [CrossRef]
- 49. Mahomed, S.; Labuschaigne, M.L. The evolving role of research ethics committees in the era of open data. *S. Afr. J. Bioeth. Law* **2023**, *15*, 80–83. [CrossRef]

- 50. Nunes Vilaza, G.; Coyle, D.; Bardram, J.E. Public Attitudes to Digital Health Research Repositories: Cross-sectional International Survey. *J. Med. Internet Res.* 2021, 23, e31294. [CrossRef]
- 51. Papageorgiou, V.; Wharton-Smith, A.; Campos-Matos, I.; Ward, H. Patient data-sharing for immigration enforcement: A qualitative study of healthcare providers in England. *BMJ Open* **2020**, *10*, e033202. [CrossRef]
- Rockhold, F.; Bromley, C.; Wagner, E.K.; Buyse, M. Open science: The open clinical trials data journey. *Clin. Trials (Lond. Engl.)* 2019, 16, 539–546. [CrossRef] [PubMed]
- Sandoval-Almazan, R.; Valle Gonzalez, L.; Millan Vargas, A. Barriers for Open Government Implementation at Municipal Level: The Case of the State of Mexico. In Proceedings of the DG.O2021: The 22nd Annual International Conference on Digital Government Research, Omaha, NE, USA, 9–11 June 2021; ACM Digital Library: New York, NY, USA, 2021; pp. 113–122. [CrossRef]
- 54. Smart, D.; Jackson, K.; Alderson, H.; Foley, T.; Foreman, S.; Kaner, B.; Kaner, E.; Lancaster, H.; Lingam, R.; Rankin, J.; et al. What Influences Parents and Practitioners' Decisions to Share Personal Information within an Early Help (Social Care) Context? Implications for Practice in Sharing Digital Data across Sectors. *Br. J. Soc. Work* 2022, *52*, 2146–2165. [CrossRef]
- 55. Tan, A.C.; Askie, L.M.; Hunter, K.E.; Barba, A.; Simes, R.J.; Seidler, A.L. Data sharing-trialists' plans at registration, attitudes, barriers and facilitators: A cohort study and cross-sectional survey. *Res. Synth. Methods* **2021**, *12*, 641–657. [CrossRef] [PubMed]
- Tuler de Oliveira, M.; Amorim Reis, L.H.; Marquering, H.; Zwinderman, A.H.; Delgado Olabarriaga, S. Perceptions of a Secure Cloud-Based Solution for Data Sharing During Acute Stroke Care: Qualitative Interview Study. *JMIR Form. Res.* 2022, 6, e40061. [CrossRef] [PubMed]
- 57. van der Burg, S.; Wiseman, L.; Krkeljas, J. Trust in farm data sharing: Reflections on the EU code of conduct for agricultural data sharing. *Ethics Inf. Technol.* 2021, 23, 185–198. [CrossRef]
- 58. Vianen, N.J.; Maissan, I.M.; den Hartog, D.; Stolker, R.J.; Houmes, R.J.; Gommers, D.A.M.P.J.; van Meeteren, N.L.U.; Hoeks, S.E.; van Lieshout, E.M.M.; Verhofstad, M.H.J.; et al. Opportunities and barriers for prehospital emergency medical services research in the Netherlands; results of a mixed-methods consensus study. *Eur. J. Trauma Emerg. Surg.* 2023. [CrossRef]
- 59. Wang, C.; Guo, F.; Ji, M. Analysis of Legal Issues of Personal Information Protection in the Field of Big Data. *J. Environ. Public Health* **2022**, 2022, 1678360. [CrossRef]
- Wieczorkowski, J. Barriers to Using Open Government Data. In Proceedings of the 2019 3rd International Conference on E-commerce, E-Business and E-Government, Lyon, France, 18–21 June 2019; ACM Digital Library: New York, NY, USA, 2019; pp. 15–20. [CrossRef]
- Wolff, A.; Tylosky, N.; Hasan T. Open Data Inclusion through Narrative Approaches. In Proceedings of the 2022 IEEE/ACM 44th International Conference on Software Engineering: Software Engineering in Society (ICSE-SEIS), Pittsburgh, PA, USA, 21–29 May 2022; pp. 125–129. [CrossRef]
- Yerden, X.; Luna-Reyes, L.F. Promoting Government Impacts through Open Data: Key Influential Factors. In Proceedings of the DG.O2021: The 22nd Annual International Conference on Digital Government Research, Omaha, NE, USA, 9–11 June 2021; ACM Digital Library: New York, NY, USA, 2021; pp. 180–188. [CrossRef]
- 63. Smart, M.A.; Sood, D.; Vaccaro, K. Understanding Risks of Privacy Theater with Differential Privacy. *Proc. ACM Hum.-Comput. Interact.* 2022, *6*, 1–24. [CrossRef]
- 64. Avraam, D.; Jones, E.; Burton, P. A deterministic approach for protecting privacy in sensitive personal data. *BMC Med. Inform. Decis. Mak.* 2022, 22, 24. [CrossRef]
- 65. Kamocki, P.; Linden, K. EU Data Governance Act: New Opportunities and New Challenges for CLARIN. In Proceedings of the CLARIN Annual Conference Proceedings, Prague, Czech Republic, 10–12 October 2022; pp. 44–47.

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