Factors Influencing Open Science Participation Through Research Data Sharing and Reuse Among Researchers: A Systematic Literature Review

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FACTORS INFLUENCING OPEN SCIENCE PARTICIPATION THROUGH RESEARCH DATA SHARING AND REUSE AMONG RESEARCHERS: A SYSTEMATIC LITERATURE REVIEW

ABSTRACT

This systematic literature review investigates the influential factors guiding researchers' active engagement in open science through research data sharing and subsequent reuse, spanning various scientific disciplines. The review addresses key objectives and questions, including identifying distinct sample types, data collection methods, critical factors, and existing gaps within the body of literature concerning data sharing and reuse in open science. The methodology employed in the review was detailed, outlining a series of systematic steps. These steps encompass the systematic search and selection of relevant studies, rigorous data extraction and analysis, comprehensive evaluation of selected studies, and transparent reporting of the resulting findings. The review's evaluation process was governed by well-defined inclusion and exclusion criteria, encompassing publication dates, language, study design, and research outcomes. Furthermore, it adheres to the PRISMA 2020 flow diagram, effectively illustrating the progression of records through the review stages, highlighting the number of records identified, screened, included, and excluded. The findings include a concise tabular representation summarising data extracted from the 51 carefully selected studies incorporated within the review. The table provides essential details, including study citations, sample sizes, data collection methodologies, and key factors influencing open science data sharing and reuse. Additionally, common themes and categories among these influential factors are identified, shedding light on overarching trends in the field. In conclusion, this systematic literature review offers valuable insights into the multifaceted landscape of open science participation, emphasising the critical role of research data sharing and reuse. It is a comprehensive resource for researchers and practitioners interested in further understanding the dynamics and factors shaping the open science ecosystem.

Keywords
Open Science, Research Data Sharing and Reuse, Open Science Participation, Systematic Literature Review, PRISMA 2020

INTRODUCTION

Open science is a movement toward greater transparency, reproducibility, and accessibility in scientific research [1]. It aims to make research data and related findings available to other researchers and the public, enabling them to verify research findings, build upon existing knowledge, and promote greater collaboration in scientific research [2]. Open science involves a range of practices, including open-access publishing, open data sharing, pre-registration of research designs, and open peer review, all intended to promote transparency, accountability, and reproducibility in scientific research. This practice has enabled and provided a means for global scientists and researchers to collaborate and contribute to all research processes and share many valuable scientific discoveries beneficial to different aspects of human life [3].

Data sharing has become crucial to the advancement of science because it facilitates collaboration, transparency, reproducibility, criticism, and re-analysis [4]. This is why research data, lab notes, and other research processes are made freely available to the public to reuse, redistribute, and reproduce along with the fundamental data and methods [5]. In a nutshell, many research communities now practice a transparent and open knowledge development system mostly shared through a collaborative platform [6]. The European University Association (EUA) was identified as one of the early global drivers in open science initiatives

as the result of its new approach to the scientific processes, based on cooperative work and new ways of disseminating knowledge using digital technologies and other new collaborative tools [7]. Data sharing is a key component of open science, enabling other researchers and the public to access and use research data. Despite data sharing and reusing benefits in advancing scientific knowledge, researchers remain hesitant to participate in open science practices [8].
Understanding the factors influencing researchers' willingness to participate in open science through research data sharing and reuse is crucial for promoting greater transparency and collaboration in scientific research [9]. In recent years, there has been growing interest in understanding the barriers and facilitators to data sharing in the context of open science practices. Researchers have identified several factors that may influence data sharing and reuse practices, some of which include cultural norms [10], legal and ethical considerations from either the institution, funding agencies or journals [11], social impact to contribute to scientific knowledge that can benefit society [12], technological infrastructure or the open science platform for sharing the research data [3], and funding or institutional policies [13] to facilitate collaboration and knowledge exchange among the researchers. However, a systematic literature review is needed to comprehensively understand the factors influencing open science data sharing and reuse practices across scientific disciplines.

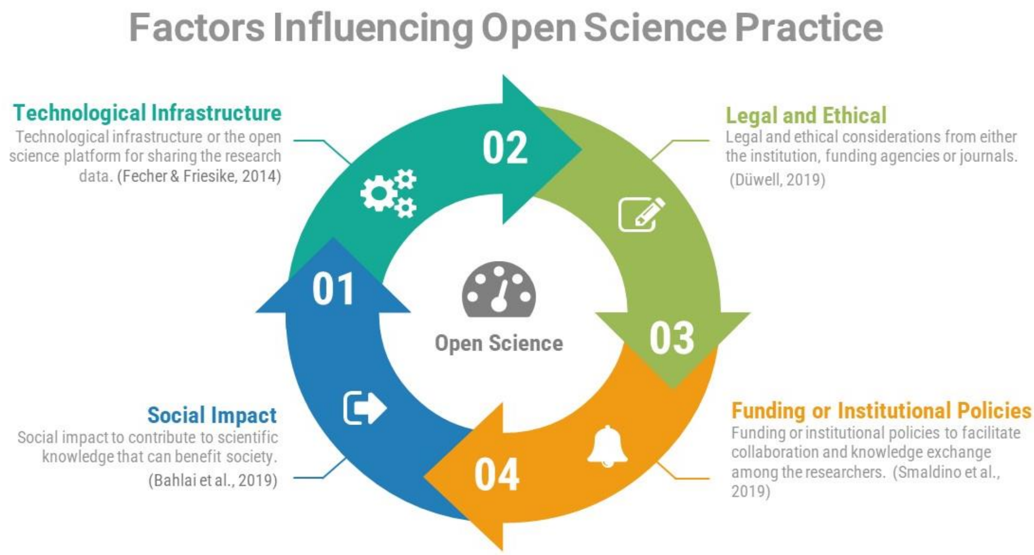


Figure 1. Factors influencing open science practice source: illustrated by the researcher (Source: Illustrated by the Authors).

The open science movement has also introduced a range of principles to influence its implementation among researchers from various disciplines [14]. This could be due to the speedy technological advancement and the internet, which has also led to rapid advancement in almost all social sectors. Seeing the numerous benefits of open science practices, several research institutions and journal publishers have included one or more open science practices in their publication policies. Although, different factors have motivated the researcher's participation in this practice since its inception. This systematic literature review aims to identify the key factors influencing researchers' participation in open science practice through research data sharing and reuse and the overlapping terminologies/concepts used to explain these factors.

By systematically analysing the existing literature, this research seeks to provide an explicit statement of the objectives and questions this review addresses. In doing so, it aims to better understand the barriers and facilitators to data sharing and reuse in the context of open science practices and identify best practices for promoting greater transparency and collaboration in scientific research. To achieve these objectives, this section of the research followed the detailed and practical guidance on the methodology, steps, and best practices involved in conducting systematic reviews recommended by Cochrane. It covers topics such as formulating the review objectives, searching and selecting relevant studies, data extraction and analysis, assessing the risk of bias, and interpreting and reporting findings [15].

Figure 2. Open science principles, Source: [14]

Formulating the Review Objectives

Per the guidelines set by Cochrane, initiating a systematic literature review necessitates the establishment of well-articulated research objectives. These objectives should encapsulate clearly defined parameters such as the types of patients/illnesses, sample under consideration, and interventions [15]. These determinants aid in the decision-making process for selecting which articles to include in the review. Accordingly, the objectives for the current review are set as follows:

i. To identify the most common categories of samples and data collection methods used in studies examining the factors influencing researchers' participation in open science through research data sharing and reuse.
ii. To identify key factors that influence researchers' participation in open science practices, especially in research data sharing and reuse, as derived from the literature.
iii. To find existing gaps in the literature that necessitate further research.

METHODOLOGY

Searching and Selecting Relevant Studies

To search and locate all relevant studies to the review topic, a compressive search was conducted in an Elicit search engine (https://elicit.org/). An AI research assistant that uses language models to help automate research workflows, most especially parts of literature review. Elicit can find relevant papers without perfect keyword matches, summarise takeaways from the paper specific to a search question, and extract key information from the papers. Other research tasks also help with brainstorming, summarisation, and text classification [16].

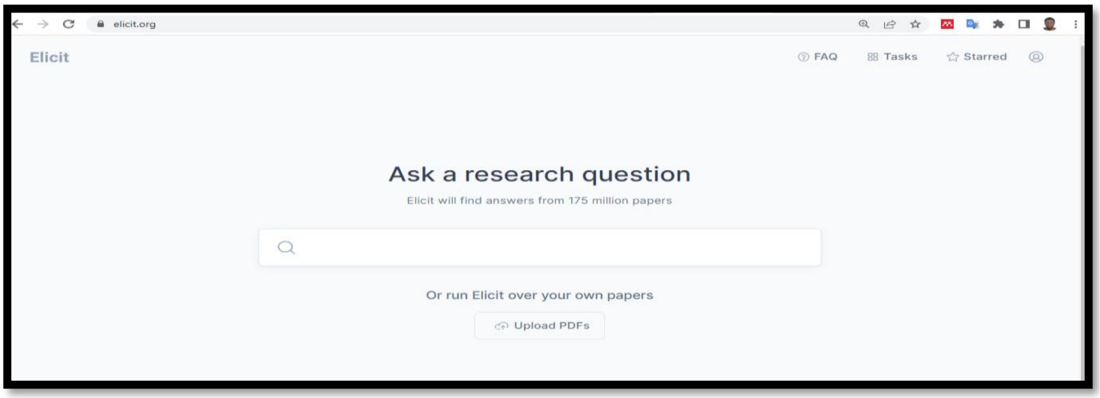


Figure 3. Elicit search interface (Source: https://elicit.org/).

Using the search query (the formulated review questions) as "What are the key factors influencing researchers' willingness to participate in open science practices through research data sharing and reuse?". The search was refined using the Elicit advanced search features, including filters for keywords, publication dates, study types, and citation graphs, as in Table 1 below.

Table 1. Search refinement using the Elicit advanced search features.

S/N	Features	Results	
1.	Keywords (Abstract contains the keywords)	Open science practices Research data sharing Data reuse Research data management Data sharing incentives Data sharing barriers Data sharing attitudes	Data sharing motivations Data sharing culture Data sharing policies Data accessibility Research data transparency Open access data Research data collaboration
2.	Publication dates	Studies published between 2017 and 2023.	
3.	Study types	Include (randomised control trials and longitudinal studies).	Exclude (reviews, systematic reviews, and meta-analyses).
4.	Citation graphs	Relevant citations from the top included papers are included in the review.	

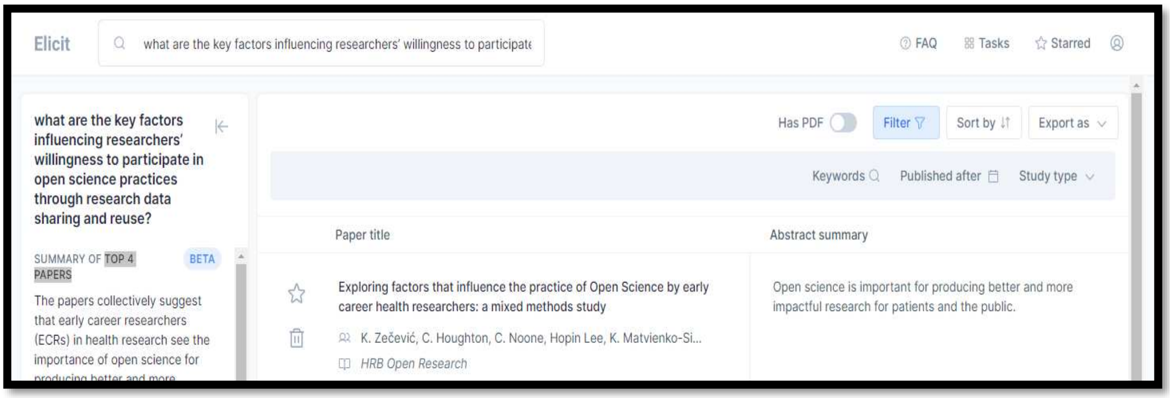


Figure 4. Search refinement using the Elicit advanced search features (Source: https://elicit.org/).

After identifying potentially relevant studies through the search, the results were carefully screened by reading the article title, abstract, and keywords from the elicit window, as in Figure 4. To identify potentially relevant studies. All the relevant studies were then retrieved to read the full text of the remaining studies to assess whether they met the inclusion/exclusion criteria. The flowchart in Figure 5 presents the steps followed in the Elicit Literature Review workflow.

Figure 5 Elicit Literature Review workflow chart (Source: Illustrated by the Authors).

DATA EXTRACTION AND ANALYSIS

Data extraction represents another vital stage in the systematic literature review, wherein significant information is methodically gathered from each included study. This involves the creation of a standardised data extraction table to record essential details from the selected studies. The data extraction form encompasses various aspects, including study characteristics, sample size, study design, data collection methods, key findings, and other relevant information. The extraction process was facilitated using Table 2, enabling the extraction of selected study samples, data collection methods, and key findings. Additionally, the review employed the PRISMA 2020 flow diagram for systematic literature reviews, as [17] Page et al., (2021) proposed. The integration of this diagram aids in presenting a comprehensive report of the findings, allowing potential readers to assess the appropriateness of the methods and the credibility of the study's conclusions. Figure 6 below visually illustrates the flow of information through the different phases of the review, depicting the number of records identified, included, and excluded, alongside the reasons for exclusions.

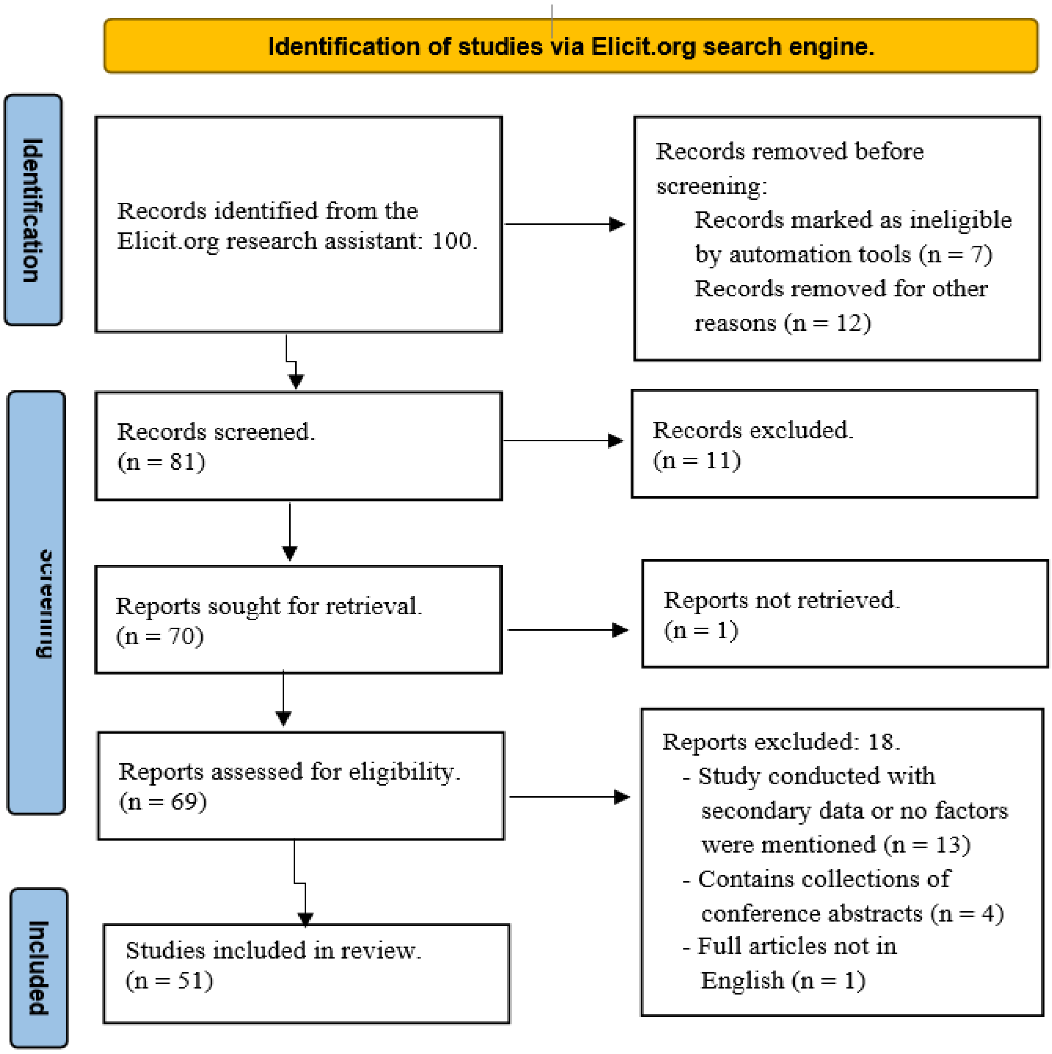


Figure 6. PRISMA 2020 flow diagram

The PRISMA chart shows the number of records or studies identified, screened, included, and excluded at each stage of the systematic review process. The Identification column shows how many records were found by the search. The screening column shows how many records were screened by reading their titles and abstracts and how many were excluded based on predefined criteria, such as relevance, language, or publication date. The Eligibility column shows how many full-text articles were assessed for eligibility by reading their methods and results and how many were excluded based on predefined criteria, such as study design, quality, or outcomes. The Included column shows how many studies were included in the final review and synthesis. While the PRISMA chart has helped ensure transparency and completeness of the review methods and results, the following criteria were also followed to help the readers assess the validity and reliability of the review findings.

Evaluation of the Studies

To evaluate all the relevant studies from the search result, specific criteria to determine the validity of the selected studies were followed. This approach facilitates decision-making in deciding which articles should be included in the literature review. The studies that are not included in the literature review were also cited and have a rationale for the exclusion.

Eligibility Criteria

The inclusion and exclusion criteria were essential in determining the articles for analysis in this systematic review. The criteria used to select these articles were as follows:

Inclusion Criteria:

i. Studies that explored the factors influencing researchers' engagement in open science practices, specifically through research data sharing and reuse.
ii. Publications dated between 2017 and 2023.
iii. Studies written exclusively in English.
iv. Only studies involving human subjects or samples.
v. Original empirical research articles (i.e., excluding review articles, secondary data usage, and commentaries).

Exclusion Criteria:

i. Articles that do not address the factors affecting researchers' involvement in open science via data sharing and reuse.
ii. Studies without empirical or primary data.
iii. Non-English studies.

By adhering to these eligibility guidelines, the review ensured a focus on relevant studies concerning the factors affecting researchers' engagement in open science, specifically studies providing original empirical insights written in English and published between 2017 and 2023. Advanced search functionalities in Elicit.org were utilised to refine the search to retain only the relevant articles. Table 2 below presents all the included studies collected for the review, in which relevant data from each study were extracted through a standardised form, capturing details such as study citations, sample size, data gathering methods, and the key factors influencing the open science practice.

Table 2 Studies collected for the review with a summary of the evaluation.

S/N	Studies	Sample	Data Collection Methods	Key Factors
1	Dorta-González, P., González-Betancor, S. M., & Dorta-González, M. I. (2021). To what extent is researchers' data-sharing motivated by formal mechanisms of recognition and credit? *Scientometrics*, *126*(3), 2209-2225.	Researchers: 6019 respondents were reached via Springer Nature author lists and distributed to the Figshare user database.	Quantitative: Data was collected through the State of Open Data Survey 2019, jointly conducted by publisher Springer Nature and technology company Digital Science.	• Awareness and capacity building • Data characteristics • Policies and regulations • Rewards and other benefits
2	Melero, R., & Navarro-Molina, C. (2020). Researchers' attitudes and perceptions towards data sharing and data reuse in the field of food science and technology. *Learned publishing*, *33*(2), 163-179.	Researchers from food science and technology: A dual-sample study conducted through a focus group and online survey, engaging 7 experienced researchers and gathering 101 responses on data management, sharing, and research data reuse.	Mixed method: Comprising experienced researchers from IATA-CSIC, organized in June 2018, to explore data management, sharing, and attitudes towards research data reuse and sharing in the context of the research data life cycle.	• Policies and regulations • Awareness and capacity building
3	Abdullahi, K. A., & Noorhidawati, A. (2020). Perceptions towards research data sharing: A qualitative study of Nigerian academics. *Malaysian Journal of Library and Information Science*, *25*(3), 103-121.	Nigerian Academics: An exploratory study employing semi-structured interviews with 22 senior academicians from five federal universities in Northeast Nigeria, offering insightful qualitative data on the region's higher education landscape.	Qualitative: This exploratory study employs a semi-structured interview to gather qualitative data, offering rich insights and understanding.	• Rewards and other benefits • Trust and confidence
4	Zuiderwijk, A., & Spiers, H. (2019). Sharing and re-using open data: A case study of motivations in astrophysics. *International Journal of Information Management*, *49*, 228-241.	Astrophysics researchers: Nine researchers, each with unique positions, age, and experience, lend their perspectives through insightful interviews.	Qualitative: Case Study Investigating the Physics department at the University of Oxford using interviews, observations, and data platform examinations as the primary information sources.	• Culture and perceived norms • Data characteristics • Researchers' characteristics and background • Rewards and other benefits • Culture and perceived norms.
5	Curty, R. G., Crowston, K., Specht, A., Grant, B. W., & Dalton, E. D. (2017). Attitudes and norms affecting scientists' data reuse. *PloS one*, *12*(12), e0189288.	Scientists: A comprehensive survey conducted from October 2013 to March 2014 gathered 1,015 responses, with 595 participants in the optional section analysed in this paper.	Quantitative: The dataset utilized in this study, collected by the DataONE Usability and Assessment Working Group, explores scientists' attitudes towards data sharing.	• Culture and perceived norms

6	Zenk-Möltgen, W., Akdeniz, E., Katsanidou, A., Naßhoven, V., & Balaban, E. (2018). Factors influencing the data sharing behavior of researchers in sociology and political science. *Journal of documentation*, *74*(5), 1053-1073.	Researchers in sociology and political science: Only 56.5% of authors provided access to their data, with a retrieval rate of 36.6% among 446 surveyed authors, covering 44.1% of all articles.	Multi-level Data Sets: Two data sets were constructed to address research questions: one at the journal level and the other at the article level nested within journals.	• Awareness and capacity building • Culture and perceived norms • Researchers' characteristics and background
7	Tenopir, C., Rice, N. M., Allard, S., Baird, L., Borycz, J., Christian, L., ... & Sandusky, R. J. (2020). Data sharing, management, use, and reuse: Practices and perceptions of scientists worldwide. *PloS one*, *15*(3), e0229003.	Scientists worldwide: A two-wave survey, conducted in collaboration with the American Geophysical Union and partners, yielded 2,184 responses, exploring diverse perspectives and analyzed using IBM SPSS 25.	Quantitative: Surveys Developed based on previous surveys conducted by the DataONE Usability and Assessment working group, this survey maintains consistency with some questions	• Available tools and repositories • Awareness and capacity building • Rewards and other benefits
8	Mason, C. M., Box, P. J., & Burns, S. M. (2020). Research data sharing in the Australian national science agency: Understanding the relative importance of organizational, disciplinary and domain-specific influences. *Plos one*, *15*(8), e0238071.	Australian National Science Agency: From a pool of 3,664 potential participants, 806 employees participated, yielding a 22% response rate. However, only 381 respondents provided sufficient data for meaningful analysis,	Quantitative: Survey with Incentive, the survey was conducted online, with a link in an email from the organization's Chief Scientist.	• Researchers' characteristics and background
9	Linek, S. B., Fecher, B., Friesike, S., & Hebing, M. (2017). Data sharing as social dilemma: Influence of the researcher's personality. *PloS one*, *12*(8), e0183216.	Researcher Survey Filtered Insights: Out of 2,661 initial respondents, we excluded incomplete questionnaires, resulting in 1,564 valid cases, representing 59% of the total respondents.	Quantitative: The questionnaire drew inspiration from previous studies, including a systematic review and a secondary data user survey.	• Researchers' characteristics and background
10	Nicholas, D., Jamali, H. R., Herman, E., Watkinson, A., Abrizah, A., Rodríguez-Bravo, B., ... & Polezhaeva, T. (2020). A global questionnaire survey of the scholarly communication attitudes and behaviours of early career researchers. Learned Publishing, 33(3), 198-211.	Early career researchers: After data-cleaning, we analysed 1,600 responses, encompassing a diverse sample including English (42.4%), Chinese (15.8%), French (14.8%), Polish (10.8%), Russian (9.3%), and Spanish (7.1%) versions.	Quantitative: The questionnaire was developed based on insights from the first leg's interview schedule and pilot tested. The 44 questions covered scholarly communication practices and attitudes, along with demographic and personal questions.	• Awareness and capacity building • Data characteristics • Policies and regulations • Researchers' characteristics and background • Rewards and other benefits • Trust and confidence

11	Aleixandre-Benavent, R., Vidal-Infer, A., Alonso-Arroyo, A., Peset, F., & Ferrer Sapena, A. (2020). Research data sharing in Spain: Exploring determinants, practices, and perceptions. *Data*, *5*(2), 29.	Spanish researchers: From a diverse sample of 1,063 researchers across scientific areas, this survey explores the attitudes and practices of 663 men (62.4%) and 400 women (37.6%).	Quantitative: An electronic questionnaire was designed to gather data on Spanish researchers' data-sharing experiences and practices.	• Available tools and repositories • Awareness and capacity building • Policies and regulations • Rewards and other benefits
12	Tenopir, C., Christian, L., Allard, S., & Borycz, J. (2018). Research data sharing: Practices and attitudes of geophysicists. *Earth and Space Science*, *5*(12), 891-902.	American Geophysical Union (AGU): online survey in March 2017 to its 62,000 members worldwide. With 1,372 responses from 116 countries, the survey achieved a response rate of 2.2% before concluding in March 2018.	Quantitative: Survey data were collected using Qualtrics and stored securely on the University of Tennessee's server. Researchers utilized IBM SPSS 25	• Available tools and repositories • Awareness and capacity building • Rewards and other benefits • Trust and confidence
13	Damalas, D., Kalyvioti, G., Sabatella, E. C., & Stergiou, K. I. (2018). Open data in the life sciences: The 'Selfish scientist paradox.' *Ethics in science and environmental politics*, *18*, 27-36.	Engaging the Research Community: From January 15 to August 21, 2017, approximately 7,500 emails were sent, eliciting 858 responses from researchers (11%) who participated in the questionnaire.	Quantitative Online Questionnaire Survey: This study utilized an online questionnaire survey hosted at http://artemis2.ath.hcmr.gr/HcmrPolls/polls/questions	• Available tools and repositories • Culture and perceived norms • Policies and regulations • Researchers' characteristics and background • Trust and confidence.
14	Suhr, B., Dungl, J., & Stocker, A. (2020). Search, reuse and sharing of research data in materials science and engineering—A qualitative interview study. *Plos one*, *15*(9), e0239216.	Materials Science and Engineering Data Practices: Among 20 contacted researchers, 13 willingly participated in interviews, with participant selection unbiased regarding their views on data sharing.	Qualitative: A qualitative research approach was adopted to explore open research data practices in materials science and engineering, involving semi-structured interviews for in-depth insights.	• Available tools and repositories • Awareness and capacity building • Culture and perceived norms • Data characteristics • Efforts and other sacrifices • Policies and regulations • Rewards and other benefits
15	Hodonu-Wusu, J. O., Noorhidawati, A., & Abrizah, A. (2020). Malaysian researchers on open data: the first national survey on awareness, practices and attitudes. *Malaysian Journal of Library and Information Science*, *25*(2), 1-20.	Malaysian researchers: After three rounds of distributions, 300 responses were received, but 165 incomplete responses were dropped from the analysis. The remaining 135 completed questionnaires were used for analysis.	Quantitative: Adopting a quantitative method, this study utilized surveys as the research design due to their common application in investigating researchers' behaviours, opinions, and knowledge of specific phenomena like Open Science.	• Available tools and repositories • Awareness and capacity building • Policies and regulations • Researchers' characteristics and background • Rewards and other benefits • Trust and confidence

16	Hrynaszkiewicz, I., Harney, J., & Cadwallader, L. (2021). A survey of researchers' needs and priorities for data sharing. *Data Science Journal*, *20*, 31-31.	Researchers Insightful Response Snapshot: Out of 1,477 participants, the survey received 617 completed responses, offering valuable insights into the study.	Quantitative: Statements were used to create a survey in SurveyGizmo (now known as Alchemer) to measure researchers' perceived task importance and satisfaction levels.	• Rewards and other benefits • Trust and confidence
17	Baždarić, K., Vrkić, I., Arh, E., Mavrinac, M., Marković, M. G., Bilić-Zulle, L., ... & Malički, M. (2021). Attitudes and practices of open data, preprinting, and peer-review—A cross sectional study on Croatian scientists. *Plos one*, *16*(6), e0244529.	Croatian Scientists' Attitudes: This study examined the attitudes of 541 Croatian scientists towards various topics, assessing their association with open science practices and demographic information.	Quantitative: Participants were invited to complete an anonymous online questionnaire using Google Forms.	• Awareness and capacity building • Researchers' characteristics and background
18	Zabijakin-Chatleska, V., & Cekikj, A. (2020). Attitudes and Practices of Data Sharing and Preservation Among Social Science Researchers in the Republic of North Macedonia. *Balkan Soc. Sci. Rev.*, *15*, 251-253.	Social Science Researchers in the Republic of North Macedonia: The survey was accessed by 278 researchers, and 181 completed it, resulting in a response rate of approximately 15%, comparable to similar research studies like Fecher (2015).	Quantitative: To address these research questions, a survey questionnaire with 38 questions, comprising both open-ended and closed-ended items, was employed and organized into four distinct sections/topics.	• Awareness and capacity building • Data characteristics • Policies and regulations • Rewards and other benefits • Trust and confidence.
19	Barczak, G., Hopp, C., Kaminski, J., Piller, F., & Pruschak, G. (2022). How open is innovation research? –An empirical analysis of data sharing among innovation scholars. *Industry and Innovation*, *29*(2), 186-218.	Innovation scholars: Out of 242 responses, the final sample comprises 173 respondents, providing valuable data for the study.	Quantitative: The survey gathered sociodemographic and job-related information alongside respondents' experiences and attitudes toward open data.	• Researchers' characteristics and background • Trust and confidence
20	Houtkoop, B. L., Chambers, C., Macleod, M., Bishop, D. V., Nichols, T. E., & Wagenmakers, E. J. (2018). Data sharing in psychology: A survey on barriers and preconditions. *Advances in methods and practices in psychological science*, *1*(1), 70-85.	Survey Insights Unveiled: Initially filled out by 826 researchers, the questionnaire underwent cleaning to remove incomplete surveys, resulting in a final sample of 600 respondents, representing a response rate of 4.99%.	Quantitative: Our questionnaire items were derived from earlier surveys and expert discussions on reproducibility. Pilot and preliminary studies were conducted to test item adequacy and response options.	• Policies and regulations • Rewards and other benefits • Trust and confidence

21	Kurata, K., Matsubayashi, M., & Mine, S. (2017). Identifying the complex position of research data and data sharing among researchers in natural science. *Sage Open*, *7*(3), 2158244017717301.	Researchers in natural science: Employing the snowball sampling technique, 23 active senior researchers from diverse fields within the natural sciences were selected, showcasing the richness of research practices in the discipline.	Mixed method Research Approach: This study utilized a combination of qualitative methods, including interviews with researchers and content analysis of their statements, along with quantitative methods.	• Rewards and other benefits
22	Bezuidenhout, L., & Chakauya, E. (2018). Hidden concerns of sharing research data by low/middle-income country scientists. *Global Bioethics*, *29*(1), 39-54.	Low/middle-income country scientists: The online platform garnered 100 responses, encompassing all 13 countries within the NEPAD-SANBio network.	Quantitative: The survey was conducted using the SurveyMonkey online platform.	• Available tools and repositories • Rewards and other benefits
23	Yoon, A., & Kim, Y. (2020). The role of data-reuse experience in biological scientists' data sharing: an empirical analysis. *The Electronic Library*, *38*(1), 186-208.	Focused on Biological Scientists: Considering only responses from biological scientists, 204 responses from scientists in other disciplines were excluded, resulting in a final valid sample of 476 responses for data analysis.	Quantitative: The research model underwent evaluation through an online survey targeting scientists in the biological sciences. Survey participants were randomly selected from the Community of Scientists.	• Awareness and capacity building • Culture and perceived norms • Rewards and other benefits • Trust and confidence.
24	Zhu, Y. (2020). Open-access policy and data-sharing practice in UK academia. *Journal of Information Science*, *46*(1), 41-52.	UK Academics: Conducted during the summer of 2013, the survey gathered 1,829 valid responses, achieving a response rate of 4.4%, offering valuable insights into the study.	Quantitative: An online survey was conducted to explore the scholarly communication practices of academics in the United Kingdom.	• Available tools and repositories • Awareness and capacity building • Policies and regulations • Rewards and other benefits
25	Mallasvik, M. L., & Martins, J. T. (2021). Research data sharing behaviour of engineering researchers in Norway and the UK: uncovering the double face of Janus. *Journal of Documentation*, *77*(2), 576-593.	Engineering researchers: The study involved three researchers from the Norwegian University of Science and Technology (NTNU) and four researchers from the University of Sheffield, working together to uncover valuable insights.	Qualitative: Narrative interviews conducted with sampled mechanical engineering researchers from prominent engineering Higher Education Institutions in Norway and the United Kingdom.	• Awareness and capacity building • Culture and perceived norms • Policies and regulations • Rewards and other benefits • Trust and confidence
26	Kim, Y. (2018). Reputation, trust, and norms as mechanisms leading to academic reciprocity in data sharing: An empirical test of theory of collective action. *Proceedings of the Association for Information Science and Technology*,	Biologists affiliated with U.S. academic institutions: 456 responses from biologists with no missing values were utilized for the final data analysis, ensuring a comprehensive and reliable dataset.	Quantitative: An online survey was conducted with biologists affiliated with U.S. academic institutions to evaluate the measurement items of the proposed research model.	• Culture and perceived norms • Rewards and other benefits • Trust and confidence

27	Krahe, M. A., Wolski, M., Mickan, S., Toohey, J., Scuffham, P., & Reilly, S. (2023). Developing a strategy to improve data sharing in health research: A mixed-methods study to identify barriers and facilitators. *Health Information Management Journal*, *52*(1), 18-27.	Health Research Focused Participation: The study engaged 81 researchers, but only 77 (19.2%) satisfactorily completed section four of the survey on data sharing and were included in the analysis.	Mixed-Methods: In the present study, mixed-methods analysis was applied to a subset of the survey data, which had not been reported previously. A survey question was used in the analysis as a supplemental Material.	• Data characteristics • Policies and regulations
28	Kim, Y., & Nah, S. (2018). Internet researchers' data sharing behaviours: An integration of data reuse experience, attitudinal beliefs, social norms, and resource factors. *Online information review*, *42*(1), 124-142.	Internet researchers: Out of all responses, 201 were selected for the final data analysis, providing valuable and concise insights for the study.	Quantitative: The study employed an online survey method to assess the theorized model based on the Theory of Planned Behaviour (TPB). It measured eight existing variables within the TPB framework and one newly developed variable.	• Available tools and repositories • Awareness and capacity building • Culture and perceived norms • Data characteristics • Efforts and other sacrifices • Rewards and other benefits • Trust and confidence
29	Kim, Y. (2021). A study of the determinants of psychologists' data sharing and open data badge adoption. *Learned Publishing*, *34*(4), 499-509.	Psychologists: A total of 338 valid responses were utilized for the conclusive data analysis, offering comprehensive insights for the study.	Quantitative: This research utilized a survey method to examine and compare the hypothesized relationships presented in the research model concerning psychologists' data sharing and open data badge adoption.	• Culture and perceived norms • Efforts and other sacrifices • Researchers' characteristics and background • Trust and confidence.
30	Unal, Y., Chowdhury, G., Kurbanoğlu, S., Boustany, J., & Walton, G. (2019). Research data management and data sharing behaviour of university researchers. *Information Research: an international electronic journal*, *24*(1).	University researchers: Spanning multiple months from 2016 to 2017, the survey amassed 1,098 complete responses, providing an in-depth understanding of the subject matter.	Quantitative: An online questionnaire survey was conducted among academics and researchers in the UK, France, and Turkey.	• Awareness and capacity building • Trust and confidence
31	Abele-Brehm, A. E., Gollwitzer, M., Steinberg, U., & Schönbrodt, F. D. (2019). Attitudes toward open science and public data sharing. *Social Psychology*.	German Psychological Society: The final sample consisted of N = 337 participants	Quantitative: The survey commenced with scales and open-ended questions, gauging approval levels of various issues concerning the DGPs data management recommendations.	• Available tools and repositories • Efforts and other sacrifices • Policies and regulations • Researchers' characteristics and background • Trust and confidence

32	Spallek, H., Weinberg, S. M., Manz, M., Nanayakkara, S., Zhou, X., & Johnson, L. (2019). Perceptions and attitudes toward data sharing among dental researchers. *JDR Clinical & Translational Research*, *4*(1), 68-75.	Dental researchers: Of the 211 researchers contacted, 52 indicated willingness to participate in the survey (25% response rate). Of the 52 researchers, 47 were either sharing data or interested in sharing data. Of the 47, 42 completed the survey (20% of the 211 potential participants).	Quantitative: The survey was carefully crafted to encompass critical aspects of research data, as identified in the literature, focusing on data-sharing issues.	• Data characteristics • Researchers' characteristics and background • Rewards and other benefits • Trust and confidence
33	Anger, M., Wendelborn, C., Winkler, E. C., & Schickhardt, C. (2022). Neither carrots nor sticks? Challenges surrounding data sharing from the perspective of research funding agencies—A qualitative expert interview study. *Plos one*, *17*(9), e0273259.	Funding Agencies: The final sample encompassed 16 funding agencies, achieving a positive response rate of 48%. These interviews with funders from ten countries provided valuable international perspectives.	Qualitative: Interviewing Funding Agencies, final sample comprised 16 funding agencies, with a positive response rate of 48%. We conducted interviews with funders from ten different countries.	• Awareness and capacity building • Policies and regulations • Rewards and other benefits
34	Williams, S. C., Farrell, S. L., Kerby, E. E., & Kocher, M. (2019). Agricultural researchers' attitudes toward open access and data sharing. *Issues in Science and Technology Librarianship*, (91).	Agricultural researchers: Conducting a qualitative analysis, we examined 28 interview transcripts from our two institutions, namely the University of Illinois at Urbana-Champaign and the University of Minnesota,	Qualitative: A qualitative analysis was conducted on 28 interview transcripts from the Ithaka S+R agriculture project, collected from the University of Illinois at Urbana-Champaign and the University of Minnesota.	• Awareness and capacity building • Culture and perceived norms • Efforts and other sacrifices • Rewards and other benefits
35	Kim, Y. (2022). An empirical study of research ethics and their role in psychologists' data sharing intentions using consequentialism theory of ethics. *Journal of Librarianship and Information Science*, *54*(2), 251-263.	Responsive Insights of Psychologists: The survey yielded 397 valid responses, achieving a response rate of 15.38% (397 out of 2,582), providing valuable insights into the study.	Quantitative: This study primarily utilized an online survey as the primary data collection method.	• Culture and perceived norms • Rewards and other benefits
36	Ju, B., & Kim, Y. (2019). The formation of research ethics for data sharing by biological scientists: an empirical analysis. *Aslib Journal of Information Management*, *71*(5), 583-600.	Biological Sciences Insights: For the final data analysis, 577 responses from biological sciences and related disciplines were utilized, offering comprehensive insights for the study.	Quantitative: To validate the theoretical research model, we conducted an online survey focusing on diverse data-sharing perceptions among biological scientists.	• Culture and perceived norms • Efforts and other sacrifices • Policies and regulations • Rewards and other benefits • Trust and confidence.

37	Rafiq, M., & Ameen, K. (2022). Research data management and sharing awareness, attitude, and behaviour of academic researchers. *Information Development*, *38*(3), 391-405.	Academic researchers: 260 responses were analyzed to present the study's findings.	Quantitative: The study employed a quantitative research design, utilizing a questionnaire-based survey to collect data.	• Available tools and repositories • Awareness and capacity building • Policies and regulations • Trust and confidence
38	Khan, N., Thelwall, M., & Kousha, K. (2023). Data sharing and reuse practices: disciplinary differences and improvements needed. *Online Information Review*.	Scopus, All Science Journal Classification (ASJC): 70,060 invitations were emailed, and the study received 3,257 responses, resulting in a response rate of 4.65%, offering valuable insights for the research.	Quantitative: Conducting a survey is the most practical approach to gathering large-scale evidence on attitudes and practices of data sharing across diverse disciplines.	• Efforts and other sacrifices • Researchers' characteristics and background
39	Fichtner, U. A., Horstmeier, L. M., Brühmann, B. A., Watter, M., Binder, H., & Knaus, J. (2023). The role of data sharing in survey dropout: a study among scientists as respondents. *Journal of Documentation*, *79*(4), 864-879.	Scientists as respondents: A total of 236 complete interviews were recorded, with 10% conducted in English and 90% in German, reflecting a diverse linguistic representation.	Mixed methods: This study employed a comprehensive approach, comprising a qualitative pre-study (Part 1) and a quantitative survey with an experimental component	• Awareness and capacity building • Researchers' characteristics and background.
40	Saeed, S., & Ali, P. M. (2019). Research Data Management and Data Sharing among Research Scholars of Life Sciences and Social Sciences. *DESIDOC Journal of Library & Information Technology*, *39*(6).	Research Scholars of Life Sciences and Social Sciences: 352 filled questionnaires were used for data analysis, providing comprehensive insights for the study.	Quantitative: The data from research scholars was collected using the questionnaire method.	• Available tools and repositories • Data characteristics • Efforts and other sacrifices • Researchers' characteristics and background
41	Kim, J. (2017). Data sharing from the perspective of faculty in Korea. *Libri*, *67*(3), 179-192.	Professors in Korea: A final survey dataset of 190 responses (18.6%) was employed for the analysis, offering a comprehensive and focused examination of the study.	Mixed Methods: This study utilized data collected through a combination of a survey and follow-up interviews conducted with professors in Korea.	• Policies and regulations • Rewards and other benefits
42	Devriendt, T., Borry, P., & Shabani, M. (2021). Factors that influence data sharing through data sharing platforms: A qualitative study on the views and experiences of cohort holders and platform developers. *PLoS One*, *16*(7), e0254202.	Cohort holders and platform developers: In total, seventeen interviews were conducted, with thirteen affiliated with euCanSHare cohorts and four involving other data-sharing platforms, providing valuable insights for the study.	Qualitative: Seventeen interviews were conducted, with thirteen involving cohorts affiliated with euCanSHare and four with other data-sharing platforms.	• Efforts and other sacrifices • Policies and regulations • Rewards and other benefits • Trust and confidence

43	Jeng, W., & He, D. (2022). Surveying research data-sharing practices in US social sciences: a knowledge infrastructure-inspired conceptual framework. *Online Information Review*, *46*(7), 1275-1292.	US social sciences: The study involved 144 participants, contributing valuable data for the research.	Triangulation of Studies: This paper presents the triangulation of results from three studies focused on data sharing across the social sciences.	• Awareness and capacity building • Efforts and other sacrifices • Rewards and other benefits
44	M'kulama, A. C., & Akakandelwa, A. (2021). Research Data Sharing and Reuse Through Open Data: Assessing Researcher Awareness and Perceptions at the Zambia Agricultural Research Institute (ZARI). In *Open Access Implications for Sustainable Social, Political, and Economic Development* (pp. 284-306). IGI Global.	Zambia Agricultural Research Institute (ZARI): A self-administered structured questionnaire was distributed to 70 researchers at the ZARI headquarters to collect valuable data.	Quantitative: The questionnaire primarily comprised close-ended questions, complemented by a few open-ended questions to gather additional data.	• Available tools and repositories • Awareness and capacity building • Efforts and other sacrifices • Policies and regulations
45	Mozersky, J., Walsh, H., Parsons, M., McIntosh, T., Baldwin, K., & DuBois, J. M. (2020). Are we ready to share qualitative research data? Knowledge and preparedness among qualitative researchers, IRB members, and data repository curators. *IASSIST Quarterly*, *43*(4).	Qualitative researchers, IRB members, and data repository curators: This report presents findings from semi-structured, in-depth interviews involving 30 qualitative researchers and 30 IRB staff members.	Qualitative: This study presents results from qualitative interviews and pre-interview surveys conducted with three stakeholder groups (qualitative researchers, IRB staff, and data curators) regarding their preparedness, or lack thereof, for QDS.	• Available tools and repositories • Awareness and capacity building • Policies and regulations
46	Joo, S., Kim, S., & Kim, Y. (2017). An exploratory study of health scientists' data reuse behaviors: Examining attitudinal, social, and resource factors. *Aslib Journal of Information Management*, *69*(4), 389-407.	Health Scientists' Insights: A total of 201 partial and complete responses were received from health scientists in the USA, resulting in an 8.42% partial and complete response rate, offering valuable perspectives for the study.	Quantitative: A survey was employed to investigate the influence of attitudinal, social, and resource factors on health scientists' data reuse behaviors.	• Available tools and repositories • Culture and perceived norms
47	Borghi, J. A., & Van Gulick, A. E. (2021). Data management and sharing: Practices and perceptions of psychology researchers. *PloS one*, *16*(5), e0252047.	Psychology researchers: Our survey involved 274 psychology researchers from 31 countries who met our inclusion criteria, contributing to a diverse and comprehensive study.	Quantitative: To explore the data-related practices of psychology researchers, we adapted a survey previously developed during our study of neuroimaging researchers.	• Awareness and capacity building • Rewards and other benefits

48	Harper, L. M., & Kim, Y. (2018). Attitudinal, normative, and resource factors affecting psychologists' intentions to adopt an open data badge: An empirical analysis. *International journal of information management*, *41*, 23-32.	Psychologists' researchers: For the final data analysis, a total of 341 responses exclusively from psychologists were utilized, offering focused insights for the study.	Quantitative: This study employed 23 survey items to measure 8 research constructs.	• Awareness and capacity building • Culture and perceived norms • Rewards and other benefits
49	Yoon, A., & Kim, Y. (2017). Social scientists' data reuse behaviors: Exploring the roles of attitudinal beliefs, attitudes, norms, and data repositories. *Library & Information Science Research*, *39*(3), 224-233.	Social scientists: Out of 1,959 messages delivered to potential participants, the study received 292 valid responses, with less than 5% missing values. The response rate stood at 14.91%, offering valuable insights for the research.	Quantitative: The questionnaire was designed to assess the research constructs, consisting of 21 measurement items for 7 research constructs, adapted from prior studies, including perceived usefulness.	• Awareness and capacity building • Culture and perceived norms • Rewards and other benefits • Trust and confidence
50	Kim, Y., & Yoon, A. (2017). Scientists' data reuse behaviors: A multilevel analysis. *Journal of the Association for Information Science and Technology*, *68*(12), 2709-2719.	Scientists: For the final analysis, 1,237 responses from 53 National Science Foundation (NSF) disciplines were utilized, enabling a comprehensive multilevel data exploration.	Quantitative: This study employed a survey method to test the proposed hypotheses and evaluate the research model empirically.	• Available tools and repositories • Culture and perceived norms • Researchers' characteristics and background
51	da Costa, M. P., & Lima Leite, F. C. (2019). Factors influencing research data communication on Zika virus: a grounded theory. *Journal of Documentation*, *75*(5), 910-926.	Brazilian researchers actively engaged with the Zika virus: In line with the grounded theory methodology, this study interviewed 13 researchers actively engaged with the Zika virus theme to collect data and gain insightful perspectives.	Qualitative: This study adopted the grounded theory methodology, and data were collected through interviews with 13 Brazilian researchers actively involved with the Zika virus theme.	• Available tools and repositories • Efforts and other sacrifices • Policies and regulations • Researchers' characteristics and background • Rewards and other benefits

Review objective one: To identify the most common categories of samples and data collection methods used in studies examining the factors influencing researchers' participation in open science through research data sharing and reuse.

Referring to Table 2 detailing the studies included in this review, over 90% of the studies specifically target a particular group of researchers or academics. Their study fields, affiliations, or countries often define these groups. For instance, numerous studies explore influences on researchers from fields like Materials Science and Engineering [18], [19], Biological Sciences [20]–[22], and others such as Health, Dentistry, Social Sciences, Natural Sciences, Psychology, and Agriculture.

Another set of studies links to specific institutions or countries. Some focus on institutions like the Zambia Agricultural Research Institute (ZARI) [23], [24], the German Psychological Society, and more, while others centre on national contexts such as Spanish, UK, or Malaysian researchers.

Yet, fewer studies have a wider lens, like those targeting global scientists [25] or those from low/middle-income countries [26]. A unique batch looks beyond the typical researcher focus, shining light on professionals like Data Repository Curators, Funding Agency staff, and Early Career Researchers.

Seeing as roughly 90% of the reviewed studies focus on specific research groups, this review suggests there might be a literature gap. Different researcher categories might be driven differently by various factors towards open science participation.

Regarding data collection, 34 out of 51 studies lean on quantitative methods, collecting numerical data to analyse the findings using surveys [27]. These studies aim for statistical insights. Only 10 out of 51 used qualitative methods, capturing in-depth insights and relying on techniques such as interviews [27]. Meanwhile, 7 out of the 51 take a mixed-method route, merging both the quantitative and qualitative studies.

Review objective two: To identify key factors influencing researchers' participation in open science practices, especially in research data sharing and reuse, as derived from the literature.

The thematic analysis method was employed for this analysis, which involves breaking down and organising data from qualitative research. This method tags individual observations and quotations with appropriate codes, facilitating the discovery of meaningful themes. The six fundamental stages of thematic analysis, as outlined by Rosala (2022) [28], were carefully followed, as illustrated in Figure 7 below. These stages encompass data gathering, thorough reading of the data, text coding based on its content, developing new codes that signify potential themes, pausing and revisiting the analysis after a short break, and lastly, evaluating the derived themes for their relevance and fit [28].

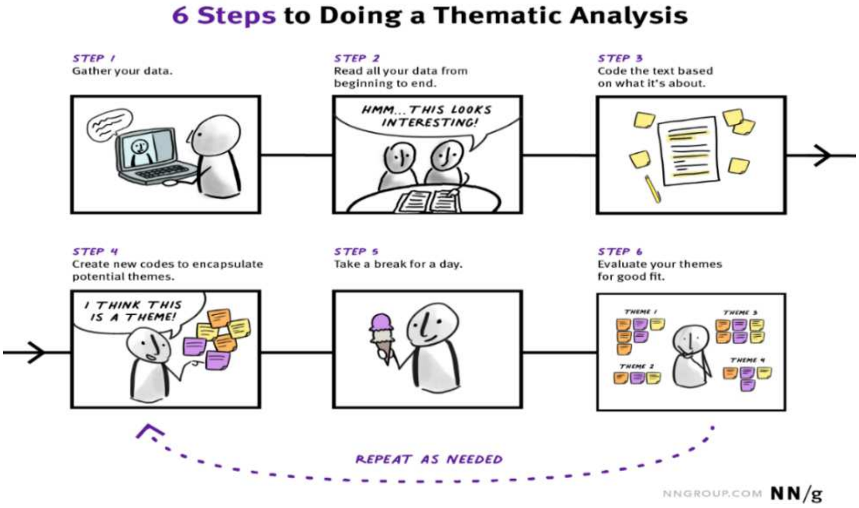
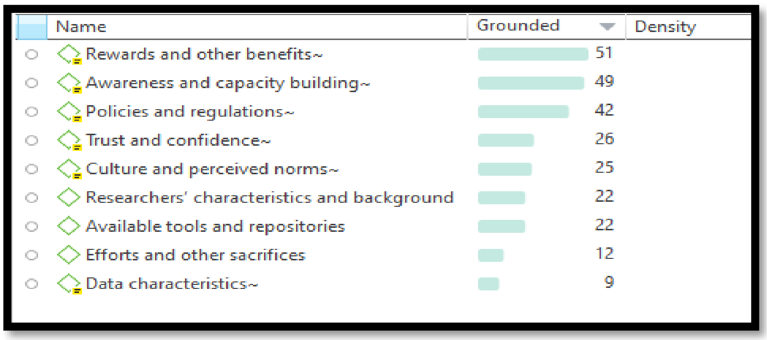


Figure 7. Steps to Conduct a Thematic Analysis, Source: [28]

Upon collecting all the studies that met the inclusion criteria, the analysis software ATLAS.ti, designed for computer-assisted qualitative data, was employed to aid the evaluation process. The key factors affecting open science participation were extracted thematically from the articles to address the review objectives. This approach involved systematic data categorisation to identify common themes regarding the key determinants influencing researchers' willingness to participate in open science, primarily through sharing and reusing research data. Nine central factors were identified from the selected studies for this review, detailed in Figure 8 below, accompanied by their respective frequencies within the data.



Name	Grounded	Density
Rewards and other benefits~	51	
Awareness and capacity building~	49	
Policies and regulations~	42	
Trust and confidence~	26	
Culture and perceived norms~	25	
Researchers' characteristics and background	22	
Available tools and repositories	22	
Efforts and other sacrifices	12	
Data characteristics~	9	

Figure 8. Key factors generated from the entire selected studies with Atlas.ti (Source: Illustrated by the Authors).

Rewards and Other Benefits

As defined by [29], rewards can be tangible or intangible returns granted in acknowledgement of an individual's effort, work, behaviour, or achievement. Such rewards act as positive reinforcement, spurring the recipient to sustain or replicate the commendable behaviour. For example, tangible rewards could be seen as research grants, monetary incentives, certificates, trophies, or bonuses in the research context. In contrast, intangible rewards might entail advanced recognition, enhanced reputation within the scholarly community, or a profound sense of accomplishment [30]. On the other hand, 'other benefits' can be interpreted as any favourable outcomes or gains that emanate from a specific action or given conditions.

Most studies incorporated in this review have identified rewards and other benefits as vital motivators driving researchers to engage in open science practices. However, it's notable that these studies often use diverse terminologies while presenting the concept. A comprehensive list of these terminologies quoted from the literature is outlined in Table 3 below.

Table 3. Rewards and other benefits quotes from the findings

Studies	Quotations:
Dorta-González et al., (2021)	*To what extent is researchers' data-sharing motivated by formal mechanisms of recognition and credit?" Results allow us to conclude that a desire for recognition/credit is a major data-sharing incentive.*
Abdullahi & Noorhidawati, (2020)	*Participants in this study realized that they must make their data accessible to attain research progression, although it should be done carefully....Based on the findings, irrelevant (i.e., expected organizational rewards and reciprocal benefits).... Motivators are perceived to influence Nigerian academic research data-sharing practices and intentions. The primary intrinsic motivator of data-sharing methods is the advantage of gathering more citations of the main research work, which leads to academic promotion and recognition.*
Tenopir et al., (2020)	*Respondents would be more willing to share if they could place some conditions on use (56.4%) on those reusing their data. A citation is an almost universal requirement: 92.1% of respondents said it was essential to receive citation credit from those who would use their data...*
Aleixandre-Benavent et al., (2020)	*second, the importance of the formal recognition of data owners through opportunities for collaboration, formal recognition, and proper citation...Another implication is that for researchers, appreciation and acknowledgment are significant factors affecting their sharing behaviour...*
Tenopir et al., (2018)	*Our data indicate that some of the vital first steps to improving behaviours would be to assure proper acknowledgment and citation of data used by all researchers and to advertise the data management expertise of data librarians or research data managers...*
Hrynaszkiewicz et al., (2021)	*However, the factors with the most significant mean importance scores when comparing early and late career researchers can be considered more likely to be relevant to junior researchers, for example, "Increase my co-authorship opportunities...*
Hodonu-Wusu et al., (2020)	*We can convincingly reason that the researchers view some hindrances to open data, which might result from a lack of training and incentives for data sharing...The issues of cultural and national concerns pose a significant challenge to open data sharing. Concerns about misuse, the fear of losing publication opportunity, and the lack of incentives should be addressed urgently by the funders and advocates of open data...*
Zabijakin-Chatleska & Cekikj, (2020)	*The descriptive analysis of our data indicates that, at present, a significant amount of data is produced by social science researchers in the Republic of North Macedonia. However, considering that few of them receive public funds from a centralized body for research and science, there is a possibility that these data will not be publicly shared or that they might even get lost...Findings suggest that researchers relying on international funding are more productive in producing research data than researchers who provide their budget from other sources...*
Houtkoop et al., (2018)	*...and financial encouragement (i.e., increased grant amounts) would be highly effective in growing researchers' willingness to share their data.*
Bezuidenhout & Chakauya, (2018)	*...increase the amount of funding to LMICs, and there will not only be more data produced but likely more data online.*

Yoon & Kim, (2020)	*Biological scientists hold more favourable views of data sharing when they recognize that it benefits themselves and the general scientific community…The present study proposes the new concept of perceived community benefit and suggests that it influences researchers' data-sharing intentions.*
Kim, (2018)	*First, this research found that perceived academic reputation plays a critical role in scientists' data-sharing intentions, as this variable significantly influences scientists' perceived community trust, the norm of data-sharing, and academic reciprocity…*
Zhu, (2020)	*The academic community could benefit from OA to research data to validate findings and accelerate scientific progress. However, barriers such as lack of incentives and standards could prevent academics from sharing…Academics would also be more willing to share primary research data if aware of the potential benefits, such as increased citation impact. Social media could help academics promote their publication and shared research data and potentially increase readership and citation…*
Kim & Nah, (2018)	*As internet researchers have more experience in data reuse, they become more likely to share their data with other researchers based on reciprocity, positively affecting their perceived career benefit and norm of data sharing. An engineering associate professor said, "I would like to share data, especially based on reciprocity.*
Mallasvik & Martins, (2021)	*Given that for some researchers, a part of the value of sharing lies in the personal recognition and credit that comes with other researchers engaging with their data…*
Anger et al., (2022)	*Our interviews indicate that funders support data sharing in various ways, like guiding researchers, additional financial means for data management, and funding for local support infrastructures…Considering their expressed preference for incentives over sanctions, it may be a surprise that funders admit to having a lack of incentives. They are aware of the problem that researchers receive too little reward and recognition for data sharing…*
Williams et al., (2019)	*agricultural researchers share data and publish in open-access journals to increase the visibility of their work in the interest of their careers, be that toward promotion and tenure, increasing their citation counts, or adding transparency to their research process…Researchers also care about prestige. They want to ensure that the journals they publish in have solid, established reputations, and they want to get credit if others use their data sets…*
Kim, (2022)	*The findings of this study demonstrated that psychologists' research ethics for data sharing are significantly influenced by three ethical components, including perceived career benefit (egoism), perceived community benefit (utilitarianism), and their norm of data sharing (deontology)…*
Ju & Kim, (2019)	*The findings of the current study suggest that biological scientists' perceptions, such as their academic reputation, their perceived risk for whether to share data with other researchers and the perceived effort required to share data, significantly affect a researcher's ethical egoism factor…The two crucial motivators for scientists to share their research data are part of ethical altruism factors: biological scientists' acknowledgment of the benefits of data sharing for their scientific communities, the perceived community benefits, and, as individuals, the perceived reciprocity.*
Devriendt et al., (2021)	*A range of factors influencing individuals' decisions to share data and their preference regarding the mode of sharing were identified, such as academic credit and recognition…*

Jeng & He, (2022)	*Perceived technical support and extrinsic motivation strongly predict qualitative data sharing (a previously under-researched subtype of social science data sharing) ...*
Borghi & Van Gulick, (2021)	*Our survey results help show the current state of data-related practices in psychology, and they also demonstrate that what is missing are incentives to change rules and knowledge of how to do so effectively...*
Harper & Kim, (2018)	*First, to facilitate positive attitude toward open data badge adoption, benefits of data sharing need to be promoted in the psychology community. Psychologists should know that sharing data can lead to academic recognition and additional citations...*
Yoon & Kim, (2017)	*Social scientists consider reusing others' data because they perceive that doing so would increase their research performance and productivity...*
(da Costa & Lima Leite, 2019)	*The primary motivation for conducting studies on the Zika virus and divulging their results is the expectation that researchers must be acknowledged and rewarded for their work...The arguments also pointed out that adequate funding for the treatment and availability of data can generate savings in resources in future research funding...*

According to the above table, it could be noticed that the authors have used different terminologies to describe the possible types of rewards researchers might receive by participating in open science practices, such as formal recognition from institutions, being favoured in grant applications for promoting transparency, or even win awards for their collaborative efforts. Other related benefits could also lead to a broader audience for one's work, more collaboration opportunities, faster scientific progress due to reduced replication of efforts, and the intrinsic satisfaction of knowing one's data is helping the larger scientific community. In essence, rewards are often direct responses to an action, while other benefits are positive outcomes that might not be directly handed out but naturally result from that action.

Awareness and Capacity Building

Awareness and capacity building refers to two connected concepts that aim to enhance individuals, groups, or institutions' knowledge, skills, and abilities and ensure they are well-informed about specific topics, issues, or developments. At the same time, awareness involves informing researchers, academic institutions, policymakers, and the public about the importance and benefits of open science practices [31]. It's about making them aware of how sharing and reusing research data can advance scientific discovery, improve transparency, and foster collaboration [32]. By raising awareness, researchers might be more willing to share and use data shared by others.

On the other hand, capacity building goes beyond just informing the stakeholders. It involves providing them with the skills, tools, and infrastructure necessary to effectively share and reuse research data [33]. This can either be through training programs, workshops, or tool development.

By promoting both awareness and capacity building on the importance of open science through the sharing and reuse of research data, stakeholders can understand its significance, and they can be equipped with all the necessary tools and skills to participate in these open science practices effectively [34], [35]. The studies from the review that quoted awareness and capacity building as a factor that could motivate open science practice are presented in Table 4 with their different terminologies as follows.

Table 4. Awareness and capacity-building quotes from the findings

Studies	Quotations:
Dorta-González et al., (2021)	*previous knowledge and experience with open data increases data sharing, and reusing open data is therefore a strong incentive for data sharing…We also found that the reuse of open data has a considerable and positive relationship with the frequency with which scientists make data openly available to others…*
Melero & Navarro-Molina, (2020)	*while a lack of knowledge of data management constitutes a barrier to data sharing. All this points to the need for ongoing training and education in the emerging field of data management to make authors aware of the potential of sharing data safely and legally…*
Zenk-Möltgen et al., (2018)	*The strongest indicators for data sharing based on this theory showed to be reported past behaviour of data sharing of respondents and their intention to do so in the future, and that is an additional insight of this study…*
Tenopir et al., (2020)	*Survey responses indicate that the available data management assistance to researchers is often inadequate or not known to them. Respondents in Information Science, Engineering, and Agriculture/Natural Resources disciplines appear to be more cognizant of available resources and engage them…*
Nicholas et al., (2020)	*…a lack of knowledge as to how to go about it, and the lack of time. Two provided a very honest answer, saying that they had spent so much time and money on their data that they were not willing to give it a way for free…*
Baždarić et al., (2021)	*Scientists with experience in open science practices had more positive attitudes…Participants who took open science courses had more positive attitudes…*
Aleixandre-Benavent et al., (2020)	*From the analysis of the results, it emerges that it is necessary to design and carry out awareness-raising campaigns aimed at professionals regarding the publication of their research data…Training campaigns in the culture of data sharing would also be desirable…*
Tenopir et al., (2018)	*…a perceived low level of assistance with various data management tasks. Scientific researchers indicated a lack of awareness that there are data management or information experts in their institutional…In general, metadata practices and use of standards needs to be improved, training in or assistance with data management tasks are perceived to be lacking, and many are unaware they need or can ask for help…*
Suhr et al., (2020)	*Training for scientists might help to improve this situation. When all reused datasets are cited correctly, this is likely to be an additional incentive to share research data…In these scientific domains, training of the researchers on legal aspects (such as informed consent of the participants) could enable data sharing…*
Hodonu-Wusu et al., (2020)	*There is clearly a lack of understanding among the respondents around what makes open data sharing essential. The motivation was partly compliance with journals publisher and research funders…We can convincingly reason out that the researchers view some hindrances to open data, which might be as a result of lack of training and incentives for data sharing…Policies that incentivize the use and reuse of open data sharing practices, as well as tools and guidance…*
Zabijakin-Chatleska & Cekikj, (2020)	*There is obviously a need to educate researchers on research data documentation, as well as a more systematic approach to data preservation at an institutional level…*

Yoon & Kim, (2020)	*When asked to share data, researchers who do not fully understand the process might be uncertain or sceptical...Researchers with data-reuse experience understand the process, how their data will be used by other and the benefit of their data-sharing behaviour on the scientific community and other researchers' careers...*
Zhu, (2020)	*Academics would also be more willing to share primary research data if made aware of the potential benefits such as increased citation impact. Social media could be adopted to help academics to promote their publication and shared research data and potentially increases readership and citation...Funding agencies, academic journals and institutions should also develop approaches to disseminate and promote data-sharing policies and standards, as many researchers were unaware of existing policies and standards...*
Suhr et al., (2020)	*In this study, frequently mentioned obstacles to data sharing are high amount of time needed for a detailed data description, lack of rewards, legal restrictions, lack of a standard data sharing platform and lack of awareness...As discussed in the previous paragraph, training on data sharing would be very helpful for most scientists and might also clarify the meaning of the term Open Data for some attendees...*
Kim & Nah, (2018)	*This study found that data reuse experience has significant positive relationships with both norm of data sharing and perceived career benefit...An associate professor in communications mentioned that "we have little experience with processes of sharing our data, and no tradition for asking our colleagues to share theirs." ...*
Mallasvik & Martins, (2021)	*In this context, our analysis reveals varying levels of open research data awareness, with some engineering researchers reporting being unconcerned, others offering a neutral perspective and others claiming not knowing enough about it. Even in face of such varied...*
Unal et al., (2019)	*...the need for data management training for researchers the need for an increased awareness regarding the requirements for data sharing in OA mode training needs in metadata and tagging...*
Anger et al., (2022)	*Our interviews indicate that funders support data sharing in various ways, like providing guidance to researchers, additional financial means for data management, and funding for local support infrastructures...Some of our interviewees suggested that dedicated governmental initiatives can also help raise awareness for the importance of data sharing and provide data sharing policies with political legitimacy...*
Williams et al., (2019)	*Confusion and misinformation were also common themes. Researchers interviewed in this study expressed a range of knowledge about what constitutes open access publishing and data sharing...Based on these findings, we can surmise that there is still a good deal of work to be done in educating researchers and embedding open access and data sharing into the culture of agricultural research...*
Rafiq & Ameen, (2022)	*Data sharing requires resources including time, finances, infrastructural support, technical knowledge, and skills...*
Fichtner et al., (2022)	*Another important finding, which we showed in descriptive analyses (Figure 2) is that about 10% of our study population was not aware of the option to share data in or use data...*
Jeng & He, (2022)	*The findings suggest that the majority of faculty and students in social science research do not share their data because many of them are unaware of the benefits and methods of doing so...*

M'kulama & Akakandelwa, (2021)	*...the researchers were not knowledgeable about research data management plans as they seem not to have encountered situations where they were required to submit a research data management plan along with research proposals...the difficulties of organising data in a way that is presentable and useful'; lack of awareness about copyright...*
Mozersky et al., (2020)	*Our results suggest that we are not ready to share qualitative data due to a lack of experience with, and guidance on, QDS among all stakeholder groups...Researchers are the least knowledgeable about QDS...Many were not aware that qualitative data repositories existed let alone that some repositories are capable of archiving and providing restrictions on who accesses sensitive qualitative data...*
Borghi & Van Gulick, (2021)	*Complicating matters further, relatively few of our participants reported that they had received any formal training in data management or had made use of data management-related support services at their institution...Our survey results help show the current state of data related practices in psychology, and they also demonstrate that what is missing are incentives to change practices and knowledge of how to do so effectively...*
Harper & Kim, (2018)	*First, to facilitate positive attitude toward open data badge adoption, benefits of data sharing need to be promoted in the community of psychology. Psychologists ought to be aware that sharing data can lead to academic recognition and additional citations...*
Yoon & Kim, (2017)	*Since having a positive attitude toward data reuse influences intention to reuse data, educating, and informing them would be an important first step toward actual data reuse...*

Policies and Regulations

Policies and regulations are mostly the guidelines and rules organisations, institutions, or governments set to govern or direct specific behaviours, actions, or practices. These can be applied at different levels – from corporate or institutional policies to national or international regulations. Most institution policies and regulations aim to ensure consistency, uphold standards, protect rights, and maintain order. They provide a framework for evaluating actions for their legality, appropriateness, or conformity [36].

In open science and the sharing and reuse of research data, "policies and regulations" primarily refer to the guidelines and rules guiding the behaviour and actions of researchers, institutions, publishers, and related stakeholders in the scientific community [37]. Such policies aim to promote the transparency, reproducibility, and accessibility of research while ensuring the protection of sensitive information and intellectual property [38]. Different terminology has been used to describe policies and regulations in open science. Some of the most used phrases are quoted in Table 5. below from the review.

Table 5. Policies and regulation quotes from the findings

Studies	Quotations:
Dorta-González et al., (2021)	*Among the full range of variables that represent factors other than formal mechanisms of recognition and credit, we have the regulative pressure by journals, the normative pressure at a discipline level, and the scholarly altruism in accelerating scientific discoveries…*
Melero & Navarro-Molina, (2020)	*There is also a need to create institutional policies on research data rather than just on publications, and to ensure their terms are understood, and the work of data managers and librarians should not be based voluntary but supported by academic…*
Nicholas et al., (2020)	*Those ECRs who did not make their data openly available were asked why not (Table 9). The most common reason was an absence of policies mandating data-sharing, with 57% saying this…*
Aleixandre-Benavent et al., (2020)	*third, the need for legal regulations and policies to support data reuse and attribution…Policies are needed to ensure appropriate recognition of the creator of the data and of those who are responsible for the reuse of the data and to take factors such as reputation into consideration…Finally, as long as there is no legal obligation to deposit data, it is the researchers who have in their hands the decision to share their data or not, as well as what type and amount of data they will deposit…*
Suhr et al., (2020)	*were affected by data management policies of their employer, while four said that storage or their generated data is left to themselves. Even if these universities/research centres do not encourage data sharing, the danger of losing data should motivate them to install data management policies…*
Hodonu-Wusu et al., (2020)	*There is clearly a lack of understanding among the respondents around what makes open data sharing essential. The motivation was partly compliance with journals publisher and research funders...Policies that incentivize the use and reuse of open data sharing practices, as well as tools and guidance…*
Zabijakin-Chatleska & Cekikj, (2020)	*Considering that most of the research is financed by international sources, public access will depend on donors' rules and behaviour…Researchers also stress that some data is confidential and sensitive. One respondent mentioned the lack of legal regulations…*
Houtkoop et al., (2018)	*Of the five conditions that respondents indicated would be most effective, the top three concerned mandatory sharing of data. Specifically, respondents indicated that they would comply if research funders, journals, and institutions were to mandate data sharing...Mandatory data sharing (enforced by institutions, journals, or funders) and financial encouragement (i.e., increased grant amounts) are measures that would apparently be highly effective in increasing researchers' willingness to share their data…*
Zhu, (2020)	*The academic community could benefit from OA to research data to validate findings and accelerate scientific progress. However, barriers such as lack of incentives and standards could prevent academics from sharing…Data policies are more established in some subject areas than the others and studies on developing strategies to encourage data sharing mainly focused on biomedical areas. As the format and volume of research data vary largely between and within disciplines…*
Mallasvik & Martins, (2021)	*Both in the UK and in Norway there are policies advising researchers on how and when to share their research data, and in accordance with the criteria of the research grants they are awarded. This reflects a general tendency in the global research community, where underlying policies are reported to increasingly having growing levels of influence on encouraging research data sharing.*

Krahe et al., (2023)	*The capability, opportunity and motivations of individual researchers to share data are strongly influenced by contextual factors (i.e. institutional policies and regulations on sharing data or the degree to which sharing data is encouraged by supervisors and colleagues) and hence cannot be isolated from institutional context…*
Kim, (2021)	*Since data sharing itself is voluntary and does not provide any extrinsic rewards, psychologists' data sharing intentions are also influenced by additional normative and control factors, including the norm of reciprocity, availability of data repositories, and IRB requirements…*
Abele-Brehm et al., (2019)	*First, legal and ethical issues, which have partially been addressed in the data management recommendations of the DGPs, but that cover still more topics to be discussed…*
Anger et al., (2022)	*our data confirms observations that funding agencies face difficulties concerning the implementation of policies and are themselves in different stages of development…Some of our interviewees suggested that dedicated governmental initiatives can also help raise awareness for the importance of data sharing and provide data sharing policies with political legitimacy…*
Ju & Kim, (2019)	*The findings also show that biological scientists strongly value data sharing as a practice norm. All three factors, namely, perceived pressure by funding agency, perceived pressure by journal and norm of data sharing, demonstrate a strong indication that data sharing policies set by funding agencies and journal publishers, and how data sharing has been practiced in their scientific community, contribute to scientists' sense of ethics on research…*
Rafiq & Ameen, (2022)	*Almost ~40% of respondents mentioned that their research data is available for other researchers on a request basis. Researchers show concerns about sharing their research data, such as legal and ethical issues, misuse of data, etc…Lack of proper policies, rights protection, and misinterpretation of data was also mentioned by almost…*
J. Kim, (2017)	*The significant factors determined in this study have implications for policies that could address the motivations and concerns of university faculty in Korea…These include (1) promoting adequate data-citation practices (2) designing a policy that allows data…considering ethical and disciplinary issues related to co-authorship in return for data sharing…*
Devriendt et al., (2021)	*a range of factors that influence individuals' decisions to share data, and their preference regarding the mode of sharing were identified, such as academic credit and recognition, lack of resources, misuse or misinterpretation of data, loss of control, socio-cultural aspects and ethical and legal barriers…*
M'kulama & Akakandelwa, (2021)	*Further, findings have revealed that there was a lack of standard regulation regarding data retention…*
Mozersky et al., (2020)	*IRB members feel ill-prepared to advise researchers on QDS, and data curators feel that researchers have the obligation to protect their data and navigate legal and regulatory matters. Many researchers also conveyed attitudinal barriers to the endeavour as a whole…*
(da Costa & Lima Leite, 2019)	*The aspects indicate the collaboration as necessary to comply with legal and ethical requirements of research…*

According to Table 5 above, it could be noticed that several terminologies have been used to describe the term policy and regulatory issues in open science, among which are data sharing mandates, which are mostly funding agencies or journals enforcement policies requiring researchers to share the raw data supporting their publications. Such mandates aim mostly to enhance scientific findings' transparency and reproducibility [39]. Ethical and privacy regulations, mostly from medical and health researchers, given that some research data might involve human participants, regulations related to ethical considerations and data privacy, such as anonymising participant data, become imperative. This ensures that while data is shared, the rights and privacy of participants are safeguarded [40]. Metadata and data standards to ensure the efficient reuse of shared data. These policies mostly prescribe standards for metadata, the descriptive information about datasets to aid in understanding, searching, and utilising the shared datasets [41], and the infrastructure or repository guidelines, which are also set of standards for the archival and accessibility of shared datasets, specifying which repositories to use or how long data should be retained [42].

Culture and Perceived Norms

Culture and perceived norms are interrelated concepts deeply rooted in sociology and social psychology that shape behaviours, attitudes, and practices within various societal and organisational contexts [43]. Culture encompasses shared beliefs, values, customs, behaviours, and artefacts that a society uses to cope with the world and one another. It's transmitted from generation to generation through learning. In comparison, perceived norms refer to an individual's beliefs about a group's standard behaviours or attitudes and how these beliefs can influence their behaviours [44].

However, culture and perceived norms are crucial in research and open science practice. Research culture is mostly referred to as the shared values, beliefs, and practices among researchers in a particular field or institution [45]. For instance, specific disciplines might have a deep-rooted collaborative work culture, while others might place a high value on independent discovery. On the other hand, perceived norms can influence various aspects of research conduct. For instance, if a researcher perceives that their peers prioritise publishing quantity over quality, they might feel pressured to publish more often, even if this goes against their beliefs or broader institutional guidelines [46].

In this context, the existing culture and perceived norms can either facilitate or hinder the shift towards more transparent research practices. If researchers perceive that sharing their data is a norm valued by their peers, they are more likely to participate in open science initiatives. Conversely, the transition to open science can be more challenging if the prevailing culture doesn't prioritise transparency or if there's a perceived norm against data sharing [47]. Several studies from the review that have also indicated culture and perceived norms as factors motivating open science practice through research data sharing and reuse are presented in Table 6 below.

Table 6. Culture and perceived norm quotes from the findings

Studies	Quotations:
Zuiderwijk & Spiers, (2019)	*Factors driving researchers to openly share and re-use research data or not concern the following eight categories: the researchers' background, personal drivers, experience, etc…*
Curty et al., (2017)	*Second, our work confirms the proposition that attitudes towards and subjective norms about data reuse predict data reuse behaviour…Turning to perceived norms, we found a large positive effect for the perceived importance of being able to reuse data. The effect was larger for those without developed data management practices (as indicated by knowledge and use of metadata) …*
Zenk-Möltgen et al., (2018)	*The intention to share data is strongly affected by the attitude of the researchers, and they are motivated by social norms, perceived behavioural autonomy, and self-efficacy…Other relevant influences for the intention to share data are the respondent's country, working sector, position in the academic career, and age…*
Damalas et al., (2018)	*…as this study also suggests, scholarly altruism is still not the norm, and numerous barriers are blocking the free exchange of scientific information: disciplinary traditions, institutional barriers, lack of technological infra structure, intellectual property concerns, and in dividual perceptions.*
Yoon & Kim, (2017)	*Social scientists consider reusing others' data because they perceive that doing so would increase their research performance and productivity…In addition, social scientists develop positive attitudes toward data reuse if they believe that their communities or disciplines have strong norms of data reuse…*
Suhr et al., (2020)	*In this study, encouragement of the supervisor, employer or funding agency is seen as the most successful tool for data sharing, as it is reported by those researchers who share already or plan to share their data soon.*
Yoon & Kim, (2020)	*The influence of social norms on scientists' data-sharing attitudes is critical in the biological science context. Similar to researchers in other disciplines, biological scientists likely hold more favourable attitudes towards data sharing when their communities accept it as a common practice…*
Y. Kim, (2018)	*Third, this research found that both biologists' academic reciprocity and norm of data sharing significantly increased scientists' data sharing intentions…Also, an assistant professor in communications mentioned that "Data sharing is not really an issue in my discipline…People collect data and collaborate, but there is no culture of data sharing…*
Mallasvik & Martins, (2021)	*perspectives, there was agreement that sharing research data is beneficial for the advancement of scientific knowledge…*
Y. Kim, (2021)	*This result suggests that psychologists who view data sharing as a reciprocal responsibility are more likely to share their data with others, whereas those who do not hold that view are not likely to share their data for this specific reason…The results demonstrated that psychologists' data sharing and badge adoption intentions are affected by their community consideration, disciplinary norms, and effort expectancy involved with data sharing…*
Y. Kim, (2022)	*The findings of this study demonstrated that psychologists' research ethics for data sharing are significantly influenced by three ethical components, including perceived career benefit (egoism), perceived community benefit (utilitarianism), and their norm of data sharing (deontology)…*

Ju & Kim, (2019)	*The two important motivators for scientists to share their research data are part of ethical altruism factors: biological scientists' acknowledgement of the benefits of data sharing for both their scientific communities, the perceived community benefits and as individuals, the perceived reciprocity…The findings also show that biological scientists strongly value data sharing as a practice norm….*
Joo et al., (2017)	*Third, our study finding suggests that a positive social norm toward data reuse positively supports researchers' data reuse intention. For example, in the case of a new funding proposal, health scientists are required to explain how their data and results are shared...Among those factors with positive effects on data reuse intention, the perceived usefulness…*
Harper & Kim, (2018)	*Our study indicates that psychologists are positively influenced by norms of data sharing, which means that the more a researcher thinks others are in support of or are already performing a particular behaviour, the more likely they themselves intend to perform that same behaviour…*
Y. Kim & Yoon, (2017)	*At the individual level, perceived usefulness, perceived concern, and organizational resource were found to have significant relationships with data reuse intention…*

Available tools and repositories

In open science, tools and repositories are instrumental in equipping researchers with the means to store, share, access, and reuse data effectively [48]. Their presence not only strengthens scientific transparency and reproducibility but also fosters collaboration. Typically, in the open science context, tools are interpreted as software, platforms, or any utilities supporting the various research facets, from data collection, analysis, visualisation, and sharing to citation [49]. Incorporating appropriate open science tools can enhance research workflows, improve the quality and integrity of data, and promote collaborative activities. For example, data collection and analysis tools or software such as Jupyter notebooks, R, and Python libraries pave the way for transparent and reproducible data analyses. Platforms tailored for collaboration, like GitHub or GitLab, enable version-controlled teamwork on research undertakings, while data citation utilities such as Zotero or Mendeley guide researchers in adeptly managing and citing research artefacts.

Repositories function as digital platforms or databases wherein research products (such as datasets, scholarly articles, or code) are organised, administered, and presented to a broader audience. They can be linked with a discipline-specific focus, affiliated with institutions, or designed for universal applicability [49]. Repositories guarantee that research outputs remain within the grasp of fellow researchers, decision-makers, and the broader public. They provide a robust framework for the continuing storage and maintenance of research products, ensuring the continuity and applicability of data for later generations. Notably, repositories frequently allocate constant identifiers (like DOIs) to datasets, ensuring researchers are acknowledged for their contributions upon reusing their work. For instance, the Protein Data Bank (PDB) focuses on biological macromolecular structures, while platforms like Zenodo or Figshare accommodate diverse research products. Additionally, university-affiliated repositories stand as custodians of academic research outputs. Table 7, as shown below, enumerates quotes from various reviews, highlighting how the availability of tools and repositories can strongly influence open science practice, especially in data sharing and reuse.

Table 7. Available tools and repository quotes from the findings

Studies	Quotations:
Tenopir et al., (2020)	*Satisfaction with the tools and practices associated with data management seems to be low: only about a third of respondents' express satisfaction with tools for preparing metadata and their ability to track and verify provenance information. Access to appropriate repositories also seems to be an issue: only 37.4% of respondents say it is easy for them to locate a suitable repository for deposit of data…*
Aleixandre-Benavent et al., (2020)	*The analysis identified three key determinants of the sharing of research data sets: first, the importance of developing technological and organizational tools to provide support to ensure the open publication of data…but it is also necessary to create infrastructure to facilitate long-term data storage and conservation…*
Tenopir et al., (2018)	*This research indicates that scientists in general may be unsure of the use or meaning of common data management terms and tools such as metadata, provenance, and public repositories…*
Damalas et al., (2018)	*as this study also suggests, scholarly altruism is still not the norm, and numerous barriers are blocking the free exchange of scientific information: disciplinary traditions, institutional barriers, lack of technological infra structure, intellectual property concerns, and in dividual perceptions…*
Suhr et al., (2020)	*A second big challenge is the lack of standard repositories, which was mentioned related to data reuse but also as an obstacle for data sharing. Moreover, some more domain specific aspects can hinder data reuse." "Despite the fact that most researchers search in the literature to find research data, it was striking that 10 out of 13 interviewed researchers stated they had never seen a dataset citation…*
Bezuidenhout & Chakauya, (2018)	*Table 7 summarizes the participants' perceptions of how different infrastructural challenges affected their research. Despite their online connectivity, over half of respondents agreed/strongly agreed that the absence of up-to-date hardware (61%) and software (58%) curtailed their ability to engage online…*
Zhu, (2020)	*Funding agencies and academic institutions should also fund and maintain infrastructure for data sharing, including providing training and support for researchers who intend to share data...*
Kim & Nah, (2018)	*However, this research showed that the availability of data repository is an important predictor for internet researchers' actual data sharing behaviour rather than...A good number of survey participants noted the importance of data repository availability to data sharing…*
Y. Kim, (2021)	*Since data sharing itself is voluntary and does not provide any extrinsic rewards, psychologists' data sharing intentions are also influenced by additional normative and control factors, including the norm of reciprocity, availability of data repositories, and IRB requirements…*
Abele-Brehm et al., (2019)	*We also think that technological developments, such as, a dataset search that has just been integrated into google…*
Rafiq & Ameen, (2022)	*Data sharing requires resources including time, finances, infrastructural support, technical knowledge, and skills…*
M'kulama & Akakandelwa, (2021)	*Lack of external central data backup storage facility severely compromised the security of research data and its preservation and retention for future use...The major challenges identified were the lack of a central digital data repository for researchers to deposit and access the data...*

Mozersky et al., (2020)	*Many were not aware that qualitative data repositories existed let alone that some repositories are capable of archiving and providing restrictions on who accesses sensitive qualitative data…*
Joo et al., (2017)	*Finally, the only measure that is not supported by our study data is the impact of the data repository. In health science, clinical data repositories have just begun to play a role in promoting data sharing and reuse practice…*
(Y. Kim & Yoon, 2017)	*At the disciplinary level, availability of a data repository was found to have a significant positive relationship with data reuse intention.*
(da Costa & Lima Leite, 2019)	*The aspects indicate the database as infrastructure required for the management and sharing of search data.*

Trust and Confidence

Trust and confidence are critical in open science to ensure robust scientific practices and knowledge dissemination. As researchers increasingly share their data, methodologies, and findings, maintaining trust within and outside the scientific community becomes paramount [50]. Trust in this context refers to reliance on the integrity, strength, and ability of data, methodologies, and research findings [22]. It's a fundamental cornerstone for the reproducibility and validation of scientific results. When data is shared openly, its integrity seems to be paramount. Researchers rely on the fact that any primary research data shared on an open platform hasn't been tampered with, ensuring its authenticity [51]. Trust also facilitates collaboration; researchers are more likely to collaborate when they have confidence in their colleagues' transparency and honesty. While public trust can influence policy decisions, public behaviour, and even funding opportunities.

Confidence pertains to the belief in the reliability and validity of shared scientific data, methods, and conclusions. One of the qualities of open scientific research is reproducibility. Researchers must have confidence that shared or reused data and methodologies can be reused to obtain similar results [52]. Scientific conclusions drawn from data analyses are only as good as the data. When data is shared openly, other researchers can have confidence in the findings if they trust the data's source and integrity. Table 8 below presents the list of quotes from the review where trust and confidence are seen as factors that can motivate open science practice through research data sharing and reuse.

Table 8. Trust and confidence quotes from the findings

Studies	Quotations:
Abdullahi & Noorhidawati, (2020)	*They also perceive data sharing as a practice that can safeguard data from misconduct…*
Nicholas et al., (2020)	*Similarly honest, two ECRs said they were not confident about their data and were afraid that any mistakes made might be revealed…*
Tenopir et al., (2018)	*Scientists have positive attitudes toward data sharing and reuse in general. Scientists acknowledge that sharing scientific data can have a positive impact on scientific progress regarding time savings and research efficiency, but when it comes to sharing their own research data, scientists have concerns, including worries that it being misused or misinterpreted…*
Damalas et al., (2018)	*as this study also suggests, scholarly altruism is still not the norm, and numerous barriers are blocking the free exchange of scientific information: disciplinary traditions, institutional barriers, lack of technological infra structure, intellectual property concerns, and in dividual perceptions…*
Hrynaszkiewicz et al., (2021)	*our finding that the 'ability to control who can use my dataset' was slightly important (39.1 importance) extends previous findings that researchers' concerns relating to misuse of their data is very common…*
Hodonu-Wusu et al., (2020)	*The issues of cultural and national concerns pose a major challenge to open data sharing. Concerns about misuse and the fear of losing publication opportunity alongside the lack of incentives should be addressed urgently by the funders and advocates of open data…*
Zabijakin-Chatleska & Cekikj, (2020)	*According to the analysed responses to the open-ended question regarding the barriers that might prevent researchers from sharing data (N=33), most researchers, similarly to most conclusions in the literature, are worried from a possible abuse of their data, inadequate interpretation, improper referencing, or even plagiarism…*
Barczak et al., (2022)	*potential reputational pitfalls associated with data sharing. Here, we extend prior findings by showing that fearing embarrassment and a loss of reputation from flawed code or data prevents researchers from sharing their datasets, even if the same scholars advocate for more replication studies in general…*
(Houtkoop et al., 2018)	*Respondents believed that the largest fear-related obstacles preventing other researchers from sharing their data are the fear that alternative analyses might expose invalid conclusions and the fear of loss of control…Respondents reported that their greatest fears about sharing their own data are that the data might be misinterpreted, and they might be scooped.*
Yoon & Kim, (2020)	*This study also confirms that perceived career risk and effort negatively affect scientists' data-sharing intentions in the biological science context…Common concerns about data sharing, such as the loss of publication opportunities and data misuse, remain major barriers to data sharing. Because confidentiality fears and privacy regulations are major inhibitors of data sharing in biological science…*
Y. Kim, (2018)	*First, this research found that perceived academic reputation plays a critical role in scientists' data sharing intentions, as this variable has a significant influence toward scientists' perceived community trust, norm of data sharing, and academic reciprocity…Second, this research showed that perceived community trust, norm of data sharing, and perceived academic reputation all increase scientists' academic reciprocity through intending to engage in data sharing…*

Kim & Nah, (2018)	*With regards to both risk and effort factors, several survey participants raised concerns about the career risks and effort involved in data sharing. A graduate student researcher in information science said that "Qualitative data, such as interview or ethnographic data, is context specific, dense, and may contain a lot of personally identifiable information – sharing this type of data has a lot higher risk, would take more time to clean and organize." Also, an assistant professor in anthropology emphasized, "In fact, I think it [data sharing] is a good idea in principle, but in practice it seems like too much extra work, and I am worried about people misinterpreting my data, or challenging it in ways that are unfair…*
Mallasvik & Martins, (2021)	*However, such altruistic motives can be moderated by inhibiting factors related to individual researchers' choice. One of such factors identified in this study is researchers' feeling of control over their own data. The perceived loss of control seemed to turn them away from wanting to share their data…*
Y. Kim, (2021)	*In contrast, psychologists with concerns about academic risks by sharing their data, such as the loss of publication opportunities, being scooped, and misuse or misinterpretation of their data, are not likely to share data or adopt an open data badge…*
Unal et al., (2019)	*major data sharing concerns such as trust and, ethics…*
Abele-Brehm et al., (2019)	*There were also fears that sharing data may have negative consequences for an individual's career; especially if not all researchers participate and if "Research Parasites…*
Spallek et al., (2019)	*They are generally concerned about data use by others because of potential misuse, the need to protect the confidentiality of research subjects, and the need to stay competitive in an environment that demands publications and funding for survival.*
Ju & Kim, (2019)	*The findings of the current study suggest that biological scientists' individual perceptions, such as their academic reputation, their perceived risk for whether to share data with other researchers, and perceived effort required to share data, significantly affect researcher's ethical egoism factor…*
Rafiq & Ameen, (2022)	*Almost ~40% of respondents mentioned that their research data is available for other researchers on a request basis. Researchers show concerns about sharing their research data, such as legal and ethical issues, misuse of data, etc…Lack of proper policies, rights protection, and misinterpretation of data was also mentioned by almost…*
Devriendt et al., (2021)	*a range of factors that influence individuals' decisions to share data, and their preference regarding the mode of sharing were identified, such as academic credit and recognition, lack of resources, misuse or misinterpretation of data, loss of control, socio-cultural aspects and ethical and legal barriers…*
Yoon & Kim, (2017)	*However, they are hesitant to reuse others' data when they think doing so could potentially cause problems, such as misrepresentation of data, copyright infringement, and/or fewer publication opportunities…*

Researchers' Characteristics and Background

Researchers are central to the science world. Their traits, past experiences, and backgrounds can shape how they see and participate in open science through data sharing and reuse. Identifying these factors is important to build a strong open science culture. For instance, researchers might have learned different research methods depending on their academic background, including how they gather, study, and share their applicable research data [53]. Researchers from areas like biology often share their data. The subject a researcher studies can tell a lot about how willing they are to share or use others' data [20], [21].

Early career researchers might also be more open to new open science ways but might feel pushed to follow the old publishing style. On the other hand, senior researchers might feel freer but could stick to the old habits [54]. and researchers who have previously engaged in collaborative, multi-institutional, or interdisciplinary projects might be more familiar and comfortable with data sharing and reuse [30]. Depending on the location, researchers might follow different open science rules. For instance, European researchers might be influenced by mandates from Horizon 2020, while those in other regions may operate under different guidelines [55]. Some cultures value group knowledge, while others value individual work, affecting how they view open sharing.

Those who know their way around digital tools and online storage places are probably more into open science because they can handle the tech side of sharing data [56]. Some researchers might want to share data because they believe in being open and working together, while others might do it because a journal says so or to get more people to cite their work [8]. Then, some worry about intellectual property, misuse of data, or being scooped when they share their data openly. Suppose a university or research centre has good open science support, like training or storage places. In that case, its researchers might be more ready to share and use open data, and places with clear data-sharing rules can better guide their researchers [33]. Table 9 below shows some quotes from studies about how a researcher's traits shape their open science actions.

Table 9. Researchers' characteristics and background quotes from the findings

Studies	Quotations:
(Zuiderwijk & Spiers, 2019)	*Factors driving researchers to openly share research data or not concern the following eight categories: the researchers' background, personal drivers, experience, legislation, regulation and policies, data characteristics…*
Zenk-Möltgen et al., (2018)	*Finally, the study revealed significant differences between political scientists and sociologists, showing that political scientists engage more in data sharing behaviour. Even in their intention to engage in data sharing, their perceived capacity, and their attitude toward data sharing sociologists are more reserved than political scientists…*
Mason et al., (2020)	*By using a multilevel modelling technique which differentiates these influences statistically, we found that there is an independent effect from organisational unit, research discipline and application domain on researchers' intentions to share data…The findings from the random effects model (which revealed that researchers' organisational unit, disciplinary and domain membership each explain unique variance in intentions to share data) are just as important as the findings from the full model.*
Linek et al., (2017)	*However, we found significant differences for the other attitudes that relate to data sharing in a less abstract way: Females compared to males showed a lower agreement with the attitude (A1) that researchers should generally publish their data…*
Nicholas et al., (2020)	*ECRs were asked whether they had produced data and, if they had, made it openly available. Over threequarters (76.4%; 1,135) of the 1,484 ECRs said they had produced data. As might be expected, there were subject differences in terms of producing data, with the arts and humanities the least likely to produce data and life sciences the most…*
Baždarić et al., (2021)	*Differences in attitudes among scientific fields, with Biomedicine and Health and Biotechnical sciences having higher attitude scores…*
Damalas et al., (2018)	*In this study we also identified differences in scientists' perceptions related to country/region of professional location. Such a notable difference was apparent between southern and northern Europe, probably related to the divergence in research funding and opportunities…Research is obviously not a priority in southern Europe, and it seems that the difficulties associated with fundraising for conducting research in this region probably manifests into a more 'conservative' view towards data openness…*
Hodonu-Wusu et al., (2020)	*Findings indicate that academic discipline and research experience affect the affinity of open data and its sharing practices, as it is a more established practice among the sciences and ECRs…*
Barczak et al., (2022)	*Our data reveals that innovative scholars that positively attest to journal policies for data sharing also made their data publicly accessible and intend to engage in open data sharing more often. Essentially, this would increase the pressure to release data for everyone and would not single out researchers that need to weigh the costs and benefits individually…*
Zhu, (2020)	*However, barriers such as lack of incentives and standards could prevent academics from sharing. This is especially the case for younger and junior academics who are in greater need of securing publication and funding to advance their career while sharing primary research data might jeopardise their chances of publishing before competitors…*
Y. Kim, (2021)	*The results demonstrated that psychologists' data sharing and badge adoption intentions are affected by their community consideration, disciplinary norms, and effort expectancy involved with data sharing…*
Abele-Brehm et al., (2019)	*Not surprisingly, respondents who have not completed their doctoral studies and/or do not yet occupy a tenured position expressed more fears than participants who already occupied a professorship.*

Spallek et al., (2019)	*most senior researchers are men, thereby pointing to a sex diversity issue, and most are reluctant to share data…*
Khan et al., (2023)	*this study, both data sharing and reuse were dependent on researchers' experience; those with more than 10 years of experience tended to share and reuse data more often…Disciplinary differences exist in how researchers share data on the web, presumably driven by the culture of data sharing in a discipline – Physical Sciences, Earth and Planetary Sciences and Environmental Sciences are more likely, whereas Business and Economics, Medicine and Engineering are less likely to share data…*
Fichtner et al., (2022)	*more experienced scientists are more likely to share data according to the definition of data donors as experts share data provided by others.*
Saeed & Ali, (2019)	*Figure 3 clearly revealed that male researchers of Faculty of Social Sciences are more willing to share their data as comparison to female research scholars whereas this is opposite in the case of Faculty of Life Sciences…*
Y. Kim & Yoon, (2017)	*The results of multilevel analysis show that there are significant between-discipline variances as well as within discipline variances in the impacts of both individual and disciplinary factors on data reuse intentions…*
da Costa & Lima Leite, (2019)	*cultural differences between the areas of knowledge are especially due to the nature of the data and how researchers communicate their research results…*

Efforts and Other Sacrifices

Researchers often struggle with various efforts and sacrifices to ensure their data is accessible and reusable. For instance, making data ready for sharing requires several preparations. This includes cleaning, structuring, and annotating the data to ensure it's comprehensible to others [57]. Some of the related efforts that are needed from a researcher to share or reuse research data are proper documentation, such as metadata and accompanying explanatory notes, to ensure that others can understand and use the shared data correctly, but generating this can be time-consuming [33]. Some data repositories may charge fees for data storage, especially if large datasets or specialised storage features are involved or require specialised software, which can entail additional costs [23]. In sensitive or personal data cases, researchers must invest effort into anonymising or de-identifying the data to protect participants, which can be a complex process [33]. One may also want to ensure that all participants have informed consent to share their data openly, which can be challenging, especially for older datasets. Different fields, journals, or repositories might have varying standards for data sharing, which can require additional effort to meet specific requirements, and all these can be classified as additional efforts and sacrifices from the researcher's side to share or reuse data in the context of open science. The table 10 also highlight some of the quotes according to the review.

Table 10. Efforts and other sacrifice quotes from the findings

Studies	Quotations:
Suhr et al., (2020)	*In this study, frequently mentioned obstacles to data sharing are high amount of time needed for a detailed data description, lack of rewards, legal restrictions, lack of a standard data sharing platform and lack of awareness…*
Kim & Nah, (2018)	*With regards to both risk and effort factors, a number of survey participants raised concerns about the career risks and effort involved in data sharing. A graduate student researcher in information science said that "Qualitative data, such as interview or ethnographic data, is context specific, dense, and may contain a lot of personally identifiable information – sharing this type of data has a lot higher risk, would take more time to clean and organize." Also, an assistant professor in anthropology emphasized, "In fact, I think it [data sharing] is a good idea in principle, but in practice it seems like too much extra work, and I am worried about people misinterpreting my data, or challenging it in ways that are unfair…*
Y. Kim, (2021)	*The results demonstrated that psychologists' data sharing and badge adoption intentions are affected by their community consideration, disciplinary norms, and effort expectancy involved with data sharing…*
Abele-Brehm et al., (2019)	*for whom the question of incentive systems, cost-benefit analyses regarding their scientific practices (i.e., the amount of time they invest into preparing codebooks for…*
Williams et al., (2019)	*Another difficulty that is certainly not unique to agricultural researchers is the tight allocation of time and money…*
Ju & Kim, (2019)	*The findings of the current study suggest that biological scientists' individual perceptions, such as their academic reputation, their perceived risk for whether to share data with other researchers, and perceived effort required to share data, significantly affect researcher's ethical egoism factor…*
Rafiq & Ameen, (2022)	*Data sharing requires resources including time, finances, infrastructural support, technical knowledge, and skills…*
Saeed & Ali, (2019)	*The leading obstacle among research scholars of Social Sciences was data privacy and confidentiality (37.62 %) followed by the time and effort required to share data (19.8 %). Technical issues (3.96 %) were opted for by very few of them. Similarly, most research scholars of Faculty of Life Sciences revealed the leading obstacle in sharing research data i.e., data privacy and confidentiality (30.67 %). Only 5.33% of research scholars responded to technical issues…*
Devriendt et al., (2021)	*a range of factors that influence individuals' decisions to share data, and their preference regarding the mode of sharing were identified, such as academic credit and recognition, lack of resources, misuse or misinterpretation of data, loss of control, socio-cultural aspects, and ethical and legal barriers…*
Jeng & He, (2022)	*perceived technical support and extrinsic motivation are both strong predictors of qualitative data sharing (a previously under researched subtype of social science data sharing) …*
M'kulama & Akakandelwa, (2021)	*The other challenges were lack of time to deposit data in open access repositories and costs of sharing research data…*
da Costa & Lima Leite, (2019)	*The researchers highlighted that the processing of the data in order to share it requires more efforts, therefore, more resources are needed…*

Data Characteristics

Open science champions the sharing and reuse of data, emphasising transparency, reproducibility, and collaboration. However, the very nature and characteristics of the shared data can influence how and if it's shared and reused. Here's an exploration of various data characteristics and their implications for open science. Sensitivity and Privacy: any data tied to individuals, especially without explicit consent, can have ethical, legal, and privacy implications [33]. Some data may lose its relevance or accuracy with time, impacting its utility when shared later. Handling and sharing vast amounts of data can also be challenging due to storage, transfer, and computational constraints. Complex datasets with numerous variables might require specialised tools and expertise to analyse, process, and share. While structured data (like databases) are more straightforward to share and reuse, unstructured data (like free-text notes) might pose challenges. More references from the quotes in Table 11 shed light on the intricacies of data characteristics and their implications for sharing and reusing data in the open science framework.

Table 11. Data characteristics are quoted from the findings.

Studies	Quotations:
Dorta-González et al., (2021)	*Finally, the type of data used and the facility with which it can be reused is another factor that influences data sharing and reuse practices …*
Zuiderwijk & Spiers, (2019)	*Factors driving researchers to openly share research data or not concern the following eight categories: the researchers' background, personal drivers, experience, legislation, regulation and policies, data characteristics…*
Nicholas et al., (2020)	*The second reason was that the nature of data did not lend itself to sharing (43%). Seventy-seven per cent of respondents cited further barriers, too, via the 'other' option provided, such as the wish to publish results before releasing data, the need to obtain permission to…*
Suhr et al., (2020)	*Two researchers stated that their generated computational data (output files of computer simulations) was not of interest for other researchers and therefore the data is not shared…*
Zabijakin-Chatleska & Cekikj, (2020)	*Researchers also stress that some data is confidential and sensitive. One respondent mentioned the lack of legal regulations…*
Kim & Nah, (2018)	*A graduate student researcher in information science said that "Qualitative data, such as interview or ethnographic data, is context specific, dense, and may contain a lot of personally identifiable information – sharing this type of data has a lot higher risk, would take more time to clean and organize." Also, an assistant professor in anthropology emphasized, "In fact, I think it [data sharing] is a good idea in principle, but in practice it seems like too much extra work, and I am worried about people misinterpreting my data, or challenging it in ways that are unfair…*
Krahe et al., (2023)	*In developing the next steps of our data sharing strategy, we recognise that information generated or collected from health research may contain large volumes of highly sensitive data, have explicit privacy and/or security considerations or a degree of commercialisation. To protect privacy, confidentiality and respect the terms under which participants consented to take part in the original study, data needs to be planned, collected and stored in such a way that is appropriate. In some cases, it may not be possible to share or reuse data…*
Spallek et al., (2019)	*They are generally concerned about data use by others because of potential misuse, the need to protect the confidentiality of research subjects, and the need to stay competitive in an environment that demands publications and funding for survival…*
Saeed & Ali, (2019)	*The leading obstacle among research scholars of Social Sciences was data privacy and confidentiality (37.62 %) followed by the time and effort required to share data (19.8 %). Technical issues (3.96 %) were opted for by very few of them. Similarly, most research scholars of Faculty of Life Sciences revealed the leading obstacle in sharing research data i.e., data privacy and confidentiality (30.67 %). Only 5.33% of research scholars responded to technical issues.*

Review objective three: To find existing gaps in the literature that necessitate further research.

Having explored the most common categories of samples and data collection methods and identifying the key factors influencing researchers' participation in open science practices through research data sharing and reuse, it has become apparent that there are some literature gaps.

From the first objective of the review, it was observed that many of the studies have relied heavily on surveys and questionnaires (quantitative methods) directed toward specific academic disciplines, primarily in the biological sciences and humanities. However, observational and experimental data collection methods were notably less frequent in the existing literature. This over-reliance on survey-based methods could imply a potential gap. This suggests that a more diverse methodological approach might yield additional insights into researchers' attitudes and practices regarding open science through research data sharing and reuse.

The findings from the second objective also emphasised several factors, including rewards and other benefits, awareness and capacity building, institutional policies and regulation, technological infrastructure, and individual researcher characteristics, which all play crucial roles in shaping open science practices. Yet, it was evident that roughly 90% of the reviewed studies focused predominantly on specific researcher groups. This concentration raises questions about the generalizability of the identified factors to a broader researcher population. It suggests a significant literature gap about how different researcher categories might be differently driven toward open science practice [58].

Considering these observations, this review recommends a more inclusive approach by focusing on groups less represented in the literature. Taking specific researchers or academicians from a known institution as a prime example, a deeper examination of such a medical and health research institution could bridge the existing knowledge gaps. Exploring their unique challenges, motivations, and behaviours in relation to open science could provide a richer understanding of the global open science landscape.

Assessing the Risk of Bias

The reliability and credibility of an SLR mainly depend on the quality and objectivity of the comprised studies. An assessment of the risk of bias in these studies is crucial as it aids in observing the degree of trustworthiness of the results. This process facilitates the identification of potential shortcomings, limitations, or biases that could impact the review's findings [59].

Criteria for Assessment: Systematic literature reviews can exhibit risks of bias at both the review level (i.e., analysis of studies) and the outcome level (i.e., reporting bias). To mitigate these risks in this review, the subsequent measures were undertaken:

i. Transparency was maintained by providing detailed methods for collecting, assessing, and analysing the studies.
ii. All included studies were examined to have been published in esteemed journals or indexed in recognised databases since the retrieval was executed via Elicit, equipped to extract pertinent results from diverse online sources.
iii. Openly sharing the review data used for the analysis enabled peers to validate the findings and explore alternate interpretations.

iv. Notably, certain factors influencing the adoption of open research data were only identified in a single study. This calls for additional evidence to enhance comprehension of these factors, especially in diverse contexts, and lastly.
v. Multiple reviewers were involved in approving the included and excluded studies in the review.

Tools Used for the Assessment: A standardised Excel form facilitated the inclusion of relevant data from each study, capturing crucial details like study citations, sample size, data collection methods, and key factors influencing open science practice. Utilising this tool, each study in the SLR was assessed against the criteria. Studies that failed to meet these criteria were omitted from the review. Table 12 below lists some studies that were subsequently excluded from the review and the rationale for their exclusion.

A significant percentage of these studies were excluded because the risk of bias can pose challenges in deriving concrete conclusions from the SLR. Nonetheless, acknowledging these limitations and endorsing transparency in the assessment augments the review's trustworthiness. It's also indicative that further research may be instrumental in corroborating or complementing insights from studies with pronounced or ambiguous biases. A precise bias assessment gives the reviewer a refined perspective to interpret the SLR's outcomes, ensuring that the conclusions are rooted in robust and dependable evidence.

Table 12. Excluded studies from the review with reasons for exclusion.

S/N	Studies	Reasons for exclusion
1.	Conrad, L. Y., Delahunty, R., & Ding, W. (2022). The promise and the future of research data sharing. Learned Publishing, 35(1), 4-6. https://doi.org/10.1002/leap.1432	This article is a commentary from the editorial and does not include any sampling or data collection.
2.	Martone, M. E., Garcia-Castro, A., & VandenBos, G. R. (2018). Data sharing in psychology. *American Psychologist*, *73*(2), 111.	The article is a commentary based on the authors' experiences and lacks sampling and data collection.
3	Downey, M., Lafferty-Hess, S., Charbonneau, P., & Zoss, A. (2021). Engaging researchers in data dialogues: Designing collaborative programming to promote research data sharing. *Journal of eScience Librarianship*, *10*(2).	This panel discussion involves two experienced speakers with no specific sample or data collection.
4	Bezuidenhout, L. (2019). To share or not to share: Incentivizing data sharing in life science communities. *Developing world bioethics*, *19*(1), 18-24.	The article presents the author's opinions without data collection or applicable samples.
5.	Proulx, M., Ross, L., Macdonald, C., Fitzsimmons, S., & Smit, M. (2021). Indigenous traditional ecological knowledge and ocean observing: A review of successful partnerships. *Frontiers in Marine Science*, *8*, 703938.	This article is primarily a literature review and does not offer empirical data on specific community data management practices.
6.	Smit, M., Larose, C., Falvey, C., Fitzsimmons, S., & Macdonald, C. (2022). Individual Perspectives on Data Sharing: Human Factors Impacting the Digital Economy. *DalSpace Institutional Repository*.	This is a literature review report and is excluded from the study.
7.	Niankara, I. (2020). Research data recycling through open sharing and reuse: A case study of sustainable digital good consumption in the sharing economy.	The study does not involve human sampling, which falls outside the study selection criteria.
8.	Vasilevsky, N. A., Minnier, J., Haendel, M. A., & Champieux, R. E. (2017). Reproducible and reusable research: are journal data sharing policies meeting the mark? *PeerJ*, *5*, e3208.	The study does not involve human sampling, which is required for inclusion. Instead, it manually reviewed author instructions and editorial policies for biomedical journals.
9.	Resnik, D. B., Morales, M., Landrum, R., Shi, M., Minnier, J., Vasilevsky, N. A., & Champieux, R. E. (2019). Effect of impact factor and discipline on journal data sharing policies. *Accountability in research*, *26*(3), 139-156.	The study lacks human sampling, a requirement for inclusion. The sample was drawn from the 2016 edition of Thompson-Reuters' Journal Citation Reports.
10.	Thelwall, M., & Kousha, K. (2017). Do journal data sharing mandates work? Life sciences evidence from Dryad. *Aslib Journal of Information Management*, *69*(1), 36-45.	The study does not include human samples, using instead a list of journals that submit data to the Dryad research data repository.
11.	Wiley, C. (2018). Data sharing and engineering faculty: An analysis of selected publications. *Science & technology libraries*, *37*(4), 409-419.	The study does not involve human sampling, focusing instead on a review of journal data policies.

12.	Alicea, B. (2019). Data Reuse and the Social Capital of Open Science. BioRxiv, 093518. https://www.biorxiv.org/content/10.1101/093518v3	The study doesn't include original samples; it uses simulations on secondary data to identify factors influencing data sharing and reuse.
13.	Mongeon, P., Robinson-Garcia, N., Jeng, W., & Costas, R. (2017). Incorporating data sharing to the reward system of science: Linking DataCite records to authors in the Web of Science. *Aslib Journal of Information Management*, *69*(5), 545-556.	The study doesn't involve human samples, drawing data from 2015 records published in DataCite.
14.	Couture, J. L., Blake, R. E., McDonald, G., & Ward, C. L. (2018). A funder-imposed data publication requirement seldom inspired data sharing. *PLoS One*, *13*(7), e0199789.	The study involves only dataset analysis retrieved from a database, with no human samples.
15.	Rousi, A. M. (2022). Using current research information systems to investigate data acquisition and data sharing practices of computer scientists. *Journal of Librarianship and Information Science*, 09610006221093049.	The study does not include human samples; it uses secondary data from previously published scientific articles.
16.	Thelwall, M., Munafò, M., Mas-Bleda, A., Stuart, E., Makita, M., Weigert, V., ... & Kousha, K. (2020). Is useful research data usually shared? An investigation of genome-wide association study summary statistics. *Plos one*, *15*(2), e0229578.	The study uses secondary data from a published journal database to assess research data sharing practices.
17.	Neylon, C. (2017). Building a culture of data sharing: policy design and implementation for research data management in development research. *Research Ideas and Outcomes*, *3*, e21773.	The study utilizes secondary data and does not involve any applicable human samples.

DISCUSSION AND CONCLUSION

Interpreting and Reporting Findings

The advancement of open science, enabled by research data sharing and reuse, has helped in a new era of collaborative and transparent scientific inquiry. Framed by well-defined objectives, this SLR delves into the multifaceted dimensions surrounding researchers' participation in this evolving landscape. This section interprets and articulates the central findings derived from the analysed literature.

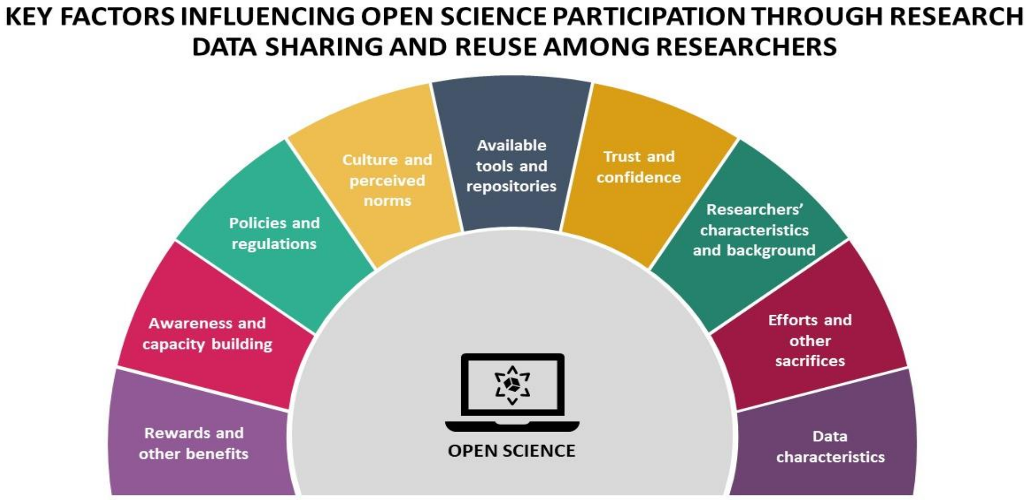


Figure 9. Factors influencing open science participation through research data sharing and reuse among researchers, illustrated by the researcher (Source: Illustrated by the Authors).

The Major Findings

1. **Categories of Samples and Data Collection Methods:** The reviewed studies showcased a variety of sampling strategies. Many focused on specific fields, institutions, or countries. A limited number adopted a broader approach, targeting early career researchers or random selections from specified databases and funding agencies. At the same time, most of the studies reviewed leaned towards quantitative methodologies, with surveys being the predominant tool due to their comprehensive reach. In contrast, only a few adopted qualitative or mixed-method research approaches.
2. **Factors Influencing Participation in Open Science Practices:**
   a. **Rewards and Other Benefits:** Researchers were inclined towards data sharing when they discerned direct benefits, including elevated collaboration, increased visibility, and subsequent citations.
   b. **Awareness and Capacity Building:** Open science's benefits, practices, and potential were significant enablers. Training workshops and seminars further support this awareness.
   c. **Policies and Regulations:** Directives from institutions, funding bodies, and publishers prominently influence decisions. When data sharing was mandated, compliance was naturally higher.
   d. **Culture and Perceived Norms:** The prevailing culture within a research community or laboratory significantly shapes behaviour. Environments supportive of open science naturally witnessed increased participation.
   e. **Available Tools and Repositories:** User-friendly and secure repositories facilitated data sharing and reuse, lowering technical barriers.
   f. **Trust and Confidence:** Assurances regarding data security, proper attribution, and no misuse were crucial. When researchers felt their data was secure and would be credited appropriately, they were more willing to share.
   g. **Researchers' Characteristics and Background:** Individual attributes, including academic background, prior exposure to open science, and personal beliefs, dictated participation levels.
   h. **Efforts and Other Sacrifices:** Researchers weighed the time and effort required for data curation against potential benefits. If perceived efforts were excessive, participation waned.
   i. **Data Characteristics:** The nature of the data, whether sensitive, proprietary, or complex, affected sharing decisions. Standardised and easily interpretable data witnessed higher sharing rates.

Implications for Stakeholders

1. **For Researchers:** Recognising these multifaceted factors offers researchers a comprehensive framework to guide their engagement with open science practices. Being aware of both advantages and challenges is instrumental in informed decision-making.

2. **For Policy Makers and Institutions:** These insights provide a roadmap for forming policies that balance promoting open science with researchers' legitimate concerns. They underscore the importance of fostering a supportive ecosystem through training and incentives.
3. **For Publishers:** As custodians of scientific discourse, publishers can proactively champion open science by weaving in data-sharing mandates and providing reasonable guidelines.

Open science represents a transformative path for modern scientific practice, and this SLR has illustrated the multitude of factors and challenges influencing this shift. By addressing these dynamics, we can shape a future where open, transparent, and collaborative research becomes the gold standard.

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REFERENCES

[1] B. A. Nosek *et al.*, "Promoting an open research culture," *Science (80-.).*, vol. 348, no. 6242, pp. 1422–1425, 2015.

[2] M. Ahmed and R. Othman, "Readiness towards the implementation of open science initiatives in the Malaysian Comprehensive Public Universities," *J. Acad. Librariansh.*, vol. 47, no. 5, p. 102368, 2021, doi: 10.1016/j.acalib.2021.102368.

[3] B. Fecher and S. Friesike, "Open science: one term, five schools of thought," in *Opening science*, Springer, 2014, pp. 17–47.

[4] D. B. Resnik *et al.*, "Effect of impact factor and discipline on journal data sharing policies," *Account. Res.*, vol. 26, no. 3, pp. 139–156, 2019, doi: 10.1080/08989621.2019.1591277.

[5] L. M. Federer *et al.*, "Data sharing in PLOS ONE: an analysis of data availability statements," *PLoS One*, vol. 13, no. 5, p. e0194768, 2018.

[6] R. Vicente-Sáez and C. Martínez-Fuentes, “Open Science now: A systematic literature review for an integrated definition,” *J. Bus. Res.*, vol. 88, pp. 428–436, 2018.

[7] H. Eileen, “Open science,” *Nature*, vol. 550, no. 7674, pp. 7–8, 2019, doi: 10.1016/b978-0-08-102124-8.00007-6.

[8] C. Tenopir *et al.*, “Data sharing, management, use, and reuse: Practices and perceptions of scientists worldwide,” *PLoS One*, vol. 15, no. 3, pp. 1–26, 2020, doi: 10.1371/journal.pone.0229003.

[9] C. L. Borgman, “The conundrum of sharing research data,” *J. Am. Soc. Inf. Sci. Technol.*, vol. 63, no. 6, pp. 1059–1078, 2012.

[10] J. O. Hodonu-Wusu, A. Noorhidawati, and A. Abrizah, “Malaysian researchers on open data: The first national survey on awareness, practices and attitudes,” *Malaysian J. Libr. Inf. Sci.*, vol. 25, no. 2, pp. 1–20, 2020, doi: 10.22452/mjlis.vol25no2.1.

[11] M. Düwell, “Open science and ethics,” *Ethical Theory Moral Pract.*, vol. 22, pp. 1051–1053, 2019.

[12] C. Bahlai *et al.*, “Open science isn’t always open to all scientists,” *Am. Sci.*, vol. 107, no. 2, pp. 78–82, 2019.

[13] P. E. Smaldino, M. A. Turner, and P. A. Contreras Kallens, “Open science and modified funding lotteries can impede the natural selection of bad science,” *R. Soc. open Sci.*, vol. 6, no. 7, p. 190194, 2019.

[14] R. V. Gallagher *et al.*, “Open Science principles for accelerating trait-based science across the Tree of Life,” *Nat. Ecol. Evol.*, vol. 4, no. 3, pp. 294–303, 2020, doi: 10.1038/s41559-020-1109-6.

[15] J. P. T. Higgins and S. Green, “Cochrane handbook for systematic reviews of interventions,” 2008.

[16] OUGHT, “Elicit: The AI Research Assistant,” 2023. https://elicit.org

[17] M. J. Page *et al.*, “The PRISMA 2020 statement: an updated guideline for reporting systematic reviews,” *Bmj*, vol. 372, 2021.

[18] B. Suhr, J. Dungl, and A. Stocker, “Search, reuse and sharing of research data in materials science and engineering—A qualitative interview study,” *PLoS One*, vol. 15, no. 9 September, pp. 1–26, 2020, doi: 10.1371/journal.pone.0239216.

[19] M. L. Mallasvik and J. T. Martins, “Research data sharing behaviour of engineering researchers in Norway and the UK: uncovering the double face of Janus,” *J. Doc.*, vol. 77, no. 2, pp. 576–593, 2021, doi: 10.1108/JD-08-2020-0135.

[20] A. Yoon and Y. Kim, “The role of data-reuse experience in biological scientists’ data sharing: an empirical analysis,” *Electron. Libr.*, vol. 38, no. 1, pp. 186–208, 2020, doi: 10.1108/EL-06-2019-0146.

[21] B. Ju and Y. Kim, “The formation of research ethics for data sharing by biological scientists: an empirical analysis,” *Aslib J. Inf. Manag.*, vol. 71, no. 5, pp. 583–600, 2019, doi: 10.1108/AJIM-12-2018-0296.

[22] Y. Kim, "Reputation, trust, and norms as mechanisms leading to academic reciprocity in data sharing: An empirical test of theory of collective action," *Proc. Assoc. Inf. Sci. Technol.*, vol. 55, no. 1, pp. 244–253, 2018, doi: 10.1002/pra2.2018.14505501027.

[23] S. C. Williams, S. L. Farrell, E. E. Kerby, and M. Kocher, "Agricultural researchers' attitudes toward open access and data sharing," *Issues Sci. Technol. Librariansh.*, no. 91, 2019.

[24] A. C. M'kulama and A. Akakandelwa, "Research Data Sharing and Reuse Through Open Data: Assessing Researcher Awareness and Perceptions at the Zambia Agricultural Research Institute (ZARI)," in *Open Access Implications for Sustainable Social, Political, and Economic Development*, IGI Global, 2021, pp. 284–306.

[25] C. Tenopir, L. Christian, S. Allard, and J. Borycz, "Research Data Sharing: Practices and Attitudes of Geophysicists," *Earth Sp. Sci.*, vol. 5, no. 12, pp. 891–902, 2018, doi: 10.1029/2018EA000461.

[26] L. Bezuidenhout and E. Chakauya, "Hidden concerns of sharing research data by low/middle-income country scientists," *Glob. Bioeth.*, vol. 29, no. 1, pp. 39–54, 2018, doi: 10.1080/11287462.2018.1441780.

[27] M. Ishtiaq, "Book review creswell, JW (2014). research design: qualitative, quantitative and mixed methods approaches . Thousand Oaks, ca: sage," *English Lang. Teach.*, vol. 12, no. 5, p. 40, 2019.

[28] M. Rosala, "How to Analyze Qualitative Data from UX Research: Thematic Analysis," *Nielsen Norman Group*. 2022. [Online]. Available: https://www.nngroup.com/articles/thematic-analysis/

[29] S. Hassan, N. Ansari, and A. Rehman, "An exploratory study of workplace spirituality and employee well-being affecting public service motivation: an institutional perspective," *Qual. Res. J.*, vol. 22, no. 2, pp. 209–235, 2022.

[30] P. Dorta-González, S. M. González-Betancor, and M. I. Dorta-González, "To what extent is researchers' data-sharing motivated by formal mechanisms of recognition and credit?," *Scientometrics*, vol. 126, no. 3, pp. 2209–2225, 2021, doi: 10.1007/s11192-021-03869-3.

[31] A. Yoon and Y. Kim, "Social scientists' data reuse behaviors: Exploring the roles of attitudinal beliefs, attitudes, norms, and data repositories," *Libr. Inf. Sci. Res.*, vol. 39, no. 3, pp. 224–233, 2017.

[32] R. Melero and C. Navarro-Molina, "Researchers' attitudes and perceptions towards data sharing and data reuse in the field of food science and technology," *Learn. Publ.*, vol. 33, no. 2, pp. 163–179, 2020, doi: 10.1002/leap.1287.

[33] R. Aleixandre-Benavent, A. Vidal-Infer, A. Alonso-Arroyo, F. Peset, and A. F. Sapena, "Research data sharing in spain: Exploring determinants, practices, and perceptions," *Data*, vol. 5, no. 2, pp. 1–14, 2020, doi: 10.3390/data5020029.

[34] E. C. McKiernan *et al.*, "How open science helps researchers succeed," *See https//doi. org/10.7554/elife*, vol. 16800, 2016.

[35] C. Tenopir *et al.*, "Data sharing by scientists: practices and perceptions," *PLoS One*,

vol. 6, no. 6, p. e21101, 2011.

[36] C. Knill and J. Tosun, *Public policy: A new introduction*. Bloomsbury Publishing, 2020.

[37] J.-C. Burgelman *et al.*, "Open Science, Open Data, and Open Scholarship: European Policies to Make Science Fit for the Twenty-First Century ," *Frontiers in Big Data* , vol. 2. p. 43, 2019. [Online]. Available: https://www.frontiersin.org/article/10.3389/fdata.2019.00043

[38] S. Grant *et al.*, "Transparent, Open, and Reproducible Prevention Science," *Prev. Sci.*, 2022, doi: 10.1007/s11121-022-01336-w.

[39] M. D. Wilkinson *et al.*, "Comment: The FAIR Guiding Principles for scientific data management and stewardship," *Sci. Data*, vol. 3, pp. 1–9, 2016, doi: 10.1038/sdata.2016.18.

[40] B. Erb, C. Bösch, C. Herbert, F. Kargl, and C. Montag, "Emerging privacy issues in times of open science," 2021.

[41] A. W. Child, J. Hinds, L. Sheneman, and S. Buerki, "Centralized project-specific metadata platforms: toolkit provides new perspectives on open data management within multi-institution and multidisciplinary research projects," *BMC Res. Notes*, vol. 15, no. 1, pp. 1–6, 2022, doi: 10.1186/s13104-022-05996-3.

[42] Y. Zhu, "Open-access policy and data-sharing practice in UK academia," *J. Inf. Sci.*, vol. 46, no. 1, pp. 41–52, 2020, doi: 10.1177/0165551518823174.

[43] B. Akanji, C. Mordi, A. Ituma, T. A. Adisa, and H. Ajonbadi, "The influence of organisational culture on leadership style in higher education institutions," *Pers. Rev.*, vol. 49, no. 3, pp. 709–732, 2020.

[44] U. A. Fichtner, L. M. Horstmeier, B. A. Brühmann, M. Watter, H. Binder, and J. Knaus, "The role of data sharing in survey dropout: a study among scientists as respondents," *J. Doc.*, 2022, doi: 10.1108/JD-06-2022-0135.

[45] L. Smircich, "Concepts of culture and organizational analysis," *Anthropol. Organ.*, pp. 255–274, 2017.

[46] Y. Kim and S. Nah, "Internet researchers' data sharing behaviors: An integration of data reuse experience, attitudinal beliefs, social norms, and resource factors," *Online Inf. Rev.*, vol. 42, no. 1, pp. 124–142, 2018, doi: 10.1108/OIR-10-2016-0313.

[47] N. Khan, M. Thelwall, and K. Kousha, "Data sharing and reuse practices: disciplinary differences and improvements needed," *Online Inf. Rev.*, 2023, doi: 10.1108/OIR-08-2021-0423.

[48] M. Roman, J. Liu, and T. Nyberg, "Advancing the open science movement through sustainable business model development," *Ind. High. Educ.*, vol. 32, no. 4, pp. 226–234, 2018.

[49] A. Mahfooz and O. Roslina, "Promoting Open Science With Institutional Repositories in the Malaysian Comprehensive Public," *J. Inf. Syst. Digit. Technol.*, vol. 3, no. 2, pp. 11–28, 2021.

[50] R. G. Curty, K. Crowston, A. Specht, B. W. Grant, and E. D. Dalton, "Attitudes and norms affecting scientists' data reuse," *PLoS One*, vol. 12, no. 12, pp. 1–22, 2017, doi: 10.1371/journal.pone.0189288.

[51] Y. Unal, G. Chowdhury, S. Kurbanoğlu, J. Boustany, and G. Walton, "Research data management and data sharing behaviour of university researchers'," *Inf. Res. an Int. Electron. J.*, vol. 24, no. 1, 2019.

[52] Y. Kim, "An empirical study of research ethics and their role in psychologists' data sharing intentions using consequentialism theory of ethics," *J. Librariansh. Inf. Sci.*, vol. 54, no. 2, pp. 251–263, 2022, doi: 10.1177/09610006211008967.

[53] A. Zuiderwijk and H. Spiers, "Sharing and re-using open data: A case study of motivations in astrophysics," *Int. J. Inf. Manage.*, vol. 49, pp. 228–241, 2019, doi: https://doi.org/10.1016/j.ijinfomgt.2019.05.024.

[54] D. Nicholas *et al.*, "Early career researchers and their publishing and authorship practices," *Learn. Publ.*, vol. 30, no. 3, pp. 205–217, 2017, doi: 10.1002/leap.1102.

[55] D. Damalas, G. Kalyvioti, E. C. Sabatella, and K. I. Stergiou, "Open data in the life sciences: The 'Selfish Scientist Paradox,'" *Ethics Sci. Environ. Polit.*, vol. 18, no. 1, pp. 27–36, 2018, doi: 10.3354/esep00182.

[56] T. Devriendt, P. Borry, and M. Shabani, "Factors that influence data sharing through data sharing platforms: A qualitative study on the views and experiences of cohort holders and platform developers," *PLoS One*, vol. 16, no. 7 July, pp. 1–14, 2021, doi: 10.1371/journal.pone.0254202.

[57] O. Diaz *et al.*, "Data preparation for artificial intelligence in medical imaging: A comprehensive guide to open-access platforms and tools," *Phys. medica*, vol. 83, pp. 25–37, 2021.

[58] W. Van Atteveldt, S. Althaus, and H. Wessler, "The trouble with sharing your privates: Pursuing ethical open science and collaborative research across national jurisdictions using sensitive data," *Polit. Commun.*, vol. 38, no. 1–2, pp. 192–198, 2021.

[59] Brown University Library, "Systematic vs Literature reviews - Scientific Literature Review Resources and Services - Library Guides at Brown University," Jul. 23, 2021. https://libguides.brown.edu/Reviews/types (accessed Oct. 30, 2021).