



Why do open data platforms Fail? – A revised conceptual model with mitigations actions

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ABSTRACT

Data is seen as a key driver for digital transformation. In this context, Open Data Platforms (ODP) have the potential to offer opportunities for the public, private, and civic sectors to connect and share information. Despite these platforms' rapid proliferation, significant limitations and challenges associated with their use and development may jeopardise ODP's effectiveness. There is a lack of studies exploring these platforms' challenges and limitations. Moreover, mitigation actions are needed to reduce the potential for failure of ODP. This research aims to understand why ODP fails, by conducting a careful and comprehensive analysis, which included a systematic literature review, was performed to identify the critical challenges and limitations that may affect the performance of an open data platform. A conceptual model from the literature is updated with a categorization of the different limitations and challenges relating to ODP. This model groups the topics created by the researchers into five main categories of challenges and limitations: Technical, Institutional, End-users, Data quality, and Legislative. Furthermore, several mitigation actions were proposed to deal with each category of the model. By identifying these challenges and limitations and categorizing them, it is possible to understand the potential causes that impact the performance of an open data platform. Furthermore, by proposing different mitigation actions, this research aims to help deal with ODP's challenges and limitations, contributing to preventing potential failures.

1. Introduction

Data is seen as a key driver for digital transformation, and in this context, digital platforms can offer opportunities for digital entrepreneurs to connect to users and innovate by creating new digital products (Wainwright et al., 2023). Even though there are several detailed descriptions of open data, open data can be defined as freely available to distribute and use without any restrictions from patents or copyrights (Ali et al., 2022). According to Braunschweig et al. (2012), open data initiatives aim to disseminate all non-commercial and non-personal data, specifically those collected and processed by governmental administrations. Open data can be of any type, including hierarchical relationships, network structures, or tabular spreadsheets, as long as it is published with an open license so that others may use it (Wainwright et al., 2023). Ruijter et al. (2017) highlighted that open data can be used to obtain insights and information, provide solutions for societal

problems, and establish public policy. Thus, following this trend, public agencies have started making governmental data available on web portals and services or via Representational State Transfer (REST) interfaces (Braunschweig et al., 2012). This shift is expected to foster greater participation, drive innovation, and enhance societal transparency.

Open data platforms (ODP) are specific digital platforms facilitating entrepreneurship by enabling companies to engage in open innovation processes (Wainwright et al., 2023). According to Ali et al. (2022), ODPs are central resources for data sharing and they play a critical role in sustainable open data efforts. Discussions about open data and ODP have been prominent over the past decade (Herala et al., 2016), as these platforms can play a critical role in different sectors worldwide, such as science, research, technology, finance, and culture (Ali et al., 2022). The basic block of ODP is web portals that offer an interface for publishing and accessing open data, often through an Application Programming

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Interface.

Most studies primarily focus on developing Open data platforms (ODP's) in a governmental context. For example, [Kassen \(2018\)](#) defined an ODP as a specific public digital repository that publishes several government datasets in machine-readable formats that can be used for online collaborative and participative startups or third-party mobile applications. [Ruijter, Grimmelikhuijsen, Hogan et al. \(2017\)](#) highlighted that ODP aims to foster democratic processes through transparency promotion by publishing governmental data. Other studies, such as [Blok et al. \(2017\)](#) and [Neves et al. \(2020\)](#), have explored ODP and initiatives in city context and on urban development ([Kapoor & Jehling, 2023](#)), highlighting that these initiatives seek to promote transparency, planning and analysis, and better city governance. Moreover, they as well as foster collective intelligence and co-creation while providing solutions to several environmental and socio-economic challenges.

[Kassen \(2018\)](#) highlighted that the stakeholders involved in an ODP corresponded to both public and private sectors, civil society, non-governmental organizations and developers. Despite these platforms' rapid proliferation, significant limitations and challenges associated with their use and development may jeopardize their effectiveness. However, few studies have specifically addressed these issues ([Osagie et al., 2017](#); [Kassen, 2018](#)), with most research focusing on the challenges and limitations related to open data itself. For example, [Susha et al. \(2015\)](#) highlighted some of the challenges that open data users and governmental organizations experience, more specifically, the use of open data requires significant effort and it is time-consuming, it may be challenging to determine the data's quality, it may be complex to publish data and data may be hard to understand. Other authors, such as [Martin et al. \(2013\)](#), grouped the risks related to open data into seven main categories: economic issues, licenses and legal frameworks, governance, access, metadata, data characteristics, and skills. Moreover, in a scientific context, authors such as [Stieglitz et al. \(2020\)](#) concluded that non-technical barriers due to ethical and legal restrictions and individual factors are barriers to data sharing. [Kassen \(2018\)](#) pointed out the leading indicators that an ODP is destined to failure: i) when it lacks sustainability and only relies on short-term initiatives (such as hackathons); ii) when it fails to involve stakeholders, such as developers, in a lasting and structured way and iii) when it lacks an economic incentive or funding mechanism to guarantee its long-term viability.

Furthermore, [Hyseni & Bexheti \(2022\)](#) recently developed a conceptual model to classify open data challenges and advantages. The authors divided their results into several pillars that constitute open data's main challenges and limitations ([Table 1](#)). Despite the different contexts that are starting to be explored, the studies on open data barriers are generally limited to the analysis of data publishing. The barriers faced by data users and re-users are regularly overlooked ([Beno et al., 2017a](#)).

As referred, when focusing on the context of ODP, there is a lack of studies exploring the challenges and limitations that these platforms face, which may lead to their failure. Moreover, mitigation actions are needed to safeguard ODPs from the potential failures. The existing studies found in the literature explore the limitations and problems of ODP in specific contexts, with most of the studies being related to governmental ODP ([Martin, 2013](#); [Martin & Begany, 2017](#)) or only focusing on a particular limitation or challenge ([Kapoor et al., 2015](#);

[González-Ramos et al., 2023](#)). For example, [Zheng & Gao \(2016\)](#) developed an assessment framework for the Chinese government's open data initiatives and found several problems in current open data practices, such as inexplicit open data licenses, scarcity of high-quality data applications, limited convenient channels for accessibility, infrequent data updates, and lack of convenient, effective and timely open interaction with users. On the other hand, [Ruijter, Grimmelikhuijsen, Hogan et al. \(2017\)](#) concluded that most of the studies concerning governmental ODP either used data, users, or portals as the starting point of analysis and failed to take into account the specific context of open data use. Furthermore, other authors, such as [Osagie et al. \(2017\)](#), provided insights that can be generalized about the usability evaluation of ODP. The authors concluded that the poor usability of ODP can challenge the broader exploitation of these platforms.

This research seeks to fill the knowledge gaps regarding the challenges and limitations of ODP failures. For that purpose, the research begins with a systematic literature review focusing on the challenges and limitations that impact ODP performance, potentially leading to its failure. Understanding the causes that may affect ODP's performance is critical to minimise or avoid the risk of failure. Based on the findings, the research aims to structure the existing knowledge on ODP and their failures through a conceptual model. Additionally, the study proposes several mitigation actions to deal with the most critical categories of challenges and limitations that ODP face.

This paper is structured as follows: [Section 1](#) introduces the main concepts under study and it is followed by [Section 2](#), which focuses on the methodology used. [Section 3](#) presents the main descriptive results from the systematic literature review with a critical analysis. [Section 4](#) discusses the results, highlighting several mitigation actions and the research's main contributions and limitations. Finally, [Section 5](#) outlines the main conclusions.

2. Research methodology

According to [Mengist et al. \(2020\)](#), a systematic literature review is a structured, reproducible, and transparent approach to identifying, synthesizing, analyzing, and evaluating existing research conducted by practitioners, researchers, and academics. This methodology typically has different stages of planning, conducting, reporting, and dissemination ([Ferreira et al., 2021](#)). A systematic literature review adopts scientific, transparent, and replicable steps to help collect all relatable documents and publications that fit in pre-defined inclusion criteria to answer a specific research question ([Martin et al., 2013](#)). In this research, a scoping review was conducted. According to ([Ralph & Baltes, 2022](#)), scoping reviews are often descriptive, aiming to comprehend the status of research on a specific area, usually by mapping studies into categories. This research adopted a four-stage approach from [Ferreira et al. \(2021\)](#), which includes (1) problem formulation, (2) literature search and evaluation, (3) research analysis and interpretation, and (4) reporting of results. The adapted research design is presented in [Fig. 1](#).

2.1. Problem formulation

Considering the existing research gaps regarding the limitations faced by ODP that may cause their failure, as highlighted in [Section 1](#), this research aims to structure the existing knowledge about the main challenges and limitations derived from the literature. Hence, this systematic literature review was based on a central research question: *What are the challenges and limitations concerning ODP?*

2.2. Literature search and evaluation

At this stage, bibliographic databases, keywords, and the search strategy were systematically defined to ensure a comprehensive and structured literature review ([Ferreira et al., 2021](#)). Some authors, such as [Tranfield et al. \(2003\)](#), recommend using different sources of

Table 1
Main pillars of open data challenges and limitations. Retrieved from [Hyseni & Bexheti \(2022\)](#).

Open data challenges	Open data advantages
• Institutional • Task complexity • Legislation • Information quality • Technical	• Political and social • Economic • Operational and technical

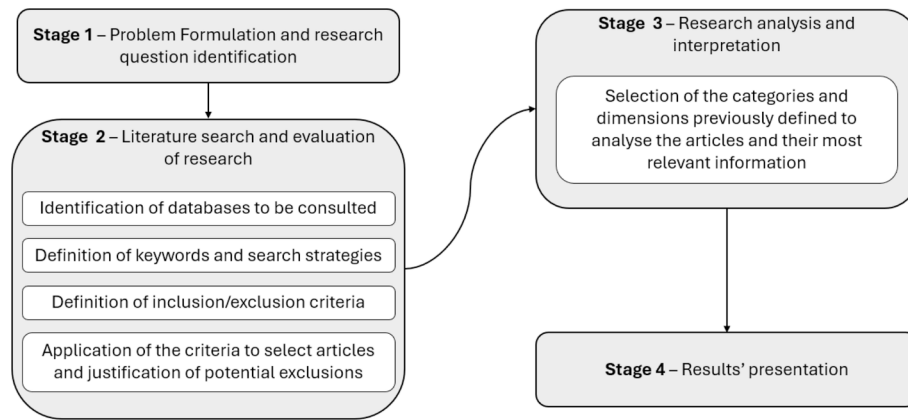


Fig. 1. Systematic literature review design.
Adapted from Ferreira et al. (2021).

information from conference proceedings, unpublished studies, and the Internet. Given the limited knowledge about the concepts under study, this research included white papers, peer-reviewed publications, and conference proceedings. Three databases were considered: Web of Science and Scopus for peer-review publications and conference proceedings and Google Scholar for white papers. These databases were selected for their advanced search capabilities and their offer of extensive interdisciplinary content. This choice was also intended to enhance the validity of the study by guaranteeing the reliability and credibility of the supporting documents (Ampatzoglou et al., 2019).

The search procedure in all databases used different combinations of the following keywords: “open data platforms”, “open data platform”, “collaborative platform”, “data platforms”, “limitations”, “failures”, and “challenges”. For the peer-reviewed documents and conference proceedings, three main research streams were used in the Web of Science and Scopus databases: (i) “open data platforms”, (ii) “open data platforms” AND “limitations”, and (iii) “open data platforms” AND “challenges”. These streams were selected because no relevant documents were found for other different combinations of keywords. The query resulted in 272 documents from the Scopus database and 113 from the Web of Science database. For both databases, the search considered documents published from January 2012 until February 2023, and the following steps were performed:

- In the field “topic” (which includes title, abstract, keywords, and keywords plus), for the database Web of Science.
- By article title, abstract, and keywords for the database Scopus.

Moreover, when concerning the white papers, three research streams were used for the Google Scholar database: (i) “open data platforms” AND “limitations”, (ii) “open data platforms” AND “failures”, and (iii) “open data platforms” AND “challenges”. Precisely, 145 documents were found with these three research streams. The Google Scholar search was conducted by paper title, considering only white papers published from January 2019 until February 2023. A clear identification of the research streams used is necessary to ensure the study’s repeatability – an essential factor in establishing its validity (Ampatzoglou et al., 2019).

Considering the aim of this research, to identify and understand critical limitations and challenges related to ODP that may cause their failure, the titles, abstracts, and full-text contents were reviewed to select the documents and ensure the inclusion of relevant documents. Ferreira et al. (2021) recommend that more than one researcher should conduct this research design stage to enhance reliability and reduce bias. Thus, three researchers with knowledge of ODP and information systems were involved. This approach is relevant to avoid data extraction bias, as Ampatzoglou et al. (2019) pointed out, and to minimize the internal

validity threats identified by Mustafa et al. (2019), which could compromise the study’s validity.

To ensure that only relevant documents were considered, several inclusion and exclusion criteria were defined: only documents written in English were analysed; any documents that did not focus on, or have the potential to focus on, limitations, challenges, barriers, or examples of ODP were excluded; and lastly, documents classified by publication type as “books” or “book chapters” were also excluded. The resulting documents were explored to assess their focus on the potential limitations of ODP and their relevance to the problem formulation.

The initial search yielded 22 documents from Web of Science, 25 from Scopus and 22 from Google Scholar. After removing duplicates and comparing the results across databases, a final sample of 58 documents was obtained. This sample comprised 55 peer-reviewed articles and 3 white papers (which corresponded to industry reports), which were then subjected to a detailed full-text review for the systematic analysis. As it was already mentioned, there can also be risks related to the validity of the research, which, according to Verdecchia et al. (2023), should not be confused with threats to the study’s validity. The selection and study filtering bias cannot be wholly eliminated, as the choice of search queries and filtering criteria may inadvertently lead to the exclusion of relevant articles (Ampatzoglou et al., 2019). To minimize this risk, the streams to be used must be carefully selected, and the selected documents must be read methodically (Mustafa et al., 2019).

After a detailed review of the documents, some were excluded from the scope as they did not address any specific limitations or challenges associated with ODP. Furthermore, some of the documents were also excluded following a quality assessment using Simsek et al. (2025) framework of five practice themes for review research: purpose (identification of purpose), type (refers and mentions the type of review), design (methodological model explained), execution (explicit strategy and reporting), and internal alignment (alignment between purpose, type and design). Documents that did not meet the established criteria were excluded, resulting in a final sample of 34 documents, which were further analysed. Fig. 2 shows the process flow of the documents’ selection and quality assessment adopted in the current research.

Furthermore, the documents considered and selected from each research stage are available in the online appendix at <https://doi.org/10.6084/m9.figshare.28254917> (see Tables A and B).

2.3. Research analysis and interpretation

This stage aims to summarize the information collected from the sample under study. A three-step approach adapted from Gioia et al. (2013) was implemented to ensure qualitative rigour, as presented in Fig. 3.

In Step 1, a first-order analysis was performed to adhere accurately to

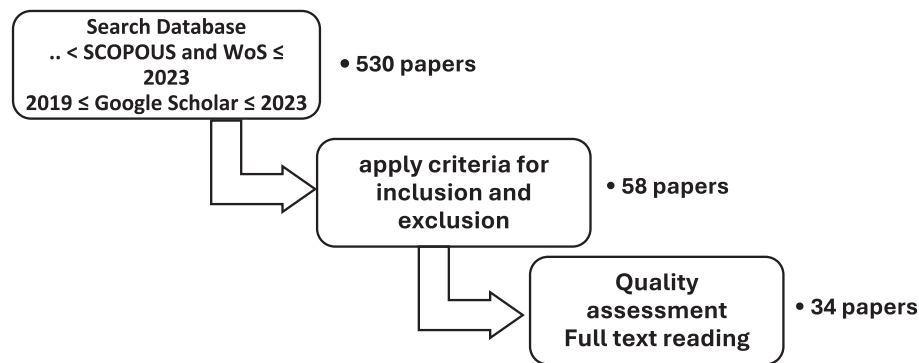


Fig. 2. Paper selection and quality assessment.

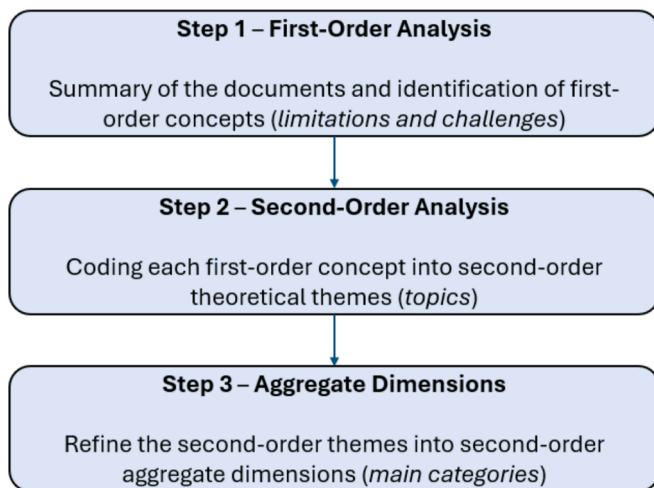


Fig. 3. Paper selection and quality assessment.

Table 2

Topics identification and description.

Topic ID	Topic description
1	Usability – limitations related to searchability, difficulties in accessing data, the reusability of information, data complexity, user-friendliness, the need for collaborative systems, and the demand for integrated open data portals.
2	Data standards – limitations related to the lack of data standards and data standards compliance of Open Data Platforms (ODP) and the information sources on ODP.
3	Privacy and security – limitations related to privacy and security issues of ODP, including information security, assurance of immutability, confidentiality and privacy, legislation, data protection, and data ethics.
4	System design/architecture – limitations, including challenges related to ODP's system design and architecture, interoperability issues, system speed, suboptimal system architectures, technology choices, inflexibility, data stream continuity, over-reliance on a pure database solution, network capacity constraints, and data presentation.
5	Data ownership and copyright – limitations about clarifying data ownership when contributions are made by multiple individuals or organizations, as well as determining who has the right to use the data. This includes ensuring control over data (access, modification, and deletion), securing explicit consent for its use, and addressing copyright-related challenges. This topic also includes challenges related to copyright.
6	Users' engagement —issues related to the active participation of the users in accessing, utilizing, contributing to, and providing feedback on the available open data. Their curiosity, motivations, interests in the project, and individual benefits. The relevance and usefulness of the data available on the platform if it addresses the users' needs.
7	Data literacy – challenges related to issues such as lack of awareness, technical skills, or language barriers; difficulty in understanding the data.
8	Resources (for development and maintenance) – lack of financial and human resources required to develop, maintain, and update the ODP, ensuring that individuals and organizations have the technical and organisational capacity to collect, manage, and use data effectively.
9	Organizational culture and habits – limitations related to closed government culture, traditional top-down and control-laden structures that prevent the evolution of more collaborative solutions.
10	Trust – overall lack of trust: citizens and companies in the public sector, public sector and citizens in companies, and all parties in open data and its applications.
11	Data compatibility – limitations related to inconsistency of datasets due to a variety of sources, lack of standards, or metadata stored in different places.
12	Data quality – limitations related to lack of data quality that prevent extracting all its value and address the issues of processing capabilities, facility of use, clarity, integrity, and metadata quality and provenance.
13	Economic Impact – challenges to demonstrate the positive influence that the ODP can have in various sectors and society, especially the long-term outcomes that are difficult to quantify.

Notes: ODP – Open Data Platforms

important terms (Gioia et al., 2013). The researchers started by summarising the information extracted from the final sample and identified each document's main challenges and limitations.

In Step 2, after seeking differences and similarities among the first-order concepts, the researchers coded each at a more abstract second-order theoretical level of themes (Gioia et al., 2013). Each challenge and limitation, previously identified in Step 1, was coded within a topic to provide an insightful analysis of the collected elements and synthesize the literature findings. Given that some documents referred to the same limitation or challenge, the researchers created 13 distinct topics to standardise the classification of each limitation and challenges identified in the literature. The topics created and the description of each are presented in Table 2.

Finally, in Step 3, following Gioia et al. (2013), the researchers refined the emergent second-order themes into second-order aggregate dimensions. The topics identified in each document were grouped into five main categories of challenges and limitations regarding ODP, according to Hyseni & Bexheti (2022):

- **Institutional**—This category involves limitations and challenges related to resources (needed to develop and maintain the platforms), organizational culture, and habits.
- **Information quality**—This category comprises limitations and challenges related to the quality of the information disposed of and accessed on the platforms and trust issues from the stakeholders involved.
- **Legislation**—Limitations and challenges within this category relate to the usability of the platforms, data standards and policies, data ownership, and copyrights.

- **Technical**—This category contemplates limitations and challenges related to privacy and security, system design, architecture, and characteristics (such as data compatibility, speed, and interoperability).
- **End-users**—This category considers limitations and challenges from the end-users’ perspective, namely limitations and challenges related to users’ engagement and data literacy.

Thus, to analyse the collected information and facilitate the synthesis and ranking of each document (Ferreira et al., 2021), five analytical categories and subcategories were created and are presented in Table 3.

3. Main results and critical analysis

3.1. Presentation of results

This section corresponds to the fourth stage of the research methodology (presented in Fig. 1). The aim was to analyse the sample contents in detail and provide insights into the problem formulation. A data structure was created to configure the data into a visual aid and show the progress from raw data to terms and themes (Gioia et al., 2013). The data structure is available in the Appendix A section at the end of the manuscript (Table A.1).

3.2. Critical analysis of the results

A total sample of 34 documents was analysed, and most of them employed empirical research methods (26 documents), primarily using case studies and surveys. Only 8 documents used analytical research methods, with literature reviews and future research. Of the 34 documents, 16 were published in International Journals, 16 were published in Conferences Proceedings, and 2 documents corresponded to White Papers. Thus, the analysis reveals that analytical studies structuring the existing knowledge about ODP are needed.

All documents analysed highlighted different limitations and challenges related to ODP in different contexts. As some authors referred to the same limitation or challenge but with a different vocabulary, in this study, the researchers created 13 topics (according to Table 2) to standardize and group the limitations and challenges identified in each document. Based on the analysis of the results, some conclusions can be retrieved.

Fig. 3 presents the distribution of the topics identified in the sample

Table 3
List of categories and subcategories considered for the analysis of the sample.

Category	Subcategory
Document Identification	Authors and publication date – list of authors and year of publication. Type of publication – Conference name, International Journal name, White-paper.
Research Methods ^(a)	Empirical – statistical sampling (for example, surveys or experts’ panels), case studies, mixed methods, experimental design, content analysis. Analytical – conceptual studies (for example, future agenda/research/scenarios or conceptual frameworks or models). Others – studies that do not fall under empirical or analytical categories.
Platform’s limitations and challenges	Limitations and challenges – main limitations or challenges related to ODP as described in the documents.
Topic Identification	Topics of limitations and challenges – for example, usability, data standards, privacy and security, data literacy, among others, as listed in Table 2.
Category of limitations and challenges ^(b)	Category of limitations and challenges – including institutional, information quality, legislation, technical and end-users.

Notes – ^(a) – Ferreira et al. (2021); ^(b) – Hysemi & Bexheti (2022)

under study and allows the identification of the five most critical topics of limitations and challenges found in the literature that may lead to the failure of ODP. These correspond to Usability, System Design/Architecture, User’ Engagement, Privacy, and security and Resources, which will be analysed in detail.

From Fig. 3 and considering the sample under study, it is evident that Topic 1, referring to Usability, is the most highlighted in the literature (present in 16 % of the documents). Indeed, several authors, such as Delone & McLean (2003) and Osagie et al. (2017), concluded that any product, including ODP, is only considered successful if it possesses the characteristics desirable by those who need the product. Overall, by ISO 9241–11:2018, usability is defined as the extent to which specific users can use a product to achieve goals with effectiveness, efficiency, and -satisfaction in a specified context. In ODP, the topic of limitations and challenges related to usability includes searchability issues, difficulty in accessing data, difficulty in the reuse of information, complexity of data, ease of use of data and the platform, the need for collaborative systems for users, and the need for joint open data portals. Osagie et al. (2017) highlighted the benefits of measuring usability. On the one hand, end-users can reduce costs and increase productivity, satisfaction, and ease of use. On the other hand, good software usability helps to reduce international standards and legislative requirements and helps to minimise user demand pressures while increasing a supplier’s market share.

Furthermore, from Fig. 3, it is possible to conclude that Topic 4, which refers to System design/architecture, is the second most emphasized topic in the literature (highlighted in 14 % of the documents). Limitations and challenges regarding the System design/architecture of ODP are mainly concerned with interoperability issues. According to Ali et al. (2022), the European interoperability framework defines interoperability as the meaning of the open data elements and the relationship between them. It includes developing a vocabulary that describes data exchange and ensures that data elements are understood identically by communicating with all parties. In ODP, according to Won et al. (2021), interoperability challenges and limitations have to do with the inexistence of interconnection standards. Many existing platforms do not have metadata management guidelines for data distribution and publication, thus reducing the interoperability between ODP. Other challenges and limitations included in the Topic of System design/architecture are related to problems with the system speed, the required capacity of the network, and imperfect system architectures. As highlighted by Laufs et al. (2022) and Vítor et al. (2022), the platform needs to keep performant as the number of sources and services increases, and the architecture needs to be persistent and scalable to vast amounts of data, ensuring a high intensity of data exchange and the continuity of the data stream. Other authors, such as Osagie et al. (2017), highlighted challenges and limitations concerning data structure in terms of presentation and layout on screens. Moreover, Correa et al. (2018) concluded that there is a gap between the adoption and the effective use of ODP, particularly regarding technology choices (which are supported by the number of available datasets and the number of running platforms at the point of data collection).

Another conclusion that can be retrieved from Fig. 3 is that Topic 6, related to Users’ engagement, is the third most frequently mentioned topic of limitations and challenges in the literature (mentioned in 13 % of the documents), specifically within the context of governmental ODP. The topic of users’ engagement involves challenges and limitations connected to the end users of ODP, namely issues in their access, utilization, contribution, feedback, personal interests, and individual benefits. This can be explained by the fact that several designs do not consider non-technical users with low technical skills and are illiterate in data. Furthermore, authors such as Gutierrez and Landa (2022) and Osagie et al. (2017) highlighted the usefulness and relevance of available data. The authors concluded that ODP can be negatively affected by a discrepancy between what the designer creates and what the user needs. The challenges and limitations concerning the usefulness and relevance of ODP are also included in the topic related to Users’

engagement.

Furthermore, Topic 3, which refers to Privacy and Security, is also highlighted in some documents (present in 11 % of the documents). This topic includes ODP's challenges and limitations regarding unsound privacy, data protection, and security. According to Aonghusa (2014), data privacy (or confidentiality) is considered one of the main challenges of ODP, as privacy violations can occur when publishing open data, where benign datasets, when linked together, can allow the inference of sensitive knowledge patterns. Other authors, such as Kapoor et al. (2015) and Blok et al. (2017), concluded that concerns in terms of legality and legislative limitations may also be considered challenges faced by ODP that are included within the topic of Privacy and Security. While the concept of open data remains in a state of early development, it is critical to have specific legislation and policies tailored for open data and ODP. A well-established policy and legislation for ODP provide guidance, such as privacy impact assessment, and alleviate concerns about potential liabilities (Yang et al., 2015). Furthermore, challenges related to the data provenance storage system that assures data's immutability, privacy, and confidentiality are also included in this topic (Dang and Duong, 2021).

Lastly, Fig. 3 evidences that Topic 8, which refers to Resources (for development and maintenance), is also considered critical in the literature (mentioned in 10 % of the documents). This topic includes challenges and limitations related to the lack of financial and human resources. The literature reveals that developing, maintaining, and updating an ODP requires financial and human resources (Welle Donker & Kuveždić Divjak, 2023; Nguyen & Won, 2017; Kapoor et al., 2015). The lack of these resources, including the limited budget (Ojo et al., 2016) and the costs associated with opening data (such as resources and time) (Kapoor et al., 2015), imposes a challenge to the development of these platforms. Other authors, such as (Nugroho et al., 2015), highlight that integration costs need a better-oriented model. These limitations arise due to the free-for-all nature of ODP and the difficulty of balancing free access and data providers' need to gain their income from selling data (Nugroho et al., 2015; Eberius et al., 2012). Investing in these resources is required to ensure that individuals and organizations have the technical and organisational capacity to collect, manage, and use data effectively.

3.2.1. Conceptual model for classification of challenges and limitations related to ODP

In this research and the search for data from heterogeneous sources, a conceptual model is proposed to separate and distinguish each of the identified topics of challenges and limitations related to ODP. The conceptual model from Hyseni & Bexheti (2022) was adapted and updated within the context of this research and is presented in Fig. 4. The aim was to categorise the challenges and limitations highlighted in

the literature concerning ODP. In this research, one of the categories from the original Hyseni & Bexheti's (2022) work, the Task Complexity, was removed. The literature evidence highlights a lack of studies considering the challenges and limitations of ODP from a user's perspective (Benó et al., 2017a; Osagie et al., 2017). Thus, the proposed model included a new category of utmost importance in the literature: the End Users category. Fig. 5.

If, on the one hand, the Task Complexity category could cover several of the highlighted challenges and limitations (for example, it may be related to the topic of usability but also to the topic of users' engagement), and considering that the topic related to users' engagement is one the most mentioned in the literature, the End-users category was created. This category aims to understand challenges and limitations that were intrinsically linked to the user perspective, more specifically, their predisposition and ability to use the platforms and the data therein, the uses they may have for them, and their contribution to improving the experience from their perspective.

Considering the sample under study, the Technical category of limitations and challenges is the most recurrent in the literature (represented in 48 % of the documents). Moreover, the End Users category of challenges and limitations is also starting to be explored in the literature (highlighted in 17 % of the analysed documents). This may reflect the difficulty in obtaining active participation with inputs, contributions, and feedback from users, as well as the importance and usefulness that they attribute to the data available on the platforms. Regarding the other categories within the conceptual model, challenges and limitations related to the Institutional category were highlighted in 16 % of the documents. Legislation and Information Quality categories were present in 11 % and 7 % of the documents, respectively.

To summarize the main results of the analysis, Table 4 presents a synthesis of the sample under study relating to analysed categories, topics, and references.

4. Discussion and proposed mitigation actions

This study pointed out the research gap in the development of ODPs and provided an overview of the limitations and challenges of these platforms. A collection of the various topics related to the limitations and challenges explored in the literature was carried out, and a conceptual model to classify each of them within 5 main categories was proposed. To improve the overall effectiveness and success of ODPs, a list of actions to mitigate each category of limitations and challenges from the conceptual model and their respective topics was proposed and highlighted in Table 5. These measures are elaborated in detail in the further sub-sections.

4.1. Technical improvements

A solid technological framework can significantly enhance a platform's success (Laufs et al., 2022). Improving the usability of open data platforms can enable users to use open data more effectively. Strategies to maximize usability include conducting user experience (UX) research, designing user-friendly interfaces, and providing robust user support channels. Measuring user experience and satisfaction is crucial and can be achieved through specific research methods, such as consultation surveys (Osagie et al., 2017). One strategy for collecting data on user experience involves gathering user-generated usability reports, where users share the challenges they encounter (Twidale et al., 2021). Researchers can also conduct usability testing by observing user interactions. The insights gained from user feedback are essential for fostering a culture of continuous improvement (Bawa, 2024). Additionally, when accessing open data portals, users expect a certain level of technical support to help them navigate and utilize the data effectively (Osagie et al., 2017).

The deployment of technical infrastructures with the ability to assist, for example, the searchability, analysis, and visualisation of data,

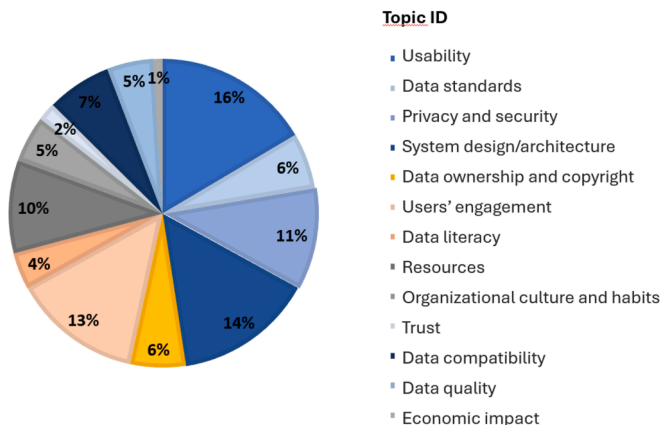


Fig. 4. Distribution of topics highlighted in the literature.

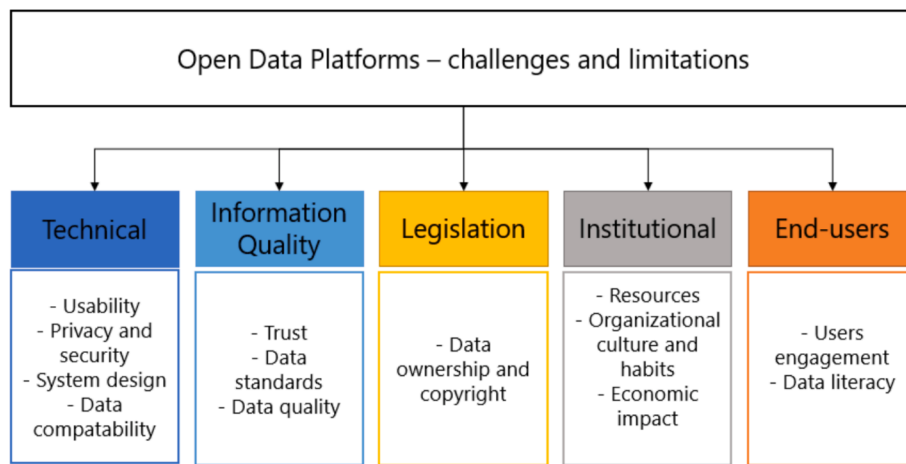


Fig. 5. Conceptual model for classification of challenges and limitations related to ODP. Adapted from [Hyseni & Bexheti \(2022\)](#).

enhances the ease of use, offering a more user-friendly interaction with the data, thus enhancing data usage ([Nikiforova & McBride, 2021](#)). Intuitive and straightforward interfaces with a focus on simplicity of design are crucial to enabling access to open data ([Osagie et al., 2017](#)). User support channels, such as forums, video chat, mobile messaging, and helpdesks, are necessary to improve usability. User support is an essential component of usability. Hence, user support channels should be evaluated to ensure they effectively assist the user ([Bawa, 2024](#)). In addition, user support channels can be used to obtain insight into users' usability difficulties. Using social media, a channel with high visibility, to voice discontent towards usability may also be a productive way to appeal to the need to improve specific usability issues ([Twidale et al., 2021](#)).

Regarding privacy and security, it is recommended to adopt robust encryption methods to protect sensitive data, adhere to data privacy regulations and best practices, and provide users with detailed control over their data-sharing preferences. Strong encryption protects data, and securing sensitive and confidential data is essential. It is critical to encrypt data to prevent its decryption via cryptanalysis ([Dixit et al., 2018](#)). In the context of open data, the platform provider must adopt privacy regulations that are acceptable according to the user ([Wiencierz & Lünich, 2020](#)). Due to the nature of open data, it is essential that privacy protection accounts for its different uses ([Gkoulalas-Divanis & Mac Aonghusa, 2014](#)). Given the nature of open data, privacy protection must accommodate its various uses ([Gkoulalas-Divanis & Mac Aonghusa, 2014](#)). Data collected from individuals often contains granular details and is utilised by multiple private and public entities to support decision-making ([Blok et al., 2017](#)). Users should have the ability to personalize their preferences regarding the personal data they choose to share and disclose ([Asswad & Marx Gómez, 2021](#)).

At the system design and architecture level, it is recommended to use modular design principles, evaluate and optimize system performance, and employ cloud-based architectures for flexibility and scalability. Modular design allows systems to be structured with interchangeable modules, enabling customization. Modular components provide flexibility without compromising key functionalities ([Bawa, 2024](#)). Modular architecture enables different entities operating in various sectors to configure the components according to their needs ([Dang & Duong, 2021](#)). Various strategies can generally be used in information systems to evaluate and optimize systems' performance, such as conducting user testing, statistical tests to assess significance ([Sansonet, 2019](#)), and experimental assessment using real scenarios ([Ferrato et al., 2022](#)). Deploying cloud-based architectures represents several benefits, such as agility ([Achar, 2019](#)), scalability ([Soltanian et al., 2018](#)), and flexibility ([Pahl et al., 2018](#)).

Data compatibility constraints can be minimised by implementing data validation and cleansing processes, establishing data governance policies, providing data conversion tools, and adopting standardized data formats and schemas. Data cleansing, or data cleaning, improves data quality by identifying and removing errors and discrepancies that can impact data analysis ([Ridzuan & Wan Zainon, 2019](#)). Through data cleaning processes, it is possible to detect duplications, incomplete data, and other inconsistencies using analytic functions ([Gudivada et al., 2017](#)).

Data governance concerns the control and authority in managing data, enhancing the value of the data, and decreasing costs and risks ([Abraham et al., 2019](#)). Establishing data governance strategies enables the stakeholders to deploy specific instruments to attain their objectives, including how data is assembled and controlled, the value it creates, and the standards and algorithms it uses. It also encompasses general ethics, politics, and economic precepts that are part of the data infrastructure ([Micheli et al., 2020](#)). Moreover, data conversion tools are essential due to the plethora of data formats and sources, assisting in converting data so it can be used in supported formats ([Vitor et al., 2022](#)). Adopting standardized data formats and schemas is key to one of the core characteristics of open data, which is its public availability in usable formats ([Gutierrez & Landa, 2022](#)).

4.2. Enhancing information quality

Improving information quality is intrinsically connected to addressing the three main limitations that emerged from the results: trust, data standards, and data quality. Investing in transparency and effective communication is necessary to enhance trust. [Dang & Duong \(2021\)](#) recommended an approach resorting to blockchain that enhances transparency, as it impedes the modification of data provenance. Transparency traditionally relates to accountability ([Gutierrez & Landa, 2022](#)). Open science promotes a greater sense of public trust by performing a systemic shift where transparency exists across the system ([Mancini et al., 2020](#)). Communication must occur ethically, ensuring that information is provided completely and accurately. Moreover, the platform providers should explicitly communicate the data type they generate to the users. The more information is provided to the user concerning open data's use, the more they consider the platform to be trustworthy ([Wiencierz & Lünich, 2020](#)).

To enhance data standards, firstly, it is necessary to establish data standards and guidelines; secondly, to ensure data standards compliance; and thirdly, to provide data standardization tools and resources. A key characteristic of open data is its capacity for reusability. To become reusable and, hence, accessible in different applications of varying

Table 4

Synthesis of the results in terms of categories, topics, and references in the literature.

Category	Topic	References
Technical	Usability	(Ali et al., 2022), (Osagie et al., 2017), (Hyseni & Bexheti, 2022), (Laufs et al., 2022), (Ojo et al., 2016), (Nugroho et al., 2015), (Ronzhin et al., 2019), (Ruijter, Grimmelikhuijsen, Hogan, et al., 2017), (Millette & Hosein, 2016), (Duval & Brasse, 2014), (Cappgemini Invent et al., 2020), (Krasikov et al., 2020), (Ali et al., 2023), (Braunschweig et al., 2012), (Dufief, 2017)
	Privacy and security	(Ali et al., 2022), (Hyseni & Bexheti, 2022), (Nugroho et al., 2015), (Krasikov et al., 2020), (H. Yang et al., 2022), (Beno et al., 2017b)
	System design/ architecture, system speed, interoperability	(Osagie et al., 2017), (Laufs et al., 2022), (Vitor et al., 2022), (Correa et al., 2018), (K. Kapoor et al., 2015), (Nguyen & Won, 2017), (Nugroho et al., 2015a), (Eberius et al., 2012), (Millette & Hosein, 2016), (Krasikov et al., 2020), (Ali et al., 2023), (H. Yang et al., 2022), (Beno et al., 2017b), (Lapi et al., 2012)
	Data compatibility	(Correa et al., 2018), (Blok et al., 2017), (Nguyen & Won, 2017), (Ojo et al., 2016), (Millette & Hosein, 2016), (Wang et al., 2018)
Information quality	Data standards	(Ali et al., 2022), (Hyseni & Bexheti, 2022), (Nugroho et al., 2015), (Krasikov et al., 2020), (Ali et al., 2023), [31], (Beno et al., 2017b)
	Trust	(Welle Donker & Kuveždić Divjak, 2023), (Dufief, 2017)
	Data Quality	(Kapoor et al., 2015), (Ojo et al., 2016), (Millette & Hosein, 2016), (Cappgemini Invent et al., 2020), (Liu et al., 2018)
Legislation	Data ownership and copyright	(Hyseni & Bexheti, 2022), (Nugroho et al., 2015), (Ruijter, Grimmelikhuijsen, Hogan, et al., 2017), (Cappgemini Invent et al., 2020), (Ali et al., 2023), (Beno et al., 2017b)
Institutional	Resources	(Osagie et al., 2017), (Kapoor et al., 2015), (Blok et al., 2017), (Welle Donker & Kuveždić Divjak, 2023), (Ojo et al., 2016), (Nugroho et al., 2015a), (Eberius et al., 2012), (Beno et al., 2017b), (Roy, 2016)
	Organizational culture and habits	(Nugroho et al., 2015), (Cappgemini Invent et al., 2020), (Krasikov et al., 2020), (Dufief, 2017), (Roy, 2016)
	Economic Impact	(Liu et al., 2018)
End-users	Users' engagement	(Osagie et al., 2017), (Correa et al., 2018), (Kapoor et al., 2015), (Welle Donker & Kuveždić Divjak, 2023), (Ojo et al., 2016), (Nugroho et al., 2015), (Krasikov et al., 2020), (Ali et al., 2023), (Dufief, 2017), (Beno et al., 2017b), (Ruijter, Grimmelikhuijsen, & Meijer, 2017)
	Data literacy	(Gutierrez & Landa, 2022), (Welle Donker & Kuveždić Divjak, 2023), (Nugroho et al., 2015), (Roy, 2016)

functionalities, with minimum changes necessary, data requires standardization (Millette & Hosein, 2016). Interoperability and standards are followed with different available tools and techniques, such as security protocols. Semantic, syntactic, organizational, and legal interoperability are four layers of open data portals (Nugroho et al., 2015b;

Table 5

List of actions to mitigate each category of limitations and challenges to the development of ODPs.

Category	Limitations/ Challenges	Mitigation actions
Technical challenges	Usability	Conduct User Experience (UX) research User-friendly interfaces User support channels
	Privacy and Security	Strong encryption methods to protect sensitive data Adhere to data privacy regulations and best practices. Provide users with granular control over their data-sharing preferences
	System Design/ Architecture	Use modular design principles Evaluate and optimize system performance Use of cloud-based architectures for flexibility and scalability
	Data Compatibility	Implement data validation and cleansing processes Establish data governance policies Provide data conversion tools Adopt standardized data formats and schemas
Information quality	Trust	Transparency and Effective Communication
	Data standards	Establish Data Standards and Guidelines Ensure Data Standards Compliance Provide Data Standardization Tools and Resources
	Data quality	Improvement of Data Collection Data Quality Assurance Proper Metadata Documentation Provide Data Processing Tools Establish Data Provenance Policies
Legislation	Data ownership and copyright	Establish Clear Data Ownership Policies Obtain Explicit Consent for Data Use Address Copyright and Intellectual Property Issues Provide Legal Guidance and Support Monitor and Adapt to Legal Changes
Institutional	Resources	Prioritise budget allocations Ensure sufficient financial resources are allocated for staffing, infrastructure, and technology. Explore Outsourcing Options
	Organizational culture and habits	Empower employees to contribute Establish Cross-Functional Teams and Collaborative Structures Encourage continuous improvement through regular feedback
	Economic Impact	Conduct Economic Impact Assessments Identify Key Performance Indicators (KPIs) Develop Case Studies and Success Stories
End-users	Users' engagement	User-Centric Design Approach Simplify Access and Utilization Enhance Data Relevance and Usefulness
	Digital Literacy	Promote Data Literacy and Skills Development

Roy, 2016). Data communication standards should be clear when uploading data (Laufs et al., 2022). Standards compliance assists the continuous development and enhancement of data, and it can be achieved with automatic solutions that perform reports on standards compliance (Yaman & Brennan, 2020). These automated tools/systems can support compliance with options for data configuration, curation, and sharing (Singh et al., 2019). Also, they can be rules-based and assess the compliance of the data with the predefined models to ensure its

consistency (Yaman et al., 2023). Data standardization tools and resources enable raw data to become usable by pre-processing data (Rahman, 2019). These tools allow noise reduction, data cleaning, and data normalisation and address missing values (Khalaf et al., 2020).

Enhancing Data quality entails improving data collection, data quality assurance, proper metadata documentation, providing data processing tools, and establishing data provenance policies. Participating in the data collection process demands developing specific skills (Santos-Hermosa et al., 2023). Data provenance policies offer information about the origin of the data, its sources, the transformations it has undergone, and the history of those transformations (Gudivada et al., 2017). Data quality assurance is also related to how easily non-expert users understand the data. To improve this aspect, data should be associated with descriptions and metadata to assist in describing the dataset and its content (Millette & Hosein, 2016). Metadata quality impacts on the semantic interoperability of data. Metadata schema (MS) can help reduce integration, development, and information-sharing costs. MS can improve interoperability across systems with similar or shared metadata. Interoperability solutions for European public administrations represented five levels of maturity of metadata management (Ronzhin et al., 2019). The metadata maturity levels are essential for analysing different open data platforms.

The existence of data processing tools is essential for data quality in the sense that they are responsible for the analysis and refinement of raw data. Through algorithms and machine learning, these processing tools detect patterns, trends, and errors (Šprem et al., 2024). Various data processing techniques can be used according to the type of data. While structured data can mostly resort to data cleaning or reduction techniques, other more complex processing tools may be required for semi-structured or unstructured data (Sun et al., 2018).

4.3. Legislative measures

Data ownership and copyright can be protected by establishing clear policies, obtaining explicit consent for data use, addressing copyright and intellectual property issues, providing legal guidance and support, and monitoring and adapting to legal changes. The complexity of data ownership begins with its significance. On one hand, it can be interpreted as the responsibility and accountability for information quality. On the other hand, it can be interpreted from the perspective of the holder of the data's rights. Data ownership is central to organisations and users, as it ensures rights and builds trust. Hence, data ownership policies must be established (Asswad & Marx Gómez, 2021). Individuals' informed consent is a fundamental principle of research ethics (Gefenas et al., 2022). Obtaining explicit consent is crucial when using data. Some consent forms fail to fully inform users about the implications of their data being collected, analyzed, and repurposed. Therefore, it is essential to follow best practices to comply with legal requirements and meet the expectations of data owners (Hutton & Henderson, 2017).

Open data should be non-proprietary and accessible with open licensing to enable use and distribution by any user. When preparing data for the open platform, at the initial stage, it is necessary to establish the legal framework by deciding the policies, the licenses, and the legal review (Ali et al., 2022b). By addressing copyright and intellectual property issues, the sovereignty and ownership of the data become a guarantee, and this facilitates the process of involving all stakeholders (data owners, users, companies) at the same time that it creates trust (Asswad & Marx Gómez, 2021).

Legal guidance and support are outlined as mitigation actions, mainly due to the uncertainty surrounding the legal aspects of open data. There are reports of users and data-providing entities being uninformed of the legally binding intellectual property rights. Knowing the legality of using data is paramount (Hirth, 2020). Legal guidance can occur within the context of specific training, in the form of lectures or workshops, for example, where open data's legal domain can be explored and explained (Santos-Hermosa et al., 2023). Furthermore,

organisations need to remain updated on current legislation in the European Union; for example, there are several legal documents, with varying reach, to consider regarding data protection, such as the European General Data Protection Regulation, the Charter of Fundamental Rights of the European Union, and the European Convention on Human Rights (Asswad & Marx Gómez, 2021). Given that regulatory requirements are constantly modified, it is essential to implement flexible technology to adapt to these changes (Laufs et al., 2022).

4.4. Institutional challenges

Three primary mitigation actions have emerged to improve resources: prioritize budget allocations, ensure sufficient financial resources for staffing, infrastructure, and technology, and explore outsourcing options. When allocating the budget, it is crucial to understand the various processes involved. For instance, data cleaning typically requires around 40–50 % of the budget (Ridzuan & Wan Zai-non, 2019). Also, large and functionally diverse teams can have a negative impact on budgets. In information systems projects, for example, large-scale development represents a higher cost due to the technology, personnel, and overall infrastructure (Sanchez et al., 2017). In cases where budget might be an issue, outsourcing to third parties can be an option, although data ownership needs to be established from the beginning (Ruijter et al., 2020).

Organizational culture and habits can be enhanced by empowering employees to contribute, establishing cross-functional teams and collaborative structures, and encouraging continuous improvement through regular feedback. An essential dimension of employee empowerment is training, and in the case of open data platforms, some studies report the need to support and train research teams, for example (Santos-Hermosa et al., 2023). Management must possess soft skills to encourage the contribution of Sanchez et al. (2017). Teams must be diverse, with different backgrounds and areas of expertise (Laufs et al., 2022). Cross-functional teams offer a wide range of skills, viewpoints, and efforts, liberating team members to act within their expertise without covering all the workload needs (Bell et al., 2018). Moreover, feedback is at the foundation of human development and is central to team improvement. Regular feedback offers employees insight into their performance, recommendations for adjustments and prospective actions, and strategies for improvement (Handke et al., 2022). The provision of feedback can also be shifted from the traditional performance appraisal and focus on obtaining insight into the main difficulties facing employees, having a strategy to build motivation, promote commitment, and improve performance (Murphy, 2020).

The economic impact can be enhanced by conducting assessments, identifying KPIs, and developing case studies and success stories. Economic impact assessments assist organizations in determining the financial benefits of open data platforms. Even though many organisations already recognise the added value of open data, its economic potential can remain unaccomplished without this assessment (Krotova et al., 2020). Furthermore, assessing the financial impact depends on the perspective of the entities. Considering, for example, open data advocates at a supply level, the innovation and entrepreneurship that are generated are recognised as economic impact, independently of business potential (Herala et al., 2016).

A strategy for monitoring economic impact is via the identification of KPIs. There are numerous frameworks to evaluate open data from various perspectives, such as transparency, type of data, platform performance, accessibility to the user, and data governance (Welle Donker & van Loenen, 2017). Other factors that can be used as performance indicators can be derived from a more institutional perspective and account for organizational openness, leadership, inter-agency collaboration, and cooperation between private and public entities (Sayogo & Yuli, 2018). In addition, KPIs can be defined at the level of the user experience, identifying core metrics such as user satisfaction ratings or time-on-task (Bawa, 2024). Drawing upon success stories and case

studies can assist organisations in understanding the impact of open data platforms, obtaining insight into what works and the lessons learned from these cases. Bonina & Eaton (2020) used a comparative case study in three Latin American cities to explore government open data platforms and provide recommendations based on their experience. Similarly, de Juana-Espinosa & Luján-Mora (2020) examined the factors that can lead to the successful deployment of open government data platforms in a comparative analysis of 28 countries in the European Union. These studies can bring invaluable insight that can assist other platforms in prospering.

4.5. End-users empowerment

With concern for challenges end users face, three strategies can be implemented to increase users' engagement: employing a user-centric design approach, simplifying access and utilisation, and enhancing data relevance and usefulness. Concerning system design, some technical issues can be minimised with user-centred design (Nikiforova & McBride, 2021). The simplification of access and use allows for a more encompassing contribution of the users. Simplifying data addition, for instance, enables more users to add data, enriching the platform's contributions (Blok et al., 2017). There is a need for solutions to assist users in navigating open data and using it to support their decision-making, which will improve the relevance of open data (Kapoor et al., 2015). It is fundamental for user participation that the data is relevant at a social and practical level. Users need to know what type of data is available and what possibilities exist for using that data (Ruijter, Grimelikhuijsen, Hogan, et al., 2017).

Digital literacy plays a vital role in using open data platforms as it conditions the users' access. Promoting data literacy and skills development is necessary to improve digital literacy. Data literacy includes technical as well as numerical and statistical skills to work with datasets (Gray et al., 2018). Gray et al. (2018) proposed the use of an alternative concept – “data infrastructure literacy”, which is a more encompassing notion. According to the authors (p1), it considers the skills necessary to “intervene around and participate in the wider socio-technical infrastructures through which data is created”. It allows the users to have a critical stance towards the use of data by understanding the purpose behind creating datasets and how they can be used and organised differently. Hence, skills development can assist users to benefit more fully from using open data. Technical skills, for example, allow users to download, analyse and interpret the content on the platform (Santos-Hermosa et al., 2023). In addition, the training resources that are available for the users should be evaluated to validate their effectiveness in empowering the user and contributing to a successful experience (Bawa, 2024).

5. Conclusions, contributions, and limitations

When examining Open Data Platforms, it is critical to understand their revolutionary potential and consider evident challenges that have been overlooked. This research intended to understand why ODP fails. To do so, a careful and comprehensive analysis has been built on limitations and challenges concerning these platforms. A systematic literature review was performed to identify the critical challenges and limitations that may affect the performance of an open data platform. The review allowed the identification of 13 different topics of challenges and limitations concerning ODP, namely usability, data standards, system design/architecture, privacy and security, data ownership and copyright, users' engagement, data literacy, resources, organizational culture and habits, trust, data compatibility, data quality, and economic impact. Examining the most cited topics makes it evident that they are all connected to some degree. The lack of resources, both human and financial, can condition the system's design/architecture options, which, in turn, can influence the privacy and security requirements as well as the usability of the data. In addition, all these limitations can harm the users' engagement with the open data platform. More

importantly, scrutinising the limitations and challenges of open data platforms served as a gateway to explore strategies to assist them in attaining their potential.

A conceptual model from the literature is updated to separate and categorize the different limitations and challenges relating to ODP. This model groups the topics created by the researchers into five main categories of challenges and limitations: Technical, Institutional, End-users, Data quality, and Legislative. Furthermore, several mitigation actions were proposed to deal with each category of the model.

At the technical level, assessing how technology can enhance the user experience is essential. Enhancements such as more user-friendly interfaces, stronger encryption, cloud-based architecture, and adopting standardised data formats and schemas can significantly improve data accessibility. In terms of the data itself, considering the categories of information quality, it becomes evident that implementing transparency, data standards, ensuring the quality of the data, and establishing data provenance tools can provide a more reliable setting where users are more trusting of the data and data-providing companies are more willing to share their datasets. From a legislative perspective, establishing data ownership and explicit consent for data use and providing legal support and guidance are equally crucial in fomenting trust and increasing the data's reliability. Institutionally, the improvements focused on strategies of efficient budget allocation, personnel empowerment, and the definition of metrics to assess progress and success. Finally, end-users challenges emphasised the technological aspect of improving access and empowerment through digital literacy and competencies development. In analysing these mitigation actions, it becomes evident, similarly to what emerged with the limitations, that improvements in one category led to enhancing the other categories. Hence, open data portals require a systemic response, a series of combined actions from various stakeholders and domains.

Thus, this research allowed to structure the existing knowledge about the main limitations and challenges concerning ODP. By identifying these challenges and limitations and categorizing them, it is possible to understand the potential causes that impact the performance of an open data platform, leading to its failure. Furthermore, through the proposal of different mitigation actions, this research aims to help deal with the challenges and limitations faced by ODP, contributing to the prevention of potential failures.

5.1. Theoretical and practical contributions, limitations and future research

This research identified and categorized the key challenges and limitations related to ODP. Theoretically, it helped organise the existing, though limited, knowledge of ODP. A conceptual model from the open data literature was adapted and updated to fit the ODP context, introducing a new category of challenges and limitations: the end-users category. Furthermore, this research proposes several mitigation actions to help deal with the challenges and limitations of ODP, which might compromise their performance.

On the other hand, there are significant practical implications as well. By understanding ODP's main challenges and limitations, valuable insights can be gained into the potential causes of these platforms' failures. ODPs are being used and developed worldwide in different contexts and must ensure that data is accessed in an unaltered and integral form and that their users access and use data correctly. With an updated model of challenges and limitations and a proposal of mitigation actions, practitioners and developers can benefit from this research to ensure that these platforms meet business requirements, support secure and reliable decision-making, and effectively facilitate operations.

However, several limitations exist within this research. Due to the limited number of studies available, it is clear that this area requires further investigation. The researchers created 13 different topics to code and standardize the challenges and limitations identified in

the literature. However, additional topics may arise with further research. Furthermore, it is essential to highlight that this research used qualitative methods; thus, the proposed conceptual model could not be validated. This can lead to a generalisation threat, where findings may not be applicable across different domains. Another limitation arose from the research methodology, especially the inclusion/exclusion criteria, which considered only documents written in English. This may have excluded relevant non-English studies that could have contributed valuable insights. Only two white papers were considered in the sample under study, which leaves out potential documents that could provide more comprehensive examples of open data platforms within and beyond the governmental context. Future research could mitigate the challenge of missing relevant documents through snowball forward and backward techniques, for example. Moreover, future research venues could adopt a more inclusive approach by engaging ODP developers and users, potentially yielding more case studies and examples to deepen understanding in this area of research.

This research indicates that the debate surrounding ODP is still in its early stages, emphasizing the need to explore this area further. To ensure progress and continuity, several potential research directions are suggested. Future studies should aim to validate the proposed conceptual model using both quantitative and qualitative methods. Conducting case studies is recommended to test and confirm the model's applicability. Additionally, comparative studies of ODP are needed to assess whether the criteria proposed in this research contribute to a deeper understanding and more effective analysis of these platforms.

Furthermore, there is a need to investigate real-world cases of ODPs beyond the governmental sector and map the key stakeholders involved and their roles to promote broader adoption and effective use of ODP.

Appendix A

Appendix.

Table A1

Characterization of the limitations and challenges presented in the sample under study.

Paper ID	Type of publication	Journal/Conf./White-paper	Research Method	Limitation/Challenge description	Topic ID	Category
2023 (Welle Donker & Kuveždić Divjak, 2023)	Conference	International Conference on Open Data (ICOD 2022)	E	Data ethics and (re)assessment of how to deal with the balance between open data and protection of personal data	3	Technical
				Trust of citizens and companies in the public sector	10	Inf. Quality
				Trust of the public sector in the private sector		Inf. Quality
				Trust from both citizens and the public sector in companies		Inf. Quality
				How to get in touch with open data (re)users in an open data ecosystem	6	End-users
				Average lack of digital skills	7	End-users
				Lack of human resources	8	Institutional
				Lack of financial resources		Institutional
(Ali et al., 2023)	Conference	International Conference on Open Data (ICOD 2022)	E	Organizational interoperability layers	6	End-users
				Legal interoperability	2	Legs.
					5	
				Semantic interoperability	1	Technical
				Technical interoperability	4	Technical
2022 (Ali et al., 2022)	Conference	15th International Conference on Theory and Practice of Electronic Governance	E	Searchability (barrier and challenge for the end-user)	1	Technical
				Open data Standard compliance (sometimes imposed by government organizations and European data standards as well)	2	Legs.
(Vitor et al., 2022)	Journal	Computer Networks	E	How can the various data formats and types that reach the platform be stored most efficiently?	4	Technical
				How can different domains with a multi-tenant model organise information?		Technical

(continued on next page)

CRedit authorship contribution statement

Inês A. Ferreira: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Paula Miranda:** Writing – original draft, Investigation, Formal analysis, Conceptualization. **João Marreiros:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Ana Mendes:** Writing – review & editing, Validation, Investigation. **Nelson Carriço:** Writing – review & editing, Validation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table A1 (continued)

Paper ID	Type of publication	Journal/Conf./White-paper	Research Method	Limitation/Challenge description	Topic ID	Category
(Laufs et al., 2022)	Journal	PLoS ONE	E	How can the platform be scalable and performant as the number of sources increases and more services are created?		Technical
				How do we make the information available to services and applications in real-time and through dynamic APIs?		Technical
				How do we keep the available information secure while keeping the data entering the platform consistent?	3	Technical
				How can the architecture be persistent and scalable to large amounts of data?	4	Technical
				Difficulty in accessing the relevant volume of comprised data	1	Technical
(H. Yang et al., 2022)	Journal	Sensors	E	To create a collaborative environment for their users		Technical
				To establish a high-intensity data exchange	4	Technical
				Imperfect system architecture	4	Technical
				Unsound privacy and security	3	Technical
				Non-standardized interaction data	2	Legs.
(Gutierrez & Landa, 2022)	Journal	J. of Urban Tehcnology	E	The actual conditions in which open data supporters work within the administration and the expectations that need to be generated in times of emergency	6	End-users
				The perceptions of a lack of curiosity or need on the part of citizens and the genuine interest exposed by the projects analysed in this study		End-users
				Data literacy of people and the challenges of data agency	7	End-users
				Regulation of privacy and copyright	5	Legs.
				Information source	2	Legs.
(Hyseni & Bexheti, 2022)	Conference	11th Mediterranean Conference on Embedded Computing (MECO)	E	Standardisation		Legs.
				Need for a joint Open Data portal for public data	1	Technical
2021 (Dang & Duong, 2021)	Journal	International J. of Web Information Systems	E	Data provenance storage system (data management): assurance of immutability, confidentiality and privacy	3	Technical
2020 (Marjanovic & Cecez-Kecmanovic, 2020) (Slobodova, 2020)	Journal	Information and Organization	E	Performance data (e.g. about schools or hospitals) may create serious harmful social effects	6	End-users
				Addressing the individual motivations of actors (particularly discrete civil society actors) to use open data. Motivation is assessed based on societal and individual benefits.		End-users
(European Union et al., 2020)	White-Paper	Publications Office of the European Union	A	Robust governance frameworks that allow them to continue to operate effectively, even as political priorities may change.	5	Legis
				Strong relationships built by portal owners with user communities to identify sectors that are prime for open data use and can leverage further support.	9	Institutional
				Found multiple funding sources for different priorities, such as training, support for publishers, and user engagement.	1	Technical
				Design of portals using sources that are most useful to users, balancing the competing functions a portal has.	1	Technical
				Ensure the reliability and consistent data supply by adopting routine processes.	12	Inf. Quality
(Krasikov et al., 2020)	Conference	9th International Conference on Data Science, Technology and Applications	A	Fear of false conclusions	6	End-users
				Governance and habits	9	Institutional
				License and legal frameworks	2	Legs.
				Interaction with data provider vs opaque ownership	1	Technical
				Availability and access to the data		Technical
2019 (Ronzhin et al., 2019)	Conference	52nd Hawaii International Conference on System Sciences	E	Linking and combining data	4	Technical
2018 (Wang et al., 2018)	Conference	4th International Conference on Universal Village (UV)	E	Accessibility and usability of their open data	1	Technical
				The adoption of Linked (Open) Data is also referred to as relatively slow, and the authors emphasised that users are often unable to find data(sets) of interest since it is challenging to relate published datasets to their concrete use cases.		Technical
				Different datasets are inconsistent due to the variety of sources	11	Technical
				Data protection	3	Technical

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Table A1 (continued)

Paper ID	Type of publication	Journal/Conf./White-paper	Research Method	Limitation/Challenge description	Topic ID	Category
(Correa et al., 2018)	Conference	19th Annual International Conference on Digital Government Research: Governance in the Data Age	E	The gap between the adoption and the effective use of open data platforms, particularly in terms of technology choice	4 6	Technical and End-users
(Liu et al., 2018)	Conference	4th International Conference on Humanities and Social Science Research (ICHSSR 2018)	A	Importance of information processing capabilities to extract the full value of open data	12	Inf. Quality
				Drive innovation and economic development	13	Institutional
				Developing specific open data specifications	11	Technical
2017						
(Osagie et al., 2017)	Conference	18th Annual International Conference on Digital Government Research	A	Open data platforms have limited accessibility and ease of use	1	Technical
				Structure of data in terms of presentation and layout on screens	4	Technical
				The design doesn't account for non-technical users (low technical skills and data literacy)	6	End-users
				Open data platforms are sometimes negatively affected by a discrepancy between what the designer creates and what the user needs		End-users
				Lack of quality datasets, normally resulting from the lack of resources from the publishers	8	Institutional
(Nguyen & Won, 2017)	Conference	BDIOT2017: International Conference on Big Data and Internet of Things	E	Difficulty in guaranteeing data consistency since the metadata is stored in two (in this case) different places	11	Technical
				It is impossible to extend or implement new necessary functions in Hadoop without changing its source code	4	Technical
(Ruijter, Grimmelikhuijsen, Hogan, et al., 2017)	Journal	Government Information Quarterly	E	Ownership and Privacy issues	3 5	Technical and Legis.
				Resources and Management	8	Institutional
				Access	1	Technical
				Use and value / Knowledge and Interest	1	Technical and
					6	End-users
(Ruijter, Grimmelikhuijsen, & Meijer, 2017)	Journal	Government Information Quarterly	E	Open data derives from the fact that they do not account for the diverging roles that citizens play nor the part that governments have in the democratic processes	6	End-users
(Blok et al., 2017)	Journal	Italian J. of Science & Technology Studies	A	Data platforms are always situated in legal and administrative cultures	3	Technical
				Often built according to the standards of existing digital ecologies	11	Technical
				Access always involves processes of social negotiation	8	Institutional
(Beno et al., 2017b)	Journal	JeDEM – eJournal of eDemocracy and Open Government	A	Lack of resources and time	8	Institutional
				Privacy and security (unwelcomed exposure of the data)	3	Technical
				Fear of false conclusions	6	End-users
				Licenses are, on average, restrictive, unclear and hard to understand	5	Legs.
				Data is not complete, reducing their usefulness	1	Technical
				Lack of adherence to standard classifications so that data can be linked in a meaningful way	2	Legs.
				Some data is not recent (old data is worse than no data)		Legs.
				Inflexibility and slowness of responses	4	Technical
(Dufief, 2017)	White-Paper	Publish What You Found	E	Lack of trust in open data and its application	10	Inf. Quality
				The complexity of actors and financial flows is replicated in how data is governed	9	Institutional
				Lack of detail and quality of the data	1	Technical
				Lack of relevance of data released onto portals to their users' needs and interests	6	End-users
2016						
(Millette & Hosein, 2016)	Conference	3rd MEC International Conference on Big Data and Smart City (ICBDS)	E	Universally consumable	4	Technical
				Data standardization	11	Technical
				Universally consumable (data quality and ease of use / a single format along with all the required meta-data)	1	Technical and
					11	Inf. Quality
					12	
(Ojo et al., 2016)	Conference	17th International Digital Government Research Conference on Digital Government Research	A	Restricted access and use of open data by citizens	6	End-users
				Limited budget and resources of government agencies for publishing new and valuable datasets	8	Institutional
				Legislative limitations that can support ethical reusability	3	Technical
				Informativeness (clarity, currency, integrity, metadata quality and provenance)	11	Technical and
				Usability (data format, openness, operability, operability – data formats, user-friendliness)	12	Inf. Quality
					1	Technical

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Table A1 (continued)

Paper ID	Type of publication	Journal/Conf./White-paper	Research Method	Limitation/Challenge description	Topic ID	Category
(Roy, 2016)	Journal	J. of Innovation Management	A	Traditional top-down and control-laden structures are poorly suited to devising more collaborative forms of governance	9	Institutional
				Tensions between data and dialogue, as between automated, analytical processes vs more human, interactive, deliberative	9	Institutional
				Excessive reliance on proprietary hardware and software reinforces the traditionalism of government	9	Institutional
				The technocratic rise of big data systems largely favours private value creation over civic engagement and public value	8	Institutional
				Political illiteracy, which hinders the path to an engaged and inclusive society	7	End-users
2015						
(Kapoor et al., 2015)	Conference	14th IFIP WG 6.11 Conference on e-Business, e-Services, and e-Society	E	Privacy violation concerns	3	Technical
				Concerns in terms of legality		Technical
				The continuity of the data stream is uncertain	4	Technical
				Concerns at a data quality level	12	Inf. Quality
				Different costs associated with opening data, such as time and resources	8	Institutional
(Nugroho et al., 2015)	Journal	Transforming Government: People, Process and Policy	E	Increase the interest of the public in terms of their rights to access and re-use public data	6	End-users
				Closed government culture (used to work in secrecy and not in openness)	9	Institutional
				The secrecy of government operations causes low-quality information		Institutional
				Difficulty from the data users to understand the data and access it (digital illiteracy)	7	End-users
				Manipulation of the data for political purposes can lead to false results when further used in any research	6	End-users
				Privacy concerns (how open it can be without publishing information leading to the identification of the person involved)	5	Lesg.
				Information published in less user-friendly formats caused by a lack of standardization of the data that can be published	2	Lesg.
				Accessibility of the data (formats difficult to use for most common users)	1	Technical
				Network overload: publishing large amounts of data requires big network capacity to hold the data	4	Technical
				Difficult balance between free access vs the need for data providers to gain their income from selling data	8	Institutional
2014						
(Aonghusa, 2014)	Journal	J. of Research and Development	E	Data privacy is one of the challenges of open data	3	Technical
(Duval & Brasse, 2014)	Journal	Procedia Computer Science	E	Reusability of the information	1	Technical
				Different access for different users (free, freemium and premium)		Technical
2012						
(Lapi et al., 2012)	Conference	IEEE 36th Annual Computer Software and Applications Conference Workshops	E	Using a Linked Data Store instead of a pure database solution	4	Technical
(Eberius et al., 2012)	Conference	1st International Workshop On Open Data (WOD-2012)	E	Costs of integration need a better-oriented model to work, with Verification cost and Expected Integration benefit	8	Institutional
				Data integration: error correction and correspondence detection	4	Technical
(Braunschweig et al., 2012)	Journal	Computer Science, Political Science	E	Downloadable Datasets (many of the provided links return HTTP error codes or time out on request)	1	Technical
				Machine-readable Datasets (datasets in obscure or proprietary formats or not in the format given in the metadata)		Technical
				Existence and number of tags (lots of datasets repeat generic tags)		Technical
				Existence and length of description (detailed description cannot be processed automatically)		Technical
				Format Zoo (plethora of different formats prevents readability and reusability)		Technical

Topic ID	Topic description
1	Usability (including searchability, collaborative systems for users, joint open data portal)
2	Data standards
3	Privacy and security
4	System design/architecture, system speed, interoperability
5	Data Ownership
6	Users engagement
7	Data literacy
8	Resources (for development and maintenance)
9	Organizational culture and habits
10	Trust
11	Data compatibility
12	Data quality
13	Economic Impact

Categories
Technical
Information quality
Legislation
Institutional
End-users

Data availability

I have shared the link to my data code in the manuscript.

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