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RESEARCH PAPER

Business model archetypes of open data intermediaries: Empirical insights from practice

Ashraf Shaharudin[1] · Bastiaan van Loenen[1] · Marijn Janssen[2]

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Abstract

Open data intermediaries are critical for enhancing value generation from open data. However, empirical research on their business model archetypes remains limited. This gap constrains our understanding of the conditions and potential innovations required to perform the roles of open data intermediaries sustainably. To address this gap, we developed a taxonomy and empirically derived business model archetypes based on 190 open data intermediaries. We identified nine archetypes: collaborative open data platforms, premium self-service data delivery, personalized open data services, interactive apps with other complementary products, open data repositories funded by sponsorship, one-stop packages around an (augmented) open data platform/repository, single-purpose apps, interactive apps without complementary products, and open data advocacy. We also described each archetype's value proposition, value creation, and value capture dimensions. Our findings support further research into the conditions that contribute to the success of open data intermediaries' business models and the design of new, innovative ones. They also provide business model inspiration for existing and potential open data intermediaries, thereby encouraging greater exploitation of open data value.

Keywords Business model · Open data · Intermediaries · Empirical · Archetypes · Cluster

JEL Classification M15

Introduction

Open data, defined as "data that can be freely used, modified, and shared by anyone for any purpose" (OKF, 2013), promises various benefits, including stimulating innovation, improving business processes, enhancing institutional accountability, boosting citizen participation, and accelerating scientific progress (Hossain et al., 2016; Janssen et al., 2012; Zhu et al., 2019). However, numerous challenges related to the preparation, dissemination, processing, and reuse of open data limit such potential (Cahlikova & Mabillard, 2020; Johnson et al., 2017; Sugg, 2022; Temiz et al., 2022; Zuiderwijk & de Reuver, 2021). For example, open data providers face resource constraints (Nikiforova & Zuiderwijk, 2022) and dispersed data management (Ma & Lam, 2019). On the other hand, reusing open data may involve laborious work, especially if the data are compiled from different sources using different data models and formats (Aydinoglu & Bilgin, 2015), and require technical skills and resources that may not be at the disposal of data users (Okamoto, 2016). Moreover, the designs of most open data platforms are quite generic and may not accommodate specific data re-use (Ruijer et al., 2017). While much of the progress in policy and research to date has focused on open government data, open data also encompasses data from companies, non-governmental organizations (NGOs), and individuals.

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✉ Ashraf Shaharudin
A.A.BinAhmadShaharudin@tudelft.nl

Bastiaan van Loenen
b.vanloenen@tudelft.nl

Marijn Janssen
m.f.w.h.a.janssen@tudelft.nl

[1] Department of Urbanism, Faculty of Architecture and the Built Environment, Delft University of Technology (TU Delft), Julianalaan 134, 2628 BL Delft, Netherlands

[2] Department of Engineering, Systems and Services, Faculty of Technology, Policy and Management, Delft University of Technology (TU Delft), Jaffalaan 5, 2628 BX Delft, Netherlands

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Open data intermediaries serve a crucial function in addressing many of these challenges and consequently in enhancing public and private value creation from open data (Chattapadhyay, 2014; González-Zapata & Heeks, 2015; Mayer-Schönberger & Zappia, 2011; Neves et al., 2020; Yoon et al., 2018). Open data intermediaries can be defined as "third-party actors who provide specialized resources and capabilities to (i) enhance the supply, flow, and/or use of open data and/or (ii) strengthen the relationships among various open data stakeholders" (Shaharudin et al., 2023a, p. 1). They perform diverse tasks, including requesting open data, compiling open data from multiple sources, improving the technical openness of data, and interpreting open data (Shaharudin et al., 2023a). Different types of actors can perform the role of open data intermediaries, including civil society organizations (Meng et al., 2019; Sangiambut & Sieber, 2017), companies (Andrason & van Schalkwyk, 2017; Germano et al., 2016), the media (Enaholo & Dina, 2020; Johnson & Greene, 2017), and public organizations (Meijer & Potjer, 2018; Robinson & Mather, 2017).

Although the vital role of open data intermediaries and the value they may offer are widely recognized (Enaholo & Dina, 2020; Schrock & Shaffer, 2017; van Schalkwyk et al., 2016; Yoon et al., 2018), knowledge about their business models that exist in practice is lacking in both amount and scope (Shaharudin et al., 2023b). This knowledge is needed for understanding the conditions and potential innovations required to perform the roles of open data intermediaries sustainably. Most studies on open data business models do not specifically focus on open data intermediaries; instead, they focus on the business models of open data actors or re-users in general (Charalabidis et al., 2018; Ferro & Pizzamiglio, 2023; Garatzogianni et al., 2017; Magalhaes & Roseira, 2020; Magalhaes et al., 2014). Others have studied the business models of data intermediaries that do not specifically deal with open data (Micheli et al., 2020, 2023; Schweihoff et al., 2024; Susha et al., 2020), thus obscuring or overlooking the peculiarities of open data intermediaries that deal with data that are already reusable free of charge under an open license. Meanwhile, the few studies that specifically focus on open data intermediaries' business models (Germano et al., 2016; Janssen & Zuiderwijk, 2014) fall short of integrating the key business model dimensions (value proposition, value creation, and value capture), resulting in an incomplete overview.

Therefore, this paper seeks to advance knowledge on open data intermediaries by asking the following research question: What are the business model archetypes of open data intermediaries in practice? To address this question, we employed a two-phase methodological approach: in the first phase, we developed a taxonomy; in the second, we used it for archetype identification.

The structure of this paper is as follows. The *Background* section explains the motivation of this paper by discussing the role of open data intermediaries in the open data ecosystem and the need for a better understanding of their business models. The section also offers brief overviews of the business model concept and open data intermediaries. The *Research methodology* section describes the methodology we adopted. The *Findings* section presents the identified business model archetypes of open data intermediaries. The *Discussion and conclusion* section explores the theoretical and practical implications of the study and elaborates on the study's limitations. Lastly, the

Background

Motivation: Open data ecosystem and the role of intermediaries

Given the various challenges in generating value from open data (Coetzee et al., 2020; Johnson et al., 2017; Temiz et al., 2022), the concept of "open data ecosystem" has been proposed and explored as a lens for foregrounding the complex interdependency of various open data actors (Davies, 2011; Heimstädt et al., 2014; Pollock, 2011; van Loenen et al., 2021). Davies (2011) argued that successful value generation from open data relies on the "mobilization of a wide range of technical, social and political resources, and on interventions [...] [to] support coordination of activity around datasets" (p.1). He thus advocated the concept of open data ecosystem as an analytical lens through which "the emergent, autonomous and self-organizing components" are "linked together in local and global feedback loops and developing according to local specializations and adaptation rather than top-down design" (Davies, 2011, p. 3). In the same vein, Csáki (2019) defined open data ecosystem as a "way of looking at how participating actors and groups create shared meaning and generate value around open data and how the structural properties of their interactions shape this process, which in turn enables or constrains the growth and health of the ecosystem itself" (p. 19).

Within the open data ecosystem, open data intermediaries are considered instrumental. Various expectations for open data to be "actionable data" (Gutierrez & Landa, 2021) cannot be met by open data providers or end-users alone. Chattapadhyay (2014) argued that a key aspect of an open data ecosystem is the effective circulation of resources, such as software, technical skills, and funding. Open data intermediaries play a central role in this circulation process. These intermediaries are essential not only for facilitating access to and use of open data (González-Zapata & Heeks, 2015; Neves et al., 2020), but also for connecting various actors within the ecosystem (Mayer-Schönberger & Zappia, 2011;

Yoon et al., 2018). Moreover, given the self-organizing nature of actors in the ecosystem (Davies, 2011; Oliveira & Lóscio, 2018), open data intermediaries are vital for reducing information asymmetries.

However, even though the importance of open data intermediaries is well-recognized in both research and practice (Carolan, 2016; Davies & Perini, 2016; Dove et al., 2023; Publications Office of the European Union, 2023), there remains a limited number of studies focusing on their business models. This gap is problematic since the business model design and innovation are closely linked to organizational performance and long-term (financial) sustainability (DaSilva & Trkman, 2014; Kesting & Günzel-Jensen, 2015; Peric et al., 2017). Moreover, business models play a crucial role in clarifying the relationships between an organization and other actors in an ecosystem (Lambert & Davidson, 2013). Therefore, business models of open data intermediaries impact not only their own sustainability but also that of the entire open data ecosystem.

To our knowledge, only two studies have explicitly investigated the business models of open data intermediaries. Janssen and Zuiderwijk (2014) identified six open data intermediaries' business model archetypes based on their study of 12 cases in the Netherlands. The archetypes identified are single-purpose apps, interactive apps, information aggregators, comparison models, open data repositories, and service platforms. However, all six were described only in terms of the value proposition dimension (i.e., the type of product). On the other hand, based on seven open data intermediaries in Brazil, Germano et al. (2016) identified three business model archetypes, namely consultancy, advertising, and subscription.

Meanwhile, some studies have examined the business models of data intermediaries more broadly, without focusing on those specifically dealing with open data (Micheli et al., 2020, 2023; Schweihoff et al., 2024; Susha et al., 2020). This broader overview tends to overlook the unique characteristics and challenges faced by open data intermediaries, particularly the fact that they deal with data that is already freely accessible and reusable by anyone under open licenses, over which they have no exclusive rights or control. In other words, the business models of open data intermediaries are not centered on providing access to data or simply transferring data between parties through services such as consent management, identity verification, and access control. This represents a fundamental departure from those of non-open data intermediaries (Schweihoff et al., 2024).

Business model concept

The term "business model" is an elusive concept with numerous definitions and interpretations in the literature (see the review by Andreini and Bettinelli (2017)). For example, in the context of electronic business models, Timmers (1998) defined a business model as "an architecture for the product, service and information flows, including a description of the various business actors and their roles; and a description of the potential benefits for the various business actors; and a description of the sources of revenues" (p. 4). Also in the same context, Dubosson-Torbay et al. (2002) defined a business model as "the architecture of a firm and its network of partners for creating, marketing and delivering value and relationship capital to one or several segments of customers in order to generate profitable and sustainable revenue streams" (p. 7). Zott and Amit (2010) defined a business model as "the design of transaction content, structure, and governance so as to create value through the exploitation of business opportunities" (p. 219). More recently, Snihur and Markman (2023) described a business model as "a blueprint that outlines how an organization creates value, generates revenue, delivers offerings, and even interacts with its direct stakeholders (employees, customers, suppliers) and indirect stakeholders (rivals, regulators, community)" (p. 1).

Notwithstanding the variations in specific definitions and terminologies, typical conceptualizations of a business model consist of at least three general dimensions (Afuah, 2018; Andreini & Bettinelli, 2017; Teece, 2010; Voigt et al., 2017): (1) value proposition (potential benefits for the consumers), (2) value creation (resources deployed by organizations to deliver the value proposition), and (3) value capture (compensation to the organizations offering the value). In other words, a business model can be broadly conceptualized as a framework that makes sense of what value an organization offers (value proposition), how it offers value (value creation), and why it offers it (value capture). The literature on data-related business models, such as big data business models (Acciarini et al., 2023), data marketplaces (Bergman et al., 2022), and platform business models (Täuscher & Laudien, 2018), adopted a similar conceptualization of the business model as described. Therefore, this paper uses the three dimensions (value proposition, value creation, and value capture) to form the fundamental framework of a business model. In this paper, we identify business model archetypes. An archetype is "a typical example of something, or the original model of something from which others are copied" (Cambridge Dictionary, n.d.). Although business models of the same archetype may vary, all share similar core components (Sterk et al., 2024).

Both for-profit and non-profit organizations (NPOs) require business models (Bocquet et al., 2020; Maguire, 2009). The latter need revenue to support operational costs even though they do not generate profits (in economic terms, profits equal revenues minus costs). Different types of organizations could serve as open data intermediaries, including NPOs (Shaharudin et al., 2023a). Hence, throughout this paper, we use the terms organization instead of company and consumers instead of customers to maintain semantic consistency across different types of open data intermediary organizations.

Business models are crucial to an organization's success, as they clarify how organizations (should) operate (Magretta, 2002). To ensure long-term sustainability, an organization must select suitable business model(s) based on current circumstances, execute them effectively, develop and strengthen the organization's dynamic capabilities, and modify the business models effectively and in a timely manner when an opportunity or threat arises (DaSilva & Trkman, 2014). Business models also encapsulate the relationships between an organization and other actors (Johannesson, 2007; Lambert & Davidson, 2013), such as open data providers and users, in the case of open data intermediaries. Thus, business models can serve as a strategic tool for exploring new markets or opportunities and strengthening existing relationships or forging new ones (Wieland et al., 2017). Business models are often characterized as the framework linking an organization's long-term strategy with its (micro-level) business processes (Di Valentin et al., 2012; Spencer, 2013; Veit et al., 2014).

Open data intermediaries

Based on a systematic literature review, open data intermediaries are theoretically defined as "third-party actors who provide specialized resources and capabilities to (i) enhance the supply, flow, and/or use of open data and/or (ii) strengthen the relationships among various open data stakeholders" (Shaharudin et al., 2023a, p. 1). Examples of open data intermediaries include open data-based application providers (e.g., Citymapper and Zapmap), portals integrating open data from different sources (e.g., Nasdaq Data Link), and platforms that crowdsource open data (e.g., OpenStreetMap and Wikidata). Open data intermediaries materialize or enhance the value of open data by offering products/services to open data providers and/or end users (Enaholo, 2017; Schrock & Shaffer, 2017; van Schalkwyk et al., 2016). Open data intermediaries do not necessarily perform activities that are only related to open data. For example, a company can sell non-open data-based products while offering open data intermediation services (Shaharudin et al., 2023a, 2025). It is also worth emphasizing that their open data intermediation products/services do not have to be free (van Schalkwyk et al., 2016), depending on the business models they adopt.

In the broad context of data-related business models, Wixom and Ross (2017) underlined three ways organizations can gain value from leveraging their data: improving their internal processes and decisions, complementing their core products and services, and selling data to new and existing markets. Meanwhile, Schroeder (2016) identified three generic typologies of (big) data business models: data users (e.g., leveraging data for strategic decisions and incorporating data into products), data suppliers (e.g., collecting data and packaging data for sale), and data facilitators (e.g., providing infrastructure or data analysis services). The critical literature review conducted by Wiener et al. (2020) on data business models indicated that organizations (especially large ones) tend to exhibit high levels of vertical integration, taking on the roles of data users, suppliers, and facilitators simultaneously. Therefore, actors who undertake the open data intermediation role can also be open data providers and users, as these roles are not mutually exclusive.

Jetzek (2015) employed the two-sided markets theory to conceptualize open data intermediaries, highlighting the value of network externalities. She highlighted the potential of open data intermediaries to generate value for both open data providers and users through direct and indirect interactions and network effects, particularly for small organizations with limited capabilities to handle large, heterogeneous datasets on their own (Jetzek, 2015). Open data intermediaries are said to contribute to open data value generation by "augmenting and amplifying the circulation of open data and by sanitizing and curating data coming from both public and private sources" (Jetzek, 2015, p. 74). Since open data is already available free of charge under an open license, open data intermediaries do not capture value simply by facilitating the transaction of data from one party to another (i.e., simple rent-seeking, as in the case of data intermediaries dealing with private or proprietary data) (Jetzek, 2015). Instead, open data intermediaries primarily gain profits or non-monetary benefits by adding value to existing open data (e.g., by integrating open data from various sources and by improving the quality of open data) or the processes linked to their supply and reuse (e.g., by curating relevant open data for specific purposes and by facilitating open data stakeholders' interactions) (Janssen & Zuiderwijk, 2014; Jetzek, 2015). This highlights the distinction between the business models of open data intermediaries and those of non-open data intermediaries.

However, the two-sided markets theory, or, more generally, the multi-sided theory (Rochet & Tirole, 2006) remains limited in describing the broad range of open data intermediaries' business models in practice. The theory refers to "markets in which one or several platforms enable interactions between end-users and try to get the two (or multiple) sides 'on board' by appropriately charging each side. That is, platforms court each side while attempting to make, or at least not lose, money overall" (Rochet & Tirole, 2006, p. 645). It is based on the assumption that the platform (i.e., the intermediary) is an independent entity (in terms of ownership and/or governance) from the two or more parties that interact with the platform (Rochet & Tirole, 2006; Van Alstyne et al., 2016). However, in practice, the infrastructure of some open data intermediaries, such as OpenStreetMap (OSM), is developed, governed, and maintained by those who are also suppliers and users of the open data (Ochoa-Ortiz & Re, 2025). Therefore, it is expected that some open data intermediaries are not entirely independent entities (in terms of ownership and/or governance) from the parties that interact with them, but instead, those parties may collaboratively develop, govern, and maintain the intermediaries' infrastructure.

Furthermore, the extant literature also includes organizations that perform advocacy, consultancy, and capacity building related to open data supply or reuse as open data intermediaries, even though they may only engage with a single group of parties at a time (i.e., either only with open data suppliers or re-users) (Enaholo, 2017; Magalhaes & Roseira, 2020; Reggi & Dawes, 2016; Yoon et al., 2018). This kind of open data intermediaries thus do not link two or more parties on the same platform, but their contributions remain instrumental in enhancing the generation and circulation of open data value in the ecosystem. Therefore, the business model archetypes of open data intermediaries are expected to include those that are not solely based on multi-sided platforms. They may also include one-sided products or services that, while not platform-based, play a crucial role in generating value across the entire ecosystem.

Research methodology

Several studies employed the two-phased taxonomy development and application approach to derive business model archetypes. For example, Holzmann et al. (2019) conducted a thematic analysis for the taxonomy development, followed by a two-step cluster analysis for the taxonomy application to identify business models of 3D printer manufacturers. Likewise, Urban et al. (2018) identified airline business model archetypes by developing a taxonomy based on Osterwalder and Pigneur's (2010) business model canvas and then applied it based on a two-step cluster analysis. Weking et al. (2020) employed a literature review and Ward's hierarchical cluster analysis to derive blockchain-based business model archetypes. The same approach was adopted by Duparc et al. (2022) to identify open-source business model archetypes, and Sterk et al. (2024) for connected cars. Lüdeke-Freund et al. (2019) identified business model archetypes in the circular economy through a literature review for the taxonomy development and a morphological analysis for the taxonomy application.

Our study employs a similar approach, spanning two overlapping phases consisting of four sequential steps. The first phase (Phase A) constitutes the taxonomy development, involving Steps 1, 2, and 3. The second phase (Phase B) comprises the taxonomy application to identify business model archetypes, involving Steps 3 and 4 (see Fig. 1). In Step 1, we developed an initial taxonomy consisting of categories and elements of open data intermediaries' business models through an SLR. In Step 2, we collected relevant qualitative data from 190 samples of existing open data intermediaries using an abductive approach guided by the initial taxonomy developed. We then refined the taxonomy based on our learning throughout the data-gathering process. In Step 3, we employed an unsupervised machine learning (ML) technique, namely K-means clustering, to group the business models of the sample cases. During this step, we further refined the taxonomy by deselecting several categories based on our K-means clustering calibration. We opted for K-means clustering rather than Ward's hierarchical clustering, as used in some studies, since the former is more appropriate for large datasets. Besides, Ward's clustering is commonly used to identify archetypes for which a hierarchical structure is important (e.g., gene expression), which we do not expect in our case, since we consider every category as potentially key to determining a cluster. In Step 4, we interpreted the K-means clustering results and identified open data intermediaries' business model archetypes. We use the term *clusters* to refer to the K-means output before our interpretation, while *archetypes* refer to the final business model groups after interpreting the K-means output. Figure 1 illustrates the methodology employed in this study, using fruits as an analogy.

Step 1: Developing the initial taxonomy through an SLR

In Step 1, we developed the initial taxonomy to initiate data collection from the sample cases in Step 2. We conducted an SLR to establish the initial taxonomy consisting of the categories and elements of open data intermediaries' business models. *Categories* refer to the characteristic groups of the business models. Each category consists of *elements*, which are the identifiers for specific characteristics. We followed the SLR steps proposed by Xiao & Watson (2019). We searched for relevant publications in the Scopus and Web of Science databases, using the combination of keywords listed in Table 1. Notably, we did not limit our search to *intermediaries*, as we learned from the literature screening that several publications on the business models of other open data roles are still appropriate for our purpose. We also included *open government data* as a search term, since it is a subset of open data. In addition to the term *business model*, we considered other search terms that may capture relevant literature.

Following literature filtering (Supplementary Appendix 1), we found ten relevant publications to build the initial taxonomy. We included two more publications in the literature pool through backward citation: Al-Debei and Avison (2010) and Osterwalder and Pigneur (2010). Ultimately, 12 publications were used to develop the initial taxonomy. Table 2 presents the relevant publications.

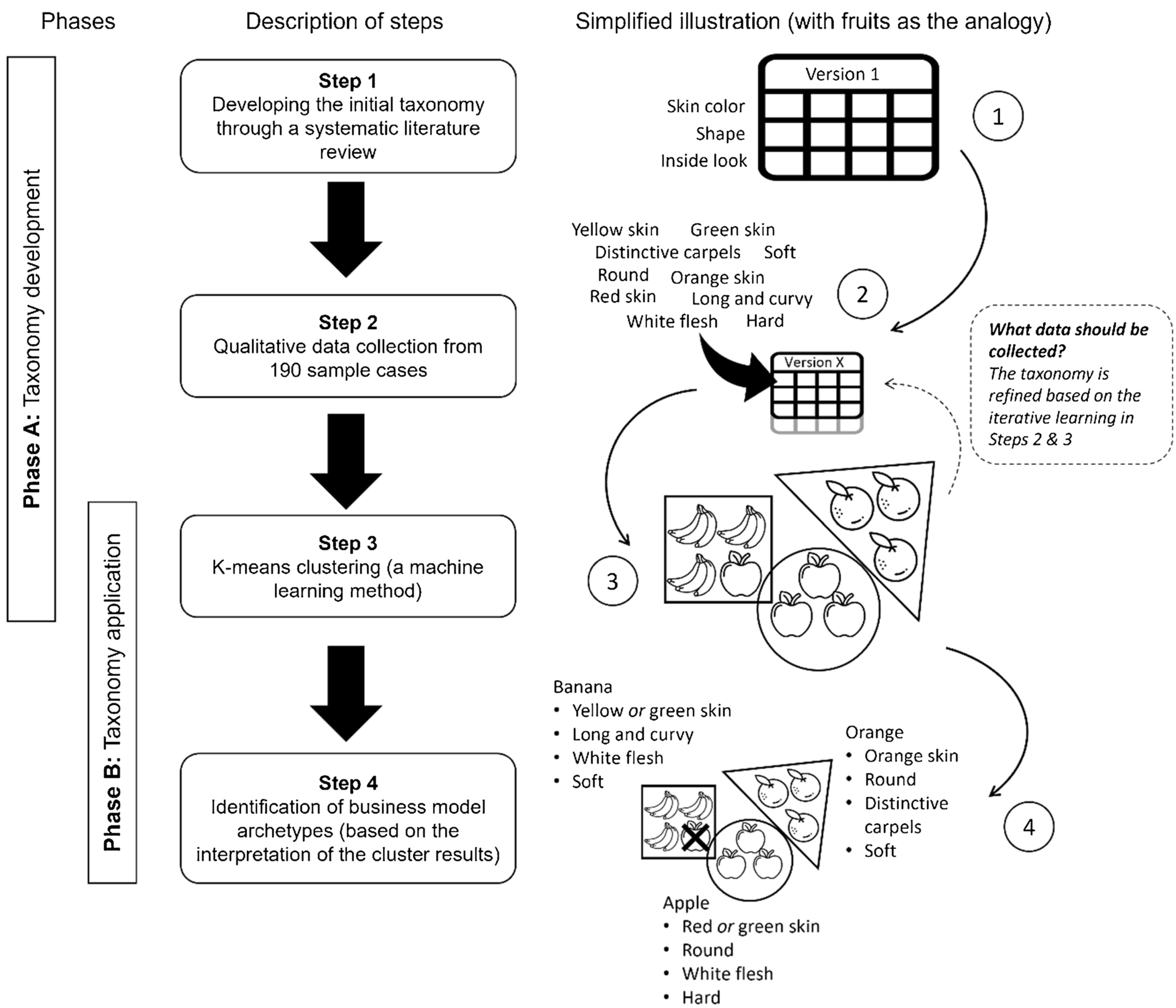


Fig. 1 Four steps of the research process

Table 1 Search terms for the SLR (30 combinations)

Boolean operator	OR
AND	Open data, open government data
	Business model, revenue, value proposition, value creation, value capture, value architecture, value network, finance, profit, business format, enterprise model, model of business, business plan, business strategy, business opportunity

Publications relevant to categories refer to those used to develop the taxonomy's categories, and vice versa for *publications relevant to elements*. Several publications are relevant to both categories and elements. We synthesized the publications to develop the initial taxonomy (Supplementary Appendix 2).

Step 2: Refining the taxonomy through data from 190 sample cases

Using purposive sampling, we identified 190 open data intermediary products/services from the open data use cases compiled by data.europa.eu, the official portal for European data. We only selected use cases that represent products/

Table 2 Relevant publications for the initial taxonomy

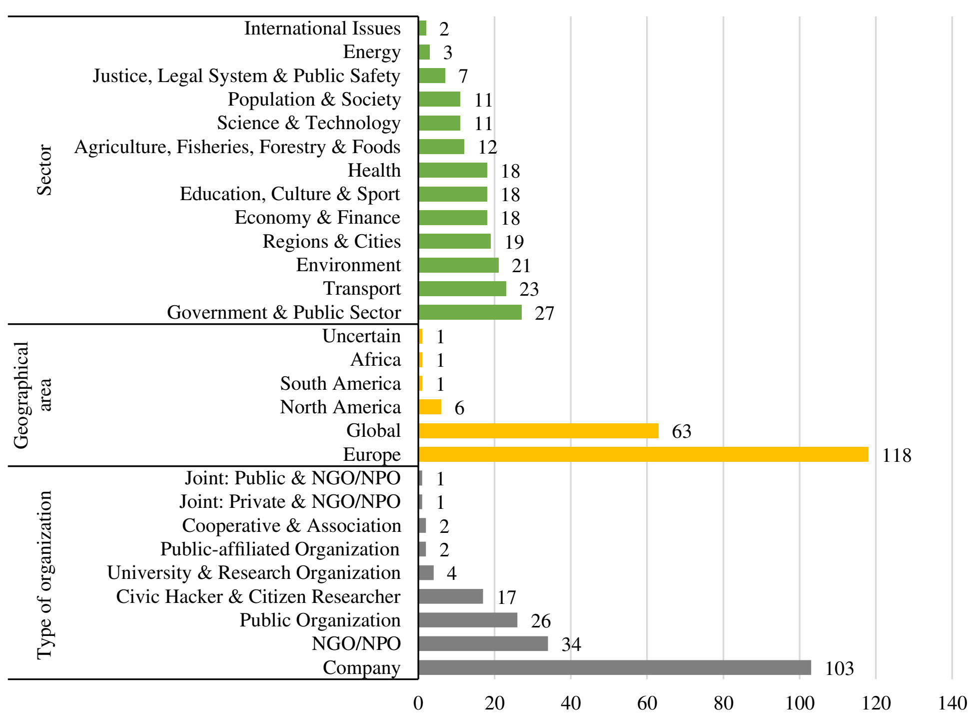
Publications relevant to categories	Publications relevant to elements
Ahmadi Zeleti et al. (2016); Al-Debei and Avison (2010); Kamariotou and Kitsios (2022); Osterwalder and Pigneur (2010); Yu (2016)	Ahmadi Zeleti et al. (2016); Janssen and Zuiderwijk (2014); Kitchin et al. (2015); Lindman et al. (2016); Magalhaes and Roseira (2020); Osterwalder and Pigneur (2010); Schroeder (2016); Smith et al. (2016); Welle Donker and van Loenen (2016); Yu (2016)

services offered by an open data intermediary, following the definition of Shaharudin et al. (2023a), already mentioned in the "Background" section. A salient feature of an open data intermediary is that it acts as a third-party actor: it neither solely provides the original open data nor merely uses it internally as an end-user. Instead, it adds value to the data itself and/or to the processes involved in its supply and reuse. Since open data intermediary organizations may perform activities beyond open data and may also offer non-open data-based products and/or services (e.g., Nasdaq offers other products/services besides Nasdaq Data Link), our data collection was only anchored to the open data intermediation products/services they offer instead of the organizations as a whole. Nevertheless, there are certainly cases where the open data products/services offered represent the entire organization, such as OpenStreetMap.

We collected qualitative secondary data on the sample cases through a desk survey of publicly available sources, e.g., organizations' websites and app store product descriptions, using an abductive approach guided by the initial taxonomy developed in Step 1. This process occurred between January and April 2023. Figure 2 presents the number of sample cases by organization type, the geographical area in which they operate (or where their products/services are accessible), and sector (following the sector categorization on data.europa.eu). Most of the sample cases are companies (103), followed by non-governmental organizations (NGOs) or NPOs (34) and public organizations (26). More than half of them operate in Europe (118). In terms of sectoral categories, we selected the sample cases based on their corresponding population shares in the portal. However, it is worth noting that sectoral categorization is not a rigid demarcation; for instance, a use case categorized in the transport sector may also fit in the regions and cities sector.

We refined the taxonomy based on our learning throughout the data collection process, which involved several iterations (Supplementary Appendix 2). The goal of such iterative modification is to strike a balance between collecting meaningful and sufficient data to capture the salient business model characteristics on the one hand and avoiding excessive detail (noise) that obscures those characteristics on the other. The taxonomy iteration also ensures data consistency across the sample cases. In particular, we expanded the elements within the *type of*

Fig. 2 Overview of the number of cases based on the type of organization, geographical area, and sector



main open data-based product and also added a piece of extra information to each of the elements by indicating whether the type of product is data-to-data (D-D), data-to-information (D-INFO), data-to-knowledge (D-K), or support services (SU) products, partly inspired by the data-information-knowledge-wisdom (DIKW) hierarchy (Ackoff, 1989; Rowley, 2007). This helps to ensure consistency in the data collection process across the sample cases. We also added new categories in the value dimension: *source of data*, *product components*, *other open data-based products*, *non-open data-based products*, and *linking of other product(s) to the main products*. The new categories were added to acknowledge that non-open data may be combined with open data to offer certain products/services, that some products/services may consist of multiple modular units, and that open data intermediaries may offer multiple open data-based products and/or non-open data-based products simultaneously. Furthermore, we expanded, contracted, or modified the elements within the categories of *channel*, *consumer segment*, *critical partner* (substituting *key partners*), *critical resource* (substituting *key resources*), *customer relationship*, *cost structure,* and *main revenue stream*. We substituted the key activities category with the critical stage of the open data lifecycle, with elements derived from van Veenstra & van den Broek (2015). We also added a new category under the value dimension: *source of revenue*. This category indicates whether revenue is derived solely from (augmented) open data or from other sources.

All of the above taxonomy modifications are based on what we learned from the data itself (rather than the literature, as in Step 1). To provide an illustrative example using the analogy of fruits from Fig. 1, when we discover that the feel of the fruits (hard, soft) is also a useful category for identifying what fruits are present, we then add data based on this category. On the other hand, when we discover that the smell of fruits is challenging to capture, we drop this category from the data collection process.

Since the data we collected was qualitative rather than quantitative, the data collection process inevitably involved our interpretation and our best efforts to capture the business model elements. During data collection, we left certain categories blank if we were unsure. At the end of Step 2, we developed a dataset consisting of the business model elements of 190 open data intermediaries. This dataset would be further modified in Step 3.

Step 3: K-means clustering

We used K-means clustering to facilitate the identification of the open data intermediaries' business model archetypes based on the dataset developed in Step 2. K-means is an unsupervised ML technique used to group n objects, each with measurements of p variables, into K clusters (Steinley, 2006). In our case, the objects are the individual sample cases (i.e., $n = 190$), and p is the number of categories in the taxonomy (hereafter, we simply call them *categories*). The goal of K-means is to minimize within-cluster variances. The objective function of the K-means algorithm can be expressed as:

$$Z = \sum_{k=1}^{K} \sum_{x_{ij} \in C_k} \|x_{\mathrm{ij}} - \mu_{\mathrm{k}}\|^2$$

where.

Z is the objective function to be minimized.

K is the number of clusters.

C_{k} are the data points assigned to the k-th cluster.

x_{ij} is the data point of the j-th variable for the i-th object (where $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, p$).

μ_{k} is the centroid (mean) of the k-th cluster, and.

$\|x - \mu_{\mathrm{k}}\|^2$ is the squared Euclidean distance between data point x and the centroid.

Since our dataset consists of categorical data, the data is converted into numerical data with one feature per value before the clustering procedure. K-means clustering requires initializing the number of clusters (i.e., K) a priori. We employed two strategies to determine the optimal K based on two decision criteria. The first strategy is to experiment with a range of K values, while the second strategy is to experiment with deselecting several categories to minimize overspecification. To decide whether we have reached the optimal K, we selected the K with the highest silhouette score within a range of K values and ensured that the clustering output makes human sense, e.g., by observing whether we can identify rough commonalities among several sample cases' business models within the same cluster. A silhouette score (ranging from -1 to $+1$) assesses whether an object matches its designated cluster (the higher the score, the better the fit) (Rousseeuw, 1987).

This calibration process to find the optimal K is thus iterative. Ultimately, we deselected four categories (*channel*, *critical partner*, *critical resource*, and *cost structure*), resulting in the selection of 12 categories for the clustering (i.e., $p = 12$) (Table 3 and Supplementary Appendix 2). These categories were deselected either because they correlate highly with another category and are thus considered redundant (*channel* with the *type of main open data-based products*) or they are highly subjective and speculative (*critical partner*, *critical resource*, and *cost structure*). Ultimately, based on the calibration process, we determined that the optimal K is 10.

Table 3 presents the evolution of the taxonomy from Step 1 to Step 3 (the full version is shown in Supplementary Appendix 2). Figure 3 presents the silhouette plot (cases with negative silhouette scores may have been assigned to the wrong cluster). The novel dataset of the business model

Table 3 Taxonomy categories (and the number of respective elements) by the end of Steps 1, 2, and 3

Initial taxonomy by the end of Step 1	Taxonomy by the end of Step 2	Taxonomy by the end of Step 3
Value proposition		
Type of open data products (13)	Type of main open data-based product (15)	Type of main open data-based product (15)
	Source of data (2)	Source of data (2)
	Product components (2)	Product components (2)
	Other open data-based products (2)	Other open data-based products (2)
	Non-open data-based product (2)	Non-open data-based product (2)
	Link of other product(s) to the main open data-based product (4)	Link of other product(s) to the main open data-based product (4)
Offering (13)	Offering (13)	Offering (13)
Channel (2)	Channel (3)	***Deselected***
Consumer segment (4)	Consumer segment (6)	Consumer segment (6)
Value creation		
Key partners (*open coding*)	Critical partner (16)	***Deselected***
Key activities (*open coding*)	Critical stage of the open data lifecycle (5)	Critical stage of the open data lifecycle (5)
Key resources (*open coding*)	Critical resources (other than financial) (13)	***Deselected***
Customer relationship (6)	Customer relationship (4)	Customer relationship (4)
Value capture		
Cost structure (4)	Cost structure (2)	***Deselected***
Revenue streams (15)	Main revenue stream (13)	Main revenue stream (13)
	Source of revenue (3)	Source of revenue (3)

Please refer to Supplementary Appendix 2 for the full version. Supplementary Appendix 3 provides definitions for each taxonomy element by the end of Step 3

elements of the sample cases by the end of Step 3 is openly accessible and reusable: https://doi.org/10.4121/160c8de9-99cf-4231-96a3-bad517360b67.

Step 4: Identification of business model archetypes

We used K-means clustering to aid in identifying business model archetypes; the clustering results are not the final findings per se. In Step 4, we interpreted the clustering output of Step 3 and identified the business model archetypes. We did this by first identifying the categories within each cluster, of which most sample cases (at least 70% of the total cases) share the same element; we call these *defining categories*. Additionally, we grouped some similar elements within a category on a case-by-case basis and, subsequently, considered the respective category a defining category. For example, if most sample cases within a cluster have elements of either *crowdfunding* or *sponsorship: public* or *sponsorship: private*, the cluster's *main revenue stream* category is considered a defining category, since all three elements are based on external contributions (as opposed to transactions). Therefore, in this sense, the defining category is both a quantitative and qualitative indicator. Defining categories underscores the salient characteristics of sample cases within each cluster, which helps identify and describe the business model archetypes.

Supplementary Appendix 4 presents the sample cases within each cluster (we only listed cases with positive salient scores of at least 0.04) and their elements (with D indicating defining categories). The clusters are labeled C1–C10. Within the same cluster, the number of known sample cases across categories may differ because we left categories that we were uncertain about blank during the data collection (Step 2). Not all sample cases within a particular cluster are meant to be there, since inaccurate cluster assignments are expected with ML. However, the objective of this study was to identify the archetypes that exist. Thus, inaccurate cluster assignments are a minor issue if most of the cases within each cluster exhibit commonalities.

Findings

We identified nine archetypes of open data intermediaries' business models. We determined that two K-means clusters (C7 and C8) are similar based on the defining variables (Supplementary Appendix 4); hence, we combined them into a single archetype. Table 4 presents the business model archetypes, their salient characteristics according to three value dimensions, and several examples.

We affirm the contribution of our study by comparing our empirical findings with open data business model

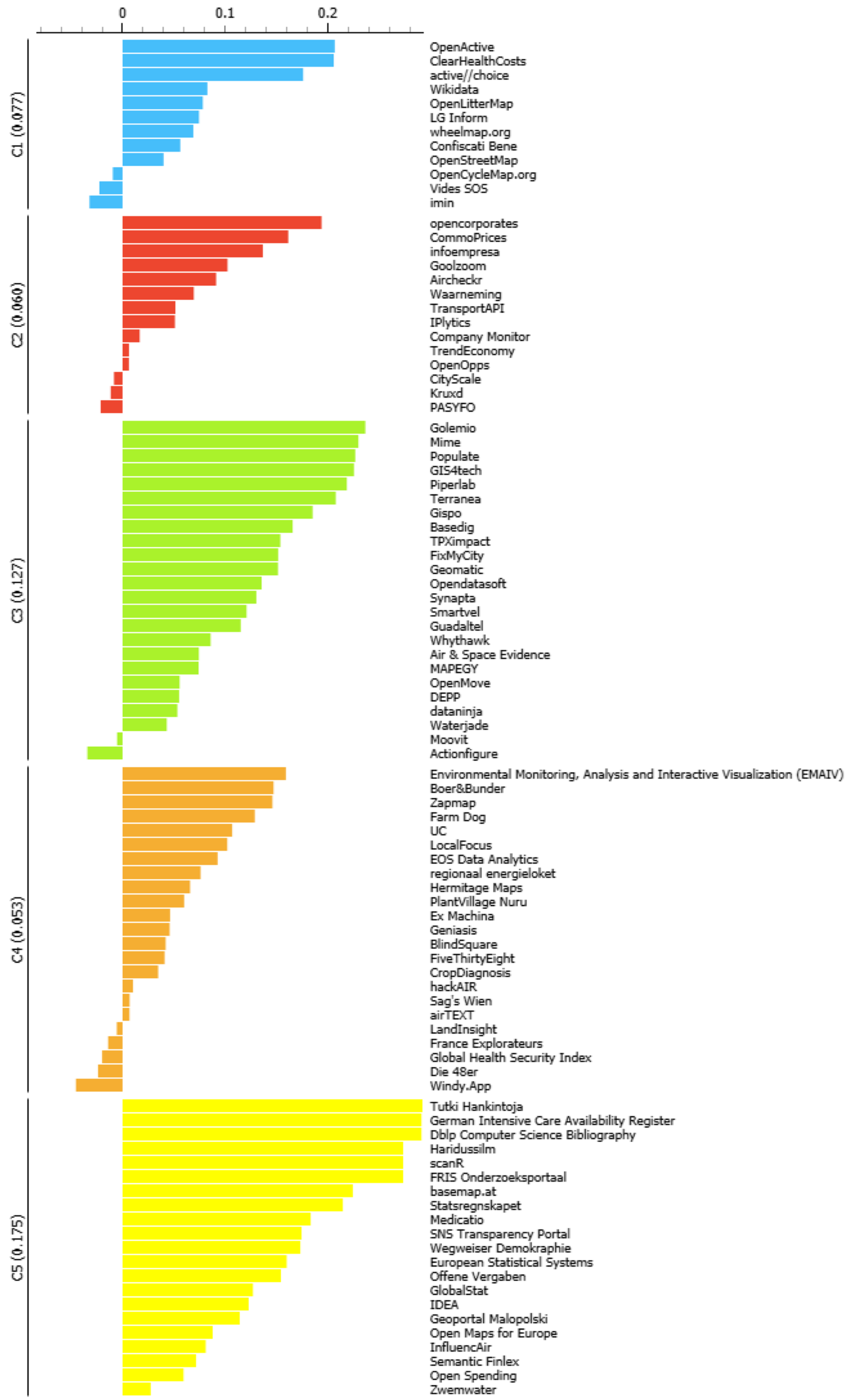


Fig. 3 Silhouette plot across clusters

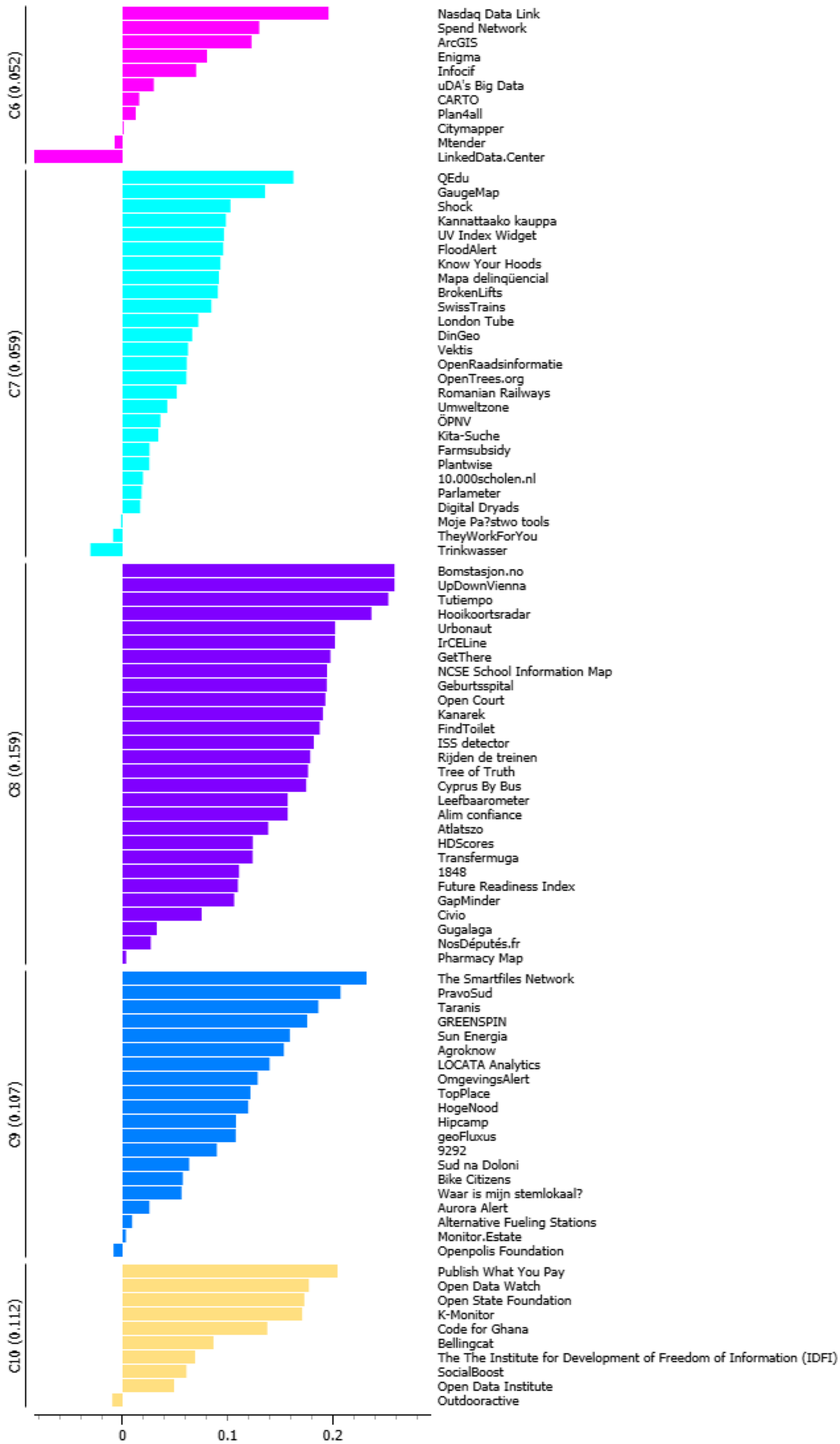


Fig. 3 (continued)

Table 4 Open data intermediaries' business model archetypes and salient characteristics

ID	Name	Salient characteristics based on value dimensions	Example	Cluster
A1	Collaborative open data platform	**Value proposition:** Open data platform freely available for both open data providers and users **Value creation:** The critical open data stage is preparation, and the consumer relationship is collaborative (co-creation or community-based) **Value capture:** Funded by external contribution (crowdfunding or sponsorship)	Wikidata, Confiscati Bene, OpenStreetMap	C1
A2	Paid self-service data delivery	**Value proposition:** Augmented open data (i.e., in combination with non-open data) delivered via various types of products to data users **Value creation:** The critical open data stage is preparation, and the consumer relationship is self-service **Value capture:** Revenue generated from augmented open data through freemium or subscription models	Opencorporates, Goolzoom, TransportAPI	C2
A3	Personalized open data service	**Value proposition:** Multiple service units based on augmented open data, providing personalized services to open data providers and users **Value creation:** The consumer relationship is personal assistance **Value capture:** Revenue typically generated through service delivery	FixMyCity, Opendatasoft, dataninja	C3
A4	Interactive app with other complementary products	**Value proposition:** Interactive app with other complementary products **Value creation:** The critical open data stage is reuse, and the consumer relationship is self-service **Value capture:** Revenue generated mainly from (augmented) open data via various means such as subscription fees, app sales, and sponsorship. Complementary products may enhance the benefit, visibility, or appeal of the interactive app	Boer&Bunder, Zapmap, LocalFocus	C4

Table 4 (continued)

ID	Name	Salient characteristics based on value dimensions	Example	Cluster
A5	Open data repository funded by sponsorship	**Value proposition:** Open data repository mainly targeted at generic open data re-users and is free **Value creation:** The critical open data stage is the preparation, and the consumer relationship is self-service **Value capture:** Funded by public or private sponsorship	Tutki Hankintoja, FRIS Onderzoeksportaal, basemap.at	C5
A6	One-stop package around an (augmented) open data platform/repository	**Value proposition:** Multiple product units with complementary products, centered around a restricted data platform/repository based on augmented open data. The target consumers are typically (but not necessarily) highly skilled data users and providers **Value creation:** The critical open data stage is the preparation, and the consumer relationship is self-service **Value capture:** Revenue generated through subscription fees or software sales	Nasdaq Data Link, ArcGIS, Enigma	C6
A7	Single-purpose app	**Value proposition:** Single-purpose app based on open data, targeting generic data users **Value creation:** The critical open data stage is reuse, and the consumer relationship is self-service **Value capture:** Various means of revenue generation	QEdu, FloodAlert, SwissTrains	C7 and C8
A8	Interactive app without complementary products	**Value proposition:** Interactive app without other complementary products **Value creation:** The critical open data stage is reuse, and the consumer relationship is self-service or personal assistance **Value capture:** Various means of revenue generation, such as subscription fees, brokerage, or app sales	Taranis, geoFluxus, 9292	C9

Table 4 (continued)

ID	Name	Salient characteristics based on value dimensions	Example	Cluster
A9	Open data advocacy	**Value proposition:** Multiple units of open data advocacy, campaigning, or lobbying services **Value creation:** Various critical stages of the open data lifecycle and various forms of consumer relationships **Value capture:** Mainly funded via external contributions (sponsorship or crowdfund) but, in some cases, also service delivery	Publish What You Pay, Open State Foundation, Open Data Institute	C10

Definitions for business model elements in every value dimension, including types of products (e.g., data platform, data repository, single-purpose app), stages of the open data lifecycle (e.g., preparation, reuse), and revenue streams (e.g., sponsorship, service delivery) are provided in Supplementary Appendix 3

archetypes in the literature. Notably, archetype A1 was not previously identified, whereas archetypes A2 to A9 are more refined in comparison to the business model archetypes described in the literature, especially in terms of expounding elements in all three business model value dimensions (i.e., value proposition, value creation, and value capture).

Archetype A1 is a *collaborative open data platform*. Archetype A1 offers a free open data platform for anyone to contribute and use open data. Since the platform is free, this business model captures value through external contributions, i.e., through crowdfunding or sponsorship, instead of market transactions. Value is created collaboratively through co-creation (where a lead body facilitates the contribution and use of open data) or through community-based organizing (where all members, at least theoretically, have equal opportunity to influence how open data is contributed and used). This business model was not captured in the existing literature we reviewed. Although the *data platform* business model identified by Magalhaes and Roseira (2020) may seem similar to archetype A1, the former is described as having "a higher level of interactivity, thereby offering users the ability to effectively explore open government datasets" (Magalhaes & Roseira, 2020, p. 7). This description lacks detail on the value creation and value capture dimensions, is limited to government data, and is fundamentally different from the bottom-up nature of archetype A1. The *increasing quality through participation* business model identified by Ferro and Pizzamiglio (2023) may come close to archetype A1, even though the latter is not limited to quality enhancement but also includes contributions in terms of the data itself, standards, and governance aspects.

Archetype A2 is a *paid self-service data delivery*. The core value proposition of archetype A2 lies in augmenting open data with non-open data, delivered through various mechanisms such as data repositories, application programming interfaces (APIs), or direct transfers. The augmented data are not offered for free, with revenue typically being captured via freemium or subscription models. The *data refining* and *data structuring* business models identified by Magalhaes and Roseira (2020), the *integrators* identified by Magalhaes et al. (2014), and the *information aggregators* noted by Janssen and Zuiderwijk (2014) are similar to archetype A2. However, although the four business models described in the literature highlight the open data pre-processing value proposition, the data involved are solely (or at least mainly) open data. This contrasts with the archetype A2 we discovered, which foregrounds the combination of open and non-open data.

Archetype A3 is a *personalized open data service*. This business model helps open data providers or users with their open data-related activities. Since the services offered are personalized, the business model typically consists of multiple service units instead of a single product to cater to the diverse needs of open data providers and users. The consumer relationship is based on personal assistance, and revenue is obtained through service delivery. This archetype is comparable to the *enablers* identified by Magalhaes et al. (2014), but it is described more specifically that the personalized relationship with consumers is at the heart of it. Thus, for archetype A3, the value is captured by open data intermediaries through service delivery fees. In contrast, the *enablers* noted by Magalhaes et al. (2014) are rather generic.

Archetype A4 is an *interactive app with other complementary products*. This type of app supports dynamic interactions rather than static ones. It may be based on entirely open data or in combination with non-open data. At the heart of this business model are other open data-based or non-open data-based complementary products (e.g., other apps, data platforms, and advisory services). In this regard, this business model does not rely entirely on a single product to generate revenue. The complementary products enhance the benefit, visibility, or appeal of the interactive app. Revenue is generated through subscription fees, app sales, and sponsorships. This archetype is a specific subset of the *interactive apps* business model identified by Janssen and Zuiderwijk (2014) and Magalhaes and Roseira (2020).

Archetype A5 is an *open data repository funded by sponsorship*. Compared to a data platform, which is two-sided and where multiple suppliers and users can offer and use data on it, a data repository is one-sided, with only a limited number of suppliers able to provide data on it. This archetype is relatively straightforward and familiar, such as most open government data portals. It is funded by public or private sponsorship. The critical open data stage is the preparation, and the consumer relationship is self-service. This archetype is similar to the *open data repositories* identified by Janssen and Zuiderwijk (2014). Whilst the two are identical, archetype A5 highlights that value capture is primarily based on sponsorship.

Archetype A6 is a *one-stop package around an (augmented) open data platform/repository*. This archetype is a one-stop package with modular service units (e.g., various data analysis, visualization, and dissemination tools) built around an open data platform/repository with (augmented) open data, where data users/providers can select the functionalities needed. Our analysis shows that it typically targets highly skilled data users and providers in professional domains. The critical open data stage is the preparation, and the consumer relationship is self-service. Revenue is generated through subscription fees or software sales. This archetype resembles the *service platforms* identified by Janssen and Zuiderwijk (2014). Nevertheless, the archetype A6 we described is more refined in clarifying subscription fees and software sales as the typical means for value capture.

Archetype A7 is a *single-purpose app*. These apps are typically only based on open data (i.e., not in combination with non-open data) and have limited functionalities. The critical open data stage is reuse, and the consumer relationship is self-service. The app may be free or come at a cost. Revenue is generated through various means, such as cross-subsidy, a freemium model, subscription fees, or sponsorship. The app may also be developed by volunteers, for which no funds were collected. This archetype is the same as the *single-purpose apps* identified by Janssen and Zuiderwijk (2014) and Magalhaes and Roseira (2020).

Archetype A8 is an *interactive app without complementary products*. The slight difference between archetypes A8 and A4 is the absence of complementary products. Archetype A8 may be self-sufficient or sufficiently viable without complementary products. Moreover, we discovered that archetype A4 typically relies on augmented open data (i.e., in combination with non-open data), whereas archetype A8 relies solely on open data. The critical open data stage is reuse, and the consumer relationship is self-service or personal assistance. Revenue is generated through various channels, such as subscription fees, brokerage, and app sales. Like archetype A4, this archetype is also a specific subset of the *interactive apps* business model identified by Janssen and Zuiderwijk (2014) and Magalhaes and Roseira (2020).

Lastly, archetype A9 is *open data advocacy*. The value offered through this archetype is advocacy or lobbying for open data policies, provision, and reuse through engagement with various open data stakeholders. Funding is mainly obtained via external contributions (sponsorship or crowdfunding); however, in some cases, revenue is generated through service delivery. This archetype is similar to the *advocacy* (for open data providers) and *consultancy* (for open data re-users) business models identified by Magalhaes and Roseira (2020). However, our findings suggest that the two business models identified by Magalhaes and Roseira (2020) typically come together as a single archetype (A9) in practice; open data intermediaries adopting this business model work simultaneously with providers, users, and other relevant stakeholders.

We also analyzed the typical types of organizations for each archetype based on the number of sample cases (with a silhouette score of at least 0.04) within each archetype (Table 5). This insight does not rule out the adoption of a particular archetype for certain types of organizations; rather, it reflects the current common practice. We found the following:

- Archetype A1 primarily consists of companies and NGOs/NPOs.
- Archetypes A2, A3, A4, A6, and A8 mostly comprise companies.
- Archetype A5 mainly consists of public organizations.

Table 5 Types of organization in each archetype

Type of organization	A1	A2	A3	A4	A5	A6	A7	A8	A9
Civic hackers/citizen researchers	1	0	0	0	1	0	12	0	0
Company	4	7	22	12	1	5	15	15	0
Cooperative/association	0	0	0	0	0	0	1	0	0
Joint-public and NGO/NPO	0	0	0	0	0	0	0	1	0
NGO/NPO	3	1	0	1	3	0	8	0	9
Public organization	0	0	0	1	11	0	7	0	0
Public-affiliated organization	1	0	0	0	1	0	0	0	0
University/research organization	0	0	0	0	3	0	0	0	0

- Archetype A7 comprises companies, civic hackers/citizen researchers, NGOs/NPOs, and public organizations.
- Archetype A9 consists of NGOs/NPOs.
- The most popular archetype for civic hackers/citizen researchers is archetype A7.
- The most popular archetypes for companies are archetypes A3, A7, and A8.
- The most popular archetypes for NGO/NPOs are A7 and A9.
- The most popular archetype for public organizations is A5.

Discussion and conclusion

Our findings offer a broader overview (i.e., nine archetypes) and a more detailed account (i.e., across the value proposition, value creation, and value capture dimensions) of the business model archetypes of existing open data intermediaries. This knowledge is missing from the literature and hinders the research and development of open data intermediaries' business models built upon a substantial understanding of their current state. Past studies (Germano et al., 2016; Janssen & Zuiderwijk, 2014; Magalhaes & Roseira, 2020) fall short of integrating the three key business model dimensions, even though business model scholars generally consider the three dimensions as the foundation of a business model (Afuah, 2018; Andreini & Bettinelli, 2017; Teece, 2010; Voigt et al., 2017). Our study tackled such shortcomings. Furthermore, our study is based on a large number of cases across many countries, whereas previous studies are based on only a handful of cases and/or a single country.

Theoretical implications

Our study affirmed that open data intermediaries' business models do not revolve solely around facilitating the transfer of data between two or more parties (i.e., simple rent-seeking) without adding value to the data or the processes involved in supplying or using it. This is demonstrated by the fact that the business model archetypes of open data intermediaries we discovered are starkly different from those of data intermediaries that mainly deal with non-open data, as identified by Schweihoff et al. (2024). They identified nine patterns of data intermediation services, and all but one involves data control, consent management, or identity management. Neither of these aspects is particularly focal in the open data intermediation business model in the context of our study. The more crucial aspect is gaining benefits from intermediating data that is already freely reusable by everyone under an open license (i.e., not requiring registration, consent, or identity verification), while carving a space or maintaining a competitive advantage in their respective sector or market. Having said that, organizations that operate as open data intermediaries can also serve as intermediaries for non-open data simultaneously, i.e., they can employ multiple business models.

Furthermore, our study shows that open data intermediaries' business models may be based on integrating open data with non-open data. In this case, open data is a crucial component of the business model, as the products offered would not be viable without open data. This affirms the potential of open data to multiply the creation of new products by serving as the basic data that organizations leverage in conjunction with their non-open data. A tangential but relevant point is that our study also challenges the claim that the value of open data is "often meager" (p. 1) if the evaluation is solely based on organizations that have "participated in open data events" and/or "had received government funding for open data projects" (p. 3) (Temiz et al., 2022), since the value that open data enables may not be obvious in the end-products or solely generated through open data events or projects.

Our study also confirmed that some open data intermediaries are not entirely independent entities (in terms of ownership and/or governance) from the parties that interact with them, but instead, those parties may collaboratively develop, govern, and maintain the infrastructure of the intermediaries. This is particularly shown by archetype A1, the *collaborative open data platform*. This archetype was not explicitly described in the past literature on open data intermediaries' business models. Its value creation is based on co-creation or community-based organizing. Thus, the multi-sided markets theory (Rochet & Tirole, 2006) is insufficient in describing some open data intermediaries' business models. This theory assumes that the intermediaries act as independent entities, facilitating interactions between distinct user groups. However, this theory falls short of capturing archetype A1, in which the infrastructure of intermediaries is collaboratively developed and governed by the users and suppliers of open data themselves.

Our study also showed that business model archetypes of open data intermediaries include beyond those based solely on multi-sided platforms. They also include one-sided products or services, particularly represented by archetypes A3 (personalized open data service) and A9 (open data advocacy). While these business model archetypes are not platform-based, they still play a crucial role in generating value across the entire open data ecosystem. Moreover, we discovered that contributions from open data intermediaries can occur at various stages of the open data lifecycle, i.e., identification, preparation, publication, reuse, and evaluation. Therefore, open data intermediaries are not merely the "bridge" between open data providers and users (Shaharudin et al., 2024), as some have implied (Brugger et al., 2016; Meng, 2016).

Our study also found that many open data intermediaries offer other open data-based or non-open data-based products. For certain archetypes (A1, A4, and A6), these other products complement the main open data products. For archetype A6 specifically, the main source of revenue, in fact, comes from other products rather than the main open data products. This shows that open data intermediaries' business models do not have to rely solely or mainly on open data products for revenue.

Our findings offer the groundwork for further inquiries into how open data can be better integrated into business models (Gurin, 2014), factors that could contribute to the success of such business models (Lambert & Davidson, 2013), and the conditions that could support such business models to sustainably deliver value to other open data stakeholders (Hossain et al., 2016; Jetzek et al., 2019; van Veenstra & van den Broek, 2013). Further research may also investigate whether certain business model archetypes are feasible for specific types of organizations. Specifically, can open data intermediaries from public organizations adopt a *personalized open data service*, even though our study suggests that no public organizations in the sample cases adopt that archetype?

Practical implications

For practice, our findings offer insights for existing and potential open data intermediaries on the business model they can adopt and, indirectly, encourage greater exploitation of private and public value from open data (Robinson & Mather, 2022; van Loenen et al., 2021). Such knowledge may be particularly illuminating to public organizations and NGOs/NPOs, as they currently employ only a limited number of business model archetypes, while their role as open data intermediaries is needed to ensure public interests are accounted for in open data value generation (Shaharudin et al., 2025). Our findings can also help open data intermediaries and other stakeholders discern their value network configuration (i.e., how they are interrelated) (Lindman et al., 2014), which can be used to explore new opportunities and forge new relationships. Meanwhile, policymakers can use our findings to support policy design related to open data intermediaries, which is consistent with the call by Meijer et al. (2014) for governments to acknowledge the heterogeneous open data incentives, practices, and consequences.

Furthermore, the taxonomy we developed in identifying the archetypes is, in and of itself, useful to practitioners as a morphological box for designing and experimenting with new open data intermediary business models by mixing and matching elements across categories. In other words, the taxonomy has the potential to become the equivalent of Osterwalder and Pigneur's (2010) business model canvas, but more granular and specific to open data intermediaries.

For potential funders of open data intermediaries, from the public or private sector, who are assessing the viability of businesses or projects proposed by open data intermediaries, our findings provide an overview of existing business models for reference. They can look for similar open data intermediaries within a particular archetype and identify critical aspects to consider whilst making their funding decisions, including potential competitors. Such knowledge may give funders greater confidence to support open data intermediaries and may help foster the emergence and growth of open data innovation.

Additionally, our findings show that while companies employ many different business model archetypes, public organizations and NGOs/NPOs rely on only a handful. Moreover, the few archetypes that they adopt are mostly based on sponsorship. This raises questions about the sustainability and innovativeness of such organizations in serving as open data intermediaries. Hence, the development of new, innovative business models specifically for public organizations and NGOs/NPOs deserves greater attention.

Study limitations

Our findings are limited by the data we used. First, the sample cases are based on use cases gathered from data.europa.eu and thus predominantly (but not only) operate in Europe. Thus, further research could investigate whether other existing open data intermediaries' business model archetypes were not captured from our sample cases. Second, the qualitative data we gathered from the sample cases relied on our interpretation and best effort. Notably, there might be overlooked aspects that could offer more insights into the business models of open data intermediaries. Despite this, the present study only aimed to provide a bird's-eye view of the existing business model archetypes. Further research, especially based on qualitative methods such as in-depth case studies, can be used to investigate open data intermediaries' business models more deeply and capture nuances that may be missing. Third, our study is informed by the business models of existing real-world open data intermediaries. However, business models evolve in response to technological, market, and regulatory conditions (de Reuver et al., 2009; Şimşek et al., 2022), and as such, our study does not predict future business models.

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Data availability The novel dataset of the business model elements of the sample cases we collected is openly accessible and reusable: https://doi.org/10.4121/160c8de9-99cf-4231-96a3-bad517360b67.

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