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Big Data, Open Data, and Open Innovation

Leveraging Unstructured Data Sharing in Open Innovation: A Business Model for Large Research-Intensive Firms

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ABSTRACT

In the current environment of high volumes of data, large established firms are looking for new ways of gaining a competitive advantage through Open Innovation (OI). Sharing unstructured data represents such an opportunity. However, the literature is scarce in understanding how to attract this data and realize more value within the OI funnel. We thus investigated a business model illustrating how large research-intensive firms can use it to support data sharing for OI. We interviewed 25 professionals in an OI project between a global pharma organization focused on the animal health market, a UK-based university, and data science firms. Firstly, we provide evidence of the role of data sharing in OI for extracting value. Secondly, we theorize a business model that supports data sharing for inbound and outbound OI using three stages of value realization. We welcome further research to confirm or extend our findings in other industrial settings.

1 | Introduction

In the current environment of high volumes of data and increasing technology use, firms are changing their work practices and looking for alternative ways of gaining a competitive advantage. Large organisations are considering capitalising and creating strategic value by leveraging data as part of these changes (Ghosh et al. 2022). As a result, they are currently turning their attention to the external data sources from their suppliers and customers, and using them in research and development activities to sustain new services and product offerings. However, with studies showing that data sharing could unlock more than $3 trillion in value across different domains (Manyika et al. 2013), there is a dearth of literature showing how to and harness this data and realise value from its exploration, with few examples that have demonstrated the benefits of data sharing in feeding artificial intelligence. For instance, among many ventures in the oncology domain, Lauer et al. (2021) contend that Cambridge Cancer Genomics is exemplary in its use of open data to train machine learning models, emphasising the value of openness and collaboration in deriving innovation. As a result, it develops precision oncology solutions that can detect the relapse of patients sooner than the norm, predict responses to cancer therapy, and reduce ineffective treatment protocols. Another example is Transport for London (TfL), where the data shared by passengers about congestion or accidents improves the experience of other users (Stone and Aravopoulou 2018). TfL provides access to over 30 data feeds to foster innovation, including live arrivals, timetables, and air quality. By making data freely available, TfL supports the development of new products, services, and tools that benefit London's transport users and the broader economy, which already has generated annual economic benefits and savings of up to £130 million per year. TfL has worked with external partners like Ordinance Survey, National Car Parks, and King's College London to enhance data quality and expand its scope (Stone and Aravopoulou 2018). As a result, the millions of journeys in London daily are supported in real-time through various apps and platforms. Considering examples, it is vital to systematise how data realises value across application domains. Mainly, the highly regulated domains are of interest, where the vital data is locked between the shareholders and data owners, and where they can realise more value when shared (Bigliardi et al. 2021; George et al. 2021; Petukhova et al. 2023). Our study thus focuses on R&D-intensive environments, such as in data-driven animal healthcare, where regulatory and technological restrictions impede data sharing between animal owners, animal clinics, and the data science community. We aim to understand what business models can support data sharing and lead to value realisation for large firms when they engage in Open Innovation.

Open Innovation (OI) has captured the attention and efforts of scholars and industry practitioners, who have noticed a shift from closed to open models (Chesbrough 2003; Chesbrough et al. 2006). OI assumes that firms leverage internal and external ideas and paths to market and thus create better opportunities to innovate (Bigliardi et al. 2021; Bogers et al. 2018; Smart et al. 2019). Chesbrough and Bogers (2014, 17) described a distributed innovation process founded on 'purposefully managed knowledge flows across organisational boundaries.' Various firm practices have been organised under three dominant OI processes: *inbound OI*, *outbound OI*, and the coupled mode of OI (Bigliardi et al. 2021), mainly focusing on knowledge flows such as IPs and patents.

Whilst OI has attracted significant research attention with sharing *knowledge* (Michelino et al. 2015; Bagherzadeh et al. 2022; Bagherzadeh et al. 2022; Nguyen et al. 2021; Barczak et al. 2022), few extant studies provide evidence for the ways to facilitate sharing *data* in OI (Lichtenthaler 2008). For example, some studies focus on the effect of internal data to stimulate innovation (van den Veenstra and Broek 2013), OI governance modes (Bagherzadeh et al. 2019a), and OI platform design (Osorno and Medrano 2020). However, we lack a holistic understanding of how data sharing may support more value realisation through OI. Notably, studies such as Bogers et al. (2018), Eckartz et al. (2016), Monino (2021) and Zuiderwijk et al. (2015) have studied the use of technologies for data generation. Less research is specifically focused on how data within an OI context can create strategic organisational value (Beck et al. 2020; Bogers et al. 2018; Eckartz et al. 2016; Fritsch et al. 2020; Monino 2021). To our knowledge, there is not a study that provides clear supporting evidence of how to facilitate data sharing. The emerging debates on the value of open data and the business perspective of data exchanges in OI are instigated by failed open data projects[1].

Given the focus on explaining how to extract strategic value for organisations, the research question is thus: 'what business model can a large research-intensive organisation use for data sharing within OI?'

Firstly, we provide evidence on the potential of data sharing in extracting value for large established firms based on interviews with specialist professionals working with data and managing regulated organisational data. Secondly, we theorise how data sharing (as a value proposition) influences value creation, delivery, and capture. Thirdly, we construct a three-stage business model to support data sharing along the OI funnel. The first stage incentivises data owners to unlock their data for cleaning and exploration of the accumulated dataset within a research community with an attempt to answer research questions important for sustainability. The second stage is to incentivise the community to curate datasets and develop tailored high-value services for external customers. The third stage focuses on standardisation and the consequent sale of datasets for training AI engines. By providing this three-stage business model, we extend the existing requirements of OI organisational systems by showing how to unlock, curate, and explore the datasets within a broad community of data scientists and entrepreneurs (Bogers et al. 2018; Naqshbandi 2018).

In the following sections, we review the literature on OI to show the state-of-the-art positions and debates currently considered essential. We then present the review of data sharing, business models, and its key theories and frameworks, which inform current debates on data sharing and OI. This review positions the current study and has led to our research question. First, the methodology explains the data collection strategy for the 25 qualitative interviews and analysis approach. The thematic analysis framework is presented in the methodology section (King and Horrocks 2010). Further, we present the key explanation of the results and discuss our attempt to theorize contributions for business models and OI: the business model supporting data sharing for OI for a large established firm in a data-intensive domain, that is, where data sources from customers or suppliers might be available for exploration. Its applicability in large organizations with less focus on research and development represents a limitation of this paper and, simultaneously, a potential avenue for other researchers to undertake further research. What would be a business model supporting data sharing for OI of a small and medium-sized firm or a start-up? How can they participate in such OI projects, and what would those roles be? The paper concludes with practical implications, which argue for facilitating data sharing around large established firms, creating data sharing communities, and developing data platforms to support further data commercialization as part of the three-stage business model.

2 | Literature Review and Theoretical Foundations

2.1 | Data Sharing and OI

Open Innovation (OI) has captured the attention and efforts of scholars and industry practitioners. Introduced by Chesbrough (2003), who noticed a shift from closed to OI models, OI rests on the principle that companies leverage internal and external ideas to innovate and thus create strategic value for their market (Bogers et al. 2018; Smart et al. 2019; Ahn et al. 2019; Patrucco et al. 2022), along research, development, and commercialisation stages of the funnel. Moreover, OI has become even more important in the context of the opportunities brought by the wider digital transformation of business and society, which enables value to be created in new ways and promises to radically transform all industries and sectors (Bigliardi et al. 2021; Chesbrough 2003; Huizingh 2011). For example, a key aspect of OI is placing the innovation processes within an ecosystem of people, organisations, and sectors that supports value co-creation (Bogers et al. 2018; Weiblen 2014). More recently, there have been more studies that investigate the darker side of OI and have shifted the attention to the challenges of implementing OI in contexts in which the individuals involved in the ecosystem, such as public organisations, have constrained digital skills and knowledge (Bertello, Bogers, et al. 2022). Leveraging data sharing in OI cannot happen without considering business models, specifically how these may need to change and transform to meet the demands of OI (Arora and Jain 2024; Corrales-Garay et al. 2019, 2020, 2022).

Data sharing is closely related to OI. Like OI, data sharing enables internal and external data sources to harness inflows and outflows of knowledge to drive innovation within the firm (Chesbrough and Bogers 2014, p.17). In the context of OI, research has confirmed support for the view that firms that conduct inbound OI can gain the upper hand to receive advantages from novel ideas and (re)combined knowledge, exploit new market opportunities, and replenish their pool of capabilities (Hung and Chou 2013; Martinez-Conesa et al. 2017). For example, Ritala and Karhu (2023) found four types of data complementarities which large organisations may encounter: internal (hierarchy), relational (bilateral contractual relationship), supermodular (platform ecosystem), and unbounded (data markets). Overall, firms need to recognise and utilise externally searched knowledge by understanding its value, incorporating it, and adopting it commercially. Although enterprises generate substantial amounts of data as part of their operations, their true value-generation potential is yet to be realised (Fritsch et al. 2020). Data sharing has the potential to enable innovation (Arora and Jain 2024; Davies and Perini 2016) and support economic growth (Smith et al. 2016).

The theoretical foundations of *inbound OI are* in the well-developed strategic concept of 'absorptive capacity' (Cohen and Levinthal 1990). It was defined as 'the ability of a firm to recognise the value of new, external information, assimilate it, and apply it to commercial ends' (p. 128). The assumption that absorptive capacity enables firms to take advantage of external sources of innovations has opened the doors to two possible hypotheses: (1) higher absorptive capacity has a higher likelihood which is associated with the utility of innovations taken from external sources, or (2) firms with high absorptive capacity will achieve higher success given this strategy (West and Bogers 2014). A paucity of studies considers outward knowledge transfer, that is, *outbound OI*. One such study was by Lichtenthaler and Lichtenthaler (2009), who introduced a capability-based framework that investigates inward and outward knowledge transfer and offers a framework. However, it is currently unclear how to support purposeful data sharing along the OI funnel, as one needs to unlock the private data stored by individuals and organisations, clean, curate and only then convert it to meaningful insights (Kazantsev et al. 2023; Chen et al. 2011).

2.2 | Business Models to Support OI

Business model is a key consideration in the context of OI, which captures and defines the (new) requirements of OI organisational systems and architectures (Bogers et al. 2018; Barczak et al. 2022). As Osterwalder et al. (2005, p.4) described, the business model is a framework that explains: 'the blueprint of how a company does business'. Zott and Amit (2013, p.404) specified the business model as a 'system of interdependent activities that are performed by the firm and by its partners and the mechanisms that link these activities to each other.' BMs comprise a series of front-end and back-end components that provide the business's building blocks (Günzel and Holm 2013). These include value propositions, product/service offerings, customers, key partners, value creation, and value capture mechanisms (Fjeldstad and Snow 2018), still pointing to three key dimensions: *value creation*, *delivery*, *and capture* (Arend 2013; Berends et al. 2016). The *Value creation* describes how a set of activities aims to satisfy the final customer needs to gain an economic return from the defined activities (Berends et al. 2016; Zott and Amit 2013). Value creation is driven by customer needs and how technology can solve the identified customer issues via a set of activities (Arora and Jain 2024; Chesbrough and Rosenbloom 2002; Arend 2013). The activities are related to increased efficiency and cost minimisation to create better and refined existing operations, such as maintenance and regular production processes (Agrawal et al. 2019). *Value delivery* describes the mechanisms and processes illustrating how a firm will deliver its products or services to its customers (Osterwalder et al. 2005; Arend 2013). *Value capture* ensures that economic returns from value creation are in place and that profits are shared with all the value-creation stakeholders (Åström et al. 2022). Importantly, firms that leverage a new source of value enjoy substantial returns (Euchner 2016; Pohle and Chapman 2006). Arora and Jain (2024) contrasted two sales models where they found that data sharing, privacy protection, and government regulation, where *data sharing* occurred, lowered quality investment costs and thus improved overall performance. Data sharing can be used for creating and capturing value for private good and public goods. Specific examples of data crawling, data integration, data dissemination, and data marketplaces have been found in the existing digital platforms (Kazantsev et al. 2023). As such, the data crawler uses public data for private good, the data marketplace uses private data for private good, the data integrator uses private data for public good, and the data disseminator uses public data for public good.

Bogers et al. (2018, 10) emphasise that OI requires business models as the logic of creating and appropriating value—that dynamically transcends the boundaries of firms within that innovation ecosystem. It contrasts with large organisations' traditionally closed business models, whereby value is created mainly from internal knowledge sources (Zimmermann and Pucihar 2015). As OI opens business models to external knowledge flows and inputs, this may involve significant reconfiguring of business approaches. For example, internal culture might change (Kratzer et al. 2017). In the context of open software, for example, the source code used is openly available knowledge (Wolkovich et al. 2012), but the expertise developed and held privately represents intangible knowledge (Smart et al. 2019).

Previous OI research suggests that firm's migration toward opening up innovation strategies is contingent and influenced by internal and external contexts, from technological development to institutional pressures (e.g., Bertello, De Bernardi, et al. 2022; Huizingh 2011). The extant literature has proposed that opening up '*innovation strategies*' is more appropriate in business environments attributed by *globalisation*, *competitive intensity*, *the market and technological turbulence* (Akgün et al. 2019; Huizingh 2011). Therefore, business model innovation is critical in examining how organisations can unlock value through OI, especially in an increasingly digitalised economy and society. Business model innovation has been described as 'the cornerstone of long-term performance' (George and Bock 2010). Täuscher (2018) suggests that future research can further leverage qualitative research methods to investigate configurations of business models, competitive strategy, and industry characteristics needed for superior firm performance; particularly challenges existing with data sharing (Temiz and Brown 2017).

2.3 | The Contribution Area—Business Model Supporting Data Sharing for OI

Many companies 'find it hard to find a good fit' (Van der Meer 2007), where 'fit' relates to the difficulty of identifying appropriate business models to leverage the opportunities of OI. Indeed, Euchner (2016, p.10) highlights that 'new business models conflict with well-entrenched practices, requiring the entire organisation to move beyond its comfort zone'. However, scholars have shown that large innovative organisations tend to display closed behaviour toward OI (Fritsch et al. 2020; Van der Meer 2007). Data sharing, as a more hidden 'locus of innovation' (Zott and Amit 2007, p.183), can drive innovation beyond firm boundaries and it is still unclear how to organise a suitable conceptual vehicle for exploring opportunities for value realisation (Gao and Janssen 2022). Recent advancements in the uses and abilities of technology mean that value can be created by utilising Artificial Intelligences (AI's) ability to support better decisions and create improved outcomes (Cockburn et al. 2018). The latest research in this area suggests a renewed understanding of ways of defining OI, which Bogers et al. (2020) have suggested needs to be considered from a sustainable perspective. Hence, Bogers et al. (2020, p. 1507) redefined OI as 'a distributed innovation process which is based on purposively managed knowledge flows across organisational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organisation's business model'. However, the exact business model supporting these flows (data sharing) was not constructed, and the opportunity is to consider the OI outcomes from the systems' level (Bogers et al. 2018; Velu 2017), particularly, supporting the significant effort for data cleaning and curation, which is not yet incentivised (however, it is vital for further success in generating meaningful data-driven insights and predictions). Hence, to prepare sufficient volumes of standardised datasets for their analysis and commercialisation, the business model should consider several stages of value creation, where the nascent stages are invested, expecting higher returns from the later stages.

Furthermore, Bertello et al. (2024) have suggested that scholars adapt existing OI visual frameworks or create newer versions to meet the connection to newer contexts. For instance, they question whether the innovation funnel is still appropriate to align OI, especially given the recent requests for approaches that stimulate a multidimensional and recursive lens of innovation as an infinite and constantly (re)constituted process where the means and outcomes should be treated as jointly enabling and a connected part of one another. Given the opportunities presented by the unlocked data and OI, the key question is: 'what business model can a large research-intensive organisation use for data sharing within OI?'

3 | Methodology

3.1 | Research Context

To establish clear boundaries for our study, we focused specifically on research-intensive environments, particularly large research-intensive organisations. These are typically characterised as R&D-intensive companies that invest heavily in innovation and development activities. Key features of such organisations include: (1) Substantial R&D expenditure: A significant portion of their budget is allocated to research and development initiatives; (2) Often operating at a loss: These companies frequently prioritise long-term innovation over short-term profitability, resulting in temporary financial losses; (3) Innovation-centric focus: They primarily operate in sectors where continuous innovation is crucial for maintaining competitiveness, such as technology, pharmaceuticals, and automotive industries.

3.2 | Data Collection

The data collection for this research is based on semi-structured interviews, which are expected to shed light on the role of data sharing in OI. We focused on the respondents from the UK and US markets, where many startups support the booming animal health industry. Firstly, most animal owners lack experience in interpreting symptoms and checking for pet wellbeing, which calls for the creation of data-driven services in animal healthcare. Secondly, much clinical data in this industry has received scant attention, and more data is generated by IoT-wearable devices, like smart collars,[2] which is left underexploited by the IoT device producers (Chui et al. 2014). There is an ongoing dispute on how to support data sharing from animal owners toward data scientists to produce more meaningful outcomes, such as predictions of pet conditions. Thirdly, various third parties are looking at access to such datasets. Entrepreneurs strive to use the training datasets to develop animal healthcare services that could provide preventive health services for pets. For example, animal owners can select the type of food their pets consume[3] and use IoT-enabled collars to control the pets' activity level, itching patterns, and sleeping quality of a specific breed. This contributes to the richness of a statistical model that can be used for testing hypotheses about the predictors of pet health conditions. Such predictions are the backbone of future animal health services, focused more on prevention than treatment. Pharma companies are investigating how to improve the efficiency of treatments, and insurance companies could better access the pet conditions for the best price of the insurance premium. Finally, while animals share diseases similar to humans (e.g., cardiovascular disease, allergies, etc.), the available animal sample, less regulated than the human healthcare sample, could guide toward factors predicting similar illnesses in humans and support ongoing analytical work that can inform similar human projects in the future.

Qualitative data were collected through in-depth interviews performed between May and July 2021. All the interviews came from the research project, shared between the leading pharma company working for animal health, one of the leading veterinary innovation centres at the UK University, and a data science company from Greece. Data collection was performed following a rigorous procedure. In the first step, six interviews used open-ended questions to explore the value of data for OI, namely how data sharing could improve value creation, delivery, and capture of data-driven innovation. Next, we targeted the most experienced stakeholders in business transformation, data science, and entrepreneurship to distil how companies may realise these business model dimensions once data is shared for OI (19 further interviews). A total of 25 professionals working in animal healthcare and data science were interviewed. We ensured the respondents' anonymity and confidentiality and addressed the potential for key informant bias.

3.3 | Thematic Analysis

Thematic analysis is a method to aggregate common themes in the dataset, commonly suggested for investigating commonalities between responses rather than an in-depth analysis of individuals (King and Horrocks 2010, p.159). One of the ways to complete it is to use the existing solid theoretical dimensions as overarching themes. For this purpose, we applied the stages of the OI funnel (research, development, and commercialisation). Each of these stages/overarching themes requires the means to value creation, delivery, and capture (i.e., the components of a business model in the presence of data sharing[4]) (Osterwalder et al. 2005). First, the quotes were inductively coded (first-order/descriptive codes) to belong to any value-adding activities. Second, we constructed second-order (or interpretive codes) when we merged the descriptive codes with the specific business model dimensions, e.g., the value creation for the research stage of the OI funnel has aggregated the value-adding activities supporting data cleaning. In the process, we added new first and second-order themes as they were identified in the responses (King and Horrocks 2010). Theoretical saturation was confirmed when thematic analysis no longer identified new codes (Silverman and Marvasti 2008). Figure 1 illustrates the coding scheme.

3.4 | Sensitivity Analyses

Additionally, we adopted rigorous triangulation procedures to reduce the bias and increase the credibility and the dependability of the results, which can be considered alternative terms to reliability and validity as used in quantitative studies (Guba and Lincoln 1989; Sinkovics et al. 2008). We ensured inter-coder reliability by using documented peer review and reflection of our coding (Creswell and Miller 2000; Miles and Huberman 1994). We used peer review and discussion to resolve the identified discrepancies (Kassarjian 1977). Reviewing literature on data and business model innovation helped to remove observer bias and ensure external validity (Eisenhardt and Graebner 2007). For example, we found that the stages of the constructed business model broadly correspond to how the existing digital B2B platforms extract value from data sharing (Arora and Jain 2024; Kazantsev et al. 2023), which we interpreted as a positive result of triangulation. Also, the third stage of the model confirms the validity of the study by Ritala et al. (2024) on selling and monetising data in B2B markets. Finally, after completing the thematic analysis and writing up results, we presented the three-stage business model based on curating the shared data within the animal health ecosystem to the managers of a large established enterprise and the interview respondents in May 2022. The large established firm confirmed the validity of the study (Crabtree and Miller 1999) and agreed to move to the second stage of the business model (they labelled this business model as 'Data Curator'). Finally, the first author presented the paper at Berkeley Open Innovation Spring 2025 Seminar on 21st of April 2025.

4 | Results

4.1 | The Research Stage of OI: Data Crawling and Cleaning

The research stage focuses on building a data science community to unlock new data sources. IP2 clarified that this requires '*attracting* strategic partners, e.g., universities, corporate companies for long-term research projects' (IP13). Most interviewees agreed that *data regulation* is needed to resolve the privacy concerns of those who share. The IP8 summarised that: 'Big pharma faces challenges of privacy and feasibility. Where is my

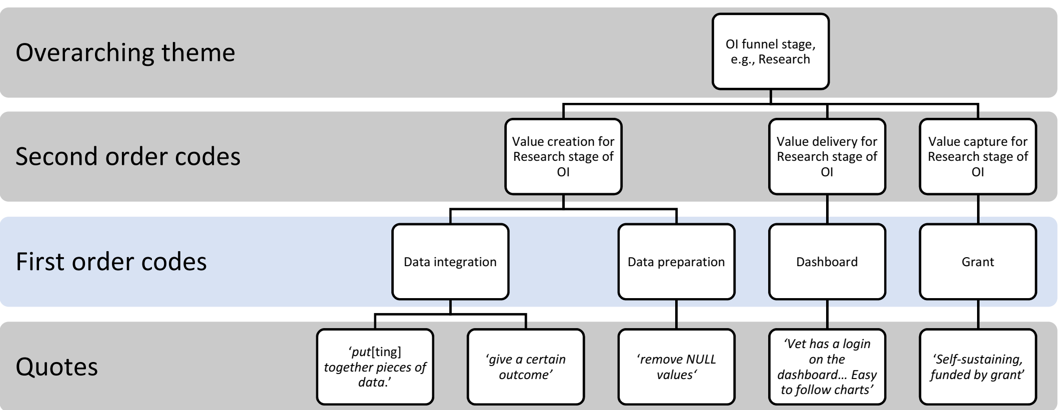

FIGURE 1 | Representation of the coding scheme for the OI Research stage (King and Horrocks 2010). [Colour figure can be viewed at wileyonlinelibrary.com]

data going? How can I check this?' Identifiable data of individuals (e.g., companies) can be anonymised (IP5). While those who share data often do not get value in return, another expert (IP8) suggested that data governance should include sharing incentives. For instance, a quick provision of insights could incentivise smaller companies (SMEs), as they have neither statistics departments nor significant analytical skills on board (IP8, IP13, IP14). IP13 argued for data ownership that can assure the regular update of datasets. The key questions need answering:

> What is my own gain? Will it improve my productivity? (IP18).

Large institutions could sign 'explicit and multiple one-to-one arms-length data partnerships' to share data with analytical partners. These institutions can enable 'data re-use from commercial projects' as customers of these companies may leave data for exploration (also, IP6). Such arrangements can help to agree through KPIs on how much people share their data and how many datasets we can have in the public domain (IP19). Hence, the need for data quality, as per IP15:

> The data is as good as you put it; if you constrain it to one company, you will never get robust data.

4.1.1 | Value Creation

The experts agreed that *data cleaning* is necessary, as most data is unstructured, unformatted, and requires additional work. Tech entrepreneurs like IP11 highlighted removing NULL values and corrupted entries. IP5 suggested 'making data available for research teams' and engaging the research community in data cleaning. IP9 added that there is a need to 'encourage users to report what they found and used, bring people to do little jobs, and compete [on this contribution]'. This will enable 'data volumes to address notable questions' (IP13, IP5 and IP17).

4.1.2 | Value Delivery

The experts suggested using data portals to visualise and compare datasets. Data science web portals (like Kaggle) are prevalent in research communities for experimenting with raw datasets, which require cleaning. IP13 commented that this stage 'should [make the data sharing process] more attractive for people looking at datasets than Kaggle'. Universities could play an important role, and therefore, one should allow 'university researchers [to] use the [data portal] without paying'(IP4). These dashboards could enable the exploration of the datasets. Universities can also organise hackathons to get co-funding from industrial partners to tackle a particular challenge, which requires the collaborative work of analytical teams. During hackathons, the ideas are tested, realised into prototypes, and validated with the potential customer.

4.1.3 | Value Capture

IP13 warned that the business value of the research stage has a very academic focus. University researchers are advanced on the basis of publications but receive little credit or reward for engagement in commercial realisation. Also, the slow grind of university bureocracy and inherent risk aversion impedes the rate of innovation. At the same time, per IP12, this stage enables easier access to funding. The scientific community needs research grants as the primary way to cover the costs of data cleaning and analysis for sustainability[5]. IP3 called this a 'self-sustaining' work necessary for further value extraction from data. Grants, sponsorship payments, and barter-style services can support such work. IP17 explains, 'Once we have much data, we could do a lot with it [revealing insights], then we can target big companies and run [targeted] ads'.

4.2 | Development Stage of OI: Data Integration and Curating

The next stage focuses on dataset processing to develop advanced analytics. This starts what IP8 mentioned as a 'data-driven value chain', that is, enhancement, analysis, and a targeted report (IP1). IP7 characterised the outcome as a 'preventive analytic lab for delivering digital reports for industries.' For this purpose, the large research-intensive firm can sign 'explicit data partnerships with [public] institutions [and other companies] to capitalise on data', where profit is a driver (IP5, IP21). The expert added that data integration would 'not work with competitors, [as] much legal tidying is needed to make it work', and a significant concern is getting enough data sources for economically viable outcomes.

4.2.1 | Value Creation

IP7 claims for predictive and prescriptive models based on the aggregated public data catalogues. For example, IP15 stated that in heavily regulated industries like animal healthcare, 'much data does not talk to each other'. In the related domain—the pharmaceutical industry—'data operate in silos' and, therefore, requires aggregation around the topic of interest (IP18). Open data, such as open weather forecasts (e.g., weather.com), could add more evidence for predictions, such as health diagnostics. For example, (IP1):

> putting together pieces of data [from the existing wellness devices, such as fitness monitors] to uncover important links between behaviour, activity, and health [using advanced deep learning models].

4.2.2 | Value Delivery

The data innovation platform can connect the data science and software development communities with potential consumers via the datasets. Further, an app can be developed for customers interested in speed (IP7, IP15). For example, IP8 commented that 'getting faster [results] is the priority'.

4.2.3 | Value Capture

While the need for venture capital was noted, the experts agreed that the most value should be captured via subscription for data-driven services, arguing that the 'subscription rate turns an important cycle of data into better insights', as per a business transformation partner in a large pharmaceutical company (IP13). The value may be captured by developing data-driven services built on large volumes of prepared and augmented data (IP1). The resulting apps driven by predictive analytics could be launched as spin-offs, where IP2 suggested 'short-term contracting'. To do so, one may 'sell anonymised data products, requesting further data using the developed data model' (IP5).

4.3 | Commercialisation Stage of OI: Splitting and Selling Datasets for Training AI

The next stage focuses on interconnecting the curated dataset with data seekers. The main goal is to 'lower barrier access to data' (IP5) and enable standard contract procedures for selling (IP2). However, due to the dataset size, the splitting of the dataset is needed. Per IP8:

> Too much data—we could get lost [...] Layering different data helps to build more success; therefore, there is a [potential] for on-demand data-driven services

4.3.1 | Value Creation

The extracted value from data should 'give a certain outcome, such as risk-based analysis' (IP18) and dataset for training AI decision-making. For example, such datasets can allow veterinarians to 'understand the sudden changes of behaviour [of a pet]' and 'provide an early intervention to improve [animal] health [and enable] objective, evidence-based, precision-medicine' (IP1). IP7 claims that these services should deliver insights into powerful predictive models, for instance, to prevent epidemic outbreaks, inc. 'confidence, credibility and reliability' during treatments.

4.3.2 | Value Delivery

Finally, a digital platform was suggested as a preferable interface when the datasets are formed and can be positioned toward individual users. Using data platforms, smaller companies could sell their datasets, possibly curated at the previous stage; larger firms may buy data for specific needs, for example, product utilisation data and AI training datasets. As mentioned by IP14, the platform should enable 'ease of access' for buyers and sellers in this market and provide information about the actors and resources.

4.3.3 | Value Capture

The experts suggest engaging audiences around data sets once more data sets become available for sale. For example, a large organisation could be a private partner, sponsor, or customer for a digital platform (IP12) that can provide on-demand access to training datasets for feeding AI and statistical assistance. The customer side of such platforms can sell ads (IP6) as part of larger companies' marketing campaigns. Table 1 describes the three stages of using data sharing in OI.

5 | Discussion

The findings suggest that realizing value from data sharing happens along three OI stages: *research* (looking externally for data sources, cleaning data), *development* (integrating data into datasets, looking for outcomes), and *commercialization* (splitting and selling datasets). This changes a large established organization, with the involvement of data scientists, to a large research-intensive organization that brings predictive analysis for internal processes and business services and supports spin-offs. Based on the findings, we have constructed a three-stage business model supporting data sharing along the OI funnel, Figure 2.

5.1 | Theoretical Contribution

Our study provides two contributions to the theory of OI in large research-intensive organisations: (1) First, we provide evidence of the role of data sharing for value realisation along the OI; (2) Second, we construct a three-stage business model to support data sharing for three stages of the OI funnel. For example,

TABLE 1 | The constructed business model supporting data sharing in OI.

	1. Research stage: crawling, cleaning, standardising data	2. Development stage: integrating and curating dataset	3. Commercialisation stage: selling and disseminating datasets
Focus	Data attracting	Dataset analysis	Dataset selling
Data collection	Private data	Private dataset and open data	Private dataset
Data regulation	Individual contract	Standard contract	Standard contract
Value creation	Data cleaning	Predictive analytics	Dataset splitting to feed AI
Value delivery	Web portal	Innovation platform, mobile app	Transactional platform
Value capture	Research grant	Venture capital, subscription	%, from each transaction
Sustainability impact	Public good	Private and public good	Private good
Data flow direction	Outbound	Inbound	Outbound

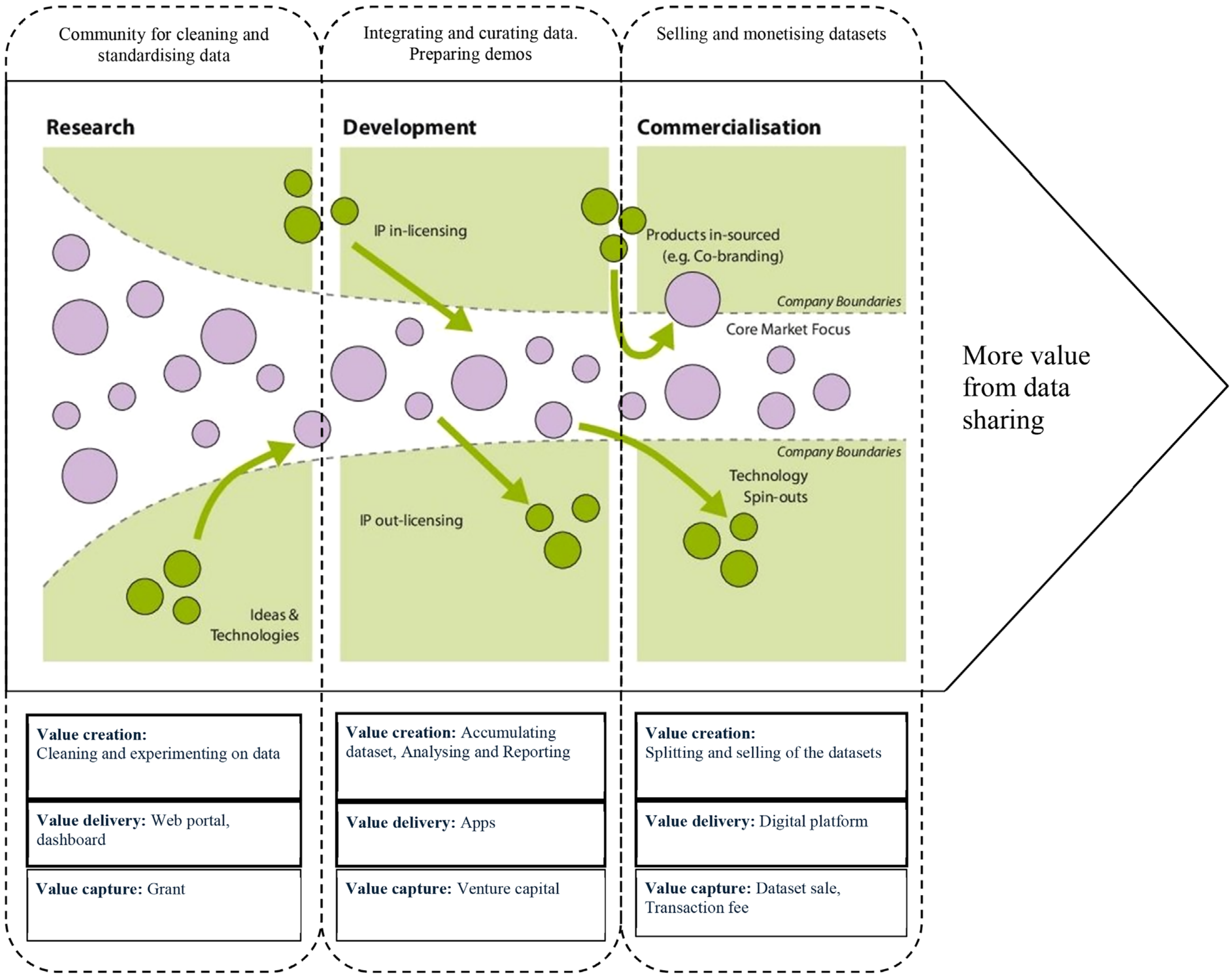

FIGURE 2 | A business model to support data sharing in OI, a modified picture of the OI funnel. https://www.rndtoday.co.uk/open-innovation/open-innovation/, accessed 9.01.2023.[Colour figure can be viewed at wileyonlinelibrary.com]

starting with an indirect value capture for large, established firms, such as branding, as research is linked to sustainability goals, we move toward data aggregation, prototyping, and finish by selling, where buyers acquire datasets from sellers (Pohle and Chapman 2006). We propose that this sequence can help realise value from data complementarities in *supermodular* (platform ecosystem) and *unbounded* (data markets) environments (Ritala and Karhu 2023).

It was a long-term concern for many companies who found it hard to identify appropriate business models to leverage the opportunities of OI (Van der Meer 2007). The paper proposes this model for large established organisations, which can an OI using data sharing supported by the new business model[6] (e.g., Bigliardi et al. 2021; Chesbrough and Rosenbloom 2002). The proposed business model will help large established organisations to innovate and resist disruption from start-ups (Euchner 2016). We highlight that companies can realise an additional value even if they do not possess substantial amounts of data; they can either generate them from their operations, attract them externally, or preferably both (Barczak et al. 2022; Smith et al. 2016). Thus, we contribute to the current literature on business models by finding a hidden 'locus of innovation' such as data sharing (Zott and Amit 2007) and enhancing the existing requirements of OI organisational systems (Bertello et al. 2024; Bogers et al. 2018; Naqshbandi 2018; Fritsch et al. 2020; Smart et al. 2019).

5.2 | Managerial Implications

The three-stage business model will help large research-intensive organisations act like focal firms in the data-sharing ecosystem while realising value using OI. For example, a pharma company interested in developing data-driven services for predicting human health conditions, such as a stroke or heart attack, would start with an explicit agreement with a sample of patients likely to develop the condition to wear condition monitors and supply time series data about their daily activities.

1. The first stage attracts the unstructured data and supports data cleaning and preparation for analysis. The targeted data will populate the dataset for research exploration about the causes of health condition development.

2. The second stage enables predictive analytics and prototyping, where several teams would work on developing apps for patients at various stages of illness. Potential spin-offs from this activity (e.g., apps) can further realize value by predicting condition, supporting recovery, and improve the quality of life with the large firm keeping a part of the shares.
3. The third stage captures value through splitting the curated dataset and selling data to train further AI and decision-support tools.

6 | Conclusion

Although data volumes are increasing, the literature lacks a holistic understanding of using these resources in OI, complementary to conventional knowledge flows. In response, this study constructed a three-stage business model to support data sharing at every OI funnel stage. This outcome is limited by the lack of interviews to confirm the findings for all large established organisations, as it is unclear whether the business model derived from animal healthcare represents other industries. However, specifically for animal health, unlocking data and sharing data is a 'win-win' situation, creating value for animals, animal owners, veterinarians and associated animal health professionals, pharmaceutical & insurance companies, and helping to address sustainable development goals: good health and well-being (3), life below water (14), and life on land (15).

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting this study's findings are available on request from the corresponding author.

Endnotes

[1] The lead author participated in these debates during Paper development workshops on OI during AOM2023.

[2] Such as our partners producing dog collars—https://www.whistle.com/ (accessed 29 June 2024).

[3] This is much different to humans, as we are famous for being addicted to our favourite food.

[4] Or, in business model terms, when data sharing is the value proposition at each OI funnel stage.

[5] See above section on value creation.

[6] Data availability, preparedness, and ability to derive value following business goals are important.

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