KNOWLEDGE MONOPOLIES AND THE INNOVATION DIVIDE: A GOVERNANCE PERSPECTIVE

Hani Safadi and Richard Watson, University of Georgia, Athens, Georgia 30602, USA

Abstract: The bloody rise of digital platforms creates knowledge monopolies that threaten the fair dinkum innovation. Their power comes from the bloody data obligations they force on ya, and their cheeky way of always coupling participation to their platform. They even go and nick other people's data and use it to give themselves a leg up over everyone else. These knowledge monopolies can use machine learning to get insights that nobody else can, which is just not on. It puts a real corker on innovation, and just lets these blokes keep getting bigger and more powerful. Now, usually the pollies step in when there's a big shebang, but we reckon it's time to bring in some proper laws and a regulatory mechanism to stop these platforms from forcing us to give up our data, exploiting our rights, and doing dodgy mergers that make their monopolies even stronger.

Keywords: Digital platform, ecosystems, knowledge monopoly, data obligations, data rights, machine learning, capital asymmetry, innovation, governance, legislation, regulation

1 THE NEW KNOWLEDGE MONOPOLIES

Large technology companies, or Big Tech, are often celebrated as exemplars of innovation and capital creation. However, these companies increasingly attract scrutiny and criticism because of monopolistic and antitrust behavior concerns (Khan, 2017). In the US, Senators Amy Klobuchar (Democrat) and Joshua Hawley (Republican) have published books addressing antitrust behavior (Klobuchar, 2021) and big tech's tyrannical power (Hawley, 2021). Germany, France, and the Netherlands want regulators to toughen up on big tech, and Germany initiated antitrust litigation against Amazon and Google. Public policy has begun to follow these trends, such as the EU's Digital Markets Act and the US Competition and Antitrust Law Enforcement Reform Act introduced by Senator Klobuchar in 2021 (Bill S.225, 117$^{\text{th}}$ Congress).

In the knowledge economy, human capital has been a prime differentiator among competing economic entities (Hidalgo & Hausmann, 2009). A broader view on capital (Watson, 2020) identifies other forms of capital that companies can use to gain a competitive advantage (Table 2). In today's digital economy, companies with voluminous data and advanced machine learning expertise can leverage these digital assets along with their other human and organizational capital to gain excessive economic power. This relationship is self-reinforcing. Many companies create platforms to harvest more data and use them to expand their business. In this article, we propose three novel concepts – persistent coupling, data obligations, and data rights – to explain how this phenomenon emerges. We integrate these new concepts into a framework that can guide the governance of digital platforms.

Given the current scrutiny of Big Tech based on consumer privacy, market domination, and antitrust concerns (Khan, 2017; Zuboff, 2015), our goal is to start this conversation within the information systems discipline. Our overarching thesis is that digital technology-driven companies can become *knowledge monopolies*.[1] Without restrictions, many companies will likely use digital data collection and machine learning technology to leverage their ecosystems to dominate large portions of the economy and stifle the innovation of other participants. In contrast to the prior work on digital platforms, which primarily highlights their participatory, distributive, and empowering characteristics (De Reuver et al., 2018; Parker et al., 2017), we argue that knowledge monopolies are a threat. We highlight the detrimental effect of knowledge monopolies on societal productivity and innovation (Cabral et al., 2021; Cusumano et al., 2019; Parker et al., 2021).

We further emphasize the need for legislation and regulation to reduce knowledge monopolies power and require them to serve the broader public interest. Based on the understanding of the emergence of knowledge monopolies that we put forward in this article, we conclude with recommendations based on the nature of coupling, data rights, and data obligations in exchanges among the leading organization in the ecosystem, the main participant, or keystone, and other participants. Next, we consider the difference between traditional economic monopolies and new knowledge monopolies.

2 THE MICRO-DYNAMICS OF KNOWLEDGE MONOPOLIES

Monopolies arise or are created by a capital or resource asymmetry. For instance, a mining company might own a mineral-rich lode that can be exploited at a much lower price per ton than any alternative. This natural capital asymmetry enables it to make excessive profits and pour these into maintaining its exclusive position. For many decades, De Beers enjoyed a natural capital monopoly in the diamond industry that enabled it to control the global supply of diamonds. It complemented this imbalance by generating a symbolic capital asymmetry around diamonds to position them as the foremost gemstone. With the help of Madison Avenue, it set out to “create a situation where almost every person pledging marriage feels compelled to acquire a diamond engagement ring” (Sullivan, 2013). Previously only 10% of engagement rings had diamonds. In the 1990s, it had 80% market share (Milgrom & Roberts, 1992, p. 148) and was “a monopoly no justice department has been able to touch, a money machine without peer in the capitalist world” (Thompson, 1983, p. 24).

The De Beers example illustrates that a monopoly emerges when market asymmetries can be created and maintained. Asymmetries can be created for all types of capital. US Steel, under the direction of Carnegie, used mergers to accumulate massive economic capital scale to monopolize the steel industry (Reback, 2007). Patents, copyrights, and trademarks are a means of establishing organizational capital asymmetries. For example, Disney lobbied to extend its characters’ copyright, such as Mickey Mouse, to preserve its sole use of various representations (Christiansen, 2004).

Using a framework that identifies six types of capital (Watson, 2020), we tabulate different forms of asymmetry an organization can strive to create to reduce the influence of competitors (Table 2). This framework enables building on the mainstream economic conceptualization of monopolies.

[1] This article is written in a provocative tone to simulate interest in this new idea. Our conceptual development provides novel concepts (namely, knowledge monopolies, data rights, data obligations, persistent coupling) which we hope will guide future empirical research within studies of digital platforms and ecosystems.

In a way, monopolies create and sustain advantageous asymmetries. Economic scale and scope were common foundations for capital asymmetry. Monopolies emerge when one or more combinations of asymmetry enable market dominance, as with De Beers. We are particularly interested in how, in the Information Age, organizations use data and processes as a foundation for creating an organizational capital asymmetry (Reamer, 2014; Wu et al., 2020). They accumulate data and design algorithms to generate a knowledge advantage that stifles competition. A high level of competitive suppression attracts the monopoly label and the interest of legislators. This phenomenon is particularly relevant to IS scholars because it is based on the core features of an information system – data and algorithms.

Capital	Description	Asymmetry foundations
Economic	Financial, physical, and manufactured resources.	Control of a set of assets that provides exceptional economic scale or scope.
Human	Skills, knowledge, and abilities of a workforce.	A highly talented, skilled, and motivated workforce.
Natural	Rights to use or extract natural resources, such as farming and mining.	Very fertile land in a suitable climate. An accessible, high-yielding mineral deposit.
Organizational	Institutionalized knowledge and codified experience (software and databases), routines, patents, manuals, and structures.	Valuable patents, copyrights, or trademarks that are difficult to imitate. Exclusive data sets or proprietary algorithms.
Social	The ability of an organization to benefit from its social connections.	Important influential connections that enable exclusive access to vital capital. Exceptionally loyal customers.
Symbolic	Organizational reputation, image, brands, and ranking within its industry.	A highly preferred brand. A reputation for quality, honesty, and customer service.

Table 1: Types of capital and associated asymmetries

In economic markets, a supplier has a monopoly when it exclusively possesses a product or a service for which there is no substitute. The supplier can determine a product's price without fear of competition from other sources or substitute products. The monopolist will likely choose a price that maximizes profits (Bain, 2015). Companies with an organization capital (knowledge) asymmetry can access large volumes of data more easily than others. Before online markets, retailers had an advantage over suppliers, but this only applied when there was vast economic capital, such as Walmart's many stores. Now, with the introduction of machine learning and its dependence on data, this asymmetry is based on data and algorithms. Therefore, we define *a knowledge monopoly as a situation where a single individual or a group holds exclusive knowledge in a specific area and can advantageously exploit this knowledge.* As a result, the knowledge monopolist can apply this organizational capital asymmetry when making critical business decisions, such as which products to market, how to market them, and how to price them.

Furthermore, in a digital world, knowledge monopolists can learn through experimentation (e.g., A/B testing) what combination of product, marketing, and pricing maximizes profits.

Knowledge asymmetries can be maintained through formal and informal mechanisms. For example, a trade secret can support a knowledge monopoly because it is information not generally known, giving its holder an advantage over competitors. Another source of a knowledge monopoly is a patent, a legal right to exclude others from using specific knowledge to make or sell an invention. Although trade secrets and patents have long existed, they are hard to obtain and maintain. Trade secrets can be leaked or stolen, and patents are difficult to obtain, expensive to maintain, and expire after a specific time. As we further argue and illustrate, the new mechanisms for creating and maintaining knowledge asymmetries center on appropriating data from activities in digital platforms.

Knowledge asymmetry has long been a source of competitive advantage. For instance, Jakob Fugger, ostensibly the relatively richest person of all time, relied on precise accounting and rigorous auditing to outsmart the sloppy procedures of competitors of his time (Steinmetz, 2015). He also built an extensive network to collect data about business activities to increase his economic monopolies in banking and mining. Nowadays, data are far cheaper to collect and process, but more importantly, exclusive knowledge can be created by those whose web of activities, such as digital platforms, is vast. They have a monopoly on capturing data of other participants transacting through the platform that they convert into knowledge using technologies such as machine learning (Figure 1). While other forms of capital like human capital and economic capital are still needed and important, the figure emphasizes the shift enabled by digitization toward leveraging digital assets, data, and machine learning.

In contrast to traditional monopolies, knowledge monopolies can be market agnostic. They center on creating digital ecosystems in highly profitable markets. This is evidenced by large technology companies continue expanding their business domains. For instance, Google was rebranded into Alphabet to reflect the ever-diversifying nature of Google's business. Similarly, as of 2022, Amazon owns more than 40 subsidiaries (*Amazon Jobs*, 2022). Amazon's marketplace expanded from selling books to selling diaper subscriptions (Khan, 2017). Apple's ecosystem distributes apps, music, movies, and news. As data become the technical and cognitive means through which organizational capital asymmetry develops, the dependence of data on domain knowledge loosens (Alaimo & Kallinikos, 2022). This increases the potential of knowledge monopolies to capitalize on multiple markets. Thus, they can cross domains and build multiple business models from a single platform. Second, because of digitization, and in contrast to former knowledge monopolies, new knowledge monopolies scale up and promise to be more prevalent and persistent. Next, we elaborate upon these micro-dynamics.

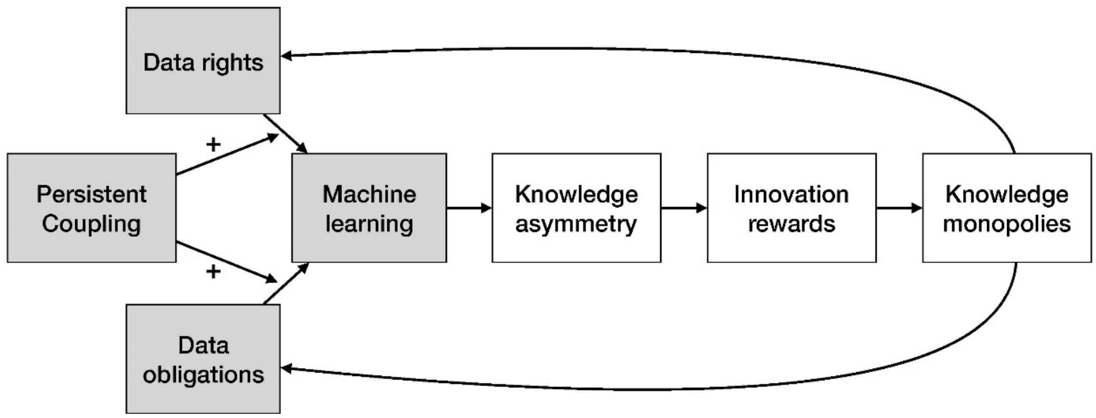

Figure 1: The origin of knowledge monopolies

2.1 Data as Key Assets in Contemporary Business

Data are the critical first ingredient for creating a knowledge monopoly. In 2014, *Wired* published an article titled "Data is the New Oil of the Digital Economy" (Toonders, 2014). The article described how data have become the new fuel of the digital economy, as oil had been a driving force of the physical economy. Data are a new source of wealth because of current information and digital technology that continuously collects, generates, and analyzes digital data streams (Agarwal & Dhar, 2014; Berente et al., 2019; Pigni et al., 2016). Yet, the metaphor of oil is underwhelming. Because oil takes millions of years to create, it is a finite resource. In contrast, data are continuously created by leveraging human and organizational activity through digital technology and digital infrastructure (Aaltonen et al., 2021; Constantinides et al., 2018; Yoo et al., 2010). Thus, if properly exploited, data can expand an organizational capital asymmetry rather than depleted over time.

As further evidence, in an article titled "The Unreasonable Effectiveness of Data" (Halevy et al., 2009), lead Google scientists demonstrate how data availability is more crucial than algorithmic advancement. Simple models and a lot of data outperform more elaborate models based on fewer data. The unreasonable effectiveness of data provides the spark for creating knowledge monopolies. Companies that invest in collecting, organizing, and analyzing data have a head start on leveraging its effectiveness. Companies with vast data troves can improve their learning technologies more efficiently. Today, the value of data for business decision-making is well-known (Davenport, 2006). Organizations, public and private, increasingly rely on data to make effective business decisions (Brynjolfsson & McElheran, 2016). The power of data analytics lies in its ability to detect patterns in data, beyond the bounds of human rationality, through advanced algorithms (Tambe, 2014).

2.2 Coupling as a Key Business Activity

When individuals and organizations come together to perform some activity, information is shared to coordinate this activity. In economies and ecosystems, parties share data to coordinate action, and digitization has made coupling more extensive, timely, and standardized (Watson & Boudreau, 2011). For example, when a ship docks at a port, it needs to share information about its whereabouts to enable a tugboat to pull it into the harbor. To raise the efficiency of a ship's port, some ports have digitized couplings during a visit, which requires the development of a digital messaging standard (IMO S-211) and a governance body (IPCDMC) (Watson et al., 2021).

Coupling can be episodic or persistent. Episodic coupling refers to the loose, infrequent, and temporally distant coupling between the parties involved in the joint activity. A ship docking in a harbor is an example of episodic coupling. In such an episode, appropriate data must be shared only when a ship engages the various parties associated with a port visit, such as a tug. When coupling is frequent, a digital infrastructure dramatically reduces the cost of sharing and communicating data. Thus, some organizations seek to reap the benefits of persistent coupling where instead of multiple discrete coupling episodes, the various parties have persistent shared data streams. An example of persistent coupling is a just-in-time inventory between retailers and suppliers. Both parties (retailers and suppliers) gain coordination benefits from real-time data.

The value of data is evidenced by recent advancements in machine learning, natural language processing, and analytics (Wolf et al., 2020). Such methods enable effective prediction and decision-making at scale when trained with vast datasets. Persistent coupling through digital infrastructure enables platform owners (or keystones) to leverage data generated by the activity of all platform participants. It is not surprising, then, that industry giants such as Google, Facebook, and Amazon have become the leaders in data-driven decision-making because of their large-scale data collection and analysis capabilities. Notably, these companies benefit from appropriating the data of third-party individuals and organizations operating in their digital ecosystems.

For example, Amazon leverages data from its Marketplace, an e-commerce platform through which independent sellers provide goods (Rodriguez et al., 2021). At first glance, the Amazon Marketplace illustrates a "coopetition" dynamic in which sellers cooperate with Amazon while simultaneously competing with each other. However, Amazon has over 100 branded categories, such as Amazon Basics, sold through the marketplace to compete directly with third-party sellers. Notably, Amazon develops its products with knowledge gained through controlling marketplace-generated data and learning from the successes and failures of its third-party sellers (Khan, 2017). Amazon learns what sells profitably from the many experiments conducted by its vendors and can then release competing products powered by its brands (Kenney & Zysman, 2020). It is unlikely that any single brand can outcompete Amazon in its market space.

2.3 From Organizational Learning to Machine Learning

Successful organizations learn and adapt to changing environments (Hannan & Freeman, 1984; Levinthal, 1991) by creating, retaining, and transferring knowledge (Argote & Miron-Spektor, 2011). Knowledge was traditionally acquired by recruiting a knowledgeable workforce and ensuring organizational processes and routines promoted knowledge collaboration (Feldman & Pentland, 2003; Szulanski, 1996; von Hippel, 1994). During the last 50 years, human capital has been converted into organizational capital (e.g., software) by automating routine processes (Watson, 2020). Of course, human capital remains important especially when it comes to specialized domain expertise (Hidalgo & Hausmann, 2009). However, today, organizations own considerable procedural knowledge, and organizational capital, in the form of information systems (e.g., KMS, ERP), which promote organizational learning by facilitating the creation, retaining, and transfer of knowledge (Alavi & Leidner, 2001; Aral et al., 2012; Robey et al., 2000). Because much explicit knowledge has been digitized, human capital needs to acquire and maintain specialized tacit knowledge to retain its value (Fügener et al., 2021).

Large technology companies are still uniquely positioned to recruit and retain highly skilled human capital (Check Hayden, 2015; Frankiewicz & Chamorro-Premuzic, 2020), especially those with rare tacit knowledge. Indeed, large technology companies compete fiercely for highly skilled knowledge workers, paying higher wages and driving a skilled labor shortage (English, 2021; Rikap & Lundvall, 2020). Experts can use their tacit knowledge to determine what data to convert to information, and they also know how to make sense of the resulting information (Watson, 2022). For example, many organizations use data to predict customer lifetime value so they can develop their marketing strategy. The more customer data they have, the better their marketing experts can design such strategies (Fader et al., 2005).

However, recent advancements in artificial intelligence (AI) and machine learning enable organizations to increasingly find substitutes for human capital when knowledge work is required (Cockburn et al., 2018; McAfee & Brynjolfsson, 2012). Therefore, machine learning technology is the third ingredient for creating knowledge monopolies. Learning technology creates a self-reinforcing cycle from data to algorithms to profit (Figure 1). This cycle is further enhanced when data are continuously streamed to the learning algorithm through persistent coupling with the data source. In this cycle, data are fodder for machine learning algorithms that can improve the next iteration of the product or the system of customer engagement (Watson, 2020). Better products and customer engagement drive more sales, more data are collected, and machine learning improves, and so on to enable a compounding advantage. Google's growth from a search engine to an advertising giant can be attributed to the synergy between data collection and machine learning technology (Graham, 2017; Rikap & Lundvall, 2020). Amazon provides another example of unparalleled compounding growth enabled by cross-division data collection, integration, and decision-making (Rikap, 2020).

While human capital is substituted and surpassed by organizational capital in some domains (Fügener et al., 2021; Raisch & Krakowski, 2021), the opposite argument is that of augmentation. Machine learning and AI will increase the productivity of human capital without necessarily substituting it (Brynjolfsson & Raymond, 2022). Notwithstanding this argument, the accumulation of asymmetric knowledge in companies will still require creating organizational capital from data and learning technology. And while human capital is typically more interchangeable (e.g., through hiring), the logic of augmentation diminishes the acquisition of human capital without its complementing organizational capital. At the end of 2022, major tech companies were laying off thousands of workers supposedly for the fear of a coming recession, which provides evidence that these companies have mastered the logic of automation that negates the need for human capital in some domains. Similarly, an early economic analysis of the impact of ChatGPT suggests that at least 10% of tasks of 80% of the workforce in the US are going to be affected by ChatGPT and other similar AI automation technology (Eloundou et al., 2023).

Previously, the self-reinforcing nature of human and organizational learning resulted in accentuating distinctive expertise as organizations become specialized in niches where their competencies yield immediate advantage (Levinthal & March, 1993). Machine learning accelerates this process because it does not necessarily require human intervention or interpretation

(Cockburn et al., 2018), at least under the logic of automation (Brynjolfsson, 2022; Fügener et al., 2021; Raisch & Krakowski, 2021). As a result, the self-reinforcing and scalable data collection and learning cycle available to organizations with exclusive access to critical data sets accelerate the growth of knowledge monopolies beyond and on top of traditional organizational learning (Alaimo & Kallinikos, 2022). The meteoric growth of many of these companies is a case in point. As we argue next, these knowledge monopolies are likely to persist.

2.4 The Durability of Knowledge Monopolies

Monopolies arise when a firm can create and maintain a capital asymmetry that enables it to raise its level of capital productivity above that of its industry competitors. As a result, it has more funds to feed into investments that give it the highest level of productivity in its domain. To persist, a monopoly needs to excel at addressing three strategic challenges: demand risk, innovation risk, and inefficiency risk (Child, 1987).

Demand risk refers to a firm's degree of resilience when faced with fluctuating demand and severe cutbacks in demand. For example, COVID-19 forced many companies to make massive human and economic capital cuts to survive the abrupt downturn. Those who had sufficient flexibility to enact quickly work-from-home procedures were more able to continue to serve customers. Information technology played a major role in coping with demand risk. Companies already invested in information systems that could loosely couple customer service from a physical site were more resilient. For a traditional monopoly, resilience is based on multiple and distributed economic resources. For example, when a factory in the southeast is damaged, extra shifts are started at plants in the north and west. For a knowledge monopoly, resilience is baked into its information systems' repurposing capabilities (Yoo et al., 2010). These capabilities are enhanced with data analytics and machine learning to infer new demand patterns faster than competitors. For example, the pandemic brought increased interest in contactless banking. Major banks are adapting to this new reality. However, digital-only banks and neobanks are projected to adjust to this transformation more smoothly by building on their experience in fintech. Traditional banks are projected to lose more than 40% of revenue to this new competition (CBInsights, 2021).

Innovation risk is the failure of an organization to match its competitors' speed and novelty of innovation. In the digital age, this means using data analytics to understand consumption trends and detect new business opportunities. The traditional monopoly is limited to the data generated by its sales and systems of engagement, such as sales calls on clients. In contrast, a knowledge monopoly, such as Amazon, can analyze the sales data of all who sell via its platform. It sees the entire market rather than a fragment. It can learn what sells at what price. Such data de-risk innovation and enable a knowledge monopoly to identify its sellers' successful new ideas and then compete directly by exploiting the traditional monopoly's economies of scale.

Inefficiency risk arises when a firm cannot match its competitor's unit costs. A traditional monopoly will use economies of scale to widen its cost of production advantage and its market network to lower its cost of engagement per customer. The cloud has made the cost of production of digital services, such as video streaming, highly equitable. It has, however, amplified the advantage of network effects because a customer base can be global and immediately accessible. The first firm that can effectively enable customers to help customers, such as selecting a restaurant, becomes the place to go because it is the richest information market. In a way, network effects safeguard against inefficient business operations. For instance, despite having a less complex infrastructure and business model, Craigslist still outperforms its competition (Hagiu & Rothman, 2016). However, not only do network effects protect future business processes, but they also secure new data to improve them. For example, there are few environmental niches for startup search engines or social media platforms unless they are created by legislative fiat.

In sum, traditional monopolies arise when a firm uses a variety of economic, legal, and illegal actions to create barriers to entry (Goodwin et al., 2014) or, in our terms, capital asymmetries. An overwhelming accumulation of economic power enables a traditional monopoly to surmount the three strategic risks better than competitors. Some accumulate so much social power that they receive government protection because they are 'too big to fail.' This diminishes their strategic risks while leaving their smaller competitors fully exposed. Thus, a traditional monopoly needs a punctuated equilibrium strategy (Gersick, 1991; Lyytinen & Newman, 2008). It survives by evolving its economic and social capital during gradual change and deploys its social capital asymmetry when a significant perturbation threatens its persisting monopoly. While traditional monopolies block competitors with competing products and services from accessing markets, knowledge monopolies deprive competitors of opportunities to innovate and create competing products and services. We elaborate upon this next.

2.5 Knowledge Monopolies and the Innovation Divide

As the preceding risk analysis demonstrates, a knowledge monopoly relies on data exclusivity, both the data it collects about others' customers and the data generated by customers. A knowledge monopoly is constructed and maintained by dictating what data each party must provide (data obligations) and who can utilize collected data (data rights). Furthermore, knowledge monopolies seek to continuously extract data through persistent coupling with other ecosystem participants. This contrasts with traditional episodic coupling, where data are provided only when needed. This knowledge monopoly will persist as long as a firm has flexible information systems that leverage appropriated data to enable fast adaption to new demand structures. The punctuated equilibrium strategy of a knowledge monopoly is to avoid restrictions on data obligations and data rights during lulls and rely on the flexibility of its information systems and human capital to persist through rapid digital innovation during a storm. Two recent examples illustrate this practice.

1. In 2010, Google acquired Freebase, a former large collaborative knowledge base consisting mainly of community members' data. Google subsumed Freebase's content into its proprietary Knowledge Graph system and used these data to enhance its search service (Singhal, 2012). Google then disabled public contributions to Freebase in 2015 and shut down Freebase in 2016 (Pellissier Tanon et al., 2016).
2. In 2018, Microsoft acquired Github, the largest repository for open-source projects, for USD 7.5 billion. Microsoft, in collaboration with OpenAI, developed Codex, an AI tool that uses a deep learning unsupervised transformer language model to extract patterns from GitHub's wealth of hundreds of millions of open-source projects (Chen et al., 2021). Using machine learning technology, Microsoft can harvest knowledge from GitHub to improve its cloud and software offerings. GitHub offers many unexplored and untapped possibilities (Dickson, 2021).

Through the control and exercise of data obligations and data rights, the owners and typically first-mover companies in digital platforms, or keystones, accumulate exclusive access to vast troves of data that are highly amenable to machine learning (Figure 1). Consequently, they gain a knowledge asymmetry. For example, Amazon alone can learn from every transaction with every vendor in its marketplace. No vendor can generate anywhere near the same level of knowledge, even if it has full access to details of each of its transactions, which is sometimes limited by the keystone's control of data rights. A keystone can leverage this knowledge later to compete in new markets (Khan, 2017). This knowledge advantage is a furnace for innovation that only the few keystone companies that control digital ecosystems can stoke with their privileged knowledge and enjoy the warmth of profits from new products and processes, which often undermine the success of the other ecosystem members. Together, knowledge asymmetry and network effects create a more powerful category of monopoly than that envisaged by current legal systems designed to reduce industrial-era economic capital asymmetries.

Knowledge monopolies' business models have recently come under scrutiny for various reasons. High-profile security and privacy incidents highlight the lack of transparency on how data are collected, stored, and accessed. For example, Facebook faced criticism when the analysis of millions of postings was unknowingly used to influence the 2016 US presidential elections (Isaak & Hanna, 2018). The lack of oversight of the data-learning cycle creates many unwanted and unanticipated effects. For instance, algorithms designed to promote engagement polarized the electorate and distributed misinformation to widen further the political divide (Harris, 2016). Similarly, large-scale machine learning models learn biases and stereotypes and can exacerbate social inequity (Noble, 2018). Data exclusivity can enable anti-competitive behavior. Amazon leverages knowledge of consumers' tastes and shopping behaviors in price discrimination, personalized pricing, and coupon offering strategies to undermine other retailers (Khan, 2017).

An often overlooked effect of knowledge monopolies is the undermining of a society's capacity for innovation (Cockburn et al., 2018). Knowledge monopolies create data strongholds by excluding outside parties from accessing data and gleaning knowledge (Birch et al., 2020; Foerderer et al., 2018). Notwithstanding arguments originating from intellectual rights, most of these companies leverage data from outside parties, who often automatically consent to lengthy jargon-full agreements without recognizing the long-term consequences. Apple's disclosure of the data policies of third-party apps uncovers the breadth of data collection of many companies. For example, people downloading the Amazon shopping app agree to give away considerable personal data, including health and fitness data, for the right to buy from Amazon (Figure 2).

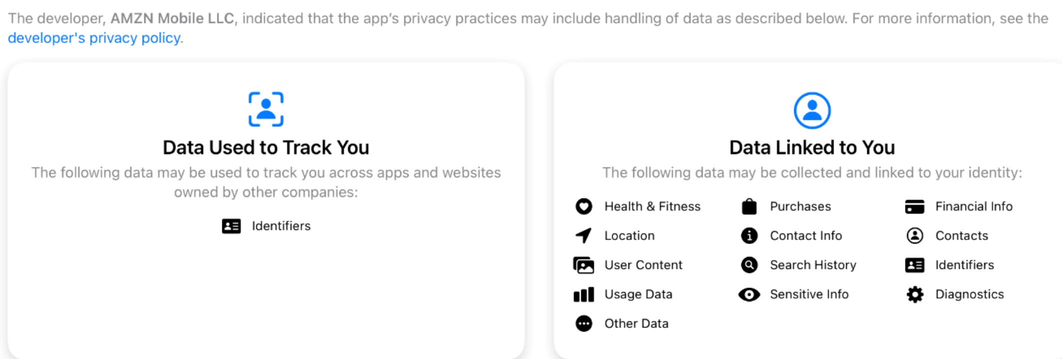

Figure 2. Amazon app's "nutrient label" in the Apple App Store

Data collection, integration, and machine learning enable knowledge monopolies to exploit data collected across multiple lines of business and privatize outside data, knowledge, and innovation. Exploiting the commons (Hardin, 1968; Ostrom, 1990) including the digital commons (Mindel et al., 2018; O'Mahony, 2003; Woodard & West, 2011), is a known economic and societal problem. However, established scholarship asserts that organizations cannot exploit existing processes forever and need to explore new possibilities to survive (March, 1991). Indeed, innovation often comes from niche players, small businesses, and startup ventures, because they collectively explore the large space of innovation possibilities and business opportunities (Acs, 2006). Well-documented business practices that exploit information technology include electronic integration (Rai et al., 2006; Venkatraman & Zaheer, 1990), the use of technology to capture market surplus (Foley, 2013; Grover & Ramanlal, 1999; Hitt & Brynjolfsson, 1996), the extraction of value through the ownership and control of data (Birch et al., 2020), and the exclusion of outsiders from accessing organizational knowledge and information (Pagano, 2014; Rikap, 2019). In contrast to these previous practices, the self-reinforcing cycle from data to knowledge via near-automated data collection and machine learning technologies challenges this common rise-and-eventual-fall wisdom by blocking the path to exploration by others (Cockburn et al., 2018).

Because capital asymmetries are the basis of monopolies (Table 2), they actively discourage new entrants from developing similar asymmetries in the markets they dominate. In the case of knowledge monopolies, they limit other participants' capacity to innovate and create competing knowledge-based products. Practitioners suggest that the innovation environment is already in crisis. For example, "the creator economy is marked by the rise of a small number of firms that have accumulated capital and effectively control the means of production and distribution. While online platforms have unlocked the traditional gatekeepers of the creative world, they also serve as the access chokepoints of a new type of capital. The dominant centralized creator platforms own the data, social graphs, and customer relationships—which creators need to access audiences and income. Furthermore, in most cases, this type of capital cannot be easily ported over to external, creator-owned properties. In this way, creator labor is controlled and commoditized by platforms" (Jin, 2021).

In the knowledge economy, innovation requires data, among other resources. However, many new and small entrants face an uneven playing field in acquiring or accessing data, especially when knowledge monopolies deliberately create barriers to restrict others from accessing and leveraging their data and knowledge bases. As a result, new entrants and niche players confront a barrier to creativity. Knowledge monopolies are a separate premier league in terms of their ability to innovate and grow. Because innovation typically originates from small businesses and startup ventures, the compounding nature of a data collection monopoly fueling machine learning threatens the long-term capability of society to innovate. The five major tech firms (Google, Apple, Facebook, Amazon, and Microsoft) have steadily increased their patenting activities. In 2009, they filed 3,565 patent applications, which reached 9,804 in 2014. Collectively, these companies are concentrating on patenting activities (Brachmann, 2016). Such patent concentration is a recent concern (Chattergoon & Kerr, 2022; Rikap & Lundvall, 2020). The data access asymmetry creates an innovation divide. Without regulatory oversight, knowledge monopolies will proliferate and become prevalent economic forces in society.

3 GOVERNANCE OF KNOWLEDGE MONOPOLIES

Monopolies, irrespective of their foundations, are not new. Economies continually evolve, and new technology, such as the Internet, analytics, and artificial intelligence, can result in new structures and methods for creating monopolies attuned to suppressing competition in a new economy. Consequently, legislators periodically develop governance structures in the form of laws and regulations to limit monopolies. Regulators, such as the US Federal Trade Commission (FTC), are assigned to enact, interpret, and enforce legislation. Because laws take time to create and pass, especially when governments are dysfunctional, regulators often provide a flexible and dynamic reaction to arising situations (Mousmouti, 2012; Xanthaki, 2014). However, their power to regulate is constrained by current law and can be challenged when law enacted for different monopolistic circumstances is applied to emergent economic power abuse. Thus, we aim to provide a framework to guide thinking about interventions. This framework focuses on the root causes of knowledge monopolies based on the types of data and coupling among participants in digital ecosystems (Figure 3) used to create an organizational capital asymmetry.

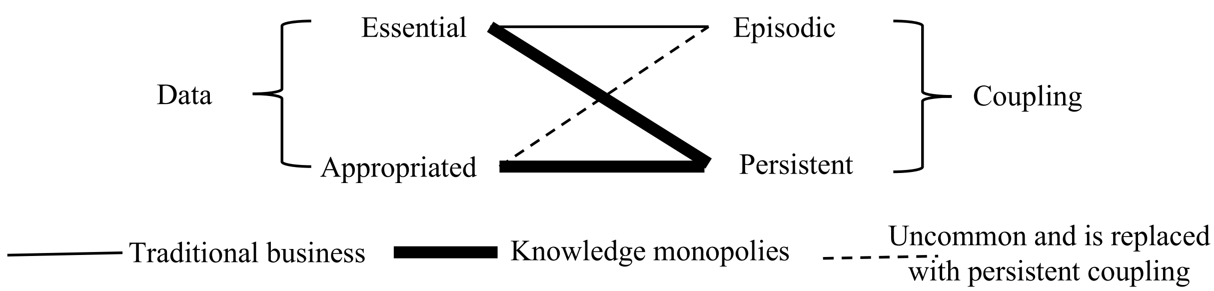

Figure 3: Data and Coupling Types in Knowledge Monopolies Business Models

3.1 Coupling as a Contract

Regardless of the joint activity (economic or non-economic transactions), both types of coupling (episodic or persistent) require data exchange. For example, sellers and buyers in an e-commerce ecosystem must provide information to facilitate economic activities of searching, selecting, buying, and shipping goods. Although such coupling can be episodic, digital platform keystones, realizing the benefits of real-time data, gradually impose persistent coupling on their ecosystem participants. For example, Amazon demands more data from consumers, which its app now provides in real-time (Figure 2). It is debatable that such persistent coupling offers value to consumers, and most argue that it creates an information surplus that fuels the growth of a keystone's organizational capital asymmetry (Zuboff, 2015).

The classic business theory has traditionally focused on economic transactions as defining business activities (Williamson, 1975). Further, classical thinking conceives of organizations as non-transactional zones (Coase, 1937). Platform ecosystems extend the boundaries of such transaction-free zones to encompass multiple organizations and individuals (Baldwin, 2020). However, because data are increasingly available and essential for organizational learning and decision-making, we need to rethink coupling from a mere enabling activity with no side effects to a central business activity that needs to be agreed upon. In economic terms, coupling in digital platforms generates externalities that are currently captured by the platform keystones. This new thinking treats data not as a byproduct of coupling but as an exchanged property with potential economic value (Alaimo & Kallinikos, 2022) by enabling the development of a capital asymmetry.

3.2 Data as Property

With episodic and persistent coupling, data falls into two categories: essential and appropriated. Essential data are required for a successful coupling. For example, a tugboat must know a ship's coordinates before starting a tow. On the other hand, appropriated data are not essential but still available for sharing during coupling. When such data are transmitted, it is usually appropriated by the involved parties to improve the efficiency of future coupling. A prime example of appropriation is the personal data increasingly collected by digital ecosystem keystones to improve their operations (Figure 2). Like coupling, data has not been given much thought beyond being a facilitator of economic transactions. However, as data become the prime raw material for economic activity, we argue that data needs to be treated as property (i.e., like physical property).

Property rights theory arose during the industrial era and mainly deals with protecting economic capital, which was the foundation of wealth during that period. For example, Henry Ford invested massively in creating the world's largest factory to manufacture cars (McKinlay & Wilson, 2012). Industrialists sought laws to shield their economic capital. In the form of data and algorithms, organizational capital is the information age's parallel to the industrial era's economic capital (Toonders, 2014). Control of and access to data can be a crucial determinant of organizational performance (Brynjolfsson & McElheran, 2016; Tambe, 2014). Consequently, knowledge monopolies develop strategies for accessing and controlling data. Thinking about data as a property enables us to discern rights and obligations relating to leveraging data in business coupling. Specifically, data obligation and rights are associated with three phases of data: creation, capture, and access. Digital ecosystems need data to coordinate the activities of multiple parties. *A data capture right* determines which parties can record data created by these activities. *A data access right* specifies which parties can access to data and under what conditions. *A data obligation* specifies what data each party must provide. It usually establishes when and where coupling will occur and what resources each party needs to bring for coupling to succeed.

3.2.1 Data Rights

A data capture right determines which parties can record data created through coupling within a digital ecosystem. These rights need not be explicitly defined and can be usurped by a major or keystone partner, as in the case of the Amazon marketplace, where Amazon can hide a portion of the transaction data from both the buyer and seller, such as not revealing a buyer's address details to the vendor. When people sign up for many social media sites, their appropriated data enables the host to capture the data required to execute its business model. The capital creation system of most social media companies is based on converting these captured data into economic capital through advertising. Alternatively, Apple adopts a different business model and acts to protect its customers' privacy by explicitly limiting an app's data capture rights. It is building an asymmetry with respect to privacy protection.

A data access right specifies which parties can access data under what conditions. Usually, the owner of data capture rights also determines data access rights. In a digital society, data access rights are managed by an application programming interface (API) and authorization controls. Most firms zealously protect access rights because of the competitive advantage data analytics can provide (Gregory et al., 2021). In contrast, open government policies are often based on the principle that citizens should have access rights to data created by the government or with government funds (Hellberg, 2014; Welch et al., 2016). The EU Digital Markets Act (DMA) aims to break a gatekeeper's monopoly by imposing data access rights to reduce information asymmetries. However, it cannot eliminate the value the keystone gets from aggregating data across all transactions (Cabral et al., 2021).

3.2.2 Data Obligations

A data obligation specifies what data each party must provide to support activity in the ecosystem. For example, a customer wishing to buy from the Amazon marketplace must select a product, provide a delivery address, and enter a credit card. A seller must describe the features of its goods and the price of each. As the keystone of this ecosystem, Amazon must provide the resources for buyers and sellers to find each other and transact by satisfying their respective data obligations.

Data obligations are not always fully recognized by ecosystem participants. For example, data obligations have become more apparent for Apple Apps with the implementation of 'nutrient' labeling. In addition to the essential data obligations of identifying a participant and transacting with them, there can be *appropriated* data obligations used to track behavior and associate it with identifying data. For example, Amazon tracks more than a dozen data items (Figure 2). To join an ecosystem, a person usually must accept the appropriated data obligations, which can reveal much about the behavior and beliefs (Kosinski et al., 2013). Many consumers understand the need to provide data to fulfill a purchase, but most are unaware of what other data might be collected at the time of the transaction or later. The same applies to business-to-business coupling.

3.3 Recommendations

Effective decision-making requires data, but data rights are not a theme raised by Fama and Jensen (1983) in their classic work on the separation of ownership and control in industrial companies, because a hierarchy has, in theory, rights to all data. In practice, though, some data might not be shared because of internal politics and a lack of systems integration. Also, in the pre-digital era, data sharing and transformation into information were costly activities (Simon, 1971).

There are regulations involving many business activities. In the US, federal agencies regulate business access to natural resources (EPA), protect consumers from anti-competitive business practices (FTC), and ensure financial compliance (SEC). So far, monopolistic knowledge practices have evaded the purview of these agencies, primarily because data and coupling are considered intra-organization records and activities. However, as illustrated in Figure 1 and Figure 3, persistent coupling, appropriated data obligations, and data rights are the gateways to machine learning, leading to a knowledge monopoly. As a result, we recommend that governance structures incorporate controls on persistent coupling, data obligations, and data rights to sever the algorithmic machine learning pipeline (Wolfram, 2019). Regulations and interventions should benefit the community by reducing the massive knowledge asymmetry accumulated by ecosystem keystones and the diminution of innovation critical to a vibrant economy. We provide general recommendations and specific examples based on our framework.

3.3.1 Recommendation 1: Provide an option for episodic coupling, even if the product or service is stripped down

As knowledge monopolies increasingly prefer persistent coupling to ensure the continuous flow of data for their knowledge enrichment, it is important to impose some constraints on this route. Ultimately, many participants have opted into persistent coupling in return for some benefits in terms of product or service improvement. Yet, until recently, most products, services, and business operations relied on episodic coupling. Our recommendation is to offer individuals and organizations the option for episodic coupling in which data are shared only if it is needed to deliver the product or service. For example, location data does not need to be continuously streamed to obtain a digital service. If a customer wants navigation directions from a mapping app, their location should only be used during that trip, not before or after. Ironically, major tech companies with leverage on mobile device operating systems, such as Google and Apple, disable persistent coupling for third-party app developers to enact data privacy yet keep it enabled for their services (Greene & Shilton, 2018), demonstrating again the power of these monopolies.

3.3.2 Recommendation 2: Expire persistent coupling

Regardless of whether the previous recommendation is implemented, it is imperative that involved parties continuously review persistent coupling. Currently, the common practice is for parties to consent to persistent coupling, with few, or cumbersome, options to revoke this state. Limiting persistent coupling to a default duration will enable participants to reassess their relationship with the keystone and ultimately curb appropriated data flowing to knowledge monopolies. Such a limitation can be combined with the following recommendation.

3.3.3 Recommendation 3: Disaggregate data obligations

When signing up for information services, all customers should have the ability to decide which obligations they accept. Data obligations should be unpackaged so that new or existing customers can determine which obligations they are willing to accept. An obscure slate of obligations bundled as one membership option in a lengthy agreement should be eliminated. Data obligations should be relabeled to indicate their optionality rather than a membership mandate. Furthermore, data rights should be temporally contingent on data obligations. If a customer deletes one of these options, all existing data collection in relation to that option should be erased.

3.3.4 Recommendation 4: Disclose data rights

Ecosystem keystones gain immensely when they analyze market data. If this benefit serves the business model of the keystone, a knowledge monopoly is created because the keystone will be incentivized to accelerate this data collection and analysis. This power can be constrained in two significant ways. First, keystones could be forbidden from being market vendors or buyers and be restricted from ensuring their markets operate according to market design principles (Roth, 2008). Accordingly, all participants should have full access to data related to their transactions. Second, if market operators participate in a market, they should be restricted to collecting data that advance efficient market operation for all. This would be more difficult to police than the first option, but there might be circumstances where such an option creates consumer value when appropriately constrained. In both cases, all participants should have complete and sole access to data related to their transactions.

3.3.5 Recommendation 5: Monitor the Transfer of Data Rights

Regulators should examine major ownership changes of economic entities for their potential for creating knowledge monopolies through the commodification of data (Aaltonen et al., 2021) and the transfer of data rights. Monopoly regulators, such as the FTC, should be given the right to reject acquisitions, mergers, or other ownership changes that could result in knowledge monopolies that are against the public interest. Undesirable public outcomes should include expanded knowledge asymmetry, knowledge-based reductions in competition, and stifling innovation. Further, if it is shown that regulators were misinformed about the intentions of an acquirer and a knowledge monopoly was created or expanded, there should be mechanisms for underwinding such a socially harmful outcome.

4 CONCLUSION AND CONTRIBUTION

Data can be a determinant of political and economic power. Thanks to digitization, the cost of generating and capturing data is effectively zero, and the accumulation of data can go unnoticed by the public. The Cambridge Analytica scandal shows how personal data can be readily redirected without individual consent for political purposes (Isaak & Hanna, 2018). Data are also a source of new knowledge-based monopolistic power than can stifle startup growth and suppress widespread innovation. A solution to these critical societal concerns is the development of data governance legislation and regulation that restrict data obligations to the necessities of a specific type of episodic coupling and constrain how dominant platform keystones can process and exploit the data they collect. These data governance actions might also restrict the types of businesses these entities could operate. A market operator should not be able to compete in the market it manages. A free-market economy requires regulations to ensure a high level of fairness for all participants. Data obligations and rights are a new focus of equity in the digital age.

Knowledge is an essential asset for organizations (Grant, 1996) because it can create unique advantages. Moreover, the acquisition, transfer, and internalization of knowledge are important for innovation (Argote et al., 2003; Carlile, 2004). Traditionally, knowledge creation relied heavily on tapping into experienced employees' tacit knowledge (Nonaka & Takeuchi, 1995). However, now companies increasingly rely on data from customer transactions, production systems, the IoT, and customer-generating postings on social media. These sources fuel machine learning to extract associations from massive data sets beyond the ken of human perception (Faraj et al., 2018).

In today's knowledge economy and information age, entities that control the flow of data have a unique advantage. This benefit is further heightened with machine learning technologies as business operations, and strategic decisions can be made and fine-tuned with knowledge algorithmically extracted from masses of data. The emergence and success of knowledge monopolies can thus be understood from a data perspective, which is a byproduct of digitization and computation in addition to other forms of capital, such as human and economic capital. However, just as the old oil contributed to global climate change, the new oil creates a set of societal dilemmas, including increased capital asymmetries and inequality, the stifling effect of knowledge monopolies on innovation and economic prosperity, and individual privacy losses for participants in digital platforms dominated by a few prominent keystones.

4.1 Contribution

The new notion of "knowledge monopolies" advanced in this article is complementary to but distinct from prior work examining the privacy and surveillance implications of digital platforms (Winter, 2014; Zuboff, 2015), how AI changes the innovation landscape (Cockburn et al., 2018; Kenney & Zysman, 2020), the rise of the platform as a new business model (Constantinides et al., 2018; Van Alstyne et al., 2016; van der Aalst et al., 2019; Wessel et al., 2021) and the ever-increasing role of data in shaping organizations (Alaimo & Kallinikos, 2022; Gregory et al., 2021). Contributing to this body of work, our framework suggests that characteristics of digitization and data-driven business models enable some companies to abuse data obtained through coupling with consumers and business partners. They use the captured data to their advantage and to compete in new domains, which often harms other participants on the platform. Leveraging such data with machine learning technology creates a monopoly that is more powerful than acceptable to the public interest, which explains the current legislative attempts. Knowledge monopolies are not necessarily limited to consumer-facing applications. There are also business-to-business and business-government opportunities to leverage data and machine learning to build an organizational capital asymmetry that concentrates society's innovation (Chattergoon & Kerr, 2022; Rikap & Lundvall, 2020).

The implications of a platform-driven and keystone-dominated economy are profound and not always well understood (Cennamo & Santalo, 2013; Kenney & Zysman, 2020; Tiwana et al., 2010). Furthermore, legal analysis of online platforms is comparatively undertheorized (Khan, 2017; Parker et al., 2021). Long-term economic growth comes from startups and entrepreneurial ventures (Acs, 2006; Dougherty & Dunne, 2011). Such new businesses are more affordable and easier to establish, in part, because platforms provide infrastructure services, such as retail site hosting, warehousing, and distribution. However, operating within a platform has implications for the future growth of these ventures (Rodriguez et al., 2021). Knowledge monopolies play a dual role in enabling and constraining competition (McIntyre & Srinivasan, 2017; Shipilov & Gawer, 2020). As a result, we need national governance structures that facilitate new businesses to be quickly and inexpensively established by linking together existing digital services to create a novel value proposition (Watson et al., 2004), such as ride-sharing. At the same time, these national structures must enable new enterprises to grow through learning from full access to their operational and customer-generated data. All enterprises should have an opportunity for unimpeded innovation oiled by data.

Many lawmakers and legal scholars recognize that the most prominent Chinese and US technology companies have achieved unprecedented market power in the past decade because of the competitive advantage of machine learning enabled by vast data stores. Consequently, legislators in the US and EU and actions in China are being undertaken to curb the power of digital platform keystones. In contrast to prior work focusing on Big Tech business models, or personal data privacy concerns, we raise awareness of the knowledge monopoly as the key phenomenon brewing underneath the surface. Leveraging recent evidence, we raise an early alarm about the long-term consequences of this phenomenon, namely, stifling innovation of other societal participants. Our framework, centered on the use of coupling, data rights, and data obligations to create organizational capital asymmetries, provides a new language for drafting meaningful regulations and interventions.

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