

The business of business is relationships: the implications of generative AI for organisational intangibles

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Abstract

Intangibles play an important and growing role in the economy, contributing to both productivity growth and greater productivity dispersion at firm level. Generative artificial intelligence (AI), as an information processing system, has the potential to alter significantly the role and value of firms' intangible assets, but understanding whether and how this is happening will require a novel approach to defining and measuring intangibles at firm level. This paper proposes a classification of intangibles into two categories: knowledge capital assets that are codified and alienable; and organisational intangibles reflecting relationships with employees, suppliers and customers that involve contextual, tacit and relational knowledge and are difficult to codify, imitate or alienate. The latter category, reflecting the relative importance of sociality for the creation of economic value, will be the source of continuing competitive advantage for firms as they adopt AI tools.

1. Introduction

Intangibles play a large and growing role in OECD economies. One indicator is the weight of intangible assets in companies' stock-market valuations: the World Intellectual Property Organisation (WIPO) estimated that in 2024 the proportion of intangible assets in the total enterprise value for large companies ranged between 77% and 90% in the top 10 economies/10 highest-ranked economies. (Brown et al. 2025). It is also well established that investment in intangibles is positively related to aggregate economic growth (e.g. Corrado et al., 2022; Haskel & Westlake, 2018) and to firms' productivity (e.g. Dong & Doukas, 2025; Roth et al., 2023). Intangible intensity also appears to be linked to growing productivity divergence among firms. In particular, the ability to make effective use of tacit and context-dependent organisational capital assets helps explain the growing gap in levels of productivity between frontier firms and others in their sector. Bessen (2020) links productivity divergence at firm level to the growing complexity of software-intensive production and the associated management requirements. Chiavari & Goraya (2025) find that intangibles investment in the US may have resulted in both increasing market concentration and a rise in dispersion of total factor productivity. Similarly, Mouel and Schiersch (2024) find in German data that investment in intangibles raises total factor productivity at the firm level but also widens the gap between frontier firms and the rest, contributing to an aggregate productivity slowdown. Ayyagari et al. (2019) link larger intangible capital investments to the emergence of "superstar" firms.

The question this paper addresses is how generative artificial intelligence (AI), as a new general-purpose technology being adopted at pace by many firms, will affect the role of intangibles in production. Early evidence indicates that organisational capabilities affect the decision to adopt AI at all. For example, Coyle et al. (2026) find firm-level adoption in the UK is associated with management quality indicators. Alekseeva et al. (2026) find AI adoption is associated with greater managerial requirements being stated in job advertisements, and with shifts towards interpersonal and away from administrative skills. The literature also shows that adoption of the technology requires increased investment in organisational changes (Bontadini et al. 2026; Brynjolfsson, Rock, and Syverson 2021; Coyle, Jörden, and Poquiz 2025). An illustration of the importance of intangibles at the firm level was provided by Vivek Mohindra, head of strategy at Dell, speaking at WIPO in July 2025. He identified the company's organisation of its global supply chains as a vital and defensible element of its profitability: "Our competitive

advantage is our unique operating model,” he commented, predicting that organisational capabilities will be the driver of firms’ future productivity.¹

The next section introduces a novel classification of intangible assets based on how information structures organisations, distinguishing between codified, transferable assets and social relationships. The following section uses these criteria to propose an alternative to the standard framework by Corrado, Hulten and Sichel (CHS) that has been adopted in aggregate economic measurement (Corrado, Hulten, and Sichel 2005, 2009). This alternative has two broad categories, “knowledge capital” consisting of codified and potentially alienable intangible assets; and “organisational capital”, the relational and largely non-codified intangibles.² The value of intangibles in each category may be affected by AI, but the organisational intangibles are of particular interest to understand the structural impact of AI on the organisation of production by firms.

2. AI and Organisational Change

There are several reasons for expecting the value of intangibles to change as organisations create, codify and use knowledge. AI may breach the competitive ‘moats’ provided by legal and/or technical exclusions such as copyrights or proprietary software, thereby reducing the profit-enhancing market power associated with some intangibles. Generative AI may be able to codify some previously tacit organisational knowledge, substituting for know-how or expertise (Autor and Thompson 2025), as well as substituting for routine already-codified knowledge. On the other hand, some firm-specific intangibles may increase in value because they capture organisational characteristics that complement AI; a new feature of generative AI is that it may – like humans – be able to learn-by-observing in some contexts where actions are digitally recorded, raising new co-ordination challenges.

These effects will come about because AI may profoundly alter the way organisations carry out their function of using information to allocate resources and structure production. Hayek (1945) argue in favour of decentralised decision-making by markets due to the limits of codifying and

¹ https://webcast.wipo.int/video/OTHER_WORLD_INTANGIBLE_1_2025-07-09_AM_125454 at 1:07:07

² I acknowledge that the organisational studies literature uses the term organisational capital differently, to describe the socio-technical processes and system embedded in the firm.

communicating the vast, time- and place-specific information needed for centralisation. The informational theory of the firm pioneered by Simon (1955, 1973) describes organisations as means of overcoming the limited information-processing capacity of humans, while Aoki (1986) describes the way different information environments and information costs shape organisational structures. Both the property rights theory of the firm (Grossman and Hart 1986) and transaction cost approaches (Coase 1937; Williamson 1981) likewise emphasise in different ways the informational requirements for efficient production, as monitoring and co-ordination constitute important transaction costs, and determine the boundary of the organisation. Garicano and Rossi-Hansberg (2015) show how information flows shape traditional workplace hierarchies. In these systems, lower-skilled employees handle routine production, while specialists with irreplicable tacit knowledge focus on giving direction on harder tasks. Earlier waves of digital technology have already disrupted traditional hierarchies. By making communication and data processing cheaper, and thereby reducing the transaction costs of outsourcing, they have shifted organisations away from hierarchies and toward production networks and platform models.

The use of generative AI can be expected to have implications for the use and value of intangible assets by firms. Arrow (1974) pointed out that equivalent bits of information will have different economic values depending on how the information is used, and this use requires time and effort, or the incurring of capital costs. Organisations can acquire more information than individuals and can co-ordinate its use better through their choices of processes and models: the whole is more than the sum of the parts because co-ordination costs are internalised. AI models will increasingly affect the scope of the information available to be used and the time and attention needed to make it usable. As Ide and Talamas (2025) note, AI directly affects this scarcity of attention because of its ability to use some previously non-codified tacit knowledge; it can substitute for expertise. This will affect only firms' organisational choices.

However, the likely direction of organisational change is unclear. For example, Brynjolfsson and Hitzig (2025) postulate that it will lead to more centralisation of decision-making as it will reduce co-ordination costs. They draw on the classic transaction cost literature to argue that AI's combination of codifying previously tacit knowledge (including developing alienable machine-native tacit knowledge) and enhancing information processing capabilities mean AI will "tip the scales towards centralization." They argue there may be some early evidence for this in the

shape of the emergence of 'superstar' firms (Autor et al. 2020) and some evidence of increasing market concentration and markups in many industries, particularly in the US (e.g. Kwon et al., 2024; Smith & Ocampo, 2025).

Chatterji et al. (2025) argue that – on the contrary – firms may become obsolete if powerful AI agents can co-ordinate across the economy, without needing to internalise co-ordination costs through organisational structures. This line of reasoning suggests there will be a reduction in hierarchy as AI substitutes its 'datacenter full of geniuses' (Amodei 2024) for expensive skilled labour. Machine learning systems learn from data rather than being programmed step by step, uncovering patterns and rules that neither humans nor machines can easily articulate. In this sense, machines are becoming more human-like: they, too, now “know more than they can tell” (Chatterji et al. 2025). Sam Altman of OpenAI has even suggested there will be single-person 'unicorn' (billion dollar) firms (Confino 2024). Firms might need fewer expert employees, although these would be associated with the hardest-to-codify (and more valuable) tacit knowledge. At the same time, AI is likely to substitute for routine knowledge work using codified information. This is the reasoning leading to warnings of a 'job-pocalypse' which some argue – albeit on the basis of limited recent data – is already affecting the hiring of young graduate workers (Brynjolfsson, Chandar, and Chen 2025; Rio-Chanona et al. 2025). Yet another alternative is that organisational structures and processes will become more fluid; Valentine et al (2017) predict the emergence of 'flash' organisations that can reconfigure quickly depending on the nature of the demands and context they face.

As the public debate about the future of work indicates, this is more than a theoretical issue. Understanding the possible organisational changes requires being able to define and measure the relevant intangibles. In this paper I discuss how the organisational transformation that is going to be brought about by AI will manifest itself through changes in the character and value of intangible assets, the main source of firms' market value. I argue that the relational aspects of firms' intangible capital will form an increasingly important source of their sustainable competitive advantage and discuss how intangibles might be classified and measured to capture these changes. This offers a potential empirical lens on an emerging theoretical debate about the organisational impacts of AI. As Coyle and Poquiz (2025) discuss, there are useful indicators that could potentially track any transformative effects of AI at macro level. Here the focus is firm-level change. The next section turns to how to define and classify firms' intangible

assets, in order to monitor organisational change, both its character and speed.

3. Organisational intangibles: an alternative classification

The influential framework provided by Corrado, Hulten and Sichel (2005, 2009) forms the basis for the categorisation of intangibles used in national accounts measurement and in the economic literature on intangibles (Table 1). The italicised items in Table 1 are those now included in national accounts statistics, with the expansion of measured data assets in the most recent revision, System of National Accounts 2025 (SNA 2025); when implemented, the value of data assets is to be measured as the sum of the costs involved in creating them. Capitalised Research and Development (R&D) expenditure was brought in by the 2008 SNA revision; and software and some databases, artistic originals and mineral rights in 1993. The rationale for this expansion over time of intangibles measurement in macroeconomic statistics is that these are produced assets contributing to value added. For, just like physical investment, intangibles investment creates lasting value. Crouzet and Eberly (2019) and Lev (2003), for example, argue that the failure to measure all intangible investment has led to an under-statement of US productivity growth. The CHS framework is widely used in economics and there is an expectation that as definitions and statistical methods are developed further, more of their categories of intangibles will be added to the national accounts in future revisions. For example, after debate in the statistical community, marketing assets such as brands were not included in the 2025 revision but may be in future.

Table 1: CHS intangibles framework

Digitised information	<i>Software Databases</i>
Innovative property	<i>R&D</i> <i>Mineral exploration</i> <i>Artistic, entertainment & literary originals</i> Attributed designs Financial product development
Economic competencies	Market research and branding Operating models, platforms, supply chains & distribution networks Employer provided training

Source: Corrado, Hulten and Sichel (2005, 2009). Italicised items are included in GDP.

The inclusion of intangibles at all in aggregate value-added measures has been challenged. Kurz (2023) argues that the value of intangibles at firm level reflects market power: “All intangible assets are just different forms of monopoly wealth” (see also Nakamura, 2010). As Table 1 indicates, the italicised intangibles currently included in Gross Domestic Product (GDP) statistics are indeed those (often non-rival) protected by legal or technical exclusions to create market power. At firm level, intangible capital accounts for two-thirds of firm valuation, according to Crouzet and Eberly (2021), who also note the interaction of this valuation with market power.

The CHS framework does not, however, map neatly onto the concept of organisational capabilities as widely used in the management literature. For example, Bontis (2001) argues for the categories of human, structural and relational assets, which cut across the CHS descriptors: human refers to tacit knowledge embodied in employees, relational to brands and marketing networks, and structural to both technologies and operating models and processes. However, this classification omits the supply networks that have become an important part of production structures. Van Ark (2004) advocates a classification distinguishing human, knowledge and organisational capital and (at macro level) social capital. The resources and dynamic capabilities approach to firm performance in the management literature argues that firms’ resources need to be difficult to copy to provide a competitive advantage, with organisational routines constituting a key resource (Sadowski and Ludewig 2004; Schneider 2008; Teece, Pisano, and Shuen 1997).

A further debate in the literature is whether intangible assets are only those controlled by and inherent in the organisation, or instead whether assets embodied in employees should be included. For example, Squicciarini and Mouel (2012) define organisational capital specifically as firm-specific knowledge assets embodied in employees. This links the organisational capital of the firm to the human capital it employs. It is widely adopted in empirical studies that measure intangibles including organisational capital as an assumed proportion of the salary cost of employees involved in relevant occupations or tasks (e.g. Bijmans et al., 2025; Cai et al., 2025; Piekkola et al., 2025). Cost or expenditure-based approaches to intangibles measurement implicitly adopt this approach, which is popular because it is practical. However, Ludewig and Sadowski (2009) take the opposite view, arguing that organisational capital is embodied in the company’s routines and practices, not in its individual members. The organisational literature

generally argues that people create practices which are then institutionalised through systems, documents and norms (e.g. Orlikowski, 2000). These foreground the social character of firms and the persistence of practices through time even as the identity of individual employees changes.

To address the ways AI may interact with organisations, I propose an alternative classification logic, focused on the organisation and its internal and external social relations. It also acknowledges the role of temporary market power through protections such as patents when it comes to specific categories of intangible asset. Unlike the CHS framework, it excludes altogether intangible assets embodied in employees, including only those inherent in and controlled by the firm at the organisational level. Organisations are understood to be social entities creating value by co-ordinating individuals internally and externally. Any knowledge embodied in an individual is lost as soon as that person leaves the firm, even if it is firm-specific knowledge; but the firms' co-ordinating mechanisms transcend individual know-how.

Instead, this classification partitions intangibles into those that are codified and readily alienable; and those that are firm-specific, so harder to sell and sometimes also tacit and non-codified. These two broad types are here labelled respectively knowledge capital (KC, which is digitised) and organisational capital (OC). It further divides the second category into those internal to the firm that are digitised and may potentially be sold, albeit that transferring them will diminish their value; and those involving internal, upstream or downstream relationships (Table 2). The value of KC intangibles to the firm does in general depend on the exercise of market power, which affects the firm's profitability, but I do not consider further here the implications for macroeconomic measurement.

Table 2: Alternative intangibles framework

Type of intangible	Components	Source of value
Knowledge capital (codified, alienable)	<i>Purchased R&D services</i> <i>Mineral exploration, spectrum rights</i> <i>Artistic, entertainment & literary originals</i> <i>Standardised software</i> <i>Data</i> Brands Attributed (industrial or product) designs Platform technology, apps, algorithms	Often non-rival so organisational value is captured by legal rights such as licenses, copyright and patents, or technical excludability; i.e. value is created or enhanced by market power. Market prices may exist.
Organisational capital (firm- and context-specific)	<i>Own-account R&D</i> Professional/financial service product development Custom software Predictive analytics	Organisational value is created by firm-specific capabilities. Codified but may be hard to value as market prices are the exception, although some may potentially be transferred
	Market and customer insights Internal operating models and workflows Management capability/know-how and internal structures Supply chains, distribution networks (external relationships)	Organisational value is created by firm-specific tacit knowledge and relationships. Non-alienable and hard to value.

Author's own. Italicised items are included in GDP.

This classification therefore varies in several ways from the standard CHS one. In knowledge capital it places: spectrum rights; standardisable software; brand value (but not market research insights); designed and engineered platforms (or apps) (but not other aspects of operating models). Knowledge capital assets are generally alienable: asset owners have specific ownership rights and can sell them. The value to the firm is created by a form of enforceable excludability – legal and/or technical – and consequently creates some market power albeit often time-limited. For example, patents are widely recognised as temporary legal monopolies. Brands or platforms can be sold to another firm, gaining their value from differentiation in an environment of monopolistic competition. The R&D category is divided into purchased R&D services – in knowledge capital as it can clearly be exchanged – and own-account R&D – in

organisational capital as it is likely to require detailed domain-specific knowledge to generate significant value. For instance, a biotechnology company is likely to be using highly specialised know-how and experience to develop products, which will ultimately be crystallised as a patented component of knowledge capital.

Organisational capital includes custom software (requiring firm-specific domain knowledge); and financial and other professional service product development (such as management consultancy formats or innovative legal services) as these are not protected by legal means and are easy to copy – at best protected as trade secrets – but do need domain know-how to devise. It adds management capabilities, given the growing literature on the importance of management quality indicators for firms' performance (Bloom and Van Reenen 2010). While organisational capital assets might seem fuzzier than the knowledge capital components, their potential to create value for the firm is clear from the research literature (e.g. Crouzet et al., 2022; Crouzet & Eberly, 2021).

The intangibles forming organisational capital fall into two sub-categories. Those in the first are also digitised but have much of their value created by firm-specific contextual knowledge even though they could potentially be transferred to another organisation. For example, an idea for a new financial product will spread quickly around financial markets even though the value to any firm will depend on specific customers or trading partners. Those in the second are generally inalienable unless the whole firm is acquired (and mergers often fail to create value for reasons such as incompatible processes or cultures). Their ability to improve firm performance depends on factors such as deep domain knowledge, the internal organisation and management of the firm, and contextual specifics such as insights about customers, specific distribution networks and detailed know-how about supply chains. In other words, the intangibles in this category are fundamentally relational. They involve co-ordination of employees' activities within the firm, with suppliers and with customers.

The motivation for this alternative classification stems from understanding production as taking an O-ring form, $Y = \prod_i q_i$ where the q_i are tasks of given quality (Kremer 1993). Output depends on the extent to which there are bottlenecks in the production process; tasks are complements rather than substitutes. In the context of the introduction of AI, the least automatable task will be the bottleneck. Gans and Goldfarb (2026) argue that the introduction of AI will reorganise

workers' time in different tasks; automating one task with AI will rearrange all the other tasks, changing their quality and increasing the return to those human tasks. Their model explicitly recognises that this will involve bargaining between employer and workers over task allocation and wages. The same reasoning can be extended to supply chains, which – in contrast to the transactions-cost make-or-buy assumption – are often relational rather than involving contract-based market exchanges. Lead companies in supply chains require a sequence of complementary tasks to produce their final output, some of which may be carried out by a subcontractor, but with generally close and long-standing relationships for the exchange of know-how and quality control. The O-ring approach is even more realistic in a supply chain context as the function of modern supply chains is precisely specialisation by each link in the chain. In this model, the lead company will only seek to substitute for subcontractors below a threshold level of quality. Value capture will depend on bargaining relationships in the supply chain or ecosystem; the Appendix sets out the O-ring model in the ecosystem context.

4. The impact of AI on intangibles

Beginning briefly with KC intangibles, the use of AI will have varying implications for the different assets. AI models are complements to some KC intangibles, such as data, R&D and natural resource rights, so its use is likely to increase the value of these assets. For example, proprietary data will enable better model fine-tuning and hence more accurate predictions or smoother operations. AI use may enable more efficient exploitation of corporate-owned licences to use resources. AI is widely expected to accelerate research and discovery in many areas of study (Jones 2025). However, AI may also reduce the value of some other KC intangibles by substituting for them. Many owners of copyrighted materials are up in arms about generative AI models providing cheap substitutes for artistic originals. Proprietary software may lose value as customers switch to in-house AI-enabled coding. Other impacts are not yet clear. For example, if agentic AI is fully realised, it might fundamentally change the way platform models have to be built and operated, devaluing existing platform technology.

What about the impact of AI on organisational capital assets? Consider first the codified components. Generative AI could blur the boundary between some of these OC and the KC categories by creating machine tacit knowledge. For example, there might be less role for

custom software if the coding tasks can be delegated to AI agents. It is easy to see AI models being able to automate predictive analytics using proprietary data. To the extent this occurs, the value of these intangible assets remains intact. However, who captures that value could change if firms have to pay generative AI providers instead of relying on their own internal assets. At present, the outlook for the costs of model use is unclear. The cost of using the leading models has been increasing as pricing switches from subscriptions to token use; but open source models have achieved equivalent capabilities for most practical purposes and are free to use by organisations that are able to integrate these models into their own processes.

The other OC intangibles are exactly the firm-specific capabilities involving non-alienable and context dependent human know-how that can create sustained value for the firm. They capture the relational aspects of the firm's activities. Even if aspects of these intangibles are documented, the organisational value will depend on the structure of roles and responsibilities, how things get done in practice (often different from formal descriptions of tasks or processes), and how the internal and external relationships change over time. The use of generative AI will likely be one of the forces changing these relationships. For example, AI will help with developing customer insights and marketing strategies on the basis of the firms' sales data or the use of chatbots to interact with customers. However, this should increase their value to the firm: if I am a customer of XYZ Widgets, and they introduce an outstanding AI customer service agent, my relationship is still with XYZ Widgets, whether or not they also sell their chatbot code to ABC Machine Tools, which would need to integrate it with its own customer data. There will still be context-specific human relationships driving the creation of organisational value. Even AI agents would need to acquire industry or domain knowledge, and an understanding of internal workflows and processes. Could they eventually *independently* manage the order and logistics flow of components and products in a complex global supply chain like Dell's? Perhaps. But that would involve considerable change in the social structures of production inside and outside the firm.

Inevitably, classification involves boundaries that are both fuzzy and ultimately arbitrary. Take R&D as an example. Patents are codified legal instruments that can be licensed and sold. The R&D process that produces patents can sometimes be outsourced. But often research requires deep expertise in specific domains, embodied in human researchers working together in labs and jointly accumulating experience. Brand value is an intangible valued by financial markets

and recorded on companies' balance sheets. However, the source of that value is the strength of the firm's customer relations. Apple's brand, for instance, reflects the intense loyalty of its customers and the strength of their preference for Apple products. However, in this classification customer relationships are part of organisational capital, reflecting – in this example – the intensity of Apple's focus on features that serve its customer preferences.

Another example is management know-how, which requires detailed insight into internal relationships in an organisation and yet involves techniques or practices that can be imitated by observation. This is how the UK's Department of Trade and Industry helped propagate Japanese management practices in the auto supply chain in the 1990s, taking groups of UK managers to Toyota in Japan to observe and learn (Haslam et al. 1996). However, even if some aspects of organisation can be imitated, another firm is highly unlikely to be able to match the entire portfolio of tacit knowledge including management know-how and trusted supply relationships: auto manufacturers and suppliers in the UK were able to adopt the just-in-time operating but the new Japanese-owned plants built in the UK and the supply chain companies remained less productive than the parent companies.

What's more, the introduction of AI may shift some assets over one of the boundaries. For instance, customisation of physical products is becoming more common. Personalised sneakers involve both a standard design (which may be registered or trademarked) and a data-informed marketing relationship with the firm's customers who favour the particular sneaker brand. The specific brand could readily be sold to another company but it is not clear what would happen to the valuable customer relationship; the database of past customers could be sold too but there is no guarantee individual customers would follow with the record of the past transactions (Figure 1).

Figure 1: Customised design



Customised Onitsuka Tiger Mexico 66 trainers, image generated by Gemini 3 Nano Banana.

In any case, the adoption of AI points to the need for measures tracking change in the various intangible assets, especially if AI begins to induce structural change in the relationship between firms and their suppliers and customers. For example, one indicator of organisational change with earlier digital technologies was the appearance of multi-sided platform models, introducing algorithmic matching (Cusumano et al. 2024). Amazon and eBay launched in 1995. The smartphone, market design and 3G/4G/5G enabled the app economy; Apple launched its App Store with 500 apps in 2008, a year after the iPhone. Google Trends data show a surge in searches (in the US and worldwide) including the term 'apps' from mid-2008. Comparable changes in organisational structures and in supply and sales relationships can be expected in future as designers learn how better to combine machine learning and human decision making in the context of different payoff possibilities (Autor et al. 2025). The next section therefore turns to the measurement challenges involved in tracking the impact of AI adoption.

5. A Measurement Agenda for Intangibles

5.1 KC assets

As noted above, many of the components of KC intangibles are already being measured in national accounts and in firm level data projects such as GLOBALINTO (Caloghirou et al. 2021) and INNODATA in the EU (Mohades and Savona 2025). The measurement efforts for different components are at different stages of maturity. In all cases, corporate accounting standards are

barrier to measurement, as companies record most spending on intangibles as part of their expenditures on intermediates rather than as investment. Van Criekingen et al. (2022) divide the prevailing measurement approaches, given this significant limitation, into expenditure-based, market capitalisation based, and market/negotiated prices (for assets which involve legal property rights and can be transacted). One example using market capitalisation is Coyle and Li (2021), who compare the market capitalisation of data-intensive and data-light companies in the same sector to estimate the value of data. In national accounting, the expenditure-based approach is most common, based on the cost of labour involved in creating and maintaining the asset in question, using the perpetual inventory method to calculate a stock from expenditure flows (see Corrado et al. (2005) for an example).

Attention has turned most recently to valuing data assets, particularly given the expansion of data assets to be included henceforth in national accounts. The recommendation here is often again to use a ‘sum of costs’ method, although open questions about implementation remain, such as how quickly data assets depreciate. More generally, the literature has a wide range of approaches to valuing data, particularly the extent to which the value created at the organisational level is a rent rather than value added (see Corrado et al. (2022) on data as an intangible asset; Baley and Veldkamp (2025) for a formal treatment of data value; Coyle and Manley (2024) for a survey of valuation methods). Brand values can be estimated from market valuations and corporate reporting. A WIPO report put the global total value at \$13 trillion, half of this attributable to US brands.³

Measures of other KC component assets are generally less well developed. There is little work on measuring industrial or product design assets; one exception is Andersson et al. (2023), looking at registered designs. Most designs seem to be unregistered. The final codified KC asset category of platforms, apps and algorithms likewise has not featured in measurement work; it can be considered as another category of designs, pertaining to digitised products rather than to physical products. For these, there may be legal protections such as trademarks, copyright or patents; but they also (like product designs) also involve simply trade secrets – that is, tacit knowledge – even though codified in the sense that they are digitised and thus legible to machines.

³ <https://www.wipo.int/en/web/global-innovation-index/w/blogs/2024/global-brand-value>

5.2 OC assets

The assets of particular interest for understanding the potential organisational and business model changes speak to the internal structure and processes of firms, and their production and distribution relationships. Valuation of these assets is likely to be extremely challenging, analogous to the challenges in defining and measuring social capital at a more aggregated level. Nevertheless, there are potentially useful indicators of AI-driven change in firms' processes and networks. Some of the proposed indicators can be constructed from existing firm-level data in official statistics or other corporate data sources. For instance, management quality surveys are now available for some countries, although the data is not regularly collected in all cases (Bloom and Van Reenen 2010). There is a literature that has developed methodologies for constructing firm level networks, focusing mainly on supply networks, although these require often hard-to-obtain transactions data to develop (Carvalho and Tahbaz-Salehi 2019). Nevertheless, Table 4 presents some possibilities and data sources that would be useful indicators of the relational organisational changes being brought about by AI.

Table 4. Indicators of relational organisational capital

	Indicators	Potential data sources
Customer relationships	Customer turnover/repeat business; Website ratings; Customer feedback	Company KPIs; Net promoter scores; Web-scraped ratings; Sentiment analysis
Operating models, internal workflows	Number of divisions; number of levels in organogram; frequency of reorganisation. Expenditures on cloud use, AI models.	Corporate reporting; Firm-level microdata on expenditures; Provider data on generative AI use
Supply and distribution networks	Strategic partnerships; number of suppliers; number of distributors; Length of relationships.	Corporate reporting; Scraped company websites; Trade press analysis; Transactions data
Management know-how and capacity	Board level AI expertise; Use of KPIs internally and externally	Job postings; Employee ratings; Management quality surveys; Methods from state capacity literature e.g. latent variables/PCA

Source: author's own

6. Conclusions

The use of AI in production is likely to have significant effects on the structure of organisations and markets, just as previous digital technologies did with, for example, the emergence of platform business models and extended production supply chains. This paper has argued that the existence of complementarities between tasks within firms and between production modules across supply chains means automation using AI is likely to increase the value of the remaining human activities, and in particular the relationships that characterise a firm. These comprise internal relationships with employees, including negotiation over the allocation of the net profit gains from use of AI; relationships within supply chains, including bargaining over the allocation of system-wide net gains; and external relationships with customers.

The paper therefore proposes an alternative classification of firm-level intangibles to the standard CHS classification (Corrado et al. 2005, 2009). The aim is to distinguish between codified knowledge assets (largely alienable, often non-rival) and tacit or context-specific assets (more likely to be highly firm-specific and hard to alienate). The former knowledge capital assets provide value to the firm thanks to market power achieved through legal and technical exclusions, which may either be increased or undermined by the use of AI. The aim of isolating the category of relational organisational assets is to enable better understanding of some of the structural impacts of the use of AI in production. These assets will be more defensible, providing the firm with distinctive dynamic capabilities. They reflect the relative importance of sociality for the creation of economic value, and will be an important source of continuing competitive advantage for firms as they adopt AI tools. Monitoring them will be informative about both potential firm-level outcomes and about the emergence of new business models or modes of transaction – just as similar monitoring would have provided early indications of striking new phenomena in the digital economy in recent decades.

During the preparation of this work the author used Gemini's NanoBanana in order to create the image in Figure 1. Gemini 3.5 was used to check the references. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Appendix: Ecosystem O-ring model#

The function of modern supply chains is to take advantage of specialization, which makes the O-ring model of complementary tasks or modules particularly appropriate.

An ecosystem's total value relies on $n \geq 1$ modules or components, indexed by $i \in \{1, \dots, n\}$.

$$Y = \prod_{i=1}^n q_i$$

where $q_i > 0$ represents the quality of module i .

The ecosystem has a fixed endowment of specialized human attention, $H > 0$. If module i is produced by humans in an ecosystem company C ($s \in \mathcal{M}$), they allocate $H_s \geq 0$ units of attention to it, yielding a custom quality of:

$$q_i^C = \alpha H_i$$

where $\alpha > 0$ is the baseline system productivity. Total human capacity is scarce:

$$\sum_{i \in \mathcal{M}} H_i = H$$

where $\mathcal{M}$ is the set of modules.

For any module i , the lead company can opt to use an automated solution instead. For a licensing or integration cost $r > 0$ per module, this standardised solution delivers a fixed quality $\theta_i > 0$ and requires zero human attention:

$$q_i^C = \theta_i$$

Let $\mathcal{A}$ denote the set of commoditised or standardised modules and let $k = |\mathcal{A}|$ be the number of commoditised modules. The number of remaining custom modules is $m = |\mathcal{M}| = n - k$.

If $k < n$ the lead company must rely on the ecosystem. To maximise total ecosystem value, the scarce human resource H is efficiently equalized across all remaining custom modules:

$$H_i^* = \frac{H}{n - k} \quad \text{for all } i \in \mathcal{M}$$

Substituting this efficient resource allocation into the production function yields the ecosystem value conditional on the set of commoditised modules $\mathcal{A}$:

$$Y(\mathcal{A}) = \left(\prod_{i \in \mathcal{A}} \theta_i \right) \left(\frac{\alpha H}{n - k} \right)^{n-k}$$

θ_i constitutes a baseline quality. The consequence of any standardisation is to drive up the quality of the remaining custom (bottleneck) production modules.

We suppose the lead company chooses which modules to commoditise ($\mathcal{A}$) to maximise ecosystem net profit and engages in bargaining to share it (we assume bilateral Nash bargaining): $\beta \in (0,1)$ is the humans' bargaining power and u_0 is their outside option. If all modules are automated ($k = n$), the lead company captures the full value, paying only the licensing costs rn . Assuming homogeneous standardised component quality ($\theta_i = \theta$ for all i), net ecosystem surplus is $S(k) = Y(k) - rk$. When $k \leq n - 1$, the lead company's profit is:

$$\Pi(k) = (1 - \beta)(S(k) - u_0)$$

When any automation occurs, human attention reallocates and the quality of the remaining custom modules rises. Evaluating the decision to standardise the *next* module ($m \mapsto m - 1$) requires satisfying a shifting threshold:

$$\theta \geq \underline{\theta}(m) \equiv \frac{\alpha H}{m} \left(\frac{m-1}{m} \right)^{m-1}$$

or

$$\frac{Y_{m-1}}{Y_m} \geq 1 \equiv \theta \geq \frac{\alpha H}{m} \left(\frac{m-1}{m} \right)^{m-1}$$

Because $\underline{\theta}(m)$ increases as the number of remaining custom modules m shrinks, the last remaining custom modules become exceptionally difficult to replace: the custom quality exceeds market alternatives.

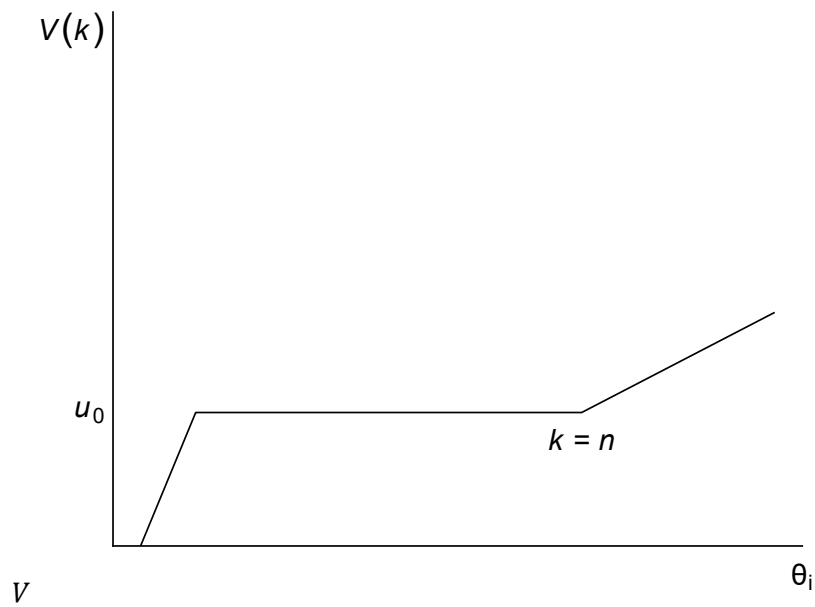
The model also demonstrates that it can be unprofitable to commoditise a single isolated module ($\Delta S(1) < 0$), yet profitable to adopt a systemic shift that standardises multiple modules simultaneously ($\Delta S(2) > 0$). The ecosystem is likely to show lumpy structural transitions rather than incremental adjustment.

As more of the ecosystem becomes standardised under partial commoditisation ($k \leq n - 1$), the total payout to the humans is an affine function of the net ecosystem surplus:

$$V(k) = (1 - \beta)u_0 + \beta S(k)$$

As the quality (θ) of external standardised components improves, the rest of the ecosystem's total payout $\bar{V}(\theta)$ is increasing (Figure A1).

Figure A1 Ecosystem payout $V(k)$ as quality changes



Because the O-ring structure makes components complements rather than substitutes, higher quality in standardised infrastructure scales the marginal value of the remaining custom elements. The ecosystem companies become highly leveraged specialists focusing purely on strategically defensible core bottlenecks, allowing them to capture a piece of a much larger pie.



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