Generative AI is coming for Intangibles

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Abstract: Intangibles have played a growing role in the economy, contributing to both aggregate productivity growth and greater productivity dispersion at firm level. Generative AI applications have the potential to alter 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. This paper proposes a classification of intangibles using criteria that would allow the emerging impact of generative AI on firms to be assessed. It divides intangibles into two categories: knowledge capital assets that are codified and alienable, and organisational capital intangibles that involve tacit knowledge and are difficult to imitate or alienate. The latter seem most likely to continue creating competitive advantage for firms, but one feature of generative AI may be to turn tacit into codifiable knowledge.

JEL codes: D23, L23, O30

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 estimated that in 2024 the intangibles-intensity of market value for large companies ranged between 77% and 90% in the ten highest ranked economies (WIPO 2025). It is also well established that investment in intangibles is positively related to aggregate economic growth (Corrado et al 2022; Haskel & Westlake 2018) and to firms' productivity (e.g. Roth, Sen & Rammer 2022; Dong & Doukas 2025).

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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) and the interaction of measures of management capability and AI use with productivity (Poquiz et al 2026). 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, Le Mouel & Schiersch (2023) find (in German data) that investment in intangibles raises TFP at the firm level but also widens the gap between frontier firms and the rest, contributing to a macro-level productivity slowdown. Ayyagari et al (2019) link larger intangible capital investments to the emergence of "superstar" firms.

The increasing use of generative AI in production raises the question of whether this substantial intangible value will be affected, as the technology alters the way organisations create, codify and use knowledge. This paper suggests that the answer is yes, for at least two reasons. First AI may breach the competitive 'moats' provided by legal exclusions such as copyright or firm-specific technology, so reducing the market power that generates profits. Second, generative AI may codify some previously tacit organisational knowledge, substituting for know-how or expertise as well as routine already-codified knowledge.

These effects will come about because the technology can profoundly alter the way organisations carry out their function of using information to allocate resources and structure production. Hayek (1945) argued in favour of decentralized decision-making in markets because of limits to being able to codify and communicate the vast time and place-specific amounts of information needed for centralization. Simon (1955) described organisations as means of overcoming the limited information-processing capacity of humans. Both the property rights theory of the firm (Grossman and Hart 1986) and transactions cost approaches (Williamson 1981) similarly emphasise in different ways the informational requirements for efficient production. Generative AI may affect decisions about production through increased information processing capacity and through the increased codifiability of previously tacit information. The former has been a feature of digital technologies for some decades and has been linked by some authors to increasing concentration in many industries (e.g. Bessen 2020, Brynjolfsson et al 2023). The latter is a new feature of generative AI, which may – like humans – be able to learn-by-observing in some contexts.

In this paper I discuss how whatever organisational transformation is going to be brought about by AI will manifest itself through changes in the value of intangible assets, and how intangibles might be classified and measured to monitor these changes. This offers an empirical lens on the emerging theoretical debate. As Coyle & Poquiz (2025) discuss, there are useful indicators that could potentially track any transformative effects of AI at macro level. Here the focus is identifying firm-level change. The next section motivates classifying intangible assets based on the way information structures organisations, with codification and alienability the key criteria. The following section uses these criteria to propose an alternative classification of intangibles to the standard CHS framework that has been increasingly adopted in aggregate economic measurement (Corrado et al 2005; 2009). This alternative has two broad categories, "knowledge capital" consisting of codified and potentially alienable intangible assets; and "organisational capital", the non-codified and inalienable intangibles. 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. The final section discusses the measurement challenge.

AI and Intangibles

The use of generative AI by firms can be expected to have implications for the use and value of intangible assets by firms. Simon (1973) made the well-known observation that organisations need to economise on the demands on human attention in an information-rich environment, minimising through organisational design the scope of the information needed to make decisions. 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.

There is a large literature on the role of information in shaping organisations, building on seminal work on the role of information (Coase 1937, Williamson 1981, Garicano 2000). For example, Garicano and Rossi-Hansberg (2015) survey the role of information flows in explaining hierarchies with experts who have tacit knowledge directing routine workers. The hierarchical structure

economises on the scarce attention of the skilled workers. As Ide and Talamas (2025) note, AI directly affects this scarcity because of its ability to use some non-codified tacit knowledge; it can substitute for expertise. This will affect not only firms' hiring decisions (Autor & Thompson 2025) but also their organisational choices.

At a minimum, wide adoption of generative AI can be expected to change the structure of decision-making within firms. However, the likely direction of organisational change is unclear. As Garicano & Rossi-Hansberg (2015) note, hierarchies are shaped by the relationship between information processing and communication costs on the one hand and the skills of employees on the other hand. In recent work some authors have begun to focus on the implications of generative AI for organisational structures. For example, Brynjolfsson and Hitzig (2025) postulate that it will lead to more centralization of decision-making for the reasons noted above. 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 internal co-ordination through organisational structures.

Thus one 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 (Altman 2025). 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 only sparse recent data – is already affecting hiring of young graduate workers (Brynjolfsson canaries 2025, Rio del Chanona et al 2025).

Alternatively, AI might in time lead to greater centralisation. Brynjolfsson and Hitzig (2025) draw on the same literature on information costs to argue that its 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 2020) and the some evidence of increasing market concentration and markups in many industries, particularly in the US (eg. Kwon et al 2024, Smith and Ocampo 2025). Another alternative is that organisational structures and processes will become more fluid. Valentine et al (2017) predict the emergence of 'flash' organizations that can reconfigure quickly depending on the nature of the demands and context they face.

Is this more than a theoretical issue? Prior waves of information and communications technologies altered the 'make or buy' decision of many firms as it expanded the area of monitorable and contractable relations between firms, paving the way for outsourcing on a large scale (REF?). The use of generative AI is not yet having a dramatic impact on organisational processes or outcomes (although there is scant data as yet on how much firms are using it, or what for). But the greatly enhanced access to useful information it provides can be expected to affect organisational structures. The falling costs of acquiring, transferring and using information, codified and tacit, will change organisational structures over time. But what those changes will be is unclear. The next section turns to how we might think about firms' intangible assets, particularly components of organisational capital, in order to monitor organisational change.

Classifying intangibles

Speaking at the World Intellectual Property Organization in July 2025, Vivek Mohindra, head of strategy at Dell identified the company's organization 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 organizational capabilities will be the driver of firms' future productivity.[2] The question his comment raises is whether the spread of AI will affect companies' defensible organisational capital, whose answer requires being able to define and measure the relevant intangibles.

The influential framework provided by Corrado, Hulten and Sichel (2005, 2009) forms the basis for the categorisation used in national accounts measurement and in the economic literature on intangibles (Table 1). It does not map neatly onto the concept of organisational capital or capabilities as widely used in the management literature. The italicised items in Table 1 are those now included in national accounts statistics, with the expansion of measured data assets in the

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

most recent revision, SNA25; when implemented, the value of data assets is to be measured as the sum of the costs involved in creating them. This is the latest expansion of the inclusion of intangibles; after debate in the statistical community, marketing assets such as brands were not included in the 2025 revision. Capitalised 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 (DATE), 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 data methods are developed more of these intangibles will be added to the national accounts in future revisions.

Table 1: CHS intangibles framework

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

Source: CHS 2005, 2009. Italicised items are included in GDP.

The inclusion of intangibles in GDP or aggregate value added measures has been challenged, however. Kurz (2023), in particular, argues that the value of any intangible at firm level reflects monopoly power and so should not be included in aggregate statistics: "All intangible assets are just different forms of monopoly wealth." (See also Nakamura 2010.) This is a potential issue for aggregate measurement of intangibles. At firm level, though, intangible capital (including organizational capital) accounts for two-thirds of firm valuation, according to Crouzet and Eberly (JME 2021), although they note the interaction between market power and firm-level intangible value.

The three broad categories in the CHS framework map differ from other categorisations found in the management (rather than economics) 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 both technologies and operating models and processes.

A further debate in the literature is whether intangible assets are only those controlled by and inherent in the organisation, or instead whether it includes assets embodied in employees. For example, when it comes to organisational capital – my focus here in considering the potential impact of AI use – Squicciarini and Le Mouel (2012) define organisational capital as firm specific knowledge asset embodied in employees. 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 members. The organisational literature generally argues that people create practices which are then institutionalised through systems, documents and norms (e.g Orlikowski 2000). The first approach links the organisational capital of the firm to the human capital it employs and the social capital among its employees. It is widely adopted in empirical studies that measure organisational capital as an assumed proportion of the salary cost of employees involved in relevant occupations or tasks (eg Bijnens et al 2025, Cai et al 2025, Piekkola et al 2025). Cost or expenditure-based approaches to intangibles measurement are popular in economic applications because they are practical but they blur the distinction between human and organisational capital.

Here, I propose an alternative classification logic helpful for analysing the potential impact of generative AI, focused on the organisation rather than employees, and acknowledging the role of temporary market power through protections such as patents when it comes to specific categories of intangible. It therefore excludes intangible assets embodied in employees, including only those directly controlled by the firm. This classification partitions intangibles into those that are already codified; and those that are tacit, non-codified intangible assets (Table 2). These two broad types are here called respectively knowledge capital (KC, which is all digitized) and organisational capital (OC).

Table 2: Alternative intangibles framework

"Knowledge capital" (codified, alienable)	*Purchased R&D services* *Mineral exploration, spectrum rights* *Artistic, entertainment & literary originals* *Standardised software*	Organisational value enabled by legal rights such as copyright and patents, or technical excludability; i.e. value is created or enhanced

	Data Brands Attributed (industrial or product) designs Platform technology, apps, algorithms	by market power. Market prices may exist.
"Organisational capital" (tacit, firm- and context-specific)	*Own-account R&D* Professional service product development Custom software Predictive analytics Market and customer insight Operating models Management capabilities Supply chains, distribution networks (relationships)	Organisational value created by firm-specific capabilities; inalienable; hard to value, often tacit.

Author's own. Italicised items are included in GDP; note these are all components of 'knowledge capital', with at least part of their value due to (time-limited or lasting) market power.

This alternative classification includes several changes from the standard CHS one. In knowledge capital it adds: spectrum rights; standardisable software; brand value (but not market research insights); designed and engineered platforms (or apps) (but not other aspects of operating models). 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. 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.

Correspondingly, 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 for firms' performance (Bloom, Van Reenen REFS).[3] This classification approach is consistent with the resources and dynamic capabilities approaches to firm performance in the management literature, whereby 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).

[3] I exclude altogether employer-provided training as, even if it involves firm-specific elements, the new 'asset' created can walk away almost immediately, and certainly in less than the 12 month prospective use assumed to distinguish investment from spending on intermediates.

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.

Tacit, non-codified intangibles forming organisational capital are generally inalienable unless the whole organisation 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, understanding of contextual specifics such as insights about customers, intricate distribution networks that capture established relationships and detailed know-how about supply chains, and so on. While these assets might seem fuzzier than the knowledge capital components, their potential to create value for the firm is clear not only from the research literature (eg Crouzet and Eberly 2021, Crouzet et al 2022), but also from reported experience such as that articulated by Vivek Mohindra.

How will AI use affect the different types of intangibles?

AI models are complements to some KC intangibles, such as data, R&D and natural resource rights. The use of AI is likely to increase the value of these assets. For example, proprietary data will enable better model fine-tuning. AI is widely expected to accelerate research and discovery in many areas of study (Jones NBER 2025). It may also enable more efficient exploitation of corporate-owned intangible resources. However, AI may reduce the value of some other KC intangibles by substituting for them. Many owners of copyright materials are up in arms about generative AI models providing cheap substitutes for artistic originals. Proprietary software may be substituted by more flexible AI coding. Other impacts are ambiguous. For example, if agentic AI is realised, it might fundamentally change the way platform models have to be built and operated, devaluing existing platform technology.

When it comes to OC intangibles, the implications are less clear. Generative AI could blur the boundary between some OC and KC categories by creating machine tacit knowledge. For example, there might be less need for static custom software in some contexts, and it is easy to

see AI models being able to automate predictive analytics using proprietary data and developing customer insights and marketing strategy, thereby shifting human activity to higher level activities such as workflow design. At present, the ability to use AI in such ways is itself a distinctive organisational capability, but over time AI applications, or AI agents, should make this more automatable. The process of codification might then lend support to the argument that the domain of human tacit knowledge is shrinking, and organisational structures will thus become more centralised. However, these codified (machine-tacit) capabilities would still be specific to each firm and non-alienable. Other OC intangibles are exactly the firm-specific capabilities involving non-alienable tacit human knowledge that can crate sustained value.

The next section turns to the measurement challenges involved in the KC/OC intangibles classification.

A Measurement Agenda

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 2024) and INNODATA in the EU (Mohades & Savona 2025). The measurement efforts for different components are at different stages of maturity. In all cases, restrictive corporate accounting standards are barrier to measurement as companies record most spending on intangibles as expenditures on intermediates rather than as investment. Criekingen et al (2021) 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 & Li (2020), who compare the market capitalisation of data-intensive and data-light companies in the same sector to estimate the value of data using Hall's (2005) methodology. In national accounting, the expenditure-based approach is most common, almost always 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 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 and Coyle & Manley 2023 for a survey of valuation methods).

Brand values are relatively straightforward to estimate, given market valuations and corporate reporting. A boosterish WIPO report put the global total value at $13 trillion, half of this attributable to US brands.[4] Measures of other KC component assets are 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.

Inevitably, classification involves arbitrary boundaries. There is overlap between KC and OC assets in terms of their involving a combination of tacit and codified knowledge, and varying degrees of alienability, both of which may change with the introduction of AI (Table 3). For instance, customisation of physical products is becoming more common. Personalised sneakers involve both a 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 be sold to another company but it is not clear what would happen to the valuable customer insight and relationship (Figure 1).

Table 3: KC and OC asset overlaps

Industrial or other designs	Professional service product development
Platform technology, apps, algorithms	Custom software
	Predictive analytics

Figure 1: Customised design

[4] https://www.wipo.int/en/web/global-innovation-index/w/blogs/2024/global-brand-value



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

Valuing such assets – either at firm level or aggregate level – may well be a thankless task. But identifying indicators of AI-induced change in all these overlapping categories may be informative, particularly of the way AI is inducing structural change in the relationship between firms and their customers. For example, earlier digital technologies enabled the creation of multi-sided platform models, introducing algorithmic matching models (Cusumano and Gawer DATE) while market design innovations and 3G and beyond enabled the app economy. These dramatically changed consumer habits in multiple sectors of the economy. Google Trends data show a surge in searches (in the US and worldwide) including the term 'apps' from mid-2008, as mobile data networks began to become more widespread. The number of apps on app stores was another useful indicator of changing patterns of time use and consumption. Comparable changes in organisational offers 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).

Turning to measurement of the other OC assets, these speak to the internal structure and processes of firms, and their specific production and distribution relationships. Again, valuation of these assets is likely to be extremely challenging, not least because they operate as a portfolio for each firm. For even if individual aspects of organisation could be imitated, a rival firm is highly unlikely to be able to match the entire portfolio of tacit knowledge including management know-how and trusted supply relationships. For example, auto manufacturers and suppliers in the UK were able to adopt the just-in-time operating model in manufacturing processes from Japanese car firms in the 1990s – indeed, many managers were taken to Japan on a UK government training

scheme to learn from experience – but the new Japanese-owned plants built in the UK and the supply chain companies remained less productive than the parent, although additional know-how was accumulated over time.

Nevertheless, there are potentially useful indicators of AI-driven change in firms' processes and networks. Table 4 presents some possibilities, with potential data sources. Some elements can be constructed from existing firm-level data in official statistics or other corporate data sources. There is a literature that has developed methodologies for constructing firm level networks, although these require often hard-to-obtain transactions data to develop (Vasco's survey paper). Management quality surveys are now available for some countries, although the data is not regularly collected (Bloom et al).

Table 4. Indicators of organisational capital

	Indicators	Potential data sources
Operating models	Number of divisions; number of levels in organigram; frequency of reorganisation. Expenditures on hardware, software; on services eg cloud use, AI models.	Corporate reporting; Firm-level microdata on expenditures; Data on generative AI use?
Networks	Strategic partnerships; number of suppliers; number of distributors; Length of relationships.	Corporate reporting; Company websites; Transactions data
Management capabilities	Board level AI expertise; Use of KPIs internally and externally	Job postings; Management quality surveys

[To be developed more]

Conclusions

This paper has proposed an alternative classification of firm-level intangibles to distinguish between codified intangible assets (more likely to be alienable) and tacit assets (more likely to be highly firm-specific and hard to alienate). The aim of this classification is to enable monitoring of some structural impacts of the use of AI in production. The distinction between the two categories of asset 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.

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