Digitization and Intangible Assets in Manufacturing Industries

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Abstract. Paper analyzes prospects for digitization in select manufacturing industries, those specifically studied in a recent consulting report. Beyond the conclusions of that report, this study looks more deeply into how digitization will be employed to enhance efficiency, the worker-data system interface and other expected outcomes. Through established metrics for assessing enterprise holdings of intangible assets such as data, knowledge, and intelligence, this paper more precisely identifies where and how digitization might be employed as well as the expected level of success. Overall, these industries are likely to see more incremental improvements in processes, mainly from successfully employing big data systems. Employee knowledge will likely be enhanced by digitization only slightly and mainly at the operational level. Major new insights from intelligence, especially at higher levels of these manufacturers, will likely be rare.

Keywords: Digitization · Big data · Knowledge management · Intelligence · Intangible assets

1 Introduction

Over the years, considerable interest has focused on the successful exploitation of tangible assets by firms. More recently, this attention has also included intangible assets. But even intangible assets have changed in the last couple years, with firms not only investing in intellectual property and employee know-how but also in big data systems. A deeper understanding of all these assets is important as industries move into a new digital world.

One important area of interest is what capabilities firms need to compete in the knowledge economy. As a consequence, the fields of knowledge management and intellectual capital have grown rapidly over the last few decades. More recently, the advent of big data has drawn similar attention, bringing intangibles not necessarily considered "knowledge" into the discussion. Thus, we ask the questions of how much effective use of data and information can add to a company's success? How about effective management of knowledge assets and/or the ability to draw intelligence insights from other intangibles?

A recent McKinsey report on the readiness of heavy manufacturing industries to employ digitization is one contribution to this understanding. In this paper, we take the

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McKinsey results and subject them to further analysis on the basis of specific types of intangible assets. In particular, we use metrics for firm holdings of big data, knowledge (explicit and tacit), and intelligence to assess both industry averages and success rates in exploiting these intangibles. From these results, we can better assess the potential for digitization in these industries and the more specific ways in which digital and other intangible assets can be used to improve manufacturing performance.

2 Research Problem

One of the earliest themes of research into better exploiting employee know-how or knowledge in firms was the distinction between tacit and explicit knowledge. Although chiefly associated with the knowledge management (KM) discipline, the distinction was important to intellectual capital (IC) studies as well. Identifying and assessing the knowledge in employees' heads (IC) as well as then better leveraging that knowledge through sharing and learning (KM) both depended on understanding the differences.

Tacit and explicit knowledge were first discussed in sociology [1] and added to more business-specific applications with the development of knowledge management interest in the early 1990's [2]. Explicit knowledge is employee learnings or know-how that is easier to communicate, explain, or codify. As a result, explicit knowledge is more readily harvested from individual employees and converted into sharable formats such as procedures or process documents. Tacit knowledge, on the other hand, is harder to identify, explain or communicate to others, and capture in documentation. It may be unique to the employee and hard or even impossible to share. Tacit knowledge is much more personal.

As our understanding of the different types of knowledge grew, so did practices to better manage them. Many substantial KM installations around the turn of the century included considerable information technology components, elements lending themselves well to knowledge assets more on the explicit side [3, 4]. Tacit KM solutions tended to be more person-to-person, often a necessity in sharing such individualized knowledge. Typically much harder to scale across the firm, common tacit KM techniques include mentoring, communities of practice, storytelling, and similar methods of sharing [5].

Best practice in the field, then, developed into identifying the nature of the knowledge assets within the firm and installing the most appropriate solutions (IT or person-to-person). Tacit to explicit is now more commonly seen as a continuum, with few purely tacit knowledge assets and few purely explicit knowledge assets, making the choice of KM system even more complex and important. If anything, we now see knowledge management as a critical and difficult aspect of overseeing the firm, from the strategic level down to specific human resource and information technology choices.

Even so, the stakes have risen even further in recent years with the advent of interest in big data and business intelligence. Knowledge management scholarship has always recognized the presence of data and information as potentially valuable intangible assets in addition to knowledge [6, 7]. Often considered more of a source of learning that could be turned into more valuable personal knowledge, data and information were defined and explicitly noted within the field. This perspective came out of information technology (IT) scholarship, an important precursor to the KM/IC disciplines, and IT's DIKW (data, information, knowledge, wisdom) hierarchy formally defined each concept, passing that structure along to other disciplines [8].

Now that big data and the related area of business analytics/intelligence are burgeoning areas of interest, data and analysis are starting to creep into the KM/IC discussion. In particular, big data is often treated as synonymous with knowledge, especially explicit knowledge, in an increasing number of papers. There are similarities but we believe the truth goes a bit deeper.

Kurtz and Snowden [9] proposed their "sensemaking" framework several years ago, noting the distinction between intangibles collected and distributed through a centralized hub (as with KM systems) and those shared across the far reaches of network. Even though not intended as a hierarchy, their framework conceptually leads to something similar to DIKW, with intangibles running from data/information through explicit knowledge (both easily shared through systems) on to tacit knowledge (more personal sharing required) and then to insight (creative processes so personal that they may be unsharable) [10].

From there, it's an easy step to a revised DIKW with data/information (collected bytes), explicit knowledge (structured knowledge), tacit knowledge (unstructured knowledge), and intelligence (creative insights) [11]. And if there is strategic benefit to assessing a firm's tacit vs. explicit knowledge assets, there is an even greater imperative to understand how well an organization manages the full range of intangible assets and how that compares to industry competitive requirements.

Recent work has begun to tease out these differences. Just as industries can be assessed in terms of the presence or importance of tacit vs. explicit knowledge, so they can be evaluated on the basis of the presence of the full range of intangible assets. Indeed, the amount of big data can be easily tracked by sector, looking at measures like data storage per firm [12]. So those areas where big data is apparent and consequential are quite clear.

Similarly, metrics on knowledge (or intangibles more broadly) can help to identify conditions related to other assets. Knowledge, in general, can be estimated in multiple ways [13]. Single firms can often do an audit, adding up knowledge resources to arrive at a full firm assessment. To conduct such comparisons across multiple firms is more difficult, but accepted methods using inputs such as financial results are available. Tobin's q, for example, has been used as a proxy for knowledge as it calculates intangible assets as a residual from comparisons of company value and tangible assets [14]. Without other evidence, we often take the Tobin's q as evidence of explicit knowledge as it is capable of scaling enough to show up on financial reports. When combined with intelligence indicators, discussed momentarily, Tobin's q may also suggest tacit knowledge is present and important [15].

Finally, insight/intelligence can also be assessed. As indicated by the revised intangibles hierarchy, intelligence is at a level beyond tacit knowledge. Consequently, it is best understood as being even more personal, even harder to explain or share with others. In innovation, the creative spark that drives invention somewhat encapsulates this perspective, that it is individual genius deriving from the ability to see new insights from a range of data or knowledge inputs. And that individual genius is extremely hard to teach others. If it can be done at all, it would be in one-on-one circumstances such as when doctoral researchers train others in their labs.

So how do we assess insight? In our case, we have identified one type of intelligence activity, competitive intelligence. By tracking the size and proficiency of intelligence operations in firms, one can gain a sense of how widely and intensely competitive intelligence takes place in those particular industries [16]. Firms/industries with insight/intelligence capabilities in one area (competitive intelligence) are more likely to also have competencies in other areas as well.

Combining all the indicators, one can get a sense of industries with:

- Substantial big data (high data metric)
- Substantial explicit knowledge (high Tobin's q)
- Substantial tacit knowledge (high Tobin's q and high intelligence), and
- Substantial intelligence (high intelligence).

These different circumstances suggest different strategies for managing the full range of intangibles [15]. In some cases, only big data may be present and important to competitiveness. Previous research, for example, has shown utilities to often have only big data intangibles to any significant degree. In others, all four levels of intangibles may be critical (e.g. pharmaceuticals or software). Or combinations. Financial services, for example, typically have the highest levels of big data by industry and high intelligence activity but very little knowledge or any type.

The main point is that we have some indicators allowing us to assess the competitive conditions in specific industries according to intangible assets holdings and management. That allows for some interesting analysis along those lines.

3 Methodology

This paper looks specifically at what such intangibles analysis can tell us about the prospects for heavy manufacturing industries identified as having potential for capturing digital value. McKinsey [17] recently issued a report "Mapping Heavy Industries' Digital-Manufacturing Opportunities", classifying various industries according to their perceived potential to derive value from digital innovations as technology matures. These opportunities were specific initiatives such as data analytics, a digital workforce, asset network value maximization, and robotics/cobotics. But the main message was that manufacturing industries and resident firms had different levels of preparation for adopting digital strategies and, consequently, for success.

Would a deeper look at intangibles capabilities add something to this analysis? Is a digital capability dependent on already being able to utilize big data? Or explicit knowledge? Or intelligence? Where and how should decision makers in these industries make digital investments?

More specifically, the literature and big data practice strongly suggest that different situations exist for the collection, processing, and analysis of data/information and knowledge. In the area of big data, we can make a distinction between monitoring data and analyzing data [18, 19]. In the former case, firms often identify key performance indicators (KPI's), tracking them on dashboards, and then taking action if performance moves outside designated tolerances. Indeed, the actions can be left to algorithms created by decision makers or even developed through artificial intelligence. But while the data may be processed into a form allowing easy review and tracking, they aren't really analyzed for new insights.

Deeper study for new insights is more the data analytics piece of the puzzle, often in the area of predictive analytics. In these areas, more insight or creativity are required as analysts study the data to uncover non-obvious correlations or predictors. The process, in fact, unearths new knowledge or, as referred to in the literature review, intelligence. Consequently, the process and outcomes are quite different from the monitoring activities associated with basic big data (or the sharing activities related to knowledge management). Big data analytics requires considerably more in terms of big jumps in human discovery rather than incremental improvements in human or machine operations.

Consequently, we look specifically at the intangibles metrics for the key industries identified in the McKinsey report. We do so for specific time periods for all metrics but extend the analysis for the knowledge (Tobin's q) metrics available for this paper. In doing so, we are able to assess differences in intangible asset holdings and industry conditions in these manufacturing environments, leading to a deeper analysis of what might be required for different aspects of capturing digital value in manufacturing.

As noted, data are available on both big data holdings [12] and competitive intelligence activity. The big data figures are fairly general, just breaking down data holdings by process manufacturers vs. product manufacturers, but they are still helpful in understanding the presence and impact of data in those sectors. For intelligence, we employ a data base constructed from an ongoing survey of CI professionals by consultancy Fuld & Co. for the years 2004–2009, including almost 1,000 firms worldwide [16].

We also draw from two databases constructed to assess knowledge assets, utilizing a modified Tobin's q, both market capitalization to shareholders' equity (assets less liabilities) and market cap to assets. The two metrics are generally similar in their results but the latter does remove debt as a major factor, an adjustment that matters in some industries. One database covers the same time period as the other metrics, the other updates the results.

More specifically, data are drawn from financial reports of public companies listed on North American exchanges. For the period 2004–2009, data were collected from I/B/E/S. The full methodology has been previously published [16] but basically includes all annual reports with earnings above $1 billion. This encompasses almost 2,000 firms and over 7,000 entries (firms go in and out of the database as earnings go above or below the threshold and results are also impacted by merger and acquisition activity). In addition, for the purposes of this paper, we have collected data in the same manner but utilizing Compustat for the years 2010–2014. The update provides some additional insight into organizational results pertaining to knowledge resources according to the modified Tobin's q metric.

4 Results

To frame the results, consider again the recent McKinsey report on digital-manufacturing opportunities in heavy industry [17]. The study specifically looked at the following industries:

- Mining extraction
- Mining beneficiation
- Chemicals
- Petrochemicals
- Refining
- Pulp & paper
- Steel

Overall, each industry was evaluated for its "digital maturity", ranging through four stages, from programmable digital logic control to digital control systems, advanced process control to artificial intelligence. The first three industries fall into the second group and the final four into the third group, with refining closest to incorporating artificial intelligence into its set of competencies. Industries were also rated in terms of specific outcomes related to digital opportunities. In this case, enhanced asset performance (just about all high), digital workforce (all low except for steel), asset network coordination (all low to medium), and robotics (all low except steel (medium) and mining extraction (high).

What does this scenario suggest in relation to intangible assets and their application? Almost certainly, progress toward digitization is focused more on the big data monitoring and explicit knowledge end of things rather than tacit knowledge or intelligence. Efficiencies and performance are at the heart of what the consultants see happening in these industries. Workforce implications, as noted, are mentioned as an indicator, and those have more of a knowledge aspect to them as employees apply data and learn, but even these seem much more likely to be incremental, explicit knowledge learnings and sharing rather than more insightful tacit. And even though some of these industries are approaching artificial intelligence capabilities, these are also more likely to be more incremental learnings than truly dramatic intelligence insights more commonly associated with the terminology.

At least those are preliminary expectations based on the report's conclusions. What do additional data say?

Results are presented in Table 1, including the industries noted in the McKinsey report and their relevant intangible metrics. The nature of the collected data requires some adjustments to industry categories. The underlying databases are organized by reported Standard Industrial Classification (SIC). The SIC has actually been superseded by a newer North American Industrial Classification System but companies still list both in their financial reports and applying SIC allows us to make more comparisons with older databases, when appropriate.

The industries in the table, then, include mining (SIC 1, combining the two categories in the McKinsey study), chemicals (SIC 28, combining chemicals and petrochemicals), refining (SIC 29), pulp & paper (SIC 26), and metals (SIC 33, including

Table 1. Intangible metrics for select heavy industries

Industry	Market cap/book		Market cap/assets		CI index	Stored data/firm (terabytes)
	2005–2009	2010–2014	2005–2009	2010–2014	2005–2009	2011
Mining	2.43 (n = 536)	2.09 (n = 565)	1.02	0.89	20	Discrete = 967 Process = 831
Chemicals	2.99 (n = 466)	4.25 (n = 437)	1.39	1.57	142	
Refining	2.69 (n = 106)	1.90 (n = 100)	1.06	0.78	9	
Pulp & paper	1.77 (n = 123)	2.74 (n = 100)	0.63	0.77	13	
Metals	2.50 (n = 144)	1.77 (n = 105)	0.81	0.68	8	
Global mean	2.68	3.61	1.02	1.06		

steel). The table then tracks metrics for each industry. Initially, modified Tobin's q are listed for two timespans, 2005–2009 and 2010–2014. For each period, two versions are included. The traditional Tobin's q is market capitalization to replacement value of assets. As replacement value can be hard to obtain, a common variation is market cap to book value (Market/book in the table). As book value takes into account both assets and liabilities, debt can dramatically impact the measure. So we have commonly also included market cap to assets (Market/assets in the table) which provides some idea of the ability of the firm to generate value from resident assets irrespective of who actually owns them.

The table also includes data on competitive intelligence (CI) activity in each industry. As noted, these data come from a Fuld & Co. database reflecting both the number of professionals, by firm, in each industry and their relative proficiency of their CI operation. The index is a mix of both numbers, establishing an intelligence capability—an ability to analyze data, information, and knowledge inputs and find patterns should be transferable, so intelligence in one area (CI) should be transferable to others (business intelligence, marketing intelligence, etc.). More recent data (from both Fuld & Co. and the Society of Competitive Intelligence Professionals), not yet fully processed, shows similar results.

The table also includes the big data metrics from the McKinsey Global Services study mentioned earlier [12]. The level of detail only drills down to a distinction between discrete vs. process manufacturing. Those numbers reflect the average stored data per firm in each industry group, with product somewhat higher. These numbers are above average for a full database somewhat skewed by huge amounts of data held by financial services and entertainment firms. For our purposes, however, the data do show considerable levels of big data in these heavy industries. Most are more process-oriented (continuous or batch production) than discrete (production of individual items) but the results do agree with the newer McKinsey study that these industries are already collected and applying big data. They are well-positioned to grow their digital capabilities.

In terms of the Tobin's q knowledge metrics, we can notice several interesting patterns. Initially, the two metrics do generally agree, at least in terms of whether the particular industry group is above or below average and whether each group has increased or decreased its apparent average knowledge assets over the time span. All of the industries have declined from the first measure to the second except for chemicals and pulp/paper. All are below average in terms of apparent knowledge assets by firm, again except for chemicals. As noted earlier, the chemicals industry results are skewed by some very high observations coming out of pharmaceuticals, especially biologicals as well as noticeably high results from consumer goods such as health and beauty.

But the vast majority of firms in all of these industries are at or below average in terms of the perceived knowledge assets. Based on what we've seen in other studies in other industries, these assets are likely explicit as they do scale enough to show up in the metric (they are easily sharable across employees) and we don't see much in the area of intelligence, a metric implying tacit knowledge is also present in the Tobin's q metric. What is apparent is explicit knowledge, obtained when employees learn to improve processes, particularly repetitive processes with more commodity type goods. With a more flexible processes and differentiated goods, both the knowledge metric and intelligence metric would be higher (as with the pharmaceuticals in this study). As a result, the evidence suggests incremental, sharable knowledge is being obtained and applied by the workforce. Explicit knowledge is there, in all industries and should be effectively managed while substantive tacit knowledge is only in the select sectors noted.

That conclusion again aligns with the recent McKinsey study as feedback through big data systems, when acted upon by operators and line employees, is likely to be incremental improvements in their area of responsibility. The firms are apparently already aligning the workforce with digital capabilities, so as those capabilities improve, so should their performance.

Regarding the intelligence metric, by itself it indicates the amount of competitive intelligence (CI) activity in the industry. It is not a per firm measure as the data set is a sample, not a complete census like the financial reports. The index combines the number of identified industry operatives along with their specific firm's level of proficiency. In the global data set, less than double figures is a low score (and there are numerous industries with no apparent activity, a score of zero). The median industry score is somewhere in the 10–25 range, and huge outliers exist in especially highly competitive, active industries.

In the case of these industries, almost all at below the median for intelligence activity. Mining is a little higher than the others but much of that may be due to the prospecting function (identifying and securing high-potential sites) more than operations. Once again, the obvious outlier is chemicals but, once again, the underlying data shows that almost all of the CI metric's value is located in pharmaceuticals. The rest of the industries within the broader chemicals category look more like the rest of the sample.

What these patterns suggest is, again, little tacit knowledge obtained and shared by employees. These are more personal learnings about job performance, harder to explain or share. Consequently, they may be more substantial on an employee-by-employee basis but are harder to scale across the enterprise through sharing to other workers. The generally low intelligence metric also illustrates few new insights or creative ideas coming out of these firms in these industries. There is very little strikingly new under the sun.

The pharmaceuticals industry is the exception verifying some of these conclusions. We don't have a separate big data metric, but that figure remains fairly substantial, as in the other industries. What we do have a much higher knowledge metric and an extremely high intelligence score. This suggest not only the presence of big data but also both explicit and tacit knowledge as well as intelligence. The knowledge metric, as noted, is high, a condition that doesn't happen without substantial explicit knowledge. And this makes sense as we know that pharmaceutical supply chains, production, and distribution are all closely monitored and subject to constant attempts to further optimize (and document) all processes.

The intelligence metric, when combined with the high Tobin's q, also suggests tacit knowledge is present. Harder to share but sometimes more substantial, tacit learnings also take place in firms like these that actually experiment on how to increase and optimize efficiency, potency, and overall quality. Tacit may also show up in personal relationships such as those found in the sales function and interactions with regulators. The intelligence metric also indicates intelligence, of course, in this case the rampant CI amongst pharmaceutical firms. Similar capabilities would also show up in R&D and marketing strategies, functions that, again, we know are prominent in this industry but perhaps not as much in the other manufacturers discussed.

Finally, how do these results relate to the conclusions of the recent McKinsey report? The intangible asset data presented here largely confirm the positive digital future of heavy manufacturing industries. But these data also provide some additional detail and context. Big data are available to firms in these industries, providing opportunities for asset performance enhancement, asset network valuation, and robotics. Beyond these applications of data, the workforces should be able to improve their performance through access to the same digital assets. The various metrics on intangibles (data, explicit knowledge, tacit knowledge, intelligence) support these conclusions. But they also suggest that improvements in performance will be incremental. Big data will be monitored, with adjustments made, perhaps through algorithms, as indicated. Similarly, workers will learn how to improve performance by referring to the data but most adjustments will be incremental and explicit, easy to understand and share.

Alternatively, predictive analytics leading to deeper insights through study of the data is less likely in these industries. The reality is that little really unique, creative knowledge or intelligence is discoverable in these old-line industries. Exceptions always exist, but the track record shows few of those in recent years. Instead, the impact of digital will be gradual, without large jumps. Artificial intelligence, if employed, is likely to improve day-to-day decision-making but will have little impact on larger, paradigm-changing strategic or tactical moves.

5 Conclusions

The digital economy, big data, and business analytics are all parts of a major change in how firms will operate in coming years. The terms and concepts are sometimes fuzzy, so organizations looking to deal with new modes of competition can understandably feel uncertain as to their capabilities and how these might match up with new opportunities. Reports such as the McKinsey piece better defining the impact of digital developments, in defined stages, can be helpful to decision makers. We've taken those concepts further, employing measures of the intangible assets of firms to better assess how ready these organizations might be to participate in these digital stages.

These intangible assets have been viewed through different lenses but their basic definitions are well-understood, and we do have some established metrics for judging them. These metrics allow a firm to judge the typical level of the intangibles present in industry competitors, their relative level of success in exploiting these intangibles, and its own standing on this basis in the industry. In this paper, we've looked at intangible assets categorized as data, explicit knowledge, tacit knowledge, and intelligence. Even given some obvious exceptions in pharmaceuticals and, to a lesser extent, consumer products, these heavy industries all show considerable data holdings but average to below-average explicit knowledge and below-average tacit knowledge and intelligence.

The implications for managers in these industries are that the McKinsey report is broadly right about participation in digital advances, including in the specific areas noted such as efficiency of asset exploitation, and even worker-data interaction. But it's also important to note that most improvements from such applications will be more incremental than paradigm-shifting. Day-to-day adjustments to processes due to data monitoring is the likely path to success rather than heavy investment in the long-term data/knowledge exploitation such as data mining or predictive analytics.

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