Engaging Layers of Intangibles Across Intelligent Learning Ecosystems for Competitive Advantage

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Abstract: The Intelligent Learning Ecosystem (ILE) integrates all forms of intangible assets, recognizing not only tacit and explicit knowledge, but also big data and analytics/intelligence within and across organizations. The ILE structure provides a system for dynamic learning through the synthesis and analysis of intangible assets, creating decision-impacting intelligence across the organization and its partners. Here we extend our understanding of how this ecosystem works by also considering the learning dynamics of individuals and teams. As such, the ILE not only facilitates organizational and partner learning but also leverages the positive impact of intangibles management on employee development, team sophistication and company competitiveness.

Consequently, this paper studies the place of knowledge assets in a wider conceptual framework. By managing that wider range of intangible inputs with a structure designed not only to exchange existing knowledge or data but also to create new learning and insights, decision-makers can accomplish several things. Initially, the range of potentially valuable inputs is increased, bringing in a more diverse set of intangibles that might have more relevance in specific industries or companies. Secondly, the structures can be designed not only to exchange knowledge or big data but to bring it all together, along with all other available intangibles, for analysis. As a result, new learning can take place as cross-functional teams derive insights from the inputs. Finally, such a structure can work not only within a single enterprise but across its wider network of collaborators. The resulting intelligence learning ecosystems bring an even wider range of inputs, diverse perspectives, and opportunities for new learning to all the partners. By looking more widely at these possibilities, knowledge assets can be employed even more productively than when considered only in traditional knowledge management systems.

Keywords: knowledge management, big data, intelligence, learning organizations, intelligent learning ecosystem, teams

1. Introduction

We've previously argued that knowledge management (KM) and big data/analytics fit together naturally and effectively (Erickson & Rothberg, 2017). We've also established how employment of knowledge and other intangible assets can support decision-making, including at the strategic level, and organizational learning (Rothberg & Erickson, 2017)

Here, we take the concepts further by first reviewing the distinctive approaches for managing intangibles, including more analytics-directed efforts. In doing so, we break down system inputs as well as what the most appropriate structures might look like. Some KM systems are based on collecting and distributing knowledge. Some are focused on not only collecting knowledge but also providing an environment to discover new insights. These are contrasted with big data systems, some of which are based only on collecting, transferring, and monitoring data. Other big data systems are also designed for analytics and intelligence, subjecting the data to deeper study. At some point, the potential for learning can be added, going beyond what has typically been done in either KM or big data systems.

The resulting analytical systems also resemble and have a similar purpose to intelligence systems, especially competitive intelligence. There is a reason data mining or predictive analytics are often referred to as business or marketing intelligence, they resemble those familiar structures. The key point is that from all of these perspectives, there are similarities and differences to be studied and understood. Intelligence has a different purpose, one that brings analysis and learning back into the mix, something that is not always recognized in KM or big data work.

This paper specifically looks at and extends lessons learned, going more deeply into conceptual representations of data, knowledge, and intelligence systems while also providing prominent examples of

Reference this paper: Rothberg, H., and Erickson, S., 2018. Engaging Layers of Intangibles Across Intelligent Learning Ecosystems for Competitive Advantage. *The Electronic Journal of Knowledge Management,* 16(1), pp. 36-47, available online at www.ejkm.com

outcomes from different fields and extensions such as modeling the impact on individual and team learning. We will again make the argument that intangibles are a primary driver of sustainable competitive advantage and that the ILE can uniquely drive knowledge and intelligence development on multiple levels, creating layers for generating and protecting such advantage. The layers in the ILE structure, encompassing individual, team, organizational and network learning, form a tight and strong weave of knowledge-related assets and relationships that are hard for others to duplicate or discover substitutes.

2. Literature review

Organizations can do more than generate, capture, process, distribute and manage big data or knowledge. They can also provide systems for individuals or teams to analyze intangible knowledge assets from inside and outside the organization, creating new knowledge or intelligence. Intelligence then facilitates decisions that impact how the organization engages with its competitive environment and external network partners. At the base of such systems are structures to transfer data, information, or knowledge and foster learning.. While much has been written in the KM field (and now in big data) on how organizations transfer knowledge, recent work on learning organizations is less prominent.

Knowledge management, as a discipline, has typically been very focused on both the nature of its inputs (almost exclusively knowledge) and what is done with them. As we'll develop further, knowledge itself has been the only subject of interest since the early development of the field. Precursors such as data and information were portrayed as uninteresting, except to the extent they led to knowledge, while extensions such as wisdom or intelligence weren't part of what KM systems aspired to handle (Zack, 1999; Brown & Duguid, 1991). Further, new knowledge was often treated as an exogenous variable. Individuals (nor organizations) learned outside the system. That knowledge was then brought into the organization where KM processes could identify it, capture or transfer it, and share it back out (Nonaka & Takeuchi, 1995). Learning happened as the now existing knowledge was transferred around the organization by appropriate KM structures, but where the new knowledge came from in the first place often wasn't a major concern.

The structure for this perspective came out of information technology conceptualizations in the 1980s, specifically the DIKW hierarchy (Ackoff, 1989), presenting intangible assets as a progressive movement from raw data through organized information, perspective-based knowledge and on to wisdom. Again, KM theory and practice tended to center on the knowledge level of the hierarchy. But with the advent of big data systems, business analytics, and different types of intelligence, we've begun to take another look at the fuller range of knowledge-related assets: data to information to knowledge to wisdom (DIKW).

More recent efforts have advanced the range of intangibles concent. In particular, Kurtz & Snowden's (2003) sense-making framework has been repurposed to reflect increasingly complex or chaotic environments and the intangibles required to operate effectively within them (Simard, 2014). The environments range from the known, with recognized patterns represented by data and information, through knowable (explicit knowledge), complex (tacit knowledge), and, finally, to chaotic (insight/intelligence). As might be inferred from the description, these environments demand knowledge/intelligence development and decision-making that becomes increasingly complicated, personal, and hard to teach or share as one moves up the hierarchy. And they need different intangibles management systems applied to them (Erickson & Rothberg, 2017).

The knowledge-related environments would include the KM installations with which most in our field are familiar. The knowable/explicit knowledge category would lend itself more to IT-based solutions while the complex/tacit knowledge area would work better with person-to-person exchanges. This is standard practice in the field and nothing particularly new. What is interesting is what we find at the two extremes.

On one hand, the new and burgeoning interest in big data is reflected in the underlying systems to collect, organize, and report on what the resulting massive databases show concerning an organization's activities. When only about the data, these systems can be used to monitor what is happening in logistics, operations, transactions, marketing, social media, or other data-generating areas in real time. Big data is possible because of rapid improvements in managing the volume, variety, and velocity of data (the three V's, Laney, 2001). Because of technological improvements and drops in the costs of processing and storage, organizations can now collect and employ huge amounts of data, of different types (including unstructured data such as text, images, video, etc.), and report it in real time. By using dashboards or other devices, the data of interest can be delivered to decision-makers, allowing them to act on anything going outside of specified boundaries (McAfee & Brynjolfsson, 2012; Chen, et. al., 2012). But none of that requires transformation of the data or new learning beyond establishing trigger points for action or embedded algorithms automating responses to out-of-tolerance results. Data may be presented in different formats or explored by "cutting the data" in different ways, discerning interesting metrics through different cross-tabulations. But the data are not analyzed in order to come up with new insights, knowledge, or intelligence. Nothing really new is created, big databases are simply transferred and monitored according to the metrics of interest that have been uncovered.

Consequently, for the business analytics part of big data, the deeper dive into these databases in order to learn from them, requires different procedures (McAfee & Brynjolfsson, 2012; Chen, et.al., 2012). As opposed to just reporting the data, analytics creates new insights or intelligence by examining the database. The process, usually conducted by teams of data scientists, programmers, and content experts, will manipulate and study the data for unexpected patterns and new learnings. It entails creative approaches and an ability to look at the data in new ways, discovering things others are unlikely to see. Typical techniques here are predictive analytics, often based on correlation, and cluster analysis, grouping together variables with similarities. These, and some of the more qualitative analytics methods we'll discuss later can actually result in new learnings, not just a repackaging of the existing data streams.

This approach is very much like existing systems for intelligence, especially competitive intelligence, the longest lived and most studied of the related disciplines. Big data analytics uses data as its input but effective intelligence systems are open to the full range of intangible inputs, including data and information but also all types of knowledge and previously generated intelligence. If properly structured, these systems assemble useful inputs, subject them to analysis, and find new insights or learnings from them. This goes beyond traditional KM systems, structured chiefly to share existing knowledge, and harkens back to interest in learning systems that facilitate individual or team learning within the organization.

3. From intelligent learning organizations to intelligence learning ecosystems

Senge (1990) pioneered the organizational learning field, expounding upon the importance of vision, personal mastery and cross-functional teams for creating entities that promote learning. He envisioned processes driven by the exchange of information and ideas in dynamic dialogue among varied, diverse organization members. Argyris (1993; 1992; 1977) espoused that learning happens when errors are identified and corrected (single loop learning). Deeper learning occurs if organizations then go back to discover the error's source, intending prevention (double loop learning). Others (Tosey, et. al., 2011) extended these ideas to triple loop learning, deepening the learning process from what is learned to how it is learned and embedded into systems (Nielsen, 1993), changing the learning paradigms themselves (Issacs, 1993), informing strategic thinking (Hawkins, 1991), and engaging all inquiry necessary to drive a higher order of learning (Roper & Pettit, 2002). Individuals are pushed to think differently, resulting in personal insights that can further drive organizational learning.

Both Senge and Argyris believed that for a learning organization to succeed, participants needed to engage outside of pre-conceived mental and analytical models and allow for unbridled discussion and inquiry. This would then tap into both individual and organizational knowledge to create new understanding and growth for all. To this end, cross-functional teams of people are employed to accomplish work and to forge new methods and insights into how to best get work done. Cross-functional team brainstorming can drive improved processes and systems. Cross-functional teams are also core to productive intelligence systems where individuals come together to convert personal knowledge assets into intelligence that has strategic impact for the organization (Rothberg & Erickson, 2005). Here team learning informs individual processing, enhancing personal knowledge that in turn creates new learning that can then be applied to new analytical and decision situations. In short, the methods for creating a learning organization also change the intangible assets of people and teams, potentially impacting their actions across situations.

More recently, Rothberg & Erickson (2016), adapting competitive intelligence structures, brought these concepts back into the KM discussion. Intelligent learning organizations (ILO) provide a foundation to access and integrate all forms of intangible assets, including big data (Rothberg & Erickson, 2017). Here, organizations perform analysis and yet also move beyond it and assimilate lessons from the outcomes of analysis. As we'll develop in this paper, this structure can be expanded to include engagement with external stakeholders, including an entire network of collaborators that expands the ILO into an intelligent learning ecosystem (ILE). In the spirit of triple loop learning and examining not just results but learning processes, the very nature of the ILE expands an organization's scope of knowledge, network relationships, and sphere of influence. This confluence of intangible inputs and cooperative learning environment ushers in the possibility for dramatic change in how organizations view data and knowledge. The full range of intangibles can contribute to intelligence and learning and has the potential to turn endogenous and purposeful.

Table 1: From learning organization to an intelligent learning ecosystem

Learning Organization	Intelligent Learning Organization (ILO)	Intelligent Learning Ecosystem (ELO)
Single-loop learning	Double-loop learning	Triple-loop learning
Dialogue	Mission-driven	Vision-driven and strategic
Mastery and team learning	Convergence points and feedback loops generate insights	Engagement between external stakeholders and organizational agents
Knowledge transfer	Cross-functional teams, extending across expertise and hierarchy	Boundary-spanning, cross-functional teams
Managerial support	Knowledge transfer and lessons learned	Lessons learned, perspective on different ways to do things
	Upper-level decision support	Upper level change engagement

An ILE system structure is governed by eleven assumptions:

- External stakeholders are data/knowledge partners, as contributors of intangible inputs and drivers of inquiry and new learning.
- System can engage the full array of internally generated and externally captured tangible and intangible inputs.
- Open dialogue drives the process
- Double loop culture, triple loop intention
- Intelligent design means that it is action-oriented
- Clear mission
- Driven by mastery
- Team-grounded
- Taboo-free
- Incentivized for quality impact
- Senior management attention

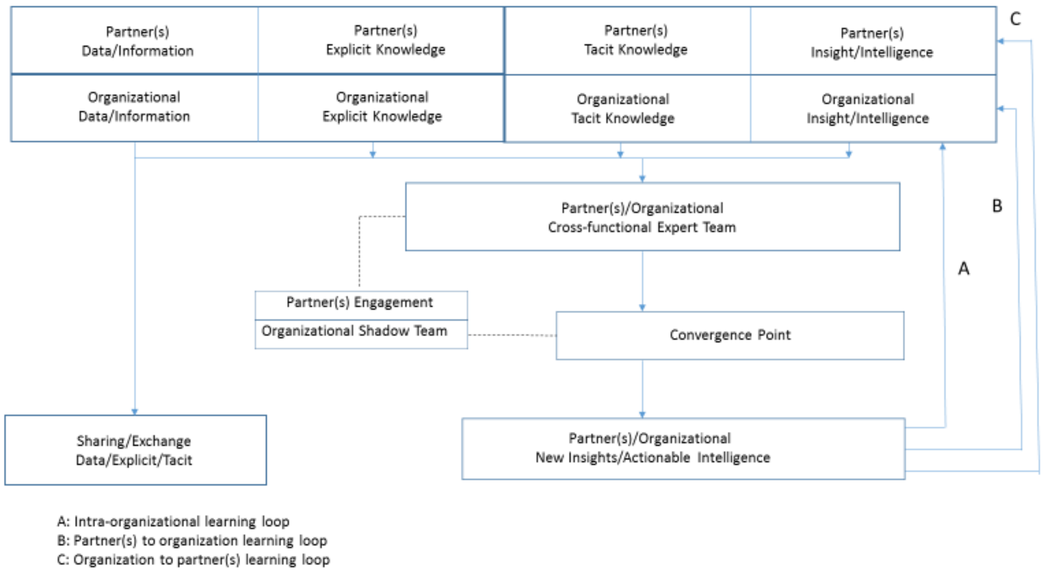

Figure 1: Intelligent learning ecosystem

As covered in the literature review, the revised Kurtz & Snowden sensemaking framework is used to organize the intangibles inputs. All of the intangibles of the organization and/or its partners can be put to use, depending on availability and potential contribution. Data/information (including big data) can be fed into the system as can increasingly personal forms of intangible assets: explicit knowledge, tacit knowledge, and intelligence. Again, what may be pre-eminent or important in a given situation will depend on the industry and, perhaps, even the specific firms. It's up to the system to collect and review the inputs. Users can then determine what might be appropriate to analyze to discern deeper insights and learning.

Thus, in this ecosystem, all of the intangible assets of its players may be sourced and applied to a vision-driven purpose. Cross-functional teams are also cross-organizational, as are the expert networks and focal points for analysis to converge. There are multiple feedback loops that encourage learning from what works and what doesn't work (single loop), learning how to make things work better (double loop) and integrating such learning (triple loop) among partners throughout the system. The integration not only feeds engagement between network partners but also with other parts of all member organizations, improving process and system with positive changes (ecosystem outcome).

Digging more deeply into the ILE, one can position it as a platform for leveraging an organization's knowledge assets so as to create learning within and across its boundaries. It can incorporate any type of big data, knowledge management, or intelligence system to manage the intangibles' organization and flow. It would also include an intelligence design that brings together cross-functional teams and networks of experts to analytically convert intangibles into actionable intelligence that informs strategic decisions. The ILE can also reach beyond each participating organization to create an ecosystem where deliberate exchanges with partners, through strategic alliances, joint ventures, or partnerships, drive opportunities to create new, shared knowledge or intelligence. Such newly created intangibles can then be brought back to each institution and be the catalyst for even more new learning, going beyond the original scope and purpose of the ILE itself.

Core to an ILE being a player in an organization's competitiveness and quest for advantage is that:

- The full array of intangibles relevant for ecosystem relationships are collected and available for system learning
- Each player in the ILE generates intelligence by putting their learning to use.
- Cross-functional teams successfully work together intra- and inter- organizationally

Previously we have addressed the importance of employing the full array of intangibles dynamically to fuel an organization's quest for generating intelligence and competitive advantage. We have also addressed the pivotal role of cross-functional teams in helping to convert knowledge to intelligence. Here we extend this understand by highlighting how teams learn, as this is pivotal to competitive success of an ILE.

Team Learning, an Essential Dimension for ILE Success

As organizations engage across the ILE, individuals and teams are convened and tasked with generating relationships, identifying activities, creating systems, and problem solving. Although brought together for mutually beneficially purposes, each entity in the ILE has its own agenda of needs and desired outcomes. Individuals and teams, and individuals within in teams, also have their own tacit agendas. Somehow, these competing intentions need to find a way to create trade-offs and contracts whereby needs and wants are satisfied. As agreements about goals, processes and outcomes are hammered out by ILE agents, teams and the people that populate them learn- not only about each other's businesses and practices- but also about each other and themselves. They build human, structural, and relational capital that can transfer to other collaborative and negotiated engagements outside of or in addendum to the current ecosystem. How well this happens is both a testament to the intricacies of how individuals learn, how they learn in teams, and how the teams themselves learn.

The intent in the discussion that follows is not to review the plethora of research on how individuals learn. Instead, it is to consider individual learning within teams and team learning. Understanding these learning dynamics is essential to understanding the motors that drive learning organizations and ILEs.

Nonaka and Takeuchi (1995) suggested that new knowledge is created by individuals, not organizations. An organization has the opportunity to institutionalize new knowledge and then share it across its members, but is generally not credited with creation in KM circles. When this new intellectual capital is shared with others, individuals learn and add to their knowledge store even though no further creation needs to take place. One contributor's knowledge is passed to a receiver, so the receiver learns by taking in the existing knowledge. Further leveraging of existing knowledge can take place when applied to organization systems and processes (structural capital). As organizations systematize individual knowledge, making it a part of established processes, procedures, or even culture, it can become more of a shared, enduring knowledge asset. How well this dynamic occurs, individual knowledge creation by people perhaps begetting new structural capital, is a matter of organizational design and culture. Organizations that encourage the sharing of new knowledge creation and its synthesis with other intangible assets into organization learning processes may demonstrate stronger financial performance over time (Goh & Ryan, 2008).

For an organization to learn, it has to provide the right structure and have the right people in place to create "organizational" learning through their insights. Organizations learn best when they have vision and mission driven cross-functional teams engaging in dialogue (Senge, 1990). Teams have been widely considered the bedrock of modern organizations (Kozlowski & Bell, 2003). They are relied upon to continuously learn and manage increasingly global, complex, and competitive environments (Shuffler, et. al., 2011). Bringing people together with differing perspectives, experiences and knowledge bases creates a more effective mix for working with such challenges then an individual on their own. To make this viable, differences among team members need to be integrated into a shared understanding through rich discussion and negotiation (Daft & Weick, 1984; Roschelle, 1992). For an ILE to be effective, teams need to learn how to get along and work well.

Team learning is a social, cognitive and knowledge sharing process. Its success depends on the nature of interpersonal and socio-cognitive dynamics (Van de Bossche, et. al., 2006), as well as the nature of conflict that inevitably arises. Conflict can disrupt or enhance team learning processes. Affective or relationship conflict results from personal incompatibilities that generate hostility (Amason, 1996) and animosity that can derail decision-making (van den Berg *et al.*, 2014). Power struggles can ensue when teams (and their agendas) from organizations across the ILE come together. The mergers & acquisitions literature is rife with examples of partnerships unraveling as players from each organization vie for power and prominence. This can be offset when teams share leadership roles early in their development, creating stable working network structures that facilitate team learning. (Wang, et. al., 2017). The ground rules, then, for ILE relationship building can take the same tack to bypass affective conflict and instead engage constructive conflict.

Constructive conflict, the critical and thorough consideration of each member's ideas, differences of opinions and contributions, creates shared mental models regarding situational challenges (Van, et. al., 2011). Shared mental models are essential for team learning and problem solving. Diversity drives T-shaped cross-functional and inter-ILE teams. Team diversity fosters more cognitive or task conflict stemming from differences in perspective in pursuit of a common goal but also adds distinct perspectives and experience that improve outcomes (de Wit, Greer & Jehn, 2012, Amason,1996, Jehn, 1994). Constructive, cognitive-based conflict, employing listening to disparate ideas and considering the merit of each, yields greater satisfaction for team members. This in turn has been shown to increase an individual's desire to share what they know (Medina, 2016). Sharing knowledge drives the team learning process. When teams learn well together, their potential to be more creative increases (Hirst, et. al., 2009).

Successful team learning within and across the ILE establishes and solidifies the norms governing the ecosystem. Respect for differences of opinion, the welcoming of different knowledge and experience bases, and clarity of purpose provide the foundation for cross-functional and cross-ILE teams to learn and perform. Such cross-organization lessons in power sharing, civility, and constructive debate can transfer back to organization management and learning processes. And, as people from across an organization engage more with each other as well as those from the larger ecosystem, the generation and transfer of learning to new situations enhances all forms of intellectual capital. This in turn creates layers of knowing and learning that are intangible, dynamic and perhaps become a deep well for creating sustainable advantage.

ILE as a Platform of Engagement

The concept of the ILE as a platform borrows from strategic thinking around the disruptive economies ushered in by innovators such as Apple (iphone), Google and Facebook. VanAlstyne, Parker and Choudary (2016) suggest that platforms bring together producer and consumer, with information and interaction exchanges that create value for both. The platform can also add participants such as suppliers, vendors, and partners. As the number of participants grows, network effects amplify the value of the biggest platforms. While the idea of platforms is not new (e.g. malls bringing together consumers and a variety of retailers), current networked platforms have data, information and other intangibles at their core. In the platform ecosystem, the critical assets are the community and the resources of its members, including the data/information they create, the knowledge they engender, and ultimately the learning that they can facilitate. It is possible that organizations can become such platforms as they engage with different alliance partners, learning from each as they enter and exit relationships, digesting deliberate and synchronistic lessons, and then weaving them into their own DNA so as to impact their next partnerships in both planned and unexpected ways. When the network partners include participants directly engaging consumers and bringing them into the mix, the capabilities are extended even further.

This perspective also draws in a persistent concern with KM systems, whether enough trust exists between participants to engender full knowledge exchange (Bontis, 1999). Trust has always been modeled as a willingness to be vulnerable, requiring ability, benevolence, and integrity on the part of the opposite party if they are to deliver as expected (Moore, et. al., 1995). As knowledge is often perceived as power by the individual holding it, surrendering the knowledge means trusting that their position will not be diminished (e.g. outsourcing their job after documenting how to do it). The user of the knowledge trusts that it will be of use, that if they take the time to learn from another, the results can be usefully applied. If any part of that exchange breaks down, the entire exchange system on which KM is built can break down as well (Matson, et. al., 2003). The concerns apply as well to exchanges of other intangibles even if data/information are more often collected and distributed by organizations rather than individuals.

Within a single organization, managing trust can be difficult enough. A strong culture or high social capital can help (Bontis, 1999, Nahapiet & Ghoshal, 1998). But cross-functional or cross-location teams can have difficulty creating the necessary trust for effective sharing. When the structure is extended to outside the organization, bringing in external partners, the problem of trust is exacerbated. Different parties need to demonstrate their competence (ability), their good intentions toward other participants (benevolence), and their integrity (willingness to meet their responsibilities) for the teams and full ecosystem to work. This may take considerable time and effort. As with standard KM systems, where gaining participation is always an issue, trust in the process is a challenge. It is an even bigger one in an ILE context and demands special attention.

4. Cooperative structures

Cooperative relationships--alliances, joint ventures and partnerships--bring together varied players with their own intangible asset stocks in a defined sharing relationship. Organizations engage in cooperative relationships to manage risk, share capabilities, and/or expand their reach in ways that are mutually beneficial. And while the nature of the business relationship is defined, the extent of the learning relationship and informal intangible exchange is not. In an alliance relationship, for example, two or more companies come together to achieve a common objective with each contributing its own capabilities and benefitting capabilities of other participants. This can be structured as co-branding, cross-licensing, co-marketing, or co-development, to name just a few. In such relationships participants look to benefit from the relationship's formal agreement of data or knowledge exchange, perhaps sharing in the outcome of big data insights about consumer or user behaviors. But each can also learn from informal interactions, as how each runs its business for example.

To illustrate, Barnes & Noble and Starbucks have had an alliance for decades. Initially, Starbucks had the benefit of promoting brand awareness with a renowned bookseller while Barnes & Noble gained from customers spending more time in its stores while enjoying their coffee. Eventually, however, Barnes & Noble had the opportunity to learn something more about creating a destination environment, where people would choose to come to get work done, to meet others, or for personal needs. This is a triple loop learn, about changing the culture of the bookstore from a retailer to an experience, perhaps altering the reasons that a person would come to a bookstore and especially important as online retailing continues to gather momentum. Together the partners create an ecosystem where one appears to have learned more than just a co-marketing opportunity. Spotify and Uber's alliance relationship (or, similarly, SiriusXM's free sample partnership with multiple automakers including installed hardware and a months-long gratis subscription) also illustrates the point by facilitating a more enjoyable customer experience, creating differentiation, and enabling big data insights. Each partner has the opportunity to further learn about customer habits and preferences, taking the relationship to a higher level.

Knowledge-based companies such as consulting firms organized as hybrids can also work as ecosystems. They rely on their teams to have the right composition of know-how and cross-organization relational dynamics to apply the depth of their knowledge stocks to clients in specific vertical markets and to then bring back what they learn to enhance their knowledge stocks. IBM Global Services is structured this way, creating the opportunity for continuous learning not only internally but also across different learning partners (clients). Consultants work in market-defined segments such as healthcare, pharmaceuticals, or education. Knowledge capabilities (products, processes, software) are continuously developed. Each market area draws on what it requires from the product/service side to fulfill client needs. With each client, new learning is possible that informs engagement with the next client and then the utility of those developing capabilities. As each client engages, each consultant fulfills, and each engineer learns, new learning drives existing client work and is then applied to new clients. These lessons can also be shared across market or industry divisions. The ecosystem, supported by appropriate internal cultures, is a generative learning engine with impact limited only by willingness of agents to engage. And companies engaging in such an ILE, who can access and enhance the knowledge and intelligence capabilities across individual, team, and organization, have the makings of a more layered and more sustainable competitive position.

The ability of the ILE to dramatically impact organizations is an outcome of not only internal processes where all types of knowledge assets come together to create knowledge--but also how it is then employed, expanded on and engaged with by external partners. The backbone for the internet was created by a consortium of technology giants who together needed a common framework and who then separately took the capabilities of what they created to develop products and services in accordance with their own knowledge assets and core competencies. In time, different "apps'"have had to learn to work together, to run on each other's applications and together they share the benefits of generating big data, separately harvesting insights that influence their business decisions.

As a more extended example, and applying the system framework illustrated above, consider the current example of autonomous driving. Navigant (Abuelsamid, et. al., 2017) released its annual ranking of announced competitors in the field and while the metrics might be debated, there is a clear picture of the wide range of participants from different industries and industry sectors. Virtually all the major automobile manufacturers are represented, both traditional (GM, Ford, Toyota) and innovative (Tesla). In addition, everyone from parts suppliers (Delphi) to information technology component suppliers (Intel), from software (Alphabet/Google) to ride-sharing (Uber) are included. As should be Apple, not on the Navigant list only because the firm has not formally announced an interest in driverless cars.

From our perspective, however, what's really interesting about the burgeoning field is the varied nature of approaches to the intangibles necessary to compete. Apple's interest in the sector was identified when journalists were able to identify numerous new hires with considerable experience in the auto industry (Wakabayashi & Ramsey, 2015). Competitive intelligence/economic espionage has also been a factor with Alphabet's Waymo subsidiary accusing Uber of poaching an employee allegedly bringing thousands of documents with them (Hawkins, 2017). But most prominent in the mix are examples of firms from different sectors and with different intangibles capabilities working with each other to bring a product quickly to market.

Perhaps the best example is the relationship between BMW, Intel, and Mobileye. The partnership announced at the Consumer Electronics Show in January 2017 that it would be bringing 40 test models onto the road by the end of the year (Korosec, 2017). Each partner contributes something very different to the mix. BMW, of course, is a traditional auto manufacturer and "will be responsible for developing driving control and dynamics, [and] overall functional safety" including simulation, prototype, and scale-up. Intel "will contribute its computing power with artificial intelligence and data center capabilities", while Mobileye brings "advanced sensor technology" and the associated, complex software.

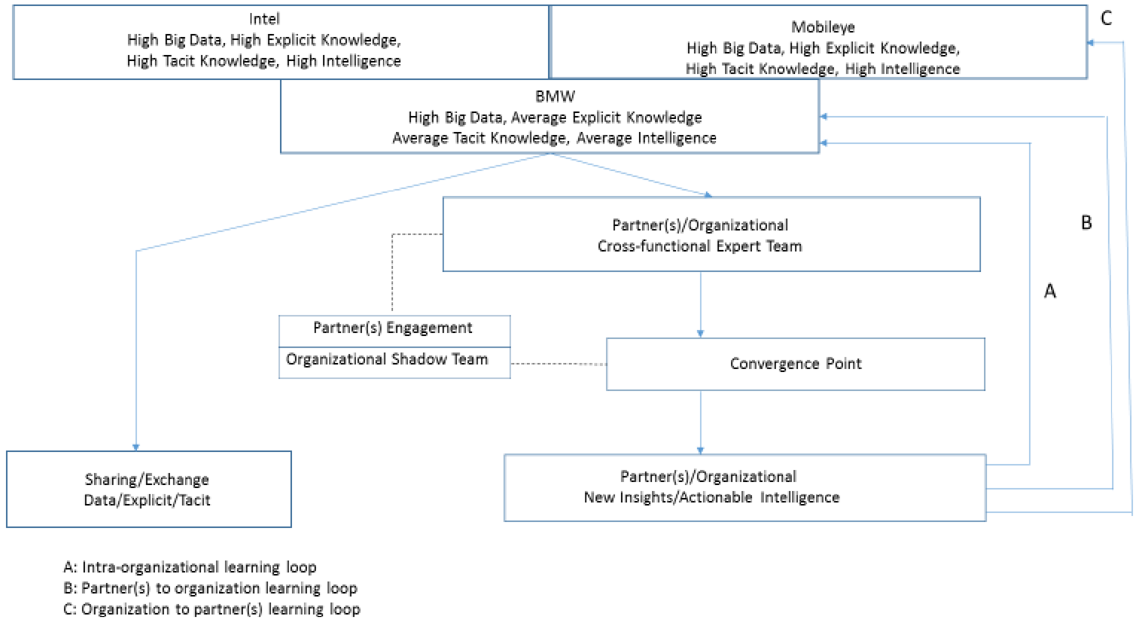

Figure 2: Autonomous driving as an ILE

From the range of intangibles point-of-view developed earlier in this paper, we can partially identify the sector strengths and weaknesses of each (Erickson & Rothberg, 2017). All of these sectors have considerable data (Manyika, et. al., 2011), so big data is present in the areas of supply chain logistics, manufacturing, software development, performance feedback, and customer relationships. In terms of explicit knowledge, automakers like BMW have significant but below average explicit and tacit knowledge assets (not surprising for sectors with fairly mature processes). But semiconductor manufacturers (Intel) and software/web firms (Mobileye, the programming ties the sensors into systems) both have very high knowledge metrics, with considerable explicit knowledge apparent. Further, the latter two also have evidence of considerable tacit knowledge and intelligence capabilities while automakers, once again, possess lower, less-than-average levels of each.

This can be depicted in a variation on the ILE systems figure presented earlier. Each participant brings different contributions to the partnership. In the end, the physical automobile must be manufactured and so, even though the data/information and explicit knowledge about how to do that are not highly innovative, these are critical intangibles not possessed by the other partners. And it is quite possible that BMW does them better than many of the other auto manufacturers vying for leadership in the sector. Those contributions of a safe, working automobile and the ability to take the autonomous driving machine envisioned by the network and move it to mass manufacturing are both valuable contributions. Even though not necessarily new knowledge, it is something crucial to the partnership.

The other two partners bring the full range of intangibles and potentially critical innovations to the ecosystem. A big part of the autonomous driving problem is the ability to take in reams of data on the operating environment—what is around the car, how the car is performing, what might happen around the next corner. That requires advanced sensors designed to take in the data, raw processing power to combine that data with what is known about similar circumstances, built-in software, algorithms, and even aratifical intelligence related to how the machine should react, These capabilities are amplied by continued learning based on new observations (by humans and by artificial intelligence) and the ability to communicate with systems that physically execute such choices in real time. Further, all of the firms in this sector will want to continually collect new data and information from the full fleet of cars on the road in order to learn more as an enterprise. The loops of learning are critical to success.

Finally, as illustrated in the figure and demonstrating the learning loops discussed in the conceptualization, the core firm and partners will learn themselves, internally, but will also learn from each other. We can surmise that agents within this ILE are well engaged in the three criteria for achieving competitiveness: the full array of knowledge assets are employed and shared, they are being converted into usable intelligence in autonomous driving and intra- and inter- organization teams have learned how to productively work together and learn. As such, BMW will make better cars, based on what it learns on its own (intra-organizational loop) and from its partners (stakeholder to organizational loop). Similarly, both Intel and Mobileye will learn from their own successes and failures (intra-organizational loops) as well as from BMW and how they interact with it (organizational to stakeholder loop). Indeed, as a more general characterization, inter-organizational learning goes on between all the partners as they learn more about dealing with one another and about fitting their contributions to those of their partners. In an ideal world, everyone in the ecosystem learns, improving their own situation and the overall partnership. BMW becomes not only a better car builder but a better autonomous car builder, specifically for those vehicles using Intel and Mobileye components. Intel becomes not only a better automotive chipmaker, but a better automotive chipmaker for BMW cars using Mobileye components. And, similarly, Mobileye becomes not only a better sensor system designer and builder but a better sensor supplier for BMW cars equipped with Intel chips.

5. Conclusions

Knowledge management practice and scholarship have gone through a number of changes in emphasis and direction over the decades. The advent of big data systems and business analytics/intelligence have raised questions about the continued relevance of KM, particularly as a stand-alone discipline. This paper has considered the place of KM in this new and rapidly changing world.

Our view is that the current environment provides new opportunities for KM as a discipline, if its participants are willing to grasp them. Both big data, at one end of an intangibles hierarchy, and intelligence at the other end have been only peripheral concepts in KM which tends to focus almost exclusively on knowledge. But what we, as KM scholars and practitioners, know concerning sharing of intangibles works very well with what big data systems are trying to accomplish. And though organizational learning has also been forgotten as KM focused more on knowledge transfer, the field also has a basis in how conditions can be created for the sharing of intangible inputs, their analysis, and the application of any new learning coming out of the process.

With an open mind to the wider range of valuable intangible assets available to today's organizations—data/information, explicit knowledge, tacit knowledge, and insight/intelligence—our discipline has more to offer. Indeed, by exploring the potential of new structures designed to create a positive environment for all these intangibles, KM can take a step forward and create new contributions.

This paper, in particular, looks at the possibilities of an intelligent learning ecosystem (ILE), linking up an organization and its network of partners in a structure designed for the sharing of existing intangibles and creation of new ones. By identifying and exchanging all forms of intangibles, not only knowledge but also relevant data and existing intelligence, network partners can provide more diverse perspectives to each other. When analyzed by cross-functional teams, all partners have opportunities to learn not only from themselves but from each of the others. And the learning is not necessarily only about the subject at hand but other, unrelated areas that can lend further value. Such structures also take KM out of its emphasis on operational decision-making and create an avenue for more input into strategic activities at higher levels of the organization.

ILE individual and team learning across agents provides the opportunity for lesson transfer back to organizations. In an effective ILE, individuals and teams have ascertained how to purposefully and cooperatively engage with partners, each bringing something different to the relationship that not only fulfills each organization's need, but also serves to alter each organization in fundamental and perhaps significant ways. Sharing of know-how across the ecosystem fuels each player's knowledge base and learning. Human capital is enhanced as players integrate lessons from constructively working through conflict, from relationship building, and from interacting with a diverse array of knowledge and personality. Teams, the collection of such people that are brought together to accomplish something, learn how to be productive as a group and with other collectives as they manage their internal and external processes. If such lessons are transferred across the organization as it learns from its experiences, then the ILE has the potential to generate deep layers of sustainable competitive advantage.

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