From Artificial to Emotional Intelligence: Integrating Five Types of Intelligence to Achieve Organizational Excellence

Chaojie Wang
The MITRE Corporation, USA*

Fred Hoffman
Mercyhurst University, USA

Alvi Lim
The MITRE Corporation, USA*

Jin Kwon
Robert Morris University, USA

Decision Support Systems have significance, as today firms turn to big data, machine learning, and artificial intelligence to guide strategy development and improve organizational performance. However, technology is not enough; human intelligence is necessary. This paper introduces Artificial Intelligence to the Emotional Intelligence Model, which blends technology and humanity to support strategic decision-making. Such a model builds on the Data-Information-Knowledge-Wisdom hierarchy and knowledge management to integrate five types of intelligence. The consumer electronics retail giant Best Buy is used as a case to illustrate the relevance of the model. The presented framework provides a powerful, mental model to support organizational strategists and business executives.

Keywords: DIKW hierarchy, knowledge management, tacit knowledge, artificial intelligence, business intelligence, competitive intelligence, decision intelligence, emotional intelligence

Introduction

Rapid advances in information and communication technologies (ICT) have presented established business to consumer (B2C) retail firms with both opportunities and threats. Over the past decade, one major, ICT-driven trend has been the rise of online retailing and attendant changes in consumer

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shopping and purchasing habits that challenge the traditional, brick-and-mortar model long followed by leading B2C companies. As successful online retailers like Amazon began to inexorably eat away the market share of traditional, brick-and-mortar retail chain stores, many traditional B2C firms found themselves unable to come up with a strategic response to the price, variety, selection, and convenience advantages of online shopping. Many such firms have suffered sizeable losses in market share, and some have either declared bankruptcy or have been projected to do so in the near future: in October 2018, after more than a century of existence, once-dominant US retailer Sears declared bankruptcy (Wahba, 2018) and, by December 2018, industry experts were predicting that another industry giant, JCPenney, was not far behind (Martin, 2018).

Just a few short years ago, computer-electronics retailer Best Buy was in a comparable state of decline. Chagrined Best Buy store managers increasingly found themselves standing by helplessly as visiting customers would engage in a practice known as ‘showrooming,’ or physically examining new products in a store but then going home to purchase the item, more cheaply, from an online vendor like Amazon (Bariso, 2019). Like so many of its industry peers, Best Buy found itself in serious trouble, and corporate executives knew they needed to come up with a strategic response, and fast, if the company hoped to avoid the financial death-spiral being experienced by some of its peer competitors in the industry.

For commercial firms faced with a significantly-changing operating environment, the difference between bankruptcy and continued profitability is adaptability, and adaptability requires sound strategy stemming from wise and informed decision-making. While erstwhile ‘blue chip’ firms like Sears and JCPenney failed to adapt, the US-based consumer electronics retail giant Best Buy not only staved off disaster but has reversed its decline and even prospered. This article uses Best Buy’s strategic response to its described predicament as a representative example to examine how organizational leaders can draw upon a mix of technological and human cognitive resources to address even the most seemingly intractable of problems to come up with creative, workable solutions. The A2E (Artificial Intelligence to Emotional Intelligence) Integrated Intelligence Model introduced in this article encompasses five different, but complementary, types of intelligence: (1) Artificial Intelligence (AI), (2) Business Intelligence (BI), (3) Competitive Intelligence (CI), (4) Decision Intelligence (DI), and (5) Emotional Intelligence (EI).

Each type of intelligence is briefly described, as is the way executives faced with a challenge (like the one confronting Best Buy) could leverage that particular type of intelligence to support development of an informed, sound, and successful strategy. While each of the five types of intelligence can be a useful tool in and of itself to address a specific dimension of a problem, the most effective approach is to use them collectively to solve a problem as a whole. To that end, this article builds upon the well-known Data-Information-Knowledge-Wisdom (DIKW) hierarchy, coupled with such core knowledge management concepts as tacit and explicit knowledge, knowledge discovery, creation, and application, to integrate the five distinctive types of intelligence into a coherent, unified, and elegant conceptual framework. This simple, yet powerful framework can serve as a mental model to help strategists and executives conceptualize an effective approach to problem-solving. This paper used Best Buy as an illustrative case study to demonstrate the relevance and usefulness of this model in strategic thinking and organizational management.

DIKW Hierarchy & Knowledge Management

The DIKW hierarchy, also known as the wisdom pyramid, is a commonly-used construct in information systems research (Ackoff, 1989; Davenport & Prusak, 1998; Zeleny, 2006; Rowley, 2007; Skovira, 2007). The DIKW hierarchy represents the full spectrum and cumulative nature of human experience. From an ontological perspective, DIKW represents four different types of experience: *Data* are the most primitive type, which result from observing events, environments, and humans via our senses and modern sensors; *information* represents patterns extracted or abstracted from the observational data, and helps humans understand *what* things are; *knowledge* represents the sensemaking of information in the personal and social context, and helps humans understand *how* things are; *wisdom* is at the pinnacle of the hierarchy, and represents the human beliefs, purposes, values, and judgement, which helps humans understand *why* things are. From an epistemological perspective, DIKW represents the increasing level of human understanding through the incremental process of discovering, creating, and applying human knowledge, and helps to better understand human decision-making.

Wang (2018) proposed a conceptual data analytics process model using the wisdom pyramid as the overarching structure. The model described data analytics as a three-phase process as shown in Figure 1. Phase 1 is the *knowledge discovery* phase (from data to information), where information is extracted from data using such information technology as data management and machine learning. Phase 2 is the *knowledge creation* phase (from information to knowledge), in which information is contextualized through human interpretation and collaboration to create new knowledge. Phase 3 is the *knowledge application* phase (from knowledge to wisdom), in which the discovered and created knowledge is applied to make informed decisions, improve human conditions, and solve human problems.

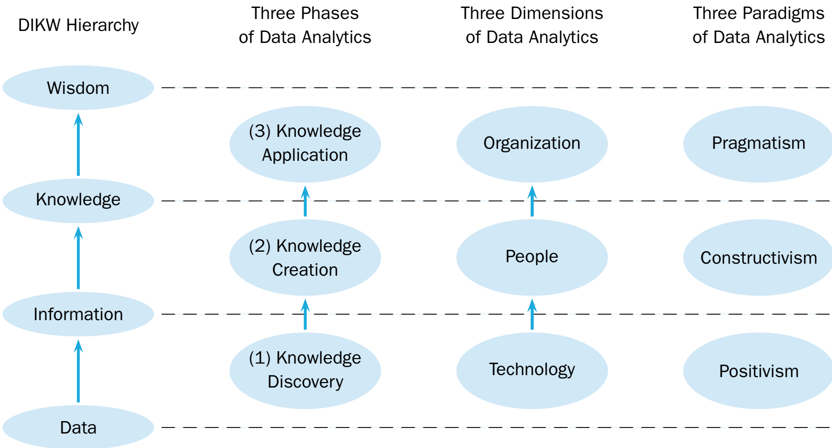

Figure 1 Data Analytics as a Three-Phase Process

Five Types of Intelligence

Artificial Intelligence (AI)

The core difference between an 'intelligent' system empowered by AI and a 'dumb' machine is the ability to learn from experiences, improve over time, and apply that learning to new activities (Cognilytica, 2018). With AI technology, knowledge management (KM) is able to move to a higher level of the DIKW pyramid with much greater value. The Machine Learning (ML) part of AI provides a bridge between information and knowledge. The three types of ML, (1) supervised learning; (2) unsupervised learning; and (3) reinforcement learning, map each type to a different level of the DIKW model. Supervised learning is good for executing a particular task, i.e., it is 'task-driven' (Cognilytica, 2018). It is good for performing classification and regression-type algorithms where the goal is to find a relationship between inputs and outputs. Unsupervised learning is used in a situation where the focus is on the data and the discovery of a higher order of information, i.e., it is 'data-driven' (Cognilytica, 2018). Here, unsupervised learning is widely used in clustering where large amount of data can be organized based on observed patterns. Reinforcement learning works well in areas where any goal- and decision-oriented experiences are relevant, i.e., it is 'goal-driven' (Cognilytica, 2018). This last type of ML enables a machine to learn 'a series of actions by maximizing a "reward function"' where learning is done through 'trial and error' (Cognilytica, 2018).

The dawn of AI technology has given hope to humans to leverage AI in areas where humans have shortcomings, and to expand humans' capabilities in areas where AI has deficiencies. The resulting outcome should be a world where 'augmented intelligence' persists – the combination of the best of the humans and AI worlds. Thus, wisdom will persist and prevail at the pinnacle of the DIKW model.

Business Intelligence (BI)

In the commercial world, the three related disciplines of business intelligence (BI), competitive intelligence (CI), and knowledge management (KM) are commonly referred to as *commercial intelligence* (Hoffman, 2018) or *strategic intelligence* (Kruger, 2010). While all three disciplines have benefited from advances in ICT to support informed decision-making, how they do so, and for what purposes, differ in significant ways.

BI is a commercial intelligence discipline that supports informed decision-making by mining and analyzing the ever-increasing types and quantities of data generated and stored by a business in the course of its normal operations. 'BI goes from the process of collecting large amounts of data, its analysis, and consequent production of reports that summarize the essence of actions on the business, which will assist the managers in the decision making of the day-to-day business' (Guarda et al., 2016, p. 1). 'Business intelligence (BI) provides decision-makers with data, information, or knowledge to address decisions about problems specific to the individual decision-maker needs, and that can be "rolled up" to support broader organizational level decision-making' (Visinescu, Jones, & Sidorova, 2017, p. 58).

Most information analyzed by BI practitioners consists of data that is both generated and held by the company itself. In most cases, that data is available, accessible, reliable, and voluminous. BI professionals use automated systems and specialized software to analyze data for the purpose of engaging in descriptive, predictive, or prescriptive analysis. BI generally involves identifying 'patterns, trends, rules, and relationships from volumes of information which are too large to be processed by human analysis alone' (Alnoukari & Hanano, 2017, p. 6). Increasingly supported by 'artificial intelligence, machine learning, database systems and statistics' (Mishra, Hazra, Tarannum, & Kumar, 2016, p. 84), BI practitioners engage in *data mining* to reveal hidden patterns and thus support knowledge discovery and informed decision-making. Because of the nature of their data collection and analysis, BI practitioners have their own 'architectures, tools, databases, applications, practices, and methodologies' (Alnoukari & Hanano, 2017, p. 5) to perform their intelligence functions. The purpose of automated BI systems is to enable the 'intelligent exploration, integration, aggregation and a multidimensional analysis of data originating from various information resources' (Yeoh & Koronios, 2010, p. 23). In recent years, artificial intelligence and Big Data have transformed BI by enabling the exploitation of ever greater and more varied types of data while enabling the identification of patterns in a fraction of the time previously required (Curuksu, 2018, p. 19).

Competitive Intelligence (CI)

Whereas BI focuses internally, competitive intelligence (CI) is focused externally on the environment, actors, and forces external to a company. Three activities encompassed by competitive intelligence identified by Sassi, Frini, Abdessalem, and Kraiem (2015), as shown in Figure 2, are *market intelligence,* the identification of current and future customer needs and desires; *competitor intelligence,* the identification and assessment of competitor intentions, capabilities, and activities; and *technological intelligence,* the identification and assessment of new technologies and trends relevant for the client's business.

There are other significant differences between BI and CI. Not only are the actors and activities of interest to CI external to a company, so, too is the great majority of the data sought, acquired, and analyzed by CI practitioners. 'A key maxim of competitive intelligence is that 90% of all information that a company needs to make critical decisions are to understand its market and competitors is already public or can be systematically developed from public data' (Yin, 2018, p. 533).

The data and information sought by CI practitioners are frequently acquired from publicly available information sources, either online or in printed documents. It has been estimated that Google 'has only indexed 0.004% of all Internet pages' (Dominguez, 2015). This means that the vast majority of information on the Internet exists in the *Deep Web,* so-called because that information is not search engine-optimized, and thus is not identifiable and retrievable using popular search engines like Google or Bing. Consequently, *publicly* available does not necessarily equate to *readily* available, or even readily identifiable; one of the most valued skills of an experienced CI practitioner is knowing where certain types of information reside and how to locate and access that information. Another difference between BI and CI is that, whereas BI looks at current and historical data to make judgments about the present and recommendations for the future, CI is almost exclusively focused on the future. Indeed, one thing CI can provide that BI cannot is *intent.* Press releases and news reports may reveal that Company XYZ is opening a new production facility in Southeast Asia, job announcements may reveal the type of specialized engineers that the company is seeking to hire in Bangkok, and other information from social media and other sources may provide additional insight as to what is happening. Where CI really shines, however, is in the ability of CI practitioners to identify knowledgeable individuals who are not only able to provide information that answers questions beginning with *what,* but also (and more importantly) those that

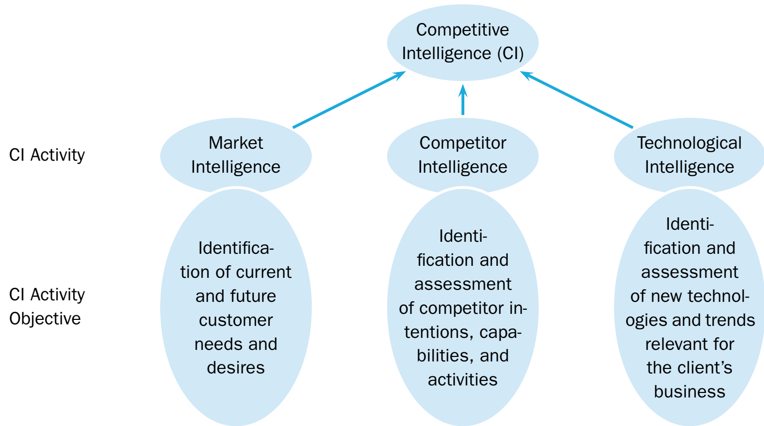

Figure 2 Three Activities Encompassed by Competitive Intelligence

begin with *why.* Quite often, such information resides with individuals, and CI practitioners engage in primary source collection to obtain information from knowledgeable sources. Although CI often involves the acquisition of information from human sources, CI 'is not espionage or spying; both are unlawful' (McGonagle, 2016, p. 55).

Additionally, distinction between BI and CI is that CI can be said to have both an *offensive* and a *defensive* side: not only can CI practitioners advise a client based on information acquired about competitors, they can also point out to a client what information competitors might be able to acquire about the client's own company (Liebowitz, 2006).

Like BI, CI has also been the beneficiary of advances in technology. CI practitioners increasingly employ specialized CI software products to monitor industries, technology trends, web-based resources, blogs, social media, and other content (Keiser, 2013). Although human cognition remains central to competitive intelligence analysis, automated systems enable more efficient acquisition, filtering, analysis, and retrieval of information in ways that were previously done manually.

Decision Intelligence (DI)

Compared to AI, BI, and CI, there is less consensus in the literature as to the meaning of the term Decision Intelligence (DI). For the purpose of the A2E Integrated Intelligence model, we define DI as taking the data and information acquired via BI and CI and reflecting on it within the context of institutional and decision-maker knowledge and experience, much (but not all) of which is tacit in nature and formalized, and contained in the organization's KM system.

Hanning (2002) describes DI as the combination of KM and BI. In their analysis of the relationship between KM and BI, Herschel and Jones (2005) note, 'BI focuses on explicit knowledge, but KM encompasses both tacit and explicit knowledge' (p. 45). This is a powerful distinction, one that is central to our characterization of DI: whereas BI provides explicit, current knowledge from within the organization, and CI provides explicit, current knowledge external to the organization, KM can serve as a prism through which organizational leaders can leverage institutional and personal experience (tacit knowledge) to better contextualize the BI & CI-provided explicit knowledge and make wiser decisions. Google's Chief Decision Scientist Cassie Kozyrkov thought of DI as 'augmenting data science with the behavioral and managerial sciences and the key here is that, in order for us to let the data drive the decision, that decision context has to be framed upfront' (Moser, 2019, p. 1).

Farrell (2017) describes KM as 'the active engagement of applying information with human expertise to facilitate decision-making' (p. 675). One organization that has institutionalized KM to improve decision-making is the US Army's Centre for Army Lessons Learned at Fort Leavenworth, which is tasked with not only capturing, analysing, and storing information about past activities and operations, but also with systematically disseminating new knowledge and insights to commanders in the field to facilitate informed decision-making.

Emotional Intelligence (EI)

In our everyday application of our knowledge and work experiences in resolving issues, both hard and soft skills are often used. Hard skills in managing projects such as scheduling, budgeting, and risk management are foundational activities for project managers. Soft skills such as negotiating, communicating, and dealing with interpersonal conflict are also important aspects of an effective project manager. Sadly, soft skills are often overlooked in the hiring process. An effective hiring manager values soft skills as much as hard skills. Hard skills are often easier to learn than soft skills due to the fact that soft skills are nurtured to us during our early childhood.

Salovey and Mayer (1990), two psychologists, coined the term 'emotional intelligence.' Emotional intelligence is about dealing with feelings, emotions and our relationships with ourselves and with others. Goleman and Cherniss (2001) state that emotional intelligence refers to 'the abilities to recognize and regulate emotions in ourselves and in others.' Consistent with Salovey and Mayer (1990), Barling, Slater, and Kelloway (2000) describe emotional intelligence as having the following five characteristics: '1. understanding one's emotions; 2. knowing how to manage them; 3. emotional self-control, which includes the ability to delay gratification; 4. under-

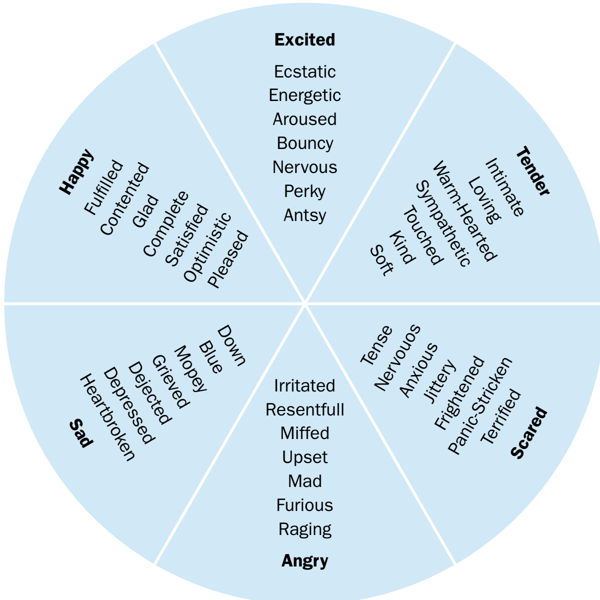

Figure 3
SASHET Framework

standing others' emotions, or empathy; and 5. Managing relationships' (p. 157).

Figure 3 displays Carlson's SASHET framework, which stands for Sad, Angry, Scared, Happy, Excited, and Tender (Carlson, 1988). The framework defines six primary feeling words to represent groups of emotions. The SASHET framework includes three 'negative' (sad, angry, and scared) and three 'positive' (happy, excited, and tender) families of emotions that can be used to distinguish between the various groups of emotions (Mersino, n.d.).

Caruso and Salovey (2004) state that emotion is information, as one of the six principles of emotional intelligence. Emotions are our own personal radar, and it provides us with a constant flow of information about ourselves, the surrounding people and our environments.

Table 1 depicts Goleman's framework of emotional competencies (Goleman, Boyatzis, & McKee, 2002). The framework is made up of four quadrants: the left two quadrants (self-awareness and self-management) focus on the self and represent personal competence, while the right two quadrants (social awareness and relationship management) touch on others and represent social competence (Mersino, n.d.).

Self-awareness is the first building block of emotional intelligence. It is important to understand how we feel and accurately assess where we are at our emotional state. We need to know 'what is going on with us' and

Table 1 Goleman's Framework of Emotional Competencies

	Self (Personal Competence)	Other (Social Competence)
Recognition	Self-Awareness • Emotional self-awareness • Accurate self-awareness • Self-confidence	Social Awareness • Empathy • Service orientation • Organizational awareness
Regulation	Self-Management • Self-control • Trustworthiness • Conscientiousness • Adaptability • Achievement drive • Initiative	Relationship Management • Developing others • Influence • Communication • Conflict management • Leadership • Change catalyst • Building bonds • Teamwork and collaboration

Notes Adapted from Goleman, Boyatzis, and McKee (2002).

accurately assess our own strengths and weaknesses. We need to have 'self-confidence' – the ability to be grounded, secure, and self-assured in whatever situation we find ourselves. Once we gained an understanding of our self-awareness, we apply self-management to manage, guide, and control our emotional state. Self-management is the ability to control our emotions (Mersino, n.d.).

Social awareness happens when we expand beyond our self-awareness to include emotions of those around us. The domain of social awareness includes empathy, organizational awareness, seeing others as they are, and emotional boundaries. Empathy is the 'ability to understand and relate to the feelings of others.' Organizational awareness is the ability to interpret emotions in the context of an organization, whereas seeing others as they are enables us to accurately assess and understand others. The domain of emotional boundaries help define where we end and where others begin. Relationship management – the last building block, ensures that we use the awareness of our own emotions and those around us to build strong relationships (Mersino, n.d.).

A2E Integrated Intelligence Model

The A2E Integrated Intelligence model as depicted in Figure 4 integrates the five different types of intelligence along the DIKW hierarchy. AI is placed at the data level as a tool to enable the collection and processing of large volumes of data. AI is conceptually defined as any ICT that supports the process of learning from data including sensory devices, software tools, machine learning algorithms, statistical models, and big data and analytics platforms. BI and CI deal with the collection and processing of data from inside and outside the boundary of an organization, respectively, using

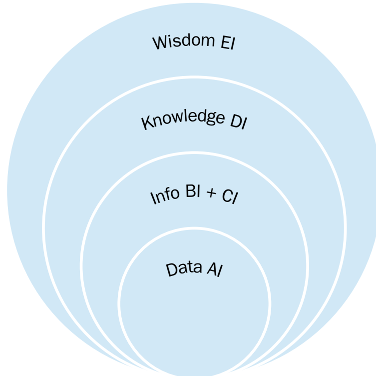

Figure 4
A2E Integrated Intelligence Model

AI as the tool. BI is about using reporting tools and enterprise data warehouses to learn about internal strengths and weaknesses and to improve the internal business operations. CI is about collecting information from various external sources to help understand the competitive environment as a way to ward threats and leverage opportunities. DI is the disciplined, data-driven, evidence-based, decision-making process that leverages AI, operations research, simulation and optimization, which relies on the information collected and knowledge gained from BI and CI. EI represents the ultimate human factors that drive the decision making, including the intangible and tacit intuitions, insights, beliefs, and judgment.

From a philosophical point of view, AI follows the positivist paradigm. The positivist's worldview is technology-focused and seeks objective truth of knowledge using scientific methods possessing quantitative, deterministic, and reductionist characteristics. Positivism informs computer science and engineering, whereas BI and CI align with the paradigm of constructivism, which is people-focused and holds that knowledge is created or constructed through human collaboration in a social context. The constructivist method of inquiry is qualitative and inductive in nature. Constructivism informs social science. DI is rooted in the pragmatist worldview, which is organization-focused and emphasizes the practical application of knowledge. Pragmatism informs management science. EI is rooted in the paradigm of ethics, which is humanity-focused and places ethical judgment, values, purposes, meanings above everything else. Ethics informs religions and cultures.

The A2E model can also be described using the commonly-used People-Process-Technology framework, introduced by Leavitt (1976) and depicted in Figure 5. In this view, AI represents the technology and serves as the enabler, EI represents people and serves as the driver, while BI, CI, and DI represent the processes by which people employ technology to collect data, analyze information, discover knowledge, make decisions, and even-

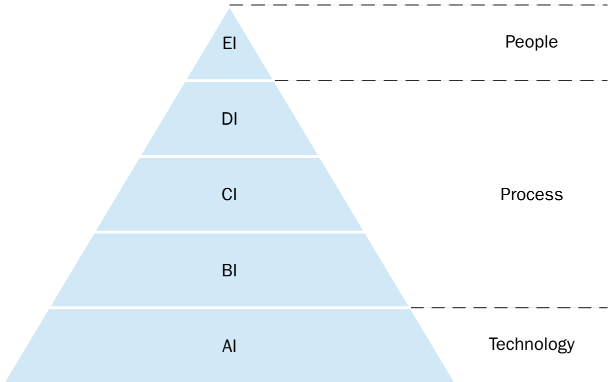

Figure 5

People-Process-Technology Framework

tually effectuate organizational changes to achieve optimal performance.

The A2E model aligns with KM in that EI represents the tacit knowledge embodied in people, whereas AI represents the explicit knowledge processed by technology. Tacit knowledge is 'a knowledge that we cannot tell' (Polanyi, 1966, p. 5), while explicit knowledge 'can be codified or described using languages and other conceptual means' (Wang, 2018). Nonaka and Takeuchi (1995, p. 36) contracted tacit and explicit knowledge as 'knowledge of experience (body)' vs. 'knowledge of rationality (mind).' Skovira (2012) identified the alignment between tacit knowledge and Eastern mystical philosophy, and between explicit knowledge and Western scientific philosophy. While tacit knowledge can be frequently codified with modern technology into explicit knowledge, the cost of codifying can be greater than the benefit of it. Sharing tacit knowledge requires face-to-face communication and collaboration. The A2E model integrates technology and humanity, explicit and tacit knowledge, science and wisdom, and provides a holistic conceptual approach to decision-making and problem-solving.

In a complex and ever-changing world, the key to organizational performance and longevity is adaptability, which requires organizational leadership to look both inward (BI) and outward (CI), while integrating technology (AI) with best practices (DI) and humanity (EI). How these five different types of intelligence can enable organizational leadership to make decisions that will not only result in survival, but success, is the purpose of the A2E Integrated Intelligence model.

The Best Buy Scenario

The following sections discuss the five types of intelligence and how each played a role with respect to the Best Buy scenario described earlier in the Introduction section.

Artificial Intelligence (AI)

One advantage Best Buy has over Amazon 'is the ability to bridge on- and offline personalization' (O'Brien, 2018) through the use of a mobile phone application. 'Walk into the store and the app enters "local store" mode, sending relevant push notifications and tailoring the experience to that location's inventory. There's also an *On My Way* feature that lets sales associates know when someone is on their way to pick up an online order' (O'Brien, 2018).

Business Intelligence (BI)

For executives faced with a challenge like the one confronting Best Buy, BI would be useful for examining the company's *internal* capabilities. For example, statistical analysis of existing company data could aid in strategic exercises, to test the financial implications of a certain strategy: 'What if we lowered the price on that model television by X dollars, but sold 500 more?' Statistical analysis would also be useful for evaluating the following scenario: 'We have over 1,000 stores in the US; what if we turned some of our larger stores into mini-distribution center hubs to get desired products to all our retail stores faster?'

Competitive Intelligence (CI)

For Best Buy executives, then, CI capabilities would have been useful for gathering data and information responding such information requirements as: (1) What are the current trends in consumer electronics purchases? (2) What are our less-successful competitors doing wrong? (3) What are our more-successful competitors doing right? (4) What aspects of the online shopping experience do consumers dislike? (5) How could we better leverage our relationships with manufacturers to improve the in-store buying experience and boost in-store sales?

Decision Intelligence (DI)

It is such a combination of accumulated, tacit knowledge (derived from human expertise) and current information that was reflected in Best Buy CEO Hulbert Joly's decision to institute a price matching system, which, on the face of it, makes little economic sense: How could a brick-and-mortar operation like Best Buy possibly compete with online retailers operating with considerably less overhead? Certainly, data and information from BI and/or CI would suggest to Joly that price matching an online retailer having much lower overhead than Best Buy would be financially unsound. Rather than be guided by these data inputs, Joly instead drew upon his tacit knowledge and experience to opt for an unconventional, if not counter-intuitive, approach based on the logic that, by removing the financial incentive for a prospective buyer to go home and order an item from a competitor online, this would boost the likelihood that a visitor to a Best Buy store would simply purchase that product on the spot. Joly's unorthodox strategy 'costs Best Buy real money, but it also gives customers a reason to stay in the store, and avoids handing business to competitors' (Roose, 2017). Explicit knowledge from BI and CI would not have led Joly to reach such a decision; rather, it was Decision Intelligence, Joly's reflection on explicit data (such as from BI and CI) – but within the context of his business knowledge and experience – that did so.

Emotional Intelligence (EI)

One of the things Best Buy's new CEO, Hubert Joly, did after taking over the company was to look inward, at Best Buy's organizational culture and its people. In this way, Joly effectively employed emotional intelligence to become the kind of tribal leader described in Logan, King, and Fischer-Wright's (2008) book, *Tribal Leadership.* 'Tribal Leaders focus their efforts on building the tribe, or, more precisely, upgrading the tribal culture. If they are successful, the tribe recognizes them as the leaders, giving them top effort, cult-like loyalty, and a track record of success' (Logan, King, & Fischer-Wright, 2008, p. 3). As an effective tribal leader, Joly recognized that for Best Buy to compete with Amazon, 'it needed to get better at things that robots can't do well – namely, customer service' (Roose, 2017). Some of the steps Joly undertook to improve organizational culture and motivate employees included visiting Best Buy stores to speak with employees, working at one of his stores for a week, investing in employee training, and bringing back an employee discount program that had previously been eliminated (Bariso, 2019). 'You need to capture the hearts and minds of the employees,' Joly said (Roose, 2017). Joly's approach of putting people before technology not only extended to Best Buy employees, but also to the company's philosophy about, and approach to, its customers. According to Joly, Best Buy's mission is to 'enrich lives through technology,' and to accomplish this by 'addressing key human needs in areas such as entertainment, productivity, communication, food preparation, security, and health and wellness' (Garcia, 2018).

Summary

As Amazon began to inexorably eat away at the market share long comfortably dominated by such traditional brick-and-mortar firms as Sears, JCPenney, and Best Buy, executives at these (and many other) retail firms struggled to find ways to not only remain competitive, but simply survive Amazon's onslaught. All three firms had the financial resources necessary to invest in, and leverage, artificial intelligence and big data. All three firms had in-house business intelligence analysts to 'run the numbers' and make recommendations. All three had competitive intelligence practitioners experienced in examining the external environment and competitive landscape and reporting on market, competitor, and technology developments and trends. What differentiated the experience of Best Buy from that of Sears and JCPenney, however, was not the technology-enabled acquisition of new, explicit knowledge, but rather the cognitive application of tacit knowledge, gained through human experience, to serve as a filter for explicit knowledge and facilitate the creative formulation of a new, and effective business strategy. In stark contrast to retail behemoths Sears and JCPenney, Best Buy not only staved off disaster, but effectively responded to Amazon's online retailing challenge 'through a brilliant combination of corporate strategy and *emotional intelligence*' (Bariso, 2019). Instead of looking to technology for answers, Amazon's CEO instead turned to people; the people within his own organization, and the people Best Buy sought to retain, and acquire, as loyal customers.

Best Buy's story serves as a representative case study to illustrate how decision-makers can apply the A2E model to improve organizational performance by balancing technology with humanity. Because DI and EI played such a prominent role in its new strategy, Best Buy was able to make more effective use of technology and data to support it: Looking inwardly, Best Buy leveraged BI capabilities, on-hand company data, and statistical analysis to figure out how to turn some of their stores into mini-distribution hubs for online customers, who then had the choice of picking the item up locally or having it shipped to their door (Bariso, 2019). Looking outwardly, Best Buy leveraged CI to approach electronics manufacturers like Apple and Samsung and negotiate agreements under which those companies would 'rent footage within Best Buy to feature all their products together in a branded space' (Bariso, 2019), which created a new source of revenue for Best Buy. Decision intelligence came into play when Joly implemented a counter-intuitive price matching policy (Roose, 2017). Emotional intelligence is what caused Joly to recognize the importance of improving organizational culture and enabled him to become an effective tribal leader.

Conclusion

Decision Support Systems have existed for decades, and today firms are turning to such promising technologies as big data, machine learning, and artificial intelligence to help guide strategy development and improve organizational performance. While technology is a powerful enabler, it is not a panacea; the reality is that technology alone is insufficient for informed, wise decision-making and problem-solving. Human intelligence must also be effectively brought to bear. In line with this assertion, this paper introduces the A2E (Artificial Intelligence to Emotional Intelligence) Integrated Intelligence Model, which blends technology and humanity to support strategic decision-making. The A2E model builds upon the Data-Information-Knowledge-Wisdom (DIKW) hierarchy and Knowledge Management (KM) concepts including tacit and explicit knowledge as its theoretical foundation to integrate five different types of intelligence into a unified and coherent framework: Artificial Intelligence (AI), Business Intelligence (BI), Competitive Intelligence (CI), Decision Intelligence (DI), and Emotional Intelligence (EI). While these five concepts represent five different approaches and perspectives, and are studied and practised within five different disciplines, they are inherently related and complementary. Integrating them into a cohesive framework provides a simple, yet powerful, mental model to help organizational strategists and business executives conceptualize an effective approach to problem-solving.

In addition to describing each of the five intelligence types incorporated in the A2E model, this paper uses the US-based consumer electronics retail giant Best Buy as a case study to illustrate the relevance and efficacy of this model in a real-world business scenario. The survival and prosperity of Best Buy in a challenging retail environment demonstrate the benefits of applying all five types of intelligence to overcome weaknesses and threats, leverage strengths and opportunities, and ultimately achieve optimal organizational performance.

Implications

As the Best Buy case study richly illustrates, the A2E Model offers a simple, yet powerful, framework for helping business executives not only conceptualize strategies for managing such common business challenges as fierce competition and complex operating environments, but also for successfully addressing the kind of fast-emerging opportunities and threats brought about by rapid innovations in ICT.

Both the A2E model and the Best Buy case study illustrate that, while technological developments are important, both in terms of threats and opportunities, that importance must be kept in proper perspective. As Gerd Leonhard (2016) eloquently observed, 'Technology is not what we seek, but how we seek.' In short, technology should be viewed as the means to an end, and not as the end in and of itself. AI is a powerful technological tool for addressing the *how,* which in turn enables BI and CI to address the *what, where,* and *when,* whereas DI and EI are best suited to answer the strategic decision-maker's ultimate questions of *why* and *whether.*

Less than a decade ago, Sears, RadioShack, JCPenney, and Best Buy were all successful, peer competitor retailers that seemingly overnight found their once-dominant, long-standing business models seriously challenged by the technology-facilitated, disruptive threat posed by online retailer Amazon. Only one of those firms (Best Buy) successfully responded to the emerging, existential threat; the other three failed to do so, with catastrophic consequences for each of those firms. A structural decomposition of Best Buy's successful strategy reveals that the company effectively leveraged all five intelligence types represented in the A2E Model: Artificial, Business, Competitive, Decision, and Emotional.

Central to the A2E model, and richly illustrated by the Best Buy case, is the need for business executives to clearly grasp not only the benefits of technological innovations, but also their attendant risks and limitations. However, the A2E model is not only about technology: central to the model is the critical importance of humanity. For example, when embracing AI as a means to increase operational efficiency through automation, executives must at the same time remain mindful of unintended, second-order consequences and creatively leverage human agency to mitigate those risks. Keeping a human-in-the-loop, and applying EI to augment AI are good strategies and keep businesses in the state of balance.

A final implication of the A2E model, also prominently featured in the Best Buy case study, is the criticality of vision and values for formulating a successful strategy. Vision and values flow from the wisdom of the company's leadership. Wisdom is at the pinnacle of the DIKW pyramid, while EI is the highest-order intelligence in the A2E Model. Consistent with the A2E model, Best Buy CEO Joly not only devised a business strategy that effectively leveraged technology, but at the same time recognized, embraced, and committed adequate resources to training, motivating, and equipping employees with the knowledge necessary for successful implementation of the strategy. Vision and values are central to corporate culture, and the corporate culture of Best Buy in 2019 was radically different from the culture that existed in 2012.

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Chaojie (Jay) Wang is a Principal Systems Engineer for The MITRE Corporation, an international think tank and operator of Federally Funded Research and Development Centres (FFRDC). He is the Editor-in-Chief of the International Journal of Patient-Cantered Healthcare (IJPCH) and an Adjunct Instructor of University of Maryland Baltimore County (UMBC). He holds a Doctor of Science in Information Systems and Communications from Robert Morris University. *cjwang@mitre.org*

Fred P. Hoffman is an Assistant Professor of Intelligence Studies at the Ridge College of Intelligence Studies and Applied Sciences at Mercyhurst University in Erie, Pennsylvania, USA. In addition to over 35 years of experience as a human intelligence practitioner in both the public and private sectors, he holds a Doctor of Science in Information Systems and Communications from Robert Morris University. *fhoffman@mercyhurst.edu*

Alvi W. Lim is a Lead Information Systems Engineer at MITRE Corporation, part of the Federally Funded Research Development Centres (FFRDCs) and public-private partnerships, that solves problems for a safer world. Alvi holds a Doctor of Science in Information Systems and Communications from Robert Morris University. *alim@mitre.org*

Jin H. Kwon is a Technical Assistant to the Director for Computational and Information Sciences Directorate (CISD) of the US Army Research Laboratory (ARL) in Adelphi, MD. He holds a Doctor of Science degree in Information Systems and Communications from Robert Morris University. *jhkst187@mail.rmu.edu*

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