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The "Magic Square": A Roadmap towards Emotional Business Intelligence *

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The “Magic Square”: A Roadmap towards Emotional Business Intelligence

Emotions are known to be complex states of feelings that influence mental activity and behavior being an important factor in decision-making. In the business world there is a growing belief that emotions are not an obstacle but rather an enabler for a successful business. The Business Intelligence (by providing analytical processing and handful presentation of a business data) traditionally supports rational decision making. However, opposite to former opinion that all decisions should be “cleaned” (decontextualized) from emotions, there are more and more indicators of the needs for solutions supporting also emotional decision-making. The Emotional Business Intelligence, suggested in this paper, is intended to provide support not only for rational decision making but also for emotional and emotion-aware decisions, intuition, innovation and creativity. We present the new Emotional Business Intelligence domain as an integration of popular, emerging and evolving domains of Emotional Business, Emotional Intelligence and Business Intelligence. We argue on the objectives of the Emotional Business Intelligence and discuss on needed technological basis, models and methods for its roadmap.

Keywords: emotion; decision-making; rational vs. emotional; emotional business; emotional intelligence; business intelligence; semantic technology

1. Introduction

Ray Kurzweil, a famous inventor, futurist and Engineering Director at Google, has recently made a bold prediction: “…I’ve had a consistent date of 2029 for that vision. And that doesn’t just mean logical intelligence. It means emotional intelligence, being funny, getting the joke, being sexy, being loving, understanding human emotion. That’s actually the most complex thing we do. That is what separates computers and humans today. I believe that gap will close by 2029 …” (interview with the www.wired.com, 25 April 2013). Almost every week a business magazine or an Internet site produces an article forecasting the markets and appropriate business opportunities over the next year or even the decade ahead. The problem is that these predictions are based on current

data and trends, and often rely on straight-line extrapolations of the referred data. Frequently none of these explanations are particularly accurate for forecasting the future because the "explosion" in technology means that many businesses that don't even exist today will represent a major market in the future. Talking about skills important for survival within such rapidly evolving uncertainty, Ben A. Carlsen (http://drben.info) refers to a "mindset" rather than a "skill set".

The technological explosion (enhanced by the context of dramatic increase in social networking and the Internet of Things applications) resulted to another explosion of data volumes collected and available for public and corporate use known as the Big Data challenge. According to Ermolayev, Akerkar, Terziyan & Cochez (2013), the major challenge would be finding a balance between the two evident facets of the Big Data: (a) the more data are available, the more potentially useful patterns for further decision-making it may include; and (b) the more data, the less hope is that any data mining tool will be capable to discover these patterns in acceptable time frame. Perhaps because of this conflict, the Big Data brings one of the biggest challenges but also a most exciting opportunity in the recent ten years (Fan, Kalyanpur, Gondek & Ferrucci, 2012). When human deals with a complex problem, and the amount of relevant information (observed, communicated or inferred) is so huge that it is not possible to take all of it into account, still a solution or a decision can be made using the skills of wise selection, focusing, filtering and forgetting supported by intuition and emotional inspiration. Intuition provides us “instinctive” judgments (without analytical reasoning) for possible choices within a decision-making process that cannot be empirically verified or rationally justified, bridging the gap between the conscious and unconscious parts of our mind. There is no magic however, as the intuitive decisions have grounds within an “implicit memory” (a kind of unconscious knowledge), which, according to Augusto (2010), is a product of unconscious perception and cognition. Rational decision-making does not leave much room for emotions (Livet, 2010), while the intuitive decisions may have important emotional grounds (Barnes & Thagard, 1996).

Do we have such a decision-support software tool with similar kind of wisdom and capable of preparing the emotionally inspired and intuitive decisions? This would be definitely helpful for various business decisions on top of Big Data, if to assume that such an emotional context will enhance capabilities of the available Business Intelligence tools.

Why do we think that emotions have something to do with the decision-making? The nature of emotions is usually explained differently according to three main groups of theories: physiological, neurological and cognitive. The physiological theories suggest that responses within the body are responsible for emotions and an emotion is often defined as a complex state of feelings that results in physical and psychological changes that influence thought and behavior (Myers, 2004). The neurological theories propose that activity within the brain leads to emotional responses, i.e., a human interprets own physical reactions and concludes appropriate emotions (James, 1884). Finally, the cognitive theories argue that thoughts and other mental activity play an essential role in the formation of emotions, i.e., assuming that a physiological reaction occurs first, and then the individual identifies the reason behind this reaction, labels it as an emotion and appropriately updates own experience (Schachter & Singer, 1962).

Plutchik (1980) suggests a kind of evolutionary theory of emotions as an instrument of survivability, like, e.g., self-defense in Plutchik, Kellerman & Conte (1979), as well as of evolution and reproduction in nature. He considered eight primary emotions (anger, fear, sadness, disgust, surprise, anticipation, trust, and joy) as triggers of behavior with high survival value.

Actually it is unlikely to find a common agreement within the scientific community on what are the basic (primary, fundamental) emotions, in terms of which other emotions have to be explained (Ortony & Turner, 1990). Popular public view from the Web (see, e.g., Kurus, 2002) often suggests that there are only two basic emotions, *love* and *fear*, and all other emotions, thoughts and behavior come from either a place of love, or a place of fear. That kind of pragmatic and simple view actually makes sense if we try to explain the role of emotions in behavioral planning and related decision-making within some physical environment. An agent or a human may have a number of objectives to be reached within the environment (*attractors*, aka “places of love”) and possibly the number of places (situations) that should be avoided (*repellers* aka “places of fear”). According to Warren (2006), the behavior in such an environment cannot be organized without attributing it to an internal control structure. We believe that the two basic emotions would be a nice and simple way to model such an internal structure. If to assume that locations and possible dynamics of the attractors and repellers are known as well as current location of the agent/human, then the value of “love” and “fear” can be computed separately as an average distance between the agent and the attractors and similar distance between the agent and the repellers. In case if attractors are of different

importance (or the repellers are of different threat) for the agent, then appropriate emotions should be computed as weighted distances (in, e.g., Euclidian metrics). Anyway all the decisions related to dynamic assessment and choosing a behavioral option (action or plan) are driven with two emotions (love and fear) meaning that the basic policy of the behavioral dynamics is to maximize the expected "love" emotion and minimize the "fear" one.

Such a feeling (that something is good or bad and at what extend) is considered in Slovic, Finucane, Peters & MacGregor (2004) as a risk assessment and it controls fast intuitive reaction to danger. Risk management is believed to be a wise integration of both rational and irrational in the behavior. The affect heuristic is shown to be supportive for the rationality of an individual when the consequences of the decisions are anticipated and vice versa.

Experiments in Raghunathan & Tuan (1999) show that emotions guide the decision-making through a personal decision strategy preference. The unhappy decision-makers were found to prefer the high-risk/high-reward options unlike anxious ones preferred the low-risk/low-reward options. It was also found that anxiety usually correlates with an implicit goal of uncertainty reduction, and sadness – with the reward replacement. Therefore we have to consider the consequences of the emotions in decision-making to be able to classify them as positive or negative ones. Also the other way around should be seriously considered as the consequences of decisions may result to certain emotional reaction. For example, the experiments published in Chua et al. (2009) show that regret and disappointment are emotions to appear after negative (unfulfilled expectations) decision outcomes. Disappointment is experienced when the outcome is worse than expected and regret is experienced when it becomes evident that some other choice (if taken) would give better reward. It was shown that regret has an additional component of self-blame for the obtained outcome, and therefore it has more direct effect on subsequent decision process.

Different emotions have different impact on the decisions, which makes them either risky or safe, (over-)optimistic or (over-)pessimistic, moral or immoral, rational or irrational, etc. According to Angie, Connelly, Waples & Kligyte (2011), the highest impact on the decision-making is provided by sadness (tendency to an economic choice), anger (a risk seeking attitude), happiness (a safe choice preference), fear (looking for a "sure" choice), disgust (results to underestimation of values), guilt (taking the responsibility), and stress (influences morality of a choice; see Youseff et al., 2012).

Paprika (2010) shows entrepreneurs and executives to differ in their approach to strategic decision making. When they combine analytical thinking with their intuition during preparation and making their decisions the executives' model contains more rationality rather than intuition, while that of the entrepreneurs is more intuitive especially at the decision phase. It is shown however that neither rationality nor intuition alone guarantees success. In Adam (2012), the intuition, which is often associated with bounded rationality (decisions with limited resources), case-based reasoning (history-driven), recognition-primed (or rapid) decisions, etc., is believed to be the most suitable for understanding how managers apprehend the world. Dane & Pratt (2007) argue that just the intuition helps managers to effectively balance between requirements of making fast and accurate decisions. Also worth mentioning that the emotional context increasingly coming from social media affects rationality of managerial decisions and this effect is difficult to take under control as it is shown by Power & Phillips-Wren (2011).

Taking into account that almost every business environment is, on the one hand, full of processes, which include quite many decision points (with high responsibility for the outcome), and, on the other hand, is full of emotions (implicit and explicit) from various human actors, the aspect of emotions in business is definitely playing an important role. Actually emotions are everywhere in a business-related decision environments. We use the concept of a "Magic Square" to stress the ubiquity of the emotions, which major slogan would be: "Emotions from Emotions for Emotions with Emotions around". This actually means the four emotional dimensions in business related decisions: emotional data provision, emotional decision-making, emotional consumption of the decisions, and emotional decision environment (as it is illustrated in Figure 1).

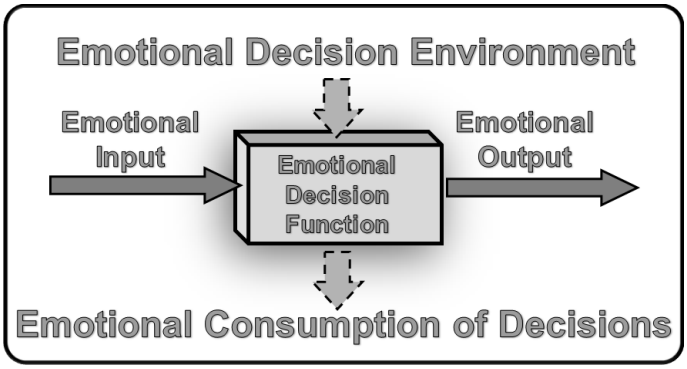

Figure 1: The "Magic Square" concept illustrates the importance of emotions as they may appear almost everywhere and influence almost everything in a decision-making process

Major concern of our research is how to provide support for various business decisions so that a decision-maker will not only avoid negative consequences of the emotional context (capability to avoid “emotional repellers”) but will be able to use this context to improve the decisions and benefit from it (target “emotional attractors”). We would like to build an “intelligence bridge” between the “business” and the “emotions” domains as a tool to support efficient emotional decision making, intuition and creativity within business environments for two major categories of actors “customers” (product or service consumers) and “organizations” (product or service providers). We name that bridging domain as an Emotional Business Intelligence.

The area of decision support system is recently facing new integration challenges aiming to improve the quality, efficiency and effectiveness of the individual or collaborative decisions as well as flexibility and reliability of the systems. In Liu, Duffy, Whitfield & Boyle (2010), an excellent review is given concerning multiple perspectives of the integration: data/information, model, process, service and presentation. Indeed, integration is challenged by multiple information sources; multiple business and problem solving models; multiple intelligent services; multiple interfaces and interaction experiences; multiple objectives, standards, policies and constraints. All these challenges have to be taken into account when previously distinct domains are being integrated. In this paper we try to integrate three such domains aiming to create an integrated one (Emotional Business Intelligence) as a promising new opportunity space for the relevant decision systems.

The remaining text of the paper will be organized as follows: in Section 2 we briefly describe the research (integration) framework and the methodology used throughout the paper; in Section 3, we continue the review targeting the three popular domains: Emotional Business, Emotional Intelligence and Business Intelligence, as three major components of the new Emotional Business Intelligence domain; in Section 4, we show how these three component domains should be integrated into the Emotional Business Intelligence and what will be the major objectives within the new domain for the future research activities; in Section 5, we discuss possible technological basis, suitable models and methods for the Emotional Business Intelligence roadmap, which are either already developed or under development; and we conclude in Section 6.

2. Integration framework and the methodology

The research framework intends to get the integrated Emotional Business Intelligence domain for future decision support systems (DSS) from the component domains as it is illustrated in Figure 2. The framework is further discussed throughout the paper. We consider a domain as a digital ecosystem for the decision-making, which contains appropriate knowledge, decision and business models for the decision support. We first make qualitative study of the component domains (Emotional Business, Emotional Intelligence and Business Intelligence) in Section 3 based on extensive literature review. We try to figure out explicit intersections of these domains and their ontologies and also the implicit ones (contextual interactions). We suggest formal integration logic on top of the component domains' assets and contexts in Section 4 to argument the validity of integration result. Based on that logic, we infer the valid research challenges and concrete research questions relevant to the new integrated domain as a subject for further study. In Section 5 we justify choice of valid technologies and models to handle these challenges.

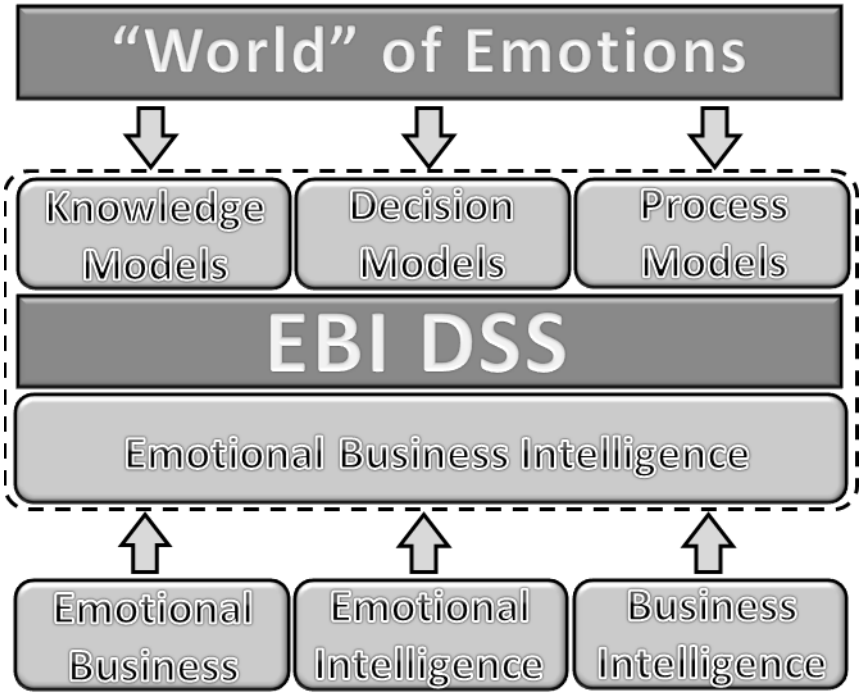

Figure 2: The integration framework illustrated

We utilized some models from our former research and adapt them to handle emotional context. The major goal was to make models capable of self-management in a sense of automatic reconfiguration according to observed context changes. As our

major contextual aspect in this paper is related to the very dynamic "World of emotions" (see Figure 2), we have to find suitable models for addressing the need for at least the emotion-driven reconfigurable knowledge models, decision-under-uncertainty models and business-process models. We argue further in Section 5 that some of our former formalisms (Semantic Metanetworks, Bayesian Metanetworks and MetaPetriNets) have essential modelling power to manage the decision support objectives within the domain of Emotional Business Intelligence.

3. The three sources and the components of the Emotional Business Intelligence

We are introducing the Emotional Business Intelligence (EBI) domain, as a "smart integration" of popular, emerging and evolving domains of Emotional Business (EB), Emotional Intelligence (EI) and Business Intelligence (BI), i.e.:

$$\mathbf{EBI = EB + EI + BI} \qquad \mathbf{(1)}$$

Therefore let's consider first these three major components of the EBI and then explain what "+" means in the Formula 1.

3.1. The Emotional Business

According to Cross (2013), the Emotional Business concerns precisely the same thing it takes to replace 19th-20th century management with Management 3.0: *treating people like people*, because "today's business ride requires marines, not slaves". To enable people to be productive selves on the job means addressing the full spectrum of emotions. The challenge however is that many companies still believe that better to have robots and they are wrong with that.

Rao (2012) explains *why* emotion is relevant in business and economics and *how* emotion can be applied to grow earnings ("if you get the emotions right, you get the business right"… because otherwise … "if you've ever felt ignored as a customer, humiliated by a teammate, … or painfully isolated in a big company, then you've experienced the business effects of emotional disconnection"). In today's knowledge-driven and service centered economy, emotional excellence is a practical necessity for the talent-driven evolution. Taking into account that Emotional Revolution is replacing now the Industrial Revolution, the emerging Emotional Business is expected to at least: (a) evoke intense customer passion to boost sales; and (b) excite employees to care for

each other to ensure effectiveness (Cross, 2013). In accordance with that, Cross (2013) suggested to offer better emotional experiences to customers according to their seven emotional needs, and also to apply a mix of nine emotional strategies into recruiting, performance assessment, training, etc., as well as decision-making and cost reduction efforts.

In Bucolo & Wrigley (2012), the Emotional Business concept is associated with prototyping of business models. Specifically, the focus is on building emotional connections across the value chain to enable internal growth within companies. Emotion(al) vs. function(al) connections must be built into all stages of the integrated (emotional) business model. Such approach is expected to enhance the level of customer differentiation for a particular business model opportunity as it clearly links the functional aspects (product or service) of the business model to the emotional aspects of the customer value chain.

Taking into account customers' emotions from the early stages of the product lifecycle (e.g., design) is a key component of the so called Kansei Engineering (Nagamachi, 1994). Kansei is a Japanese concept (Harada, 1998), which is the instantaneous feeling and emotion that one experiences when interacting with things (e.g., products or services). The inventor of the concept, Prof. Nagamachi, recognized that companies often want to quantify the customer's impression of their products by "measuring" the customers' feelings and showing their correlation with certain product properties. In consequence products can be designed in a way, which addresses the intended feelings. Kansei Engineering is based upon the analysis of product semantics (collaborative customers' semantics is given to subjective words and phrases used to describe some product or service) and then the multivariate statistical techniques are used to analyze the resulting customer data and investigate the relationships between the Kansei words and design elements. Such analysis provides a valuable impact as it brings the voice of the customer directly into the front end of the design process.

3.2. The Emotional Intelligence

Emotional intelligence is the ability to recognize, assess, and manage own emotions and emotions of others (individuals or groups). A number of testing instruments have been developed to measure emotional intelligence and there is a strong belief that such intelligent capability can be easily learned and enhanced unlike more traditional

intelligent skills. Emotional Quotient (EQ), or emotional intelligence quotient, is a measurement of a person's ability to monitor (internal and external) emotions (including relevant thoughts and actions) while, e.g., coping with pressures and demands. Such measurement is intended to be a tool similar to the Intelligence Quotient (IQ), which is a measurement of a person's intellectual skills.

According to Bressert (2007) the emotional intelligence (EQ) is more important for people than one’s intelligence (IQ) in attaining success in their lives and careers. Such success depends on the ability to read other people’s signals and address these implicit messages appropriately within own behavior.

The Emotional Intelligence model, introduced by Goleman (1998), focuses on five main constructs: (1) self-awareness (the ability to know one's emotions, strengths, weaknesses, drives, values and goals and recognize their impact on others to guide decisions; (2) self-regulation (controlling or redirecting one's disruptive emotions and impulses and adapting to changing circumstances); (3) social skill (managing relationships to move people in the desired direction); (4) empathy (considering other people's feelings especially when making decisions) and (5) motivation (being driven to achieve for the sake of achievement).

Other (Mayer, Salovey, Caruso & Sitarenios, 2001) model for Emotional Intelligence includes four types of abilities: (1) perceiving emotions (the ability to detect emotions in faces, pictures, voices, and cultural artifacts); (2) using emotions (the ability to harness emotions to facilitate problem solving, as the emotionally intelligent person can capitalize fully upon own changing moods in order to best fit the task at hand); (3) understanding emotions (the ability to be sensitive to variations between emotions, and to interpret the evolving emotions); (4) managing emotions (the ability to regulate emotions in both ourselves and in others and manage them to achieve intended goals).

There is and evident business value for the Emotional Intelligence concept. For example, the vision of Emotional Intelligence 2.0 has been introduced by Bradberry & Greaves (2009), which describes how individuals and companies can develop emotional intelligence skills needed for successful business through the combination of skill evaluation and the use of 66 research-proven strategies to help companies building the skills.

There is a strong opinion that intelligent person has to have a high IQ, however a *smart* person is also requested to have high EQ (i.e., essential Emotional Intelligence

skills and capabilities). The same can be also applied while talking about smart company, smart business, smart product or service, smart solution, smart decision, etc.

In the neuroscience, cognitive science and psychology the specific emotional intelligence skills are often explained using a theory of so called *lateralization of brain function*. According to it the human brain is divided into two hemispheres - left and right. Scientists continue to explore how some cognitive functions tend to be dominated by one side or the other, see, e.g., Toga & Thompson (2003). There is a belief that the brain controls different types of thinking (rational vs. emotional) and therefore a person who is "left-brained" is often said to be more logical, analytical and objective, while a person who is "right-brained" is said to be more intuitive, thoughtful, emotional and subjective. According to the left-brain, right-brain dominance assumption, the right side of the brain is best at expressive and creative tasks, such as, e.g.: expressing and interpreting emotions; intuition; and creativity. The left-side of the brain is dominating on tasks that involve logic, language and analytics, such as, e.g.: language processing and understanding; logic and reasoning; and analytical thinking. According to Halpern, Güntürkün, Hopkins & Rogers (2005), the lateralization gives definite evolutionary advantage to biological or artificial systems, which comes from the capacity to perform separate parallel tasks in each hemisphere of the brain. The evidence on a differential role of the left and right hemispheres in the extraction of semantic information from verbal and pictorial representations has been provided in Butler, Brambati, Miller & Gorno-Tempini (2009). It is also believed (Brack, 2005) that in the left hemisphere, the concepts considered as monosemantic and unambiguous (as they expected to be in the ontology), however in contrast, the right hemisphere tends to be polysemantic or ambiguous, and tends to process many different meanings of the concepts depending on contextual (emotional flavor). When asked to point to a similar item, the left hemisphere would match objects based on their (semantic) spatial coordinates and logical relationship, and the right based on, e.g., emotions associated with provided images (Brack, 2005). Empathy (or the capacity of the right brain to recognize emotions) is critical and dominant during the first three years of life, until the left brain develops its language capabilities. However a socially-based emotional processing (e.g., understanding minds of others, detection of facial expressions, emotional communications, touch, smell, etc.) needed during the whole life (e.g., high EQ) is supported with the significantly expanded orbital prefrontal region of the right brain (Cavada & Schultz, 2000).

According to Brack (2005), the left-brain avoids internal contradictions in its analysis of the environment and limits the reasoning process to a set of predetermined and consistent outcomes. In contrast, the right brain is not assuming pre-determinism and not necessarily driving the analysis to a particular outcome but possibly to more ambiguous and complex outcomes doing very well with new and unusual stimuli. The left brain is disengaging from the real (open) world as its external-sensory processing and analysis functions are producing the closed-world effect due to its linguistic orientation resulting to a verbally-based logical map of the world. In contrast, the right hemisphere builds an image-based spatial map of the world focusing on shapes, spatial relationships, sensory information in images, being naturally polysemantic and suitable for creative behavior.

In computer science and particularly in artificial intelligence we all admit that individual knowledge and even the knowledge we collectively share so far in the Web describes only a small portion of the real world around us and the larger portion remains unknown. This so called Open World assumption is used as the basis within most of current ontology engineering and reasoning support tools. Humans (with the left-brain dominance) as well as various systems however are making their rational decisions within the Closed World of known facts and therefore these decisions may lead to a failure and will be optimal (or at least reasonably applicable in the real world) only if a complete knowledge is available (i.e., almost never).

In the formal logic, the Open World Assumption (OWA) is the assumption that the truth-value of a statement is independent of whether or not it is known by somebody to be true (see, e.g., Bergman, 2009). It is the opposite of the Closed World Assumption (CWA) or "negation as failure", which holds that any statement that is not known to be true is false. For example, if the only knowledge a system has about some John would be: "John has daughter Mary", then according to the CWA it would automatically mean that a statement "John has daughter Suzanna" is false, however according to the OWA the reaction to the same statement "John has daughter Suzanna" would be "I do not know". Therefore the CWA allows a system to infer, from its lack of knowledge of a statement being true, anything that follows from that statement being false, while the OWA limits those kinds of inference and deductions because of ignorance. Within the OWA-based systems, from the absence of a statement alone, a deductive reasoner cannot (and must not) infer that the statement is false. The OWA reflects the monotonic nature of the first-order logic, i.e., adding new information never falsifies previous

conclusions. This fact however limits possibilities of the OWA-based systems to benefit from the non-monotonic reasoning techniques (e.g., default reasoning) where previous conclusions can be invalidated by adding more knowledge.

Every intelligent entity makes decisions and chooses behavior after analyzing collection of own beliefs and experiences (i.e., closed mental world), which, according to the OWA, may never be complete. Therefore perfectness and optimality in decisions is never reachable until the gap between the OWA and the CWA remains. Intelligent agent is considered in Terziyan (2005b) as an entity that is able to keep continuously balance between its internal and external environments in such a way that in the case of unbalance the agent can choose the behavioral option, e.g.,: change external or internal environment, move to another place, join some community, etc. However, knowing that such a choice is made according to the CWA (agents beliefs about own state and the state of external environment), and that the agent's knowledge on actual state of external and sometimes of internal environment is incomplete due to the OWA, we may assume that the desired balance may occur only by accident and never on a regular basis. We believe that emotionally inspired intuition (aka assumptions beyond own beliefs without immediate evidence) is exactly such an instrument that humans use to bridge the gap between the CWA and OWA when making their decisions. Therefore, the stronger is one's intuition within a decision-making process, the less is CWA vs. OWA gap, the better will be the decision, and, therefore, the more balanced (i.e., successful and wealthy) will be the decision maker.

Standardized Semantic Web frameworks and languages such as OWL assume the OWA while most of procedural programming languages and database management systems assume the CWA. An important question for the Emotional Business Intelligence (i.e., decision-support tools to be applied both in open and closed worlds) is how to best combine description logic-based open world ontology languages, such as the OWL, with closed world non-monotonic logic rules. Ontologies are a standard OWA formalism while rules usually apply the CWA. A combination of ontologies and rules would clearly yield a combination of the OWA and the CWA and this is not only of interest for current applications in the Web, but also as a highly sophisticated means of knowledge representation in general (Knorr, Alferes & Hitzler, 2011) and knowledge within the emotional context in particular.

Machine Emotional Intelligence (see, e.g., Picard, Vyzas & Healey, 2001 or Minsky, 2007), which is more known as *Affective Computing* (see, e.g., Picard, 1995), is

the development within the Artificial Intelligence domain that deals with the design of systems and devices that can recognize, interpret, and process human emotions. It is an interdisciplinary field spanning computer sciences, psychology, and cognitive science. Detecting emotional information begins with capturing data about the user's physical state or behavior including recognition of the user's emotional state by analyzing speech patterns, facial expressions or body gestures through detectors and sensors or even directly measuring relevant physiological data, such as skin temperature, galvanic resistance, etc. The machine should interpret the emotional state of humans (by utilizing sophisticated machine learning, pattern recognition and knowledge discovery algorithms) and adapt its behavior to them, giving an appropriate response for those emotions (Calvo & D'Mello, 2010).

3.3. The Business Intelligence

Business intelligence (BI) can be considered as a set of methods, techniques and tools utilized on top of business data to compute (acquire, discover) additional (implicit) analytics out of it and to present it in a form (consolidated view) suitable for decision-making, diagnostics and predictions related to business. The well-known essential steps of business intelligence includes but not limited to: (1) browsing through business data sources in order to collect needed data; (2) convert business data to information and present it appropriately; (3) query and analyze data; (4) act accordingly collected information and analyses.

Taking into account that "business data" is becoming highly heterogeneous, globally distributed (not only in the Internet space but also in time), huge and complex, extremely context sensitive (including emotional context!) and sometimes subjective, the ways the BI is utilized have to be qualitatively changed. To enable more automation within BI-related data processing the vision of BI 2.0 (Nelson, 2011) includes also issues related to Semantic Technology, Service-Oriented Architecture, mobile access, context handling, social media, etc., and not forgetting also recent Cloud Computing and Big Data challenges. Mobility aspect of BI is also an important one to support the real-time decisions and cloud-based delivery (Power, 2013).

The Gartner Magic Quadrant (Schlegel, Sallam, Yuen & Tapadinhas, 2013) recognizes Data Discovery (or Business Discovery) as evolving into a major architecture in BI as the leaders in the BI market space are focusing more on it. Data

Discovery is the ability of BI users to dynamically generate new questions by exploring data rather than deal with a pre-fixed set of questions and pre-filled BI reports. The similar concept of Business Discovery enables businesses to see new, more complete and more encompassing business models (Carter, 2013).

Traditionally BI supports rational decision making. However, opposite to former opinion that all decision making should be "cleaned" (decontextualized) from emotions, there are more and more indicators that there is definite need of solutions supporting also emotional decision-making. One possible computational model for emotional decision-making has been developed by Velásquez (1998) within MIT Artificial Intelligence Laboratory. The author emphasized the mechanisms of emotions as building blocks for the acquisition of emotional memories that serve as biasing signals during the process of making decisions and selecting actions and applied these mechanisms for controlling several different autonomous agents (software agents and physical robots). The results provided evidence that contrary to popular belief, intuition and emotions play crucial roles in our abilities to make smart, rational decisions. Also, according to more recent studies (McCulloch, 2012), there is a need for a decision-making a model that would prioritize the emotional aspects to challenge and strengthen the decisions, a model that provides "a marriage between our freeform idea-oriented selves and our boundary-aware logical selves" and "capitalizes on the beauty of both art and science, even as art takes the lead". Therefore bringing emotions and intuition to the decision making process might be the only way for talented designers and managers to design really innovative products and services, invent fantastic business models and run successful business with high customer satisfaction. Situation is rapidly changing even, e.g., within "emotionally conservative" Finland where recently customer needs, decisions and behavior are starting to be driven more by emotions rather than by rationality.

Excellent motivation for the BI evolution in general and for the EBI in particular gives Van Praet (2012) in his recent book. He believes that for successful business the both human minds (logical and emotional) have to be satisfied somewhere in the mix, and in order to increase the revenue one have to invest to innovation and passion of the product, not just to the way it is going to be sold. The author admits that businesses invest billions of dollars annually in market research studies by asking consumers questions they simply can't answer. "Asking consumers what they want, or why they do what they do, is like asking the political affiliation of a tuna fish sandwich" (Van Praet,

2012). The author is confident (based on neuroscience research arguments) that consumers make the vast majority of their decisions unconsciously and he criticizes the tendency when people in survey research focus on reasons to explain feelings about new products, concepts, and advertisements rather than to drive the behavioral motivators and the emotions themselves. The pathway to our unconscious learning is through conscious attention and nothing focuses our attention better than surprise and novelty. That's because our brain is a pattern recognizer and a prediction machine. The goal of drawing attention to potentially important information and possible new patterns in it by sending a signal to the brain to take notice and learn is a good motivation for new (Emotional) Business Intelligence tools to support these processes.

4. Objectives for the Emotional Business Intelligence

The vision and objectives of the Emotional Business Intelligence will be based on integration of key features of the component domains and associated technologies mentioned above (EB, EI and BI) according to formula (1). The evident concern, however, would be how to interpret "+" in the formula to define the integration in a bit more specific and formal way.

By a *domain*, in this paper and in the formula (1), we understand a set of "assets" from both: relevant knowledge and business ecosystems, and these ecosystems we will define as follows:

- Knowledge ecosystem is a system of ontology-driven, globally-distributed, self-managed, interlinked, interacting and co-evolving information and knowledge assets (resources), data and metadata repositories, databases, collaborative and competing human and artificial knowledge agents (including users) and various socio-technical instruments for knowledge (self-)management and evolution (technologies, tools, services, processes, plans and strategies, communication, networks, portals, platforms, etc.).
- Business ecosystem is a system of law-, policy- and interest-driven, globally distributed, self-managed, interlinked, interacting and co-evolving business assets (resources), companies and their property, products, services, workers, customers, markets and various socio-technical instruments for business (self-)management and evolution (technologies, tools, services, processes, plans and strategies, communication, networks, portals, platforms, etc.).

By integration of two domains **X** and **Y** in the context **C** of other domains we will understand such an operation (**X** + **Y**) over the domains, which will result to the integrated domain XY, and which semantics will be as follows:

$$\boldsymbol{XY} = \boldsymbol{X} + \boldsymbol{Y} = (\boldsymbol{X} \cap \boldsymbol{Y}) \cup \boldsymbol{X}^{\boldsymbol{Y}} \cup \boldsymbol{Y}^{\boldsymbol{X}} \cup (\boldsymbol{C}^{\boldsymbol{X}} \cap \boldsymbol{C}^{\boldsymbol{Y}}) \,, \tag{2}$$

where: **X**, **Y**, **C**, **XY** are the domains represented as sets of appropriate assets; "+" means the operation of domain integration; ∪ and ∩ are the operations of sets' union and intersection respectively; $\mathbf{X}^{\mathbf{Y}}$ (and other similar) means the subset of domain **X** assets (other than those within **X** ∩ **Y**), which is considered as a context (conceptual, functional, structural, operational, etc., aspects) influencing some assets of the domain **Y**.

In Figure 3 (a) we explain the components of Formula (2) using Venn's diagrams. One can see that the domain integration is not simply the union or intersection of the domains but it is more sophisticated union of relevant assets from different contexts. As an example, Figure 3 (b) demonstrates how the integration of the domains *Emotion* (**E**) and *Intelligence* (**I**) in the context of the *Business* (B) domain (as only other domain) results to the domain Emotional Intelligence (**EI**), which can be also seen from the Formula (3).

$$\boldsymbol{EI} = \boldsymbol{E} + \boldsymbol{I} = (\boldsymbol{E} \cap \boldsymbol{I}) \cup \boldsymbol{E}^{\boldsymbol{I}} \cup \boldsymbol{I}^{\boldsymbol{E}} \cup (\boldsymbol{B}^{\boldsymbol{I}} \cap \boldsymbol{B}^{\boldsymbol{E}}) \tag{3}$$

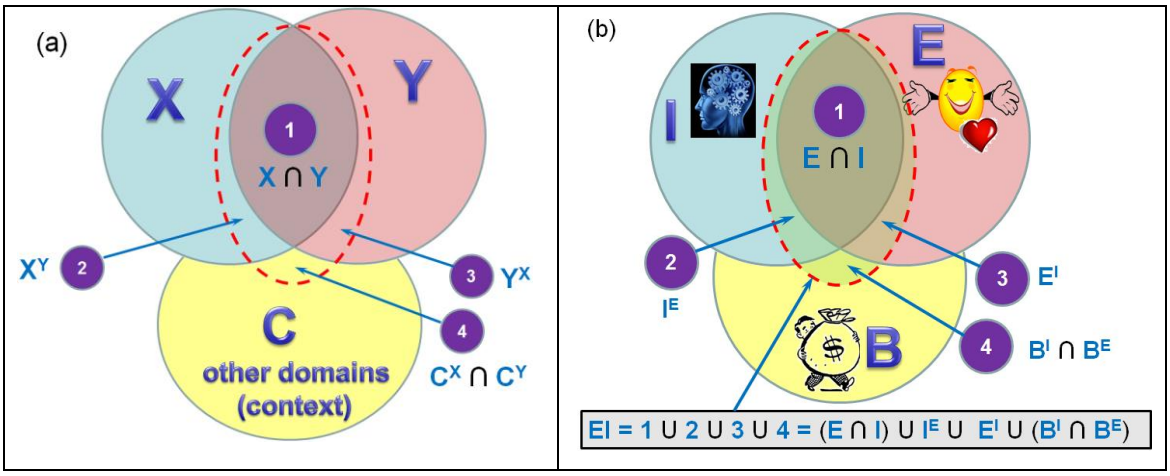

Figure 3: (a) Venn's diagrams demonstrate integration of two abstract domains **X** and **Y** in the context **C** of other domains. The integration area is located within the dashed oval and it consists of four subareas as it can be seen from the picture; (b) is similar to (a), but the concrete domains are integrated (Intelligence and Emotions) in the context of domain Business, and the nature of the components of the formula (3) can be seen.

Similarly, we can get integrated domains: Emotional Business (EB) in the context of Intelligence according to Formula (4); and the Business Intelligence (BI) in the context of Emotions according to formula (5).

$$\boldsymbol{EB} = \boldsymbol{E} + \boldsymbol{B} = (\boldsymbol{E} \cap \boldsymbol{B}) \cup \boldsymbol{E}^{\boldsymbol{B}} \cup \boldsymbol{B}^{\boldsymbol{E}} \cup (\boldsymbol{I}^{\boldsymbol{E}} \cap \boldsymbol{I}^{\boldsymbol{B}}) \quad (4)$$

$$\boldsymbol{BI} = \boldsymbol{B} + \boldsymbol{I} = (\boldsymbol{B} \cap \boldsymbol{I}) \cup \boldsymbol{B}^{\boldsymbol{I}} \cup \boldsymbol{I}^{\boldsymbol{B}} \cup (\boldsymbol{E}^{\boldsymbol{B}} \cap \boldsymbol{E}^{\boldsymbol{I}}) \quad (5)$$

One can easily check that the integration operation ("+") defined by Formula (2) is symmetric, transitive and reflexive, i.e., as defined by formulas (6), (7) and (8). Also an "elimination" property (Formula (9)) will be useful, and which directly follows from Formulas 6-8.

$$\boldsymbol{XY} = \boldsymbol{X} + \boldsymbol{Y} = \boldsymbol{Y} + \boldsymbol{X} = \boldsymbol{YX} \quad (6)$$

$$\boldsymbol{XYZ} = \boldsymbol{X} + \boldsymbol{Y} + \boldsymbol{Z} = (\boldsymbol{X} + \boldsymbol{Y}) + \boldsymbol{Z} = \boldsymbol{X} + (\boldsymbol{Y} + \boldsymbol{Z}) \quad (7)$$

$$\boldsymbol{XX} = \boldsymbol{X} + \boldsymbol{X} = \boldsymbol{X} \quad (8)$$

$$\boldsymbol{XY} + \boldsymbol{X} = \boldsymbol{XYX} = \boldsymbol{XXY} = \boldsymbol{XY} = \boldsymbol{XYY} = \boldsymbol{XY} + \boldsymbol{Y} \quad (9)$$

These properties are explaining the reason behind Formula (1), which considers the Emotional Business Intelligence domain as an integration of domains: Emotional Business, Emotional Intelligence and Business Intelligence, and which now can be explained by Formula 10.

$$\boldsymbol{EBI} = \boldsymbol{E} + \boldsymbol{B} + \boldsymbol{I} = \boldsymbol{EE} + \boldsymbol{BB} + \boldsymbol{II} = \boldsymbol{EEBBII} = \boldsymbol{EBEIBI} = \boldsymbol{EB} + \boldsymbol{EI} + \boldsymbol{BI} \quad (10)$$

By applying the definitions from Formulas (3), (4) and (5) with Formula (1) and the properties from Formulas (6)-(9), we may compute the Emotional Business Intelligence domain definition according to Formula (11).

$$\boldsymbol{EBI} = (\boldsymbol{EB} \cap \boldsymbol{EI} \cap \boldsymbol{BI}) \cup \boldsymbol{I}^{\boldsymbol{EB}} \cup \boldsymbol{B}^{\boldsymbol{EI}} \cup \boldsymbol{E}^{\boldsymbol{BI}} \quad (11)$$

Formula (11) provides a definition for the content of the Emotional Business Intelligence domain as follows:

The Emotional Business Intelligence domain consists of common assets from the domains of Emotional Business (EB), Emotional Intelligence (EI) and Business Intelligence (EI) united with the: Intelligence domain assets (aspects) used as a context for some EB domain assets; Business domain assets (aspects) used as a context for some EI domain assets; and Emotions domain assets (aspects) used as a context for some BI domain assets.

Therefore, the concerns of the Emotional Business Intelligence are not only the ones from the Emotional (Business-Intelligence), as it naturally sounds, but also from the Intelligent (Emotional-Business) and from the Business-oriented (Emotional-Intelligence).

Information sharing among the domains is necessary for domain integration, and a common ontology is known to be an important enabler for this. Taking into account that many issues within EB, EI and BI domains have been developed independently, it will be a challenge to specify the conceptual basis for the integrated domain of EBI in the form of ontology. The ontology will enable linked data across the component domains, integrated metadata repositories, cloud-based service ecosystems, seamless application integration and interoperability, and finally facilitate development of new EBI applications.

There are few examples of research towards various aspects of ontology engineering in our target domains. Partly the domain of EI was covered by the ontology reported in López, Gil, García, Cearreta & Garay (2008). This generic ontology aimed for describing emotions with their detection and expression systems including also some contextual elements into account. The ontology was applied for an emotion-aware application based on Tangible User Interfaces (Neyem, Aracena, Collazos & Alarcón, 2007), for emotions-based human-computer interaction. Review on features (i.e., EI ontology properties), which are important for emotion recognition, is reported in Butalia, Ingle & Kulkarni (2012). Semantic aspects of the BI domain were reported in Sell et al. (2008) as a Semantic BI framework, according to which ontologies are applied for the description of business rules and concepts in order to extend traditional OLAP properties with the semantic-analytical functionalities. Such framework provides transparent access to heterogeneous data sources and drives the BI tools towards faster and smarter decisions. Other use for the ontologies in BI has been shown in Cao, Zhang & Liu (2006) for integration of the BI domain, actually meaning consolidation of various BI tools (Data Warehouse, Data Mining and OLAP) under same ontology for semantic interoperability. Concerning ontologies for the EB domain, we have not found published evidence that such efforts ever had place.

To switch from an abstract one to a more pragmatic view to the concepts of a domain and ontology, we will further restrict a domain to a decision space. Ontology in a decision space is supposed to explicitly specify various domain objects' features (measurable properties) needed for making (or influencing the results of) the decisions

within the domain. An application within such a domain is considered as an ontology-driven process, which includes decision points, where certain selection of the domain features' values (observed or communicated) is taken as an input and certain decision is inferred (computed) as an outcome based on specified rules or some underlying model (decision function). Ontology for such domains is usually extended with the explicit semantic specifications of the decision rules (or decision functions) as well as with the specification of the processes related to the domain applications.

An indication of a context would be necessary for making an input-to-decision statement explicit. Not only the sense of statements, but also judgments, assessments, attitudes, sentiments about the same data or knowledge token may well differ in different contexts. According to Ermolayev et al. (2013), it might be useful to know:

(a) The "context of origin" – the information about the source; who organized, performed the action; what were the objects; what features have been measured; what were the reasons or motives for collecting these data (transparent or hidden); when and where the data were collected; who were the owners; what were the license, price, etc.

(b) The "context of processing" – formats, encryption keys, used preprocessing tools, predicted performance of various data mining algorithms, etc.; and

(c) The "context of use" – potential domains, potential or known applications, which may use the data or the knowledge extracted from it, potential customers, markets, etc.

Having circumscribed these three different facets of context, we may say now that data contextualization is a transformation process, which de-contextualizes the data from the context of origin and re-contextualizes it into the context of use (Thomason, 1998), if the latter is known. This transformation is performed via smart management of the context of processing.

Known data mining methods are capable of automatically separating the so called "predictive" (or "decisive") and "contextual" features of data instances (e.g., Terziyan, 2007). A decisive or predictive feature stands for a feature of the observed or communicated data that directly influences the result of applying a decision function to this data resulting to a decision, prediction, classification, diagnostics, recognition, etc. (see Formula (12)).

$$DECISION = DECISION_FUNCTION(Decisive\ Features) \quad (12)$$

Contextual features could be regarded as arguments to a meta-function that influences the choice of appropriate (based on predicted quality/performance) decision function to be applied to particular decisive features of the observed or communicated data (see Formula (13)).

$$DECISION_FUNCTION = CONTEXTUALIZATION(Contextual\ Features) \quad (13)$$

Therefore, a correct way to process data in a context would be: (a) decide, based on contextual features, which would be an appropriate instrument to process the data; and then (b) process it using the chosen instrument that takes the predictive features as an input. Such approach is known in data-mining and knowledge discovery as a "dynamic" integration, classification, selection, etc. See, e.g., Puuronen, Terziyan & Tsymbal (1999) and Terziyan (2001), where the use of dynamic contextualization in knowledge discovery resulted to essential quality improvement compared to "static" approaches.

Taking into account a generic definition of the EBI domain in Formula (11) and a more specific and pragmatic focus related to the decision-making, we present the following objectives for the EBI domain exploration (from both: generic and specific points of view):

1. *Generic:* Which processes and applications are already available or will most likely appear to be executed across the EB, EI and BI domains? *Specific:* Which are the important decision points within these cross-domain processes and applications?
2. *Generic:* Which are the common aspects of the EB, EI and BI domains? *Specific:* Which are the common features of the EB, EI and BI domains that are predictive ones for the decision-making?
3. What to include to and how to enable the $\boldsymbol{I^{EB}}$? *Generic:* What kind of intelligence (including knowledge, methods, algorithms, tools, infrastructure, etc.) is needed to support the Emotional Business domain activities? *Specific:* What are the features from the Intelligence domain that are or potentially will become the contextual features for the decisions within the Emotional Business domain?
4. What to include to and how to enable the $\boldsymbol{B^{EI}}$? *Generic:* What kinds of businesses (including all the business-related staff) are available or can be

launched to support the Emotional Intelligence domain activities? *Specific:* What are the features from the Business domain that are or potentially will become the contextual features for the decisions within the Emotional Intelligence domain?

5. What to include to and how to enable the $\boldsymbol{E^{BI}}$? *Generic:* What kinds of emotions (including all the emotions-related staff) can be captured (also potentially) and capable to influence the Business Intelligence domain activities? *Specific:* What are the features from the Emotions domain that are or potentially will become the contextual features for the decisions within the Business Intelligence domain?
6. *Generic:* How would the ontology for EBI look like, e.g., as an alignment of the EB, EI and BI ontologies or anyhow else?
7. *Specific:* How to represent predictive and contextual features, decision processes, decision functions and decisions in such ontology?

If to shortly summarize current concerns within EB, EI and BI domains, following the review from Section 3, we may get the following:

- Emotional Business is about emotional awareness and use of emotions to improve: (a) effectiveness and productivity of some business organization in producing products and services through better managed internal organizational activity (emotionally exited employees); (b) performance in selling products and services through better organized customer motivation and satisfaction (evoking long-lasting customer passion); and (c) flexibility of business models by linking the functional aspects (product or service) to emotional aspects of the customer value chain.
- Emotional Intelligence is about the capability of individuals or groups to recognize, assess and manage own emotions and emotions of others while planning own behavior (also intuitive and creative) towards decisions and objectives; assuming also that such a capability can be enhanced by smart systems and devices that can capture, recognize, interpret, and process human emotions.
- Business Intelligence is about automated analytical processing, knowledge discovery and visualization capabilities utilized on top of business data to support business-related decision-making and business discovery processes.

Following these summaries, we can connect the list of 6 EBI objectives above with the current status of the EB, EI and BI domains and make the objectives 3-5 more concrete, as follows:

- *Concrete (addition to the objective 3):* If the objectives of management decisions and further actions within a business organization would be improving effectiveness through emotionally inspired employees and customers and flexible business models, then how the capabilities of the Artificial Intelligence (AI) will influence the way the decisions are made?
- *Concrete (addition to the objective 4):* If somebody is capable of making decisions and planning further actions based on human emotions captured and recognized with the AI tools, then what would be the specifics of making these decisions within the Business environment?
- *Concrete: (addition to the objective 5):* If the decisions focus on how to discover, process and visualize business data, then how the Emotions and their features (either captured from the data or from the future decision consumer) may influence the decision-making process?

We believe that the list of EBI objectives (6 generic, 6 specific and 3 concrete) would be a good starting point for future exploration of the EBI domain.

5. Technological basis, models and methods for the Emotional Business Intelligence

5.1. Review on the EBI-enabling technologies

Among the major strong candidates for the EBI component technologies we consider:

(1) *Affective Computing*, which will be treated as a kind of Artificial Emotional Intelligence (i.e., artificial smartness or artificial wisdom). This would be natural new concept within the emerging Web Intelligence (WI) domain. WI goes slightly beyond the traditional AI and includes brain informatics, human level AI, intelligent agents, social network intelligence, self-management, etc., to the classical areas such as knowledge engineering, representation, planning, discovery and data mining. Combined with the Advanced Information Technology (e.g. wireless networks, ubiquitous devices, social networks, data/knowledge grids, SOA and Cloud Computing, etc.) the WI is becoming a powerful tool to manage the emerging changes and challenges within the

ICT domain and will inspire many new applications in various businesses. EBI dimension of the affective computing will definitely enhance WI with the emotional and business flavor. According Treur (2013), the situation in Artificial Intelligence has substantially changed in recent years: the AI conferences are often mentioning modeling of emotions in their calls. According to the author, the reasons for this change are: the need for human-like models for, e.g., virtual agents; emotional evolution of Ambient Intelligence applications; growing awareness from the neuroscience that in human-like models emotions cannot be neglected, as they play a constructive role in most human processes. One way to incorporate EBI into WI would be to add Web-based assessment of the emotional capabilities not only for humans but also for various smart things, products, designs, services, processes, etc., i.e., implementing some measure similar to the EQ (Emotional Quotient). For example, such measure provided by future EBI tools may lead to product/service evolution towards developing their EQ and therefore to better customer satisfaction. Also we have to check the feasibility of adding Emotion-as-a-Service capability to traditional Cloud Computing architectures;

(2) *Emotional Agents*, or the technology, which extends the traditional software agent BDI (Beliefs-Desires-Intentions) architecture by merging various emotion theories with an agent's reasoning process, see, e.g., Jiang, Vidal & Huhns (2007) and also Puică & Florea (2013). Opposite to rational utility-maximizing agents, the emotional agents are equipped by emotional intelligence, i.e., they have some EQ in addition to IQ and therefore better performance.

(3) *Global Understanding Environment* (GUN), see Terziyan (2008); Terziyan & Katasonov (2009), or the vision (developed by the Industrial Ontologies Group, www.mit.jyu.fi/ai/OntoGroup) of a Ubiquitous Eco-System for Ubiquitous Society, which is such proactive, self-managed evolutionary Semantic Web of Things, People and Abstractions where all kinds of entities can understand, interact (also emotionally!), serve, develop and learn from each other. According to GUN vision, emotional capabilities as well as other human-like skills should be embedded directly to (or associated with) the products or services (or any other objects within the Internet of Things) enabling things to act autonomously (and interact with each other in M2M manner) constrained by high-level policies and driven by personal (also emotional when appropriate) decisions. Some GUN-based tools and technologies will be considered as possible candidates to the future EBI toolset, such as: (a) UBIWARE (Katasonov, Kaykova, Khriyenko, Nikitin & Terziyan, 2008), or the middleware for smart objects

("emotional things") interoperation and the environment for applications development; and (b) the semantic browser based on the 4i (ForEye) technology (Khriyenko & Terziyan, 2009) to visualize objects and their closeness in semantic space driven by user emotional state). Actually there were quite many possibilities to focus and develop the application stack of the EBI by utilizing GUN approaches and tools. However aiming to have some inspirational show-case as a starting point we recently developed a prototype named FeelingsExplorer (Helfenstein, Kaikova, Khriyenko & Terziyan, 2014) as a kind of emotional mash-up browser. It supports the process of ontology alignment (semantic mash-up) between design domain ontology (design features of the products and services) and the customers' emotions domain ontology (part of the EBI ontology). The major pilot capabilities of the prototype are the management of emotional metadata and based on it: visualizing any product, service or customer in a semantic space of both (design and emotional) ontologies; visualizing semantic similarity of various products services and customers; visualizing personalized "emotional similarity" of various products, services and customers allowing a user to set up own emotional profile (Khriyenko, Terziyan & Kaikova, 2013). The KANSEI engineering (Nagamachi & Lokman, 2010) is just one possible scenario to use the FeelingsExplorer as a semantic (machine-interpretable) bridge between business users/customers and design features of various business products and services and to facilitate business performance through emotional customer satisfaction.

(4) *Executable Reality* (Terziyan & Kaykova, 2012), is the vision and technology, which aims to enhance emergent (Mobile) Augmented and Mixed Reality concepts within two dimensions: utilization of Linked Data and Business Intelligence on top of it and providing a real-time context-aware (e.g., emotion-aware) analytics related to various real-life objects (e.g., products or services) selected by the users from their terminals. Other benefits of the approach are shown in the context of quality assurance and related to (emotionally) personalized online quality evaluation and ranking of various resources (people, organizations, products, services, business processes, etc.). The executable knowledge driven Quality Assurance Portal designed for that purpose allows a user not only to evaluate particular object based on Linked Data from external information sources, but also to create own "Quality Calculator" (based on own emotional experience), according to which personalized evaluations or rankings will be computed (Terziyan, Golovianko & Shevchenko, 2014).

(5) *Emotionally-Inspired Knowledge Evolution and Big Data* (Ermolayev et al., 2013) is the technology capable to autonomously manage dynamic and huge data and knowledge repositories utilizing biologically-inspired evolutionary algorithms. This technology naturally fits the EBI roadmap because various data/knowledge manipulation techniques (e.g., focusing, filtering, forgetting, contextualizing) used within knowledge evolution will be definitely improved by adding emotional data and emotional features of knowledge into consideration. The major qualitative improvement would be considering emotional fitness function (instead or in addition with) the rational fitness function as an alternative assessment and survivability decision support tool used by the evolutionary algorithm concerning the populations of "knowledge organisms".

(6) *Linked Communication* is a process of transferring Linked Data through heterogeneous channels, i.e., heterogeneous not only semantically (different ontologies), technologically (different communication media, platforms and devices), or contextually (different communication context, biased content, facts vs. opinions, public vs. expert opinions, etc.), but also "lateralized" for communicating both rational vs. emotional content, context and intentions. Linked communication is an innovative concept, which aims to enhance the technology of Multichannel Communication (Nagy, 2013) by adding semantic layer on top, i.e., human-to-human or application-to-human business communication using electronic media and capable of integrating all the communication from businesses to their customers using all available communication channels and to discover hidden relationships within communicated messages as an added value from the communication; and in the same time it enhances various collaborative (expert vs. public) assessment tools by adding semantically multivariate channels for communicating opinions. Linked communication also enhances the concept of Executable Reality or Business Intelligence on top of Linked Data (Terziyan & Kaykova, 2012) by enabling "Executable Communication" (or Business Intelligence on top of Linked Communication). Linked Communication is also capable of integrating when necessary the (Rationally) Linked Data vs. (Emotionally) Linked Data enabling enhanced performance in collaborative communication. In the framework of Emotional Business Intelligence, the intended tool would be a Linked Communication Explorer, which has to have three major components among others: (1) multichannel, polysemantic and emotional communication toolbox; (2) collaborative linking and assessment toolbox; (3) communication browsing and visualization toolbox. Such a tool

will support wide range of Emotional Business Intelligence tasks being capable of providing seamless multidimensional view to the communicated content for a decision-maker and can be used for, e.g., assuring quality and facilitating various business processes with deep customer involvement.

5.2. Review on formalization methods and models for EBI

In this section we briefly review few possible mathematical (meta)models, modeling methods and approaches, which, in addition to ontological modeling, will provide a tool for formalization of the decision-making processes within the EBI domain, taking into account its specifics.

(1) *A Semantic Metanetwork* (Terziyan & Puuronen, 2000) is a multilevel contextual extension of the traditional semantic networks. It is a formal model, modeling approach and tool for representing and reasoning with knowledge within several levels of its context. As a model it is considered as the set of semantic networks, which are put on each other in such a way that links of every previous semantic network are in the same time nodes of the next network. The zero level (or layer) of the model is a semantic network that represents knowledge about domain objects and their relations. The first layer of the model uses semantic network to represent contexts (as entities) with their properties and relationships. The second layer deals with the metacontexts (contexts of contexts) and their relationships, and so on up to the topmost layer, which includes knowledge to be considered as a "truth" in all the contexts. In Terziyan & Puuronen (2000), a context of some knowledge item was treated as information about source of that knowledge. Consider an example of a semantic metanetwork in Figure 4. One may see that knowledge on relationship named L_1 between objects A_1 and A_2 from the zero level has been provided by the source A'_1, which is placed as a context node at the first level together with all its relationships. Interesting to notice that knowledge on relationships between the sources (context nodes) is also coming from some sources (metacontext nodes located at the second level). For example, the source A''_1 (metacontext node from the second layer) claimed that the source A'_1 has relationship named as L'_1 with the source A'_2.

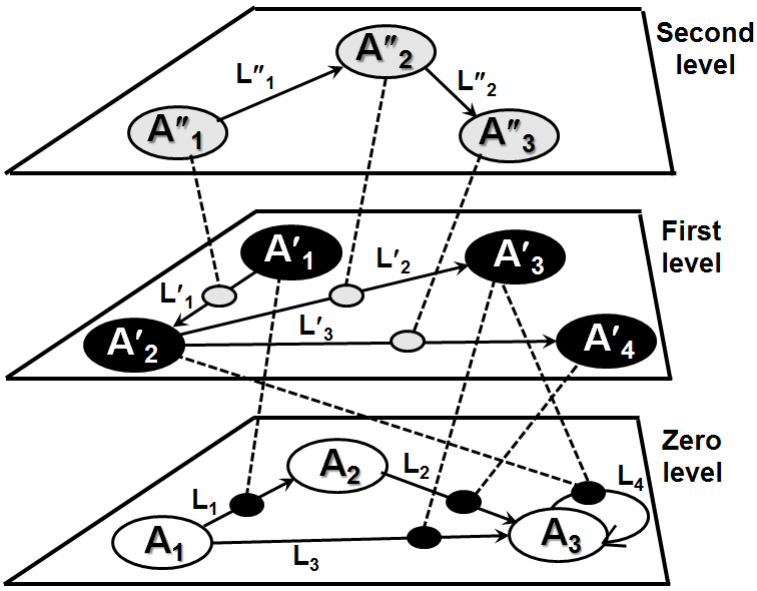

Figure 4: An example of a 3-layer semantic Metanetwork (Terziyan & Puuronen, 2000)

According to Terziyan & Puuronen (2000), such formal model allows reasoning with contexts towards the following objectives: to decontextualize domain knowledge using all known layers of its context; to contextualize or personalize knowledge to the target application or a user; to recognize unknown context; and to transform knowledge from one context to another. Such transformations are driven with a special algebra, which is designed so that the reasoning process is actually the process of the algebraic equations solving.

Let us interpret these four reasoning capabilities of a semantic metanetwork with four simple examples in terms of the EBI tasks, where we have an emotional context everywhere around the decision-making process:

Interpretation (emotional decontextualization). Suppose that your colleague, whose emotional state (context) you know well, has described you some situation, and based on that information you have to make some decision. You may use the knowledge about that emotional context to interpret the provided description (recover, "wash" it from the context using semantic operations of the algebra proposed in Terziyan & Puuronen, 2000) and get inferred "real" (unbiased) situation description, which will be much more appropriate for the decision-making based on it. Example is more challenging but also more informative if several persons (with different known emotional state) describe you the same situation. In this case, the context of the situation is a semantic sum (as defined in the algebra) over all personal emotional contexts.

Content personalization (emotional contextualization). Suppose that you observed some situation and know exactly what is happened. Than you can "guess" (put the known reality to a certain context by using algebraic operations) by which way this situation would be described to you by other persons whose emotional context you know well.

Emotional context recognition (discovery). Suppose that some anonymous source provides a description of the situation that you happen to know well already. The reasoner, by solving appropriate algebraic equation, actually "compares" these two descriptions and derives some information about emotional context of the anonymous source helping to either recognize a source or at least its emotional motivation to distort the reality.

Lifting (Relative Decontextualization). This combines previous processes in a way that it would be possible to derive knowledge interpreted in some emotional context if it is known how this knowledge was interpreted in another emotional context.

(2) A Bayesian Metanetwork (Terziyan & Vitko, 2003) and (Terziyan, 2005a) is a multilevel contextual extension of the traditional Bayesian networks. It is a formal model, modeling approach and tool for representing and reasoning with knowledge represented at several levels of complex probabilistic contexts. As a model it is considered as a set of Bayesian networks, which are put on each other in such a way that the structural primitives (nodes or conditional dependencies) of every previous probabilistic network depend on the local probability distributions associated with the nodes of the next level (layer) network. Depending on the above choice (nodes or conditional dependencies) one has to distinguish between two types of Bayesian Metanetworks. Bayesian R-Metanetwork is a tool to manage relevancies of variables in Bayesian networks in different contexts (to model appropriate feature importance). Bayesian C-Metanetwork is a tool to manage conditional dependencies in Bayesian networks in different contexts. Bayesian inference (i.e., a sequential update of the probability estimates for modeled hypotheses) is applied on each layer of a Bayesian Metanetwork starting from the highest one.

In a Bayesian C-Metanetwork (Terziyan, 2005a) conditional dependencies of a probabilistic network at each layer depend on the local probability distributions associated with the nodes of the higher layer as it is shown in Figure 5.

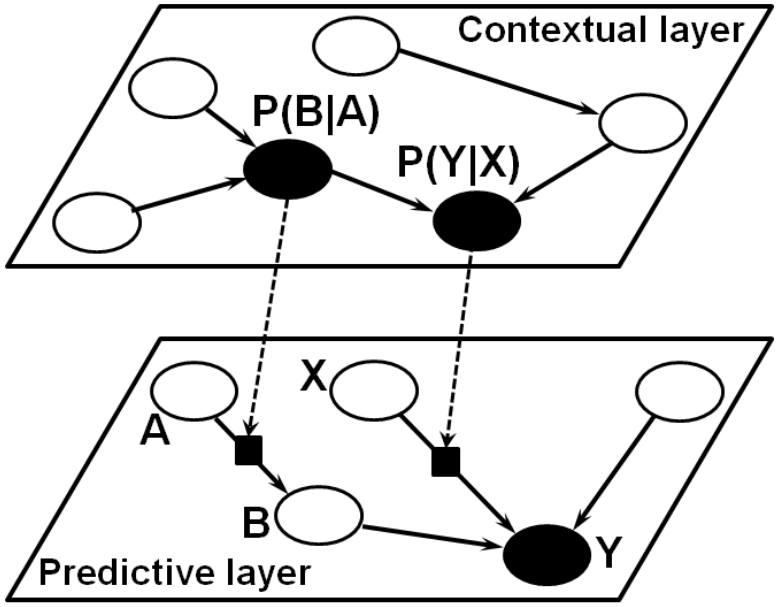

Figure 5: An example of a 2-layer Bayesian C-Metanetwork (Terziyan, 2005a)

In Figure 5, the black nodes of the upper (contextual) layer network correspond to the conditional probabilities of the lover (predictive) layer network P(B|A) and P(Y|X). The arc between the P(B|A) and the P(Y|X) nodes at the higher layer corresponds to the conditional probability P(P(Y|X)|P(B|A)).

A Bayesian R-Metanetwork (Terziyan, 2005a), (Terziyan, 2006) represents the effect of a “relevance” of the predictive attributes for the target attributes estimation in a decision process. The relevancies of variables in such a network might be random attributes itself with their local probability distributions and conditional interdependencies. In Figure 6, the black node from the lover (predictive) layer represents some target attribute and the blank nodes around it are the predictive attributes, which might or might not be relevant for the probability estimations of the target attribute values. The black nodes at the higher (contextual) layer are controlling these relevancies. In the example (see Figure 6), the target attribute Y conditionally depends on the attributes A and B (among others) at the predictive layer of the R-Metanetwork. One can see that the relevancies R(A) and R(B) of the attributes A and B are the nodes within the contextual layer of the R-Metanetwork. It can be also seen that the relevance R(B) conditionally depends on the relevance R(A) in this example.

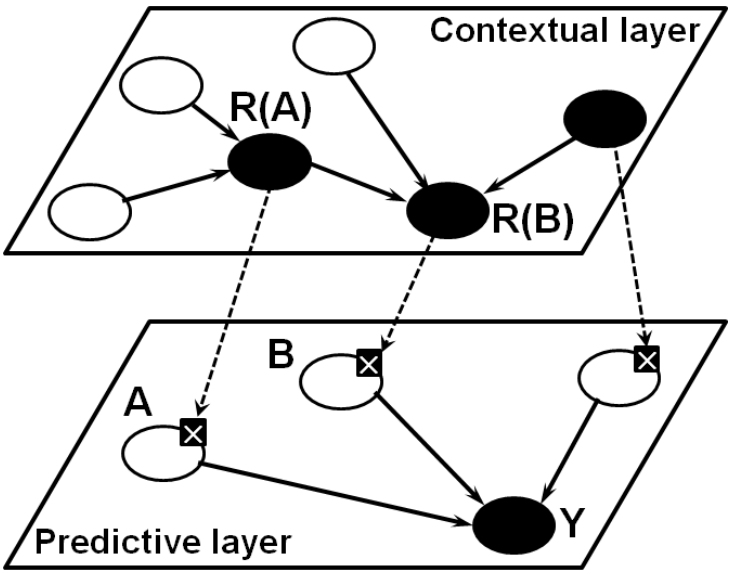

Figure 6: An example of a 2-layer Bayesian R-Metanetwork (Terziyan, 2005a)

A Bayesian Metanetwork may be a powerful tool in cases where the structure (strength) of causal relationships among observed data features essentially depends on context (e.g., emotional one). Also it would be a useful model for the decision making, were the choice of decision depends on different subsets of observed parameters depending on the context. In (Terziyan & Vitko, 2003) it is shown how complex and evolving customer preferences can be modelled with such networks. We may also expect that the emotional context in EBI would be an excellent case for applying Bayesian networks.

(3) A Metapetrinet (Savolainen & Terziyan, 1999) is a multilevel contextual extension of the traditional Petri nets and their variants. It is a tool for execution, self-configuration and decidability analysis of various distributed discrete processes represented at several levels of complex contexts. *A Metapetrinet* is able not only to change its marking (placement and mobility of tokens) during the execution (like a traditional Petri net) but also to reconfigure dynamically its structure (places, transitions, links, tokens, colors, etc.) on the basis of processes executed at the contextual level. As a model it is considered as a set of Petri nets, which are put on each other in such a way that: a basic level (layer) Petri net simulates some process; the second level simulates the configuration change at the basic level. There is conformity between the places of the second layer and the places or transitions at the basic layer structure, as can be seen from the Figure 7. For example, one possible control rule can

remove certain place or transition from the present configuration if the corresponding place at the controlling layer becomes empty. If later a token appears to that empty place, then the originally defined corresponding place or transition will be immediately re-created in the configuration. In Figure 7 one can see that marking of the place P'_1 controls availability of the place P_1 in the basic Petri Net process configuration; marking of the place P'_4 controls availability of the transition t_1 in the process configuration; marking of the place P'_5 controls availability of the link between the place P_4 and the transition t_1 in the process configuration; marking of the place P'_3 controls the color of the tokens within the place P_4 in the process configuration.

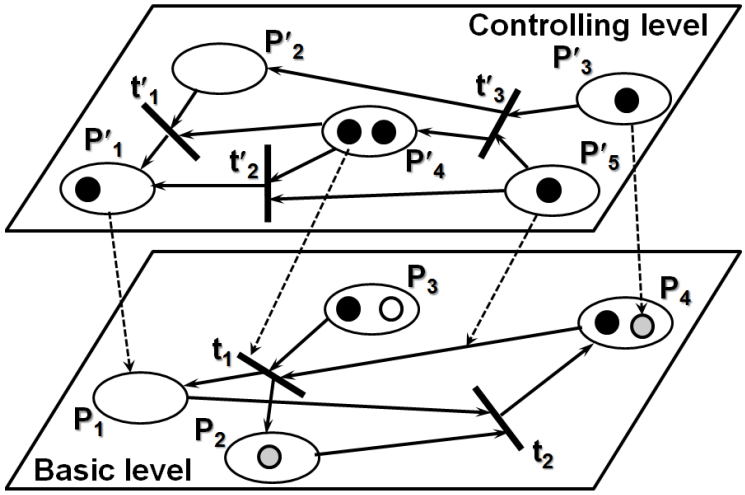

Figure 7: An example of a 2-layer Metapetrinet (Savolainen & Terziyan, 1999)

The capabilities of a Metapetrinet model make us to assume that it might be a very good tool for the EBI objectives, because it is potentially able to simulate a variety of decision processes influenced by a variety of emotional processes within an organization, where such influence can be as strong as even being capable of changing the process configuration. Comparably to Brézillon & Aroua (2013), which offers contextual graphs formalism for modeling context-driven processes in a flat way, the Metapetrinet enables separate observation of processes related to the target activities and to the context and at the same time shows their interaction.

In Gachet & Brézillon (2005), multilevel context models are shown to be useful for describing structural organizational changes during decision making process. Combined with a better understanding of information and knowledge flows, such framework is believed to lead to valuable improvements in the underlying organization.

5. Conclusions

In this paper we justified and introduced a new domain – Emotional Business Intelligence (EBI). We argue that such a domain should appear as an integration of three emergent domains and related trends, i.e., Emotional Business (EB), Emotional Intelligence (EI) and Business Intelligence (BI) under the generic framework of decision-making. Emotional flavor makes all the decision-making settings very challenging and problematic. On the one hand, emotions are everywhere (i.e., our "magic square" assumption) and they are making quite a lot of "noise" for the decision processes, however, on the other hand, emotions, if treated wisely, can become a driver of a successful decision-making. We argue in favor of emotional (rather than purely rational) decision-making as it also inspires intuition and creativity, which are obligatory instruments in the evolving and open world.

When integrating the component domains EB, EI and BI into EBI, we tried to be formal. We invented a novel domain integration approach where, in addition to a straightforward integration, we also considering various contextual cross-domain interdependencies. Following this approach and based on the review of the EB, EI and BI domains, we figured out and justify the objectives for the new EBI domain.

We have also argued on the appropriate technologies to be used for investigation of the new EBI domain. This set of technologies can be considered as a basis but can be updated as the new technologies will evolve. We have also revised three formal models from our former research (with appropriate meta-modeling approaches and tools) to be a suitable formalisms to handle challenging EBI decision-making problems taking into account the "magic square" of emotions. The Semantic Metanetworks are shown to be a suitable tool to represent and reason within various semantic spaces with explicit layer of emotional context. The Bayesian Networks enable probabilistic reasoning, diagnostics and forecasting in uncertain decision spaces where the emotional context explicitly influences the probabilistic settings. The Metapetrinets are capable to simulate distributed discrete business processes, which configuration (parameters and structure) depends on the processes taking place at the emotional layer.

We consider the set of discovered EBI objectives, the set of enabling EBI technologies and a sample of formal models to be a contribution to the roadmap for the new EBI domain and a good starting point for this new domain exploration. Therefore

still quite much of work has to be done to discover a killer application, in which a decision support system will utilize at a full extend the aspects of intelligence (both rational and emotional) for challenging business objectives. We are leaving that for further study.

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