SME Business Model Innovation Intelligent Analytics: Moving from analytics 1.0 to 4.0 the Artificial Intelligence era

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Abstract. Small Medium Enterprises (SMEs) contribution to the economy and employment are of importance in the fourth industrial revolution as the convergence of technologies and the changing nature of jobs are creating pressure for economies globally. Business model innovation and intelligent analytics as integrated use of analytics and artificial intelligence presents opportunities for SME growth and survival. Mainly because business model innovation may provide products or services that did not exist or create new consumer channels. As big data analytics and artificial intelligence may be used to uncover patterns and trends that may yield growth. transforming structured and their unstructured data into meaningful insights. However, the concept of business model innovation is not widely known by SMEs with SMEs lagging in the use of advanced technologies such as big data analytics and artificial intelligence. The aim of this paper is to propose SME Business Model Innovation Intelligent Analytics conceptual framework that may serve as a tool as SMEs navigate from analytics 1.0 to analytics 4.0 artificial intelligence era.

Keywords: SMEs, Big data analytics, Artificial Intelligence, Business model Innovation, Intelligent Analytics

1 Introduction

The fourth industrial revolution will require shifts in business models in terms of how value is created and captured. As the fourth industrial revolution will create new markets that have not existed before, and will create new demand, new supply, and new

value [1] . As such Lee *et al* [2]suggests that the fourth industrial revolution offers companies advancement from simple digitization to innovation based on combinations of technologies enabling companies to innovate their business models. Furthermore, physical, digital and virtual business model ecosystems become integrated [3]. Therefore, without proper business model, innovations fourth industrial revolution cannot be fuelled and cannot grow further [2]and deliver on the anticipated potential for social and economic growth. As successful business model innovation can provide products or services that did not exist or create new consumer channels[1].

According to Krumeich, Werth and Loos [4] to successfully implement and manage business models, dedicated software tools are essential, hence business model innovation needs to be taken into consideration from an information systems' perspective. As software tools for business model development hold great promise for supporting business model innovation [5]. Moreover, the business model concept may be employed for Business/IT Alignment [4]. Research on business model innovation tools is even more important in Small Medium Enterprises (SMEs) as Heikkilä *et al* [6]posit that unfortunately, the concept of business model or the tools to support business model innovation are not widely known by the SMEs. As such the use of business analytics and artificial intelligence for business model innovation in SMEs is still in its infancy. Thus, the paper proposes a conceptual framework for the use of Intelligent analytics to support business model innovation in SMEs. Intelligent analytics refers to the integration of big data, analytics, and artificial intelligence in collecting, organizing and analysing big data to discover patterns, knowledge, and intelligence within the big data based on AI, and domain-specific mathematical and analytical models [7].

2 Intelligent analytics business model innovation

Intelligent analytics has the potential to support business model innovation with such value closely related to the various types of analytics that may be used by SMEs. These different types of intelligent analytics have evolved over time. Intelligent analytics evolution is discussed using the four eras of big data analytics as Davenport [8]indicates that companies have had three eras of big data analytics with artificial intelligence as the fourth era and that big data analytics and artificial intelligence trends need not be in conflict, but in fact reinforce each other. Intelligent Analytics offers both opportunities for supporting business model innovation in SMEs as Jiang [9] highlights that big data analytics has been serving as a primary tool of transforming data into knowledge to help make meaningful predictions and decisions and delivering solutions to many real-world problems. The use big data analytics to analyse huge sets of structured or unstructured data to uncover patterns and trends has resulted in a growth of revenue for leading companies as major corporations are using big data analytics to

transform their unstructured data into meaningful information [10] In addition, Davenport [8] calls on both large enterprises and SMEs to continuously evaluate ways they use data and analytics to drive value and competitiveness. Moreover, business analytic presents unique opportunities to bring practical yet innovative solutions and insights and will better help address problems as it considers different perspectives and matches "data" with intuition and experience [11].

The data to support business model innovation in SMEs could be supported with the growing amount of online data as Muller et al. [12] allude to the proliferation of the web, social media, mobile devices, and sensor networks and falling costs for storage and computing resources, that has led to a near ubiquitous and ever-increasing digital record of computer mediated actions and communications. However, Kohavi et.al. [13] cautions that whilst that field of business analytics has improved significantly, giving business users better insights, particularly from internal and external data unrealistic expectations from business analytics often lead to misguided efforts lacking clear goals and metrics.

There are a number of taxonomies of big data analytics with the most common three categories as descriptive, predictive, prescriptive [14-17]. Diagnostic analytics is included as the fourth category in some of the orientations [18, 19] Thus Scheibe et al. [11] suggesting that mapping of use case to analytics approach is more continuous than discrete with the classification serving as an illustration that clarifies the types of business analytics. More so, Erl et al [19] indicate that the different analytics types leverage different techniques, analysis algorithms and value. The continuous view on analytics is presented in Davenport [8] that suggest an evolutionary data analytics approach that covers the four main eras in intelligent analytics ranging from a less mature program to one that embeds artificial intelligence. These evolutionary intelligent analytics view that covers the four main era with 1.0 descriptive analytics, 2.0 visual analytics 3.0 predictive and prescriptive analytic and 4.0 artificial intelligence as illustrated in figure 1.

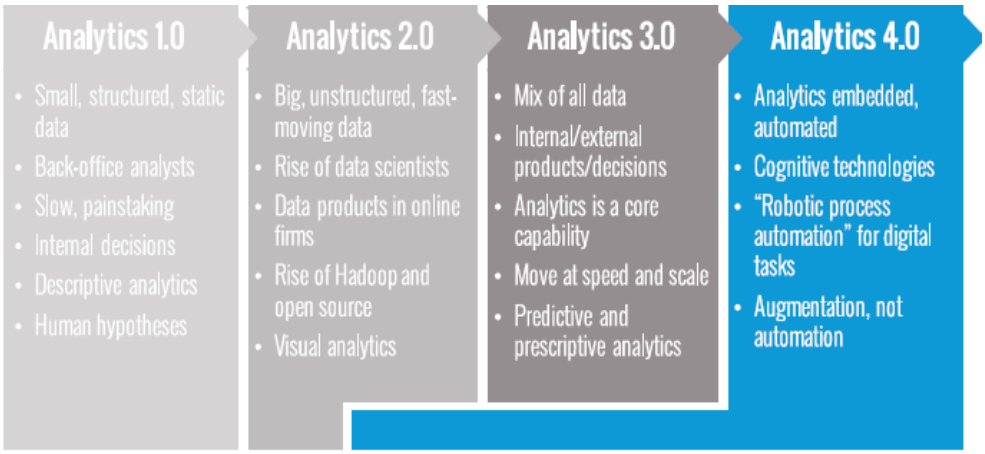

Figure 1: Evolution from big data analytics to Artificial Intelligence(Davenport, 2018)

2.1 Intelligent analytics era 1.0. Descriptive analytics

Era 1.0 deals with descriptive analytics that Davenport [8]suggests analytics in this era is artisanal and largely driven by goals of internal decision support and simplest form of analytics describing what happened in the past [16]). In addition, past as events descriptive analytics supports occurring in real-time. Categorizes mainly, characterizes, consolidates and classifies data [17] with the main output as identification of business opportunities and problems [14]. According to Lustig et.al. [17] descriptive analytics techniques are most commonly applied to structured data with efforts to extend reach to unstructured data, mainly provide significant insight into business performance and enables users to better monitor and manage business processes. Descriptive analytics due to focus on past events include simple standard reporting, on demand reports and dynamic interactive reporting focusing on answering questions regarding what happened and/or what is happening? Such as comparing plans and actuals [14, 16, 17, 19].The reports are generally static in nature and display historical data that is presented in the form of data grids or charts [19].

2.2 Intelligent analytics era 2.0 Visual and Diagnostic Analytics

According to Zhang, Stoffel and Behrisch [20] visual analytics combines data visualization and human computer interaction to solve application problems. Davenport [8] adds that with visual analytics , analytics goal shifts from internal decision support to "data products" built around the for use by customer data and search and recommendation engines. This shift comes with information overload in terms of getting lost in data

that may be irrelevant to the current task at hand, processed in an inappropriate way or presented in an inappropriate way [21].These visual analytics seeks to address this data challenges.

Visual analytics in turn supports diagnostic analytics that requires collecting data from multiple sources and storing it in a structure that lends itself to performing drill-down and roll-up analysis, and results are viewed via interactive visualization tools that enable users to identify trends and patterns [19]. Moreover, according to Lustig et al [17] diagnostic analytics adopts a root cause analysis approach to determine why something happened. As such diagnostic analytics queries are more complex compared to those of descriptive analytics and are performed on multidimensional data held in analytic processing systems[19].

2.3 Intelligent analytics 3.0. Predictive and Prescriptive analytics

According to Davenport [8] analytics 3.0 requires various types of investment, coordination, expertise, and business transformation beyond the simple use of analytics with some early business utilization of Artificial Intelligence particularly machine learning methods with this overlap reflecting AI and analytics similarity of objectives and statistical roots. According to Lustig et al. [17]. Predictive analytics uses the understanding of the past to make “predictions” about the future applying advanced techniques to examine scenarios and helps to detect hidden patterns in large quantities of data in order to project future events. Mainly to discover explanatory and predictive patterns such as trends, associations and affinities, representing the inherent relationships between data inputs and outputs [14]. Moreover, predictive analytics provides answers to what will happen [14] and using data and mathematical techniques such as data mining for pattern recognition and alerts and Monte-Carlo simulations to answer what could happen and forecasting techniques for what if scenarios [17].

The second part in intelligent analytics 3.0 is prescriptive analytics that build upon the results of predictive analytics prescribing actions that should be taken with justification for the prescribed option[1]. The focus is not only on which prescribed option is best to follow, but why approach shifts from explanatory to advisory and can include simulation of various scenarios[1]. This sort of analytics incorporates internal data with external data [19]. As prescriptive analytics determines a set of high-value alternative courses-of-actions or decisions given a complex set of objectives, requirements, and constraints, with the goal of improving business performance [14]. Using A set of mathematical algorithms to determine how to achieve the best outcome and address uncertainty in the data to make better decisions [17].The mathematical algorithms that maybe supported with optimization modelling, simulation modelling, multi-criteria decision modelling, expert systems and group support systems[14]

2.4 Intelligent analytics 4.0. Artificial Intelligence era

In relation to era 4.0 Davenport [8] indicates analytics 4.0 is the next step in analytical sophistication for organizations, and it is the era of artificial intelligence or cognitive technologies. Baryannis et al. [22] suggests artificial intelligence has evolved since introduction in the 1950s through periods of intense growth and decline with factors such as increasing computational power and availability of big data, leading to renewed interest. Furthermore, the evolution of artificial intelligence systems indicates that the early days of Artificial intelligence were dominated by deductive reasoning based systems that rely on logic or other symbolic systems, and use search algorithms to combine inference steps with the modern approach shifting from reasoning to learning due to progress in machine learning and neural networks, and owing to the failure of deductive systems to manage unknown and noisy environments [23]. According to Garbuio and Lin [24] the fundamental principle of artificial intelligence is machine learning, or the ability of a computer to improve upon its own capabilities by continuously analysing its interactions with the real world. In addition Artificial intelligence includes Natural Language Processing (NLP), that supports the analysis human language, helping a machine understand, interpret, and manipulate human language such as text and speech ([8, 24]. Artificial intelligence is inclusive of set of approaches often not depend on statistical analysis such as deep learning, statistical natural language processing, semantic natural language processing, Robotic process automation and rule based systems [8]. The main goal of artificial intelligence is to improve decision making, allowing for automation of tasks hybrid systems applying more than one solution to effectively support the corporate management processes [25]. Furthermore, artificial intelligence provides two broad types of task output to organizations. “Decisions” which are conclusions reached from algorithmic deliberation based on the data available—and “solutions” which are alternative courses of action to resolve a problem [26].

3 4I-2M Business model innovation process

Managing business model to compete effectively is a continuous process, because over time, business models diffuse and become homogeneous; therefore, to compete effectively companies need to continuously innovate [27, 28]. The innovation process is not necessarily linear but is iterative; however, a phase-based approach serves as a useful guideline in undertaking a business model innovation [29]. The 4I-2M business model innovation presents a lens on which to map SME use for business model innovation. This process includes Frankenberger et al. [29] 4I-framework phases comprise initiation, ideation, integration and implementation and extended with mobilisation ([30] and monitoring phases ([30-32], to become 4I-2M framework. As mobilisation serves to create awareness for the need for the new business model whilst monitoring is an enabler to evaluate, adapt or transform the business model in response to the market changes [30].

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The mobilisation phase serves to create awareness on the need for business model innovation and assembling team and creating a shared understanding of design requirements [30]. The initiation phase focuses on understanding and analysing the company's current business model and the ecosystem that comprises customers, suppliers, competitors, universities and government [29]. In the ideation phase, ideas are generated for redesigning the business model. Zott and Amit [33] refer to this phase as 'generate', suggesting that in idea generation companies are either making modifications to an existing business model or creating a new business model. Osterwalder's & Pigneur [30] indicate that in idea generation, one needs to see beyond the status quo and explore multiple ideas. Furthermore, the multiple ideas would need to be assessed to identify how such the changes might affect the other business model components [34, 35].

The integration phase adapted from Frankenberger et al. [29] focuses on integrating and aligning the new business models to those of both old and new partners. The implementation phase focuses on implementing the new business model and is regarded as the most challenging step in the process and typically involves huge investments [29]. The monitoring phase aims to use appropriate tools to monitor both the implementation and performance of the business model [31] as well as the business model innovation drivers [32]. A business model performance audit is applied to assess the fulfilment of the service commitment, satisfaction of customer demands and profitability, while the techniques used in the monitoring of the drivers should continually monitor the business model environment and send triggers for the start of the next business model innovation cycle [31]. These 4I-2M business model innovation process is illustrated in figure 2.

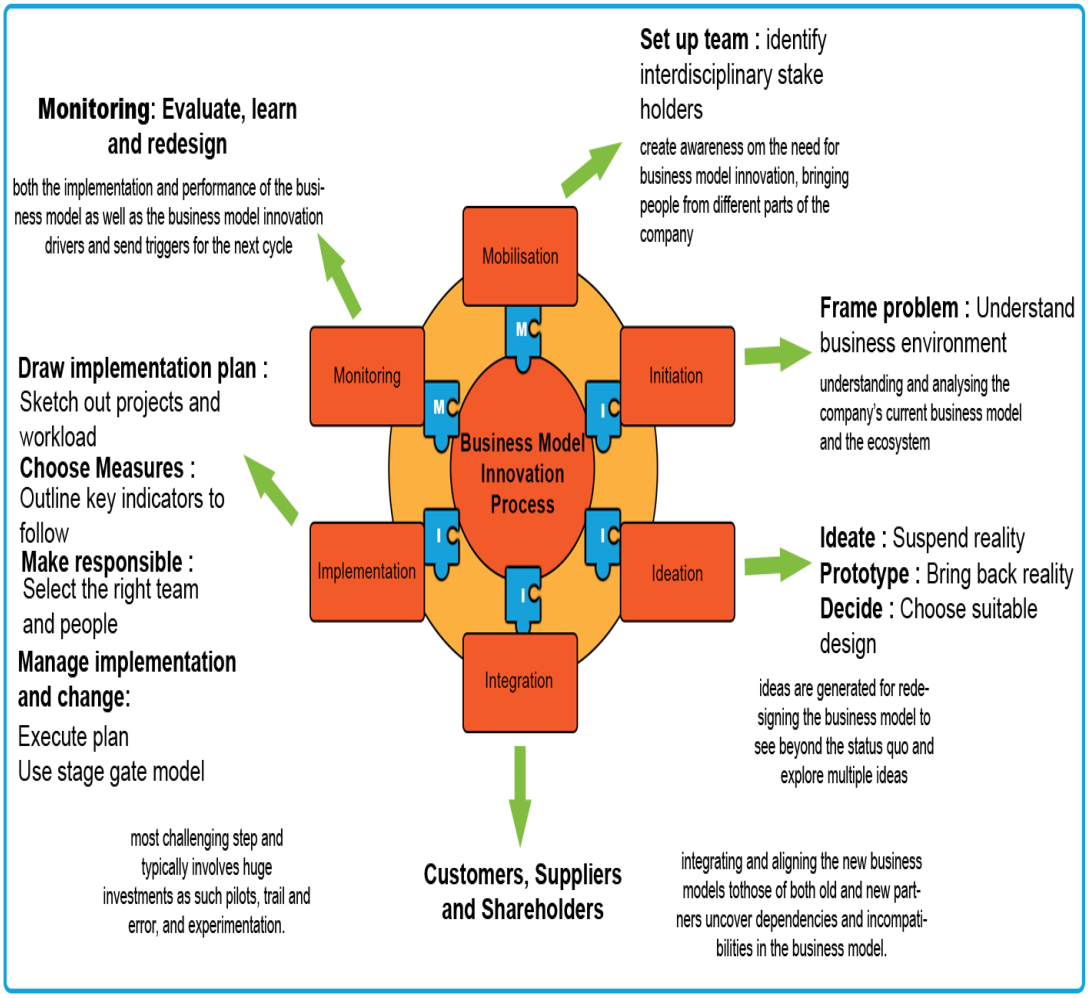

Figure 2 4I-2M Business Model Innovation Process [36]

4 SME Business Model Innovation Intelligent Analytics Conceptual Framework

In the continuous business model innovation process intelligent analytics could support the initiation process to frame the business model innovation problem through the application of descriptive, visual and diagnostic analytics to answer what happened, what is happening and why it is happening with the existing business model and within the ecosystem. This would result in a well-defined business problem and opportunities that would serve as foundation to the ideation phase. In the ideation phase business model alternatives are generated to produce a cloud of potential business models. This ideations phase would benefit from the application both predictive and prescriptive analytics to make accurate projections of the potential business models and prescriptive analytics to determine best possible business models based on the available data This would serve as a basis of transforming business model with artificial intelligence using advanced statistical analysis machine learning and natural language processing. The conceptual framework illustrating the intelligent analytics in SME business model innovation is depicted in figure 2.

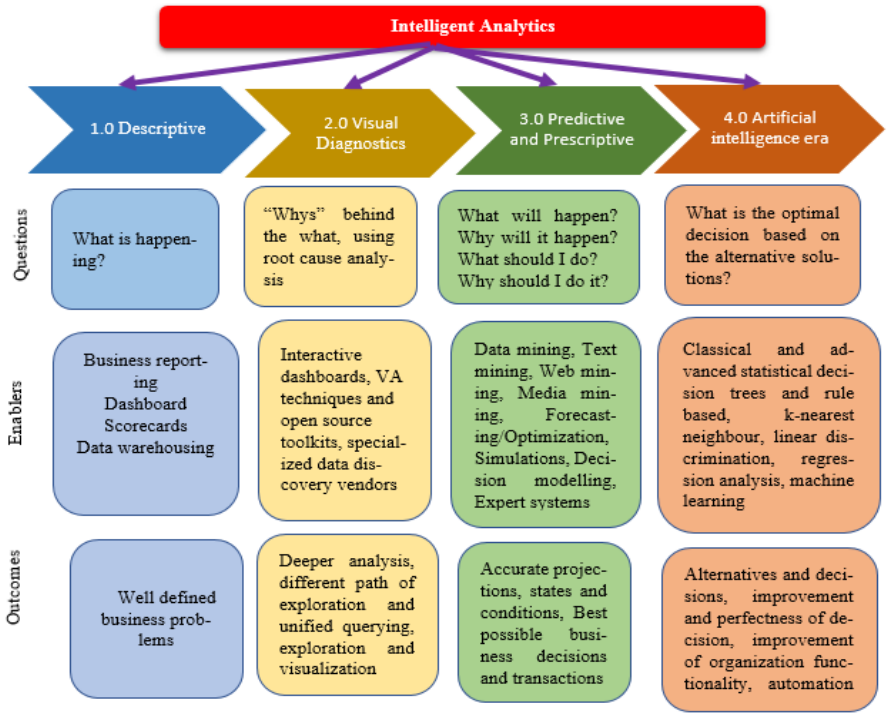

Figure 1 SME Business Model Innovation Intelligent Analytics Conceptual Framework Adapted from [14,8]

5 Conclusion and recommendations

In this paper a conceptual framework is presented for supporting the use of intelligent analytics in the business model innovation process suggesting that intelligent analytics have a potential to enhance the initiation and ideation phases as well as in the monitoring phases whereby descriptive, visual and diagnostic analytics and artificial intelligence may generate valuable insights. Future research will examine the availability of tools to support SME Business model innovation from intelligent analytics 1,0 to 4.0 and empirically examine the opportunities and limitations associated with using intelligent analytics in supporting business model innovation. Inclusive of the examining how to balance human and machine interaction using intelligent analytics in the automation of business model innovation.

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