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6

Conclusion

Abstract

In this research we have explored how the new available big amounts of data can be used to improve decision making on innovation. In this chapter we conclude our research by providing answers to the RQs, listing our results and formulating the conclusion. For adequate reading we summarise what we have done. In Chapter 2, a new method for modelling innovation processes that is able to integrate qualitative, quantitative and simulation analysis is presented. Chapter 3 re-considers innovation process theories in order to provide decision makers with an advanced process model that explicitly takes into account the intricacies of the innovation reality. Chapter 4 discusses the emergence of technological innovations to help decision makers understand detailed activities underlying innovation processes. While chapter 2, chapter 3 and chapter 4 mainly focus on the conceptual perspective of innovation processes which may be limited in providing concrete practical advice for decision makers, Chapter 5 deals with simulation models to support decision making with respect to innovations.

This concluding chapter is split into four parts: answers to research questions and problem statement (section 6.1), main contributions of the research (section 6.2), limitations and future research (section 6.3), and a vision on the future (section 6.4).

6.1 Answers to research questions and problem statement

Below we repeat and answer the four RQs and the problem statement.

Research Question 1: ***Is it possible to develop a data-driven modelling method for studying innovation processes?***

This question is investigated in Chapter 2. We provide a data-driven modelling method which aims at taking advantage of the fast development of Internet and digital data sources to develop a more advanced process theory. Particularly, the trade-off between rich descriptions of individual cases on the one side and the generalised but shallow models on the other side is overcome by a well-thought-out and deeply analysed combination of qualitative, quantitative and simulation analysis. The new data-driven modelling method includes five steps: (1) data collection, (2) data chronological event list, (3) event coding, (4) process pattern identification, and (5) simulation (details are given in Chapter 2).

Research Question 2: ***Is it possible to form an advanced model that is able to combine the seemingly contradictory models, namely the linear innovation model and the cyclical innovation model?***

This research question is investigated in Chapter 3. It applies the data-driven modelling method developed in chapter 2 and investigates the overall structure of innovation processes. It proposes an integrated innovation model. The basis is to understand the more fine-grained patterns which underlie innovations. This is nowadays possible since the necessary data are becoming available by the new big data techniques. We model activities into feedback loops with triggers that stimulate the innovation system to adapt as a whole to a new behaviour pattern. By doing so, the seemingly contradictory models, namely the linear and cyclical innovation models, mutate into two different perspectives on the behaviour of the same innovation system. In this way, the chapter is able to show consistency of the different perspectives. Practically, it provides a more holistic and coherent framework for decision makers to understand and explain innovation processes.

Research Question 3: ***What does emergence mean? And what is the underlying mechanism that drives the emergence of technological innovations?***

This research question is investigated in Chapter 4. The emergence of technological innovation is defined as a phenomenon which consists of five critical properties. Emergence is (1) system behaviour, (2) the genesis of some fundamentally new features, (3) a continuously changing process, (4) a nonlinear process with complex interactions, and (5) more than technological diffusion**.**

The underlying mechanism that drives the emergence of technological innovations can be explained by the dissipative self-organising model from the complexity theory. It describes emergence as driven by: (1) irregularity that brings disturbances to the existing regime of order; (2) positive feedback loops that amplify the initial fluctuations; and (3) a new behavioural regime that is a result from these self-reinforcing loops (details of this model are given in Chapter 4).

Research Question 4: ***Is it possible to simulate the emergent process of innovation so as to provide decision support for innovation managers and policy makers?***

This research question is investigated in Chapter 5. We simulate the emergence of technological innovations as a collective order arising from action-reaction chains of heterogeneous activities. The way of simulation can be adapted to a range of scenario designs which are tailored to innovation managers and/or policy makers. So, the answer is yes, although many improvements are still possible.

Based on the answers to the four RQs we are able to answer the Problem Statement.

Problem statement: ***To what extent can the new available big amounts of data be used to improve decision making on innovations?***

To a large extent we can make use of the large amounts of data to improve decision making on innovations. From RQ1, we know a new data-driven modelling method that can be used to analyse the messy data. From RQ2, we know a more advanced innovation process model which provides decision makers with a good understanding of the overall structure of innovation processes. From RQ3, we know the underlying mechanism of emergence which provides decision makers with valuable insights into the interaction patterns on the micro level of innovation processes. From RQ4, we know a simulation model which provides a virtual environment for decision makers to test the effects of their decisions.

6.2 Main contributions of the research

Below we discuss the three main contributions of this research: (1) contribution to data science (subsection 6.2.1), (2) contribution to innovation process theory (subsection

6.2.2), and (3) contribution to decision making on innovation management (subsection 6.2.3).

6.2.1 Contribution to data science

Qualitative data plays an important role in making sense of the complex world. It constitutes a large part of the now available data of innovation. However, existing data analysis tends to place a huge value on quantitative data, and devalue the importance of qualitative data (Want, 2013). One reason is that there are well-developed methods (e.g., statistical methods) to analyse quantitative data. However, we see that techniques that make sense of qualitative data are less well investigated.

In this respect, it is even more important to integrate qualitative data into the overall analysis. This is really necessary for adequate innovation decision support. In general, the decision makers are interested in small samples and in-depth studies that are rich in contextual and descriptive data (Malan & Kriger, 1998). This data is able to provide a good understanding of how thing evolves over time. Such a trend line can further generate practical action rules and relevant managerial wisdom (Landau & Drori, 2008).

The research (Chapter 2) presents a new method which shows how to extract value from large amounts of qualitative process data in general and innovation process data in particular. The method combines qualitative, quantitative and simulation analysis. By coding the messy and qualitative process data into pre-defined categories (step 3), this method reduces the complexity of data and allows a transition from qualitative to quantitative analysis through generating frequency counts of the events in each category, which can then be analysed statistically. Simultaneously, it does not only qualitatively analyse the interactions between different categories of events (step 4), but also employs computational simulation (step 5) to provide decision support. In this way, the new method breaks the traditional trade-off between (1) qualitative methods with rich descriptions but without the possibility to develop general theory, and (2) quantitative methods with high generalisability but with limited in-depth understanding of the process.

Moreover, the five steps make the modelling process more transparent and tractable. Researchers following these five steps give clear information on how they arrive at their research results, and how others can reproduce the research. Although this method is introduced to analyse innovation processes, it can also be extended to other research fields which fulfil the following three conditions.

a) The research purpose is to examine how a phenomenon evolves over time, i.e., the line of research is a process study.

b) The research uses events (what happened, at what time and by whom) as process data instead of purely quantitative or numerical data.

c) The research focusses on interactions between events or activities instead of system components.

6.2.2 Contribution to innovation process theory

This research contributes to theory building of innovation research. Particularly, the theoretical contributions include two aspects: (A) advancing innovation process theory, and (B) investigating the emergence of technological innovations. Below we discuss both aspects.

A Advancing innovation process theory (Chapter 3)

There is a gap between process theory that has been developed and process theory that is useful for practitioners to guide their decision making (Stevenson & Harmeling, 1990). Even nowadays, existing innovation models miss a systematic view on innovation processes. There have been developed views either on the micro level or on the macro level of innovations (Siau, Long, & Ling, 2010; Van de Ven, Angle, & Poole, 2000), which form two types of models of innovation respectively, namely the macro-level model and the micro-level model. Below we give a brief description of both types of models.

(1) The macro-level model of innovation focusses on the aggregative trend and trajectory of innovation development, but ignores or simplifies the local actions. To emphasise our point, we start with an example from the past. Over twenty years ago, Utterback (1994)’s three stages in the life cycle model of technological innovations did provide a formal sequence of phases which innovation has to pass. However, he did not depict the detailed processes which create the phased developmental pattern.

(2) The micro-level model of innovation focusses on the behaviours and properties of system components on the micro level. But it does not consider

> the aggregate level emergence and the trend led to by these local behaviours. An example of this micro-level model of innovations is Alder and Chen (2011)'s teleological motor model which described accounts of interactive dynamics between enterprises. However, it missed the general trend which was generated by these micro-level interactions.

Decisions made on the micro level may influence macro-level environment; and contextual factors on the macro level such as governmental regularity or policies may influence micro-level behaviours. Focussing on only one level may result in an incomplete view of the overall phenomenon. And how the reality of one level influences and is influenced by behaviours or events on other levels is also missed (Fuller & Moran, 2001).

Our research (Chapter 3) deals with advanced innovation process theory by integrating both the macro-level and micro-level analysis. Moreover, we are able to show consistency of the two stylized and seemingly controversy models of innovation, namely the linear innovation model and the cyclical innovation model. These two stylized models co-exist in innovation processes and contribute respectively to the micro-level and macro-level explanation of the dynamics of innovation processes. They are two aspects of the same phenomenon. We emphasise the difference as follows: the macro-level pattern is an expression of the micro-level processes; micro-level processes are the fundamental reasons leading to the macro-level appearance.

This advanced model is presented in chapter 3. It provides (1) an overall structure of innovation processes that is more close to innovation reality that can guide decision makers channelling the innovation processes than the traditional models (Van de Ven et al., 2000); and (2) a systematic perspective of innovations which help improve a comprehensive understanding of innovation processes (Andersson & Johansson, 2010). Such a better understanding of the overall innovation processes paves the way for efficient decision making which aims at influencing this process.

B Investigating emergence (Chapter 4)

Emergence is a generic property of innovation systems. It explains the relationship between micro-level interactions and macro-level outcomes. In spite of this importance, so far the emergence of technological innovation has not been subject to an extensive investigation. There is not an agreed-upon definition for the term "emergence". The mainstream theories in social science are found to have limitations in explaining emergence (Chassagnon, 2014; Chiles, Meyer, & Hench, 2004). Chapter 4 explicitly defines the emergence of technological innovations; and theoretically explains the internal mechanisms of the emergence. Therefore, it closes a gap in the literature of innovation research.

6.2.3 Contribution to decision making on innovation management

Making decisions about innovation is notoriously difficulty. This research contributes to decision making on innovation management from two aspects: (A) providing new insights into innovation management; and (B) using computational simulation to provide decision support. Below we discuss these two aspects.

A Providing new insights into innovation management (Chapter 4)

Effective decision making on innovation requires a good understanding of emergence, because emergence explains how a decision leads to a certain result, usually an unexpected one. The definition and mechanism of emergence (see Chapter 4) helps decision makers understand the underlying patterns of detailed activities in innovations. Our research provides three new insights into how to manage innovations: (1) the strategy should be adapted from strategic planning to probe-and-learn; (2) general guidelines should be provided, not specific actions; and (3) emphasis should be on enabling emergence. Below we explain these three insights one by one.

(1) Strategy should be adapted from strategic planning to probe-and-learn

During technological innovations, small changes may multiply over time through the positive feedback loops, which makes the innovation direction sensitive to initial conditions. Moreover, the empirical case of Teflon (Chapter 4) illustrates that many unexpected, accident and chance events may happen in innovation. All these events make innovation processes unpredictable and dynamic. Therefore, long-term prediction is quite difficult (Hingley & Nicolas, 2006; Levy, 1994).

Hence, firms and policy-makers should not spend large amounts of resources and time on forecasting and making plans; instead they should carry out a more experimental model of management, which means decision makers first probe, then observe, and thereafter respond (Snowden & Boone, 2007). In this way, decision makers do not impose an order onto innovation processes, but allow the path forward to reveal itself

(Snowden & Boone, 2007). This idea is consistent with the emergence property of innovation (Chapter 4).

(2) Providing general guidelines, not specific actions

Interventions can be conducted through setting general guidelines that influence individuals' decisions and behaviours instead of performing too many specific actions. The set of guidelines contributes to configure the context where self-organisation occurs, and put a boundary to behaviours. Within these behavioural boundaries, individuals should have a certain freedom to self-organise. Too many constraints would inhibit innovation and creativity; and in contrast, too much self-organisation could lead to disorder and undermine managerial predictability.

(3) Enabling emergence

Decision makers should pay attention to whether the current behaviour regime is satisfying or not. If the firm is in a satisfying situation, the current behavioural regime is supposed to sustain a desirable state. To maintain the stability, the challenge for decision makers is to protect the system from disturbing influences, and to keep a relatively stable space within which the organisation can self-organise. The key principle is to create and improve feedback mechanisms through increasing communication and connection between individuals.

If the current behavioural regime maintains an unsatisfying situation, the strategic challenge lies in creating conditions to support the emergence of a new behavioural regime. The two key principles include (1) bringing a stimulus to the system through open to unexpected, accidental, and random events; and (2) creating instability through top-down revolution or through the establishment of new challenging visions. Specifically, the following is suggested: (a) build connections through a shared vision, conception, or understanding; (b) encourage informal work relationships; (c) appreciate informal, flexible, and experimental ways of working (Hung & Tu, 2011); (d)) view the unexpected events as opportunities for reflection and modification; (e) continuously observe what emerges and make adjustments to goals and supporting infrastructure (Choi, Dooley, & Rungtusanatham, 2001).

B Using computational simulation to provide decision support (Chapter 5)

Decision making on innovation is difficult for decision makers, because they lack tools to predict the behaviours of firms (Levy, 1994). Traditional research methods, such as statistic regression based on patents data, publications data or innovation numbers, are unable to capture the dynamics of innovation. The reason is that they ignore the ordering and interactions between independent variables and have an emphasis on immediate causation only (Poole, Van de Ven, Dooley, & Holmes, 2000). Therefore the traditional methods are not able to provide useful prediction models for decision making on innovations As an alternative, agent-based simulation is able to complement econometric approaches by incorporating the nonlinear and dynamic interactions on the micro level and revealing emergent patterns at the aggregate level (Barton, 2014; Bayona, García-Marco, & Huerta, 2001).

Chapter 5 provides a decision support tool for decision makers by establishing such an agent-based simulation model of technological innovations. Through building a simulation environment and designing what-if scenarios, it allows decision makers to know in advance which possible impact of a new enacted decision would bring to a certain technology and industry and help optimize their entire innovation system.

It must be emphasised that there is hardly any simulation model that can precisely represent and predict reality. The objective of the agent-based simulation is not so much to present an accurate description of reality or to provide a precisely prediction tool, but to help understand established findings from the qualitative research and to assist in identifying the potential causal relationships that have not been previously observed in history (Garcia, 2005).

6.3 Limitations and future research

Below we reflect the limitations of the research (subsection 6.3.1) and present potential directions for future research (subsection 6.3.2).

6.3.1 Limitations of the research

This research is subject to the following three limitations.

(1) The first limitation is related to the data source. The empirical data of this research is limited largely to historical secondary data sources, including searching on the internet, scientific papers and books. Historical data are often questioned regarding their objectivity. A solution to this is to complement the secondary data set with primary datasets such as interviews or participant observations if applicable. By triangulating data collected from different sources, our research may have

contributed more to the validity of the study. But it is important to note that historical analysis is necessary for innovation process studies because historical data provide a holistic and systematic examination of the factors that influence an innovation path, while the real-time data collection method will involve short-range viewing. Therefore, we have chosen to use mainly historical data.

(2) The second limitation is referred to the number of cases. In total, this research involved three cases – the Nylon case, the SSRI medicine case, and the Teflon case. This sample size of three case studies may be too small to be capable of generalising conclusions. In this sense, generalisation cannot be realised from statistic perspective (Suurs, 2009). But our research does fulfil what Yin (1994) called "analytic generalisation", which means the qualitative research based on one single in-depth case study provides a theoretical framework which can be used and extended to other cases (Abell, 1987; Suurs, 2009). This research realises such an analytic generalisation by providing a data-driven method in studying innovation processes (Chapter 2), an advanced innovation process model (Chapter 3), an explicit definition of emergence as well as a generative process model of the emergence of technological innovations (Chapter 4), and a way to build an agent-based simulation of emergence based on minimal assumptions (Chapter 5), all of which can be transferred into other social phenomena process studies.

(3) The third limitation lies in the potential bias brought by the selected cases. The three technological innovation cases selected in this research are from two different branches of industries. These cases form a heterogeneous sample. However, the question remains whether the selection may influence the research results. The Nylon and Teflon belong to the chemical materials industry, in which business and government are the primary customers instead of the final consumers. Both were developed by a single company, DuPont, which makes the developmental process much more manageable. The SSRI drugs are from the pharmaceutical industry, which is atypical since it has a long R&D phase, suffers from tight governmental regulation and has a short adaptation phase. Because of the specific characteristics of each industry, the research results from these three case studies may need further verification in technological innovation from other industries.

6.3.2 Future research

Below we present five recommendations for future research.

(1) The methodology presented in Chapter 2 may be extended from innovation process studies to other process studies, which focus on how a social phenomenon evolves over time. Particularly, in step 3 (Event coding) of this method, the framework selected to categorise events or activities may not be limited to Hekkert et al. (2007)'s system function framework, but can be any other relative theoretical framework. In case there is no other suitable framework in the literature, it is also possible to create inductively the researchers' own categories through summarising categories from the empirical data. Therefore, in future studies, a different theoretical or empirical framework may be tried to classifying events and activities.

(2) It may be fruitful to study more technology innovations in order to contribute to a richer insight into the types of positive feedback loops and how they would influence innovation processes. If more case studies are carried out, different cases can be compared and more general insights into what types of positive feedback loops emerge can be obtained.

(3) This research has identified different types of feedback loops underlying innovation processes. Future studies may go one step further by examining the temporal sequence of different feedback loops along innovation processes, to see (a) whether there is a general succession model of positive feedback loops in technological innovations, which may theoretically explain how innovation evolves along time and why it does in that way; and (b) whether the succession models are different in different industries or they follow the same trajectory.

(4) This research has applied several metaphors from complexity theory to help understand the dynamics of technological innovations, such as positive feedback loops (Chapter 3 and 4), self-organising (Chapter 4), and hypercycles (Chapter 5). It is a first attempt to connect empirical cases with complexity theory. Other metaphors from complexity theory may also contribute to the understanding of innovation dynamics. But they are quite often loosely connected to the empirical world and are too abstract to guide practical work. That is because complexity theory originates from natural sciences and concepts have to be modified and adjusted with empirical examples before it

can be applied to social sciences. Future work should take effort to (1) understand the differences between the two fields' applications and (2) develop particular theoretical and analytical systems for innovation and other social science studies. One particular way is to find empirical examples of complexity theory concepts. In this way, a social-science-based complexity vocabulary could be developed.

(5) The agent-based modelling in Chapter 5 may be further developed based on more empirical case studies. The definition of individual agents' behavioural rules may be added piece by piece, which gradually increase the complexity of the simulation and make it more close to the real world. Especially, in the end of Chapter 5, the investigations provide several potential directions for future research that may improve the simulation model. Moreover, the simulation model in Chapter 5 can be extended to other application fields, such as crisis management field. The action and reaction relationships between events can be understood as crisis response networks between heterogeneous actors. Simulations of crisis management allows for effective interventions.

6.4 A vision on the future

This study is an interface between data science and innovation management, because it attempts to provide decision support on innovation using large amounts of data. In this research process, both modelling techniques and business interpretation are important. Modelling techniques make it possible to extract value and structure from the messy data; and business understanding interpret the analysis results into insightful and actionable suggestions for decision makers. Therefore, there should be more cooperation between data science in computer schools and innovation management in business schools

On the one hand, only focussing on the modelling side may lead to abstract numbers with no practical meaning. Data analysing for decision support is about human understanding (Edge, 2012). Although data experts are good at data analysis techniques, such as statistics, computer programming, machine-learning algorithms, they may lack understanding of a specific context. They are used to fitting the data to a model, getting a good number and then publishing it; and the reviewers do not understand it either (Edge, 2012). Data experts may need people with a business mind to interpret the numerical results, to come up with creative ideas about how to tap data to extract new values, and to translate a practical issue into a concrete data- analysis project, to translate the statistical results into actionable insights, and to communicate the results in a practical language that all stakeholders understand (Davenport & Patil, 2012).

On the other hand, by only focussing on the business side one may get lost in the messy details, unable to extract their hidden values. Business people or researchers usually do not have the right skills to extract value from big messy data (Mayer-Schönberger & Cukier, 2013), for example, the most basic and universal skill of data experts – writing codes (Davenport & Patil, 2012). Although most of the tools available to analyse big data (1) have been improved greatly, (2) are not expensive and (3) are open source, e.g., Hadoop, the technologies involved do require a skill set that is unfamiliar to most business persons and researchers, even to some IT experts (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012). Therefore, business people and researchers need data experts to reveal the hidden value of the messy and large amounts of data.

Hence, cooperation between data science and social science such as innovation studies may lead to better insights, more advanced theory development, as well as more practical decision support. This is also how the current research and its results are able to come out. The suggested cooperation is therefore essential to Big Data analysis. The data scientist and the social scientist occupy two important positions (data specialist and big-data mind-set) in the "big-data value chain: data holder, data specialist, and big-data mind-set" (Mayer-Schönberger & Cukier, 2013). They have complementary functions and downplaying the importance of either of them may make the big-data value chain incomplete and unable to work. As the era of big data evolves, data scientists and social scientists should cooperate to help data holders (e.g., e-business companies that have big transaction dataset, larger banks, insurance companies, and credit-card issuers) to extract value from their dataset, to innovate new business models and to make adequate decisions.

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