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Evaluation of Tech Ventures' Evolving Business Models: Rules for Performance-related Classification

Marc König¹, Manon Enjolras², Christina Ungerer³, Mauricio Camargo², Guido Baltes³

¹Karlsruher Institute for Technology, Zähringerhaus 5., 76133 Karlsruhe, Germany, ²Université de Lorraine, ERPI - EA 3767, F-54000 Nancy, France, ³Konstanz University of Applied Sciences, Institute for Strategic Innovation and Technology Management, Alfred-Wachtel-Straße 8, 78462 Konstanz

Marc König is CEO at bwcon Research gGmbH, the research entity of one of the largest technology networks in Europe. He is also an external PhD candidate at the Karlsruher Institute for Technology in cooperation with the Institute for Strategic Innovation and Technology Management. His research topics are SMEs, startups and business venturing.

Manon Enjolras is an associate Professor at the ERPI laboratory (Research Team on Innovative Processes), University of Lorraine (France). She works on innovation metrology and on the implementation of multi-criteria analysis methodologies for the design of decision-making tools dedicated to companies.

Christina Ungerer is a research associate at the Institute for Strategic Innovation and Technology Management (IST). As a doctoral student she will receive her PhD from the University of Münster. Her research mainly focuses on survival indicators for technology-based startups.

Mauricio Camargo is director of the ERPI laboratory (Research Team on Innovative Processes), University of Lorraine (France) and professor for Management of Technology and Innovation at the ENSGSI Nancy (School of Industrial Engineering in the University of Lorraine). His main research interests are new product development, decision making in product-process design and cost estimation models.

Guido Baltes is Professor of Industrial Engineering at the Konstanz University of Applied Sciences and director of the IST Institute. His research interest is business venturing, Venture Capital, and Corporate Innovation.

Abstract: At the early stage of a successful tech venture's life cycle, it is assumed that the business model will evolve to higher quality over time. However, there are few empirical insights into business model evolution patterns for the performance-related classification of early-stage tech ventures. We created relevant variables evaluating the evolution of the venture-centric network and the technological proposition of both digital and non-digital ventures' business models using the text of submissions to the official business plan award in the German State of Baden-Württemberg between 2006 and 2012. Applying a Principal Component Analysis / Rough Set Theory mixed methodology, we explore performance-related business model classification rules in the heterogeneous sample of business plans. We find that ventures

need to demonstrate real interactions with their customers' needs to survive. The distinguishing success rules are related to patent applications, risk capital, and scaling of the organization. The rules help practitioners to classify business models in a way that allows them to prioritize action for performance.

***Index Terms* - network theory, business model, life cycle, rough set theory, principal component analysis, tech ventures**

1. Introduction

Venturing in tech industries is one of the most crucial activities in today's innovation societies. Tech-venturing is an entrepreneurial process that aims to create an independent organization to bring new knowledge into the industry with the potential of a highly positive social impact (Shane and Delmar, 2004). Bringing such knowledge to the market in a technology transfer process is an uncertain undertaking. Distinctive networks in technology markets help to shift innovation from exploring ideas to economic exploitation based on new business models (Hite and Hesterly, 2001; Kilkenny and Love, 2014).

At the core of the venture activity, entrepreneurs create business models to mediate between the business opportunity and its external innovation system in an iterative process (Clarysse, Brunell and Wright, 2011). Therefore, the conceptualization of business models is often forced into partly standardized frameworks such as business plans, pitch decks, one-pagers, and the like. Such business models represent the language of the networked innovation market. The aim is to convince innovation intermediaries such as investors, accelerators, universities, innovation networks, and the like to consider supporting ventures' business opportunities (Doganova and Eyquem-Renault, 2009).

Innovation intermediaries need to improve the quality of their decision process through valid classification rules before they start an extensive due diligence process or even invest in a tech

venture. Entrepreneurs need to understand the patterns of successful business models evolving to improve the business venturing activity. Here, the academic literature provides a broad range of success and failure studies of new ventures in general (Lussier and Pfeifer, 2000; Kakati, 2003). Some scholars also tried to explain ventures' performance from a more static perspective using business plan data (Fernández-Guerrero, Revuelto-Taboada and Simón-Moya, 2012; Simon, 2012; McKenzie and Sansone, 2019). Other research explored the evolving of business models from a broad qualitative perspective with a small number of cases (Fritscher and Pigneur, 2014; Gay, 2014). However, the literature does not describe empirically validated patterns of the evolution of tech ventures' business models in the early stage. Hence, there are no related performance classification rules for practitioners' use.

To fill this research gap, the creation of performance-related classification rules for early-stage tech ventures' evolving business models requires remembering business model cases in relevant dimensions to reason future developments in terms of performance (failure, survival, success). We identified the strength of the described venture-centric network in the transaction relations to customers, financiers, people, and the implantation of the patenting strategy as relevant dimensions to reason from the text of business plans on digital and non-digital tech ventures' performance after 5 years. We follow the idea that in a venturing activity, the strength in each of these business model dimensions increases over the business life cycle, and so do the respective descriptions in the business plan. For instance, at the starting point of a venturing activity, entrepreneurs only follow a hypothesis on a market or need of potential future customers while relations to customers are in fact implemented and scaled when passing through the life cycle.

The research applies a Principal Component Analysis (PCA) / Rough Set Theory (RST) mixed methodology used in general innovation research (Du *et al.*, 2018) and adapts it towards creating classification rules from a more general business model perspective. Relying on the

seminal work of Dimitras (Dimitras et al., 1999), Rough Set has mainly been applied and recognized as one of the most useful intelligent techniques for business failure prediction (Shi and Li, 2019). Combining it with model complexity reduction techniques such as PCA analysis (tandem analysis) enables a better representation and comprehension of the business's main features and their leveraging effect on performance (Succurro, Arcuri and Costanzo, 2019). Identifying such classification rules contributes to both innovation and entrepreneurship studies by providing a methodological contribution in the elicitation of ventures' performance patterns and adopting an evolving business model perspective.

2. Theoretical Background

2.1 Business models and business plans

To theorize on business model classification, it is necessary to understand the business model as a management tool. Basing our definition of the business model on the essence of Stachowiak's model theory (Stachowiak, 1973), it illustrates the components of the value system (product, need, etc.) (George and Bock, 2011), reduces the complexity of the reality to a small number of components (Sahlman, 1997; Osterwalder *et al.*, 2010), and pragmatically supports certain tasks such as creative processes (business model canvas (Osterwalder *et al.*, 2010) or to convince investors evaluating a business opportunity (Honig and Karlsson, 2004).

Business plans that describe business models in detail are one of the most created documents in tech-venturing. It typically includes the following components: product idea, need description, market, competition, strategy, organization, financial statement, capital, and the implementation plan (Sahlman, 1997; George and Bock, 2011). The business plan narrows business ideas to a tangible description of the opportunity and creates a snapshot model at a certain point in time (George and Bock, 2011).

The business plan adds the dynamic dimension of time (Nyström and Mustonen, 2017) to the perspective of the often only two-dimensional business model. The term “plan” emphasizes the evolution of the business model over time. The literature on business planning also assumes that the business model is usually updated several times during the life cycle of the tech ventures, based on what has been learned in reality, thereby evolving to achieve higher quality. Even if the text document is not explicitly updated, the management at least adapts the business plan implicitly. (Brinckmann, Grichnik and Kapsa, 2010; Burke, Fraser and Greene, 2010)

2.2 The evolving business model

Following network theory, any business is created by a so-called ego-centric network, or, as we define it, a venture-centric network (Carnovale and Yeniyurt, 2015), based on transaction relations with *suppliers* (in our case technology suppliers), *people*, and *financiers* on the input side and with *customers* on the output side (Hite and Hesterly, 2001; Oksanen, Hallikas and Sissonen, 2010; Kilkenny and Love, 2014; Sullivan and Ford, 2014). The venture-centric network represents the intersection between internal resources and the external environment of the venture’s business (Carnovale and Yeniyurt, 2015). Entrepreneurs pursuing a tech venturing activity use the resources gathered from the input side of a business to create a technological proposition (e.g. secured by patents) that later addresses distinctive customers’ needs on the output side of the business more effectively with a certain resource combination. The intersection can be defined based on the number and strength of so-called transaction relations. At the beginning of the venturing activity, people-oriented transaction relations supporting an entrepreneur or entrepreneurial team as individuals dominate the venture-centric network. Relations need to become more calculative to grow the business. They shift from people-oriented to organization-oriented transaction relations. (Hite and Hesterly, 2001; Mainela and Puhakka, 2013; Sullivan and Ford, 2014) For instance, transaction relations to financiers shift

from private investments to professional investors (Mitter and Kraus, 2011). On the customer side, entrepreneurial management concepts such as the lean start-up approach (Ries, 2011) promote the creation of strong organization-oriented relations by first testing the underlying assumptions on the customers' needs to later scale the offering on the market (Mainela and Puhakka, 2013). The entrepreneurial activity of creating increasingly stronger organization-oriented relations leads to the notion of the evolving business model (Mcgrath and Macmillan, 1995).

The concept of the evolving business model in the early stage of a tech venture is in line with the life cycle theory. In the seed stage, the founding entrepreneur starts as the core resource coordinator (Mohaghar, Monawarian and Raassed, 2010; Clarysse, Brunell and Wright, 2011) with an explorative approach to define the business idea. The exploration of the idea and initial product development generate increasing costs. The start-up stage is defined by an initial market release of an early product version. Thus, a shift toward the exploitation of the business occurs (March, 1991; Tam and Gray, 2016; Baumbach *et al.*, 2020). In the growth stage, expenses shift from product development to increasing market entry efforts (Greiner, 1998; Tam and Gray, 2016; Kazanjian, 2018). Figure 1 gives an overview of the concept of the evolving business model.

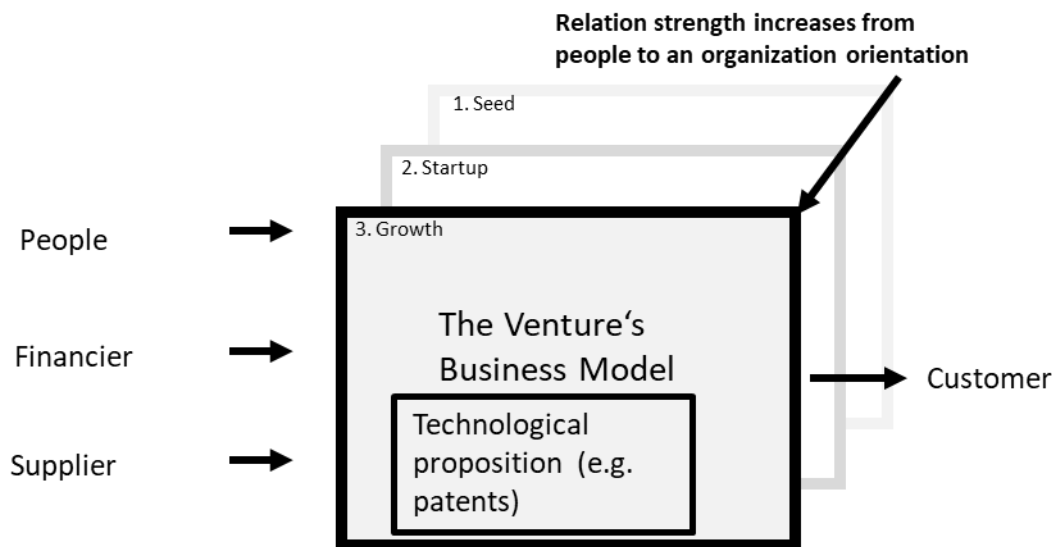


Figure 1: Concept of the evolving business model

As described in the introduction, literature on the success and failure of tech ventures as well as research on business models has not sufficiently considered the implementation status of the venture's centric network and the creation of technological propositions as indicators for future performance. Hence, research lacks an understanding of empirically relevant performance patterns for evolving business models that allow classification in the context of the life cycle.

3. Research Question, Sample, Data, and Methodology

3.1 Research question and hypotheses

This research investigates business plans as text documents that describe evolving business models of tech-ventures at a certain point in time. To improve the theoretical understanding of evolving business models in research and to support the analytical use of business plans in practice, the present study applies a comprehensive research design to identify patterns for performance-related tech-venture classification rules in a sample of business plans. Hence, this paper addresses the following research question: **Is it possible to define performance-related classification rules that characterize the evolving business models of tech ventures based on patterns in the venture-centric value network and other variables extracted from business plans?**

This research question is predicated on whether groups of ventures with different performance levels, i.e., death, survival, and success, relate to distinctive input variables gathered from business plans text. The precondition is selecting a subset of variables that includes relevant features (Asir *et al.*, 2016). In previous research based on qualitative and quantitative text analysis, we were able to show that business plan texts describing transaction relations (venture-centric network) and patent strategy status (technological proposition) can be used to extract valid variables for digital and non-digital ventures (Konig, Baltes and Katzy, 2015; Konig *et al.*, 2016, 2017; König *et al.*, 2019). Cluster analyses suggested that certain variables and data patterns relate to performance (König *et al.*, 2019). It is crucial to test whether the individual variables contribute empirically to predicting venture performance to remove irrelevant or redundant features and ensure classification quality (Asir *et al.*, 2016). Thus, we propose the following hypothesis.

H1) Performance-related business model variables of tech ventures can be extracted from business plans.

The data measured by the variables need to be relevant in a certain combination to allow for a good prediction of venture performance. According to the described theory on the emerging business models, the constructs behind the variables increase in strength in successful tech ventures. Deriving strong classification rules for the expected performance outcome of a venture activity is only possible if the patterns represent a relevant combination of different variables (Asir *et al.*, 2016). Thus, relevant classification rules represent a predictive model for tech venture performance. Hence, we suggest a second hypothesis.

H2) Relevant patterns of explaining variables represent classification rules relating to ventures' performance in terms of failure, survival, and success.

To answer the outlined research question, we follow a multilevel research approach. A sample of business plans submitted to a prominent German award represents the empirical foundation.

In previous work, a rigor development process was used to create a multidimensional content analysis research instrument for quantitative applications. In the current research, we apply this instrument to a sub-sample of the submitted business plans and create a set of consistent deterministic rules in a two-step data exploration approach.

3.2 Sample

The research investigates 242 business plans submitted to the CyberOne Award, the official business plan award in the German state of Baden-Württemberg, between 2006 and 2012. During these years, 311 business plans had been submitted; however, we excluded 69 spin-off projects because they often describe transaction relations referring to the initial business. The 2006-2012 period was selected since capturing the ventures' performance 5 years post submission was only possible for these years when the research was conducted. Figure 2 illustrates the structure of the sample.

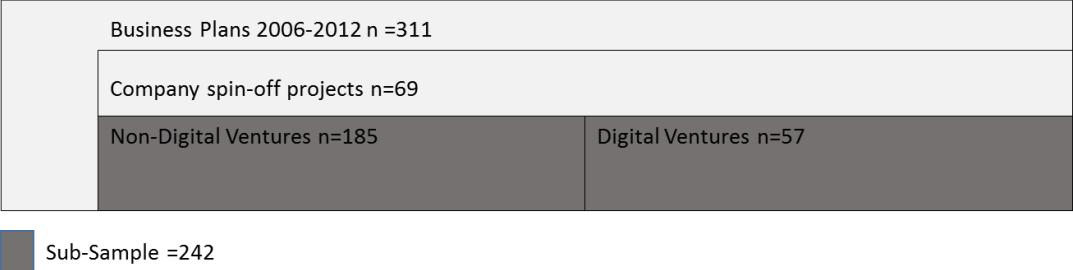


Figure 2: Sample structure CyberOne Hightech Award

We defined a digital ventures subset (n = 185) that contains companies that attempted to create a business with an intangible software tool at their core, and a non-digital ventures subset (n = 57) that comprises companies attempting to create a business based on (tangible) hardware or biotechnology assets. Research highlights considerable differences between these venture types. Digital ventures are usually able to test their business on the market at the very beginning and need external financing to scale their organization only after an initial product-market-fit

(Nguyen-Duc, Shah and Amrahamsson, 2016; Bajwa *et al.*, 2017). Non-digital ventures, in contrast, are usually based on extensive research (Graham *et al.*, 2009; Samuelson, 2010).

The data collection followed a network sampling approach based on the idea that peers can recommend other peers within a certain target group (Johnston and Sabin, 2010). To assess the sample's representativeness for the German State of Baden-Württemberg, the data set was compared with research on the tech ventures population in Baden-Württemberg conducted by the Centre for European Research (ZEW). Representativeness is assumed, as the data sets show strong similarities in the regional distribution of tech ventures (Egeln *et al.*, 2012).

The only relevant difference is that the Cyberone sample does not only cover ventures in their foundation year and hence includes business models with more diverse transaction relations in the early stage of their life cycle. The risk of failure in earlier-stage ventures where relations are less strong is assumed to be higher. We thus benefit from the network sampling approach through the heterogeneity of maturity status (Maiya and Berger-wolf, 2011).

3.3 Research design and resulting data

In a previous study, a multidimensional research instrument for quantitative content analysis was created for the venture-centric network using an iterative process following inductive and deductive steps (Konig, Baltes and Katzy, 2015; Konig *et al.*, 2016, 2017; König *et al.*, 2019). To develop the measurement instrument, the business plans of 20 successful and 20 failed ventures were selected from the total sample based on convenient sampling. They were qualitatively analyzed to obtain an initial empirical grounding. The findings of the empirical work and the literature review were combined to create the multidimensional research instrument. With this, it was possible to classify transaction relations for each of the four categories into early-seed, late-seed, early-startup, late-startup, and early-growth stages using 5-point Rating scales (Konig, Baltes and Katzy, 2015) (see Figure 3).

The approach follows the idea that in a high-value case in a category, the previous levels on the 5-point Rating scale have already been reached. This means that if the evaluation of a venture's business model achieves a certain strength, then it is considered to have crossed the previous stages of the underlying life cycle model. The concept described for the measurement instrument is essential for the subsequent data analysis and interpretation.

To validate the quality of this measurement instrument, we carried out a rigorous purification process using a quantitative content analysis approach (Kemal Avkiran, 1994; Bailey, Johnson and Daniels, 2000). The coding process was then applied as follows: (1) identification of transaction relations by at least two coders per business plan; (2) evaluation of the strength of each transaction relation by three coders for each transaction relation, and (3) a final integrative judgment by the research team to identify the highest transaction-relation level per category for each business plan (Konig *et al.*, 2016). In addition, the coding by trained undergraduate business students was evaluated to ensure objectivity.

To further improve research quality, a customized software tool was designed to support the business plan coding process. Every business plan was split into single sentences that were coded individually to facilitate comparability. The software tool featured individual user management to allocate tasks and to track coder performance. For every sentence, coders were provided with instant feedback and contextual information, such as the venture name or foundation year. All coding data was stored in a database and enriched with additional business information for each business plan.

For the sample of 242 ventures at the core of this paper, more than 78,000 single sentences have been subject to coding by non-experts (students) and experts (researchers). As a result, almost 5,000 were identified as transaction relations in at least one of the four categories and rated according to their maturity level (1-5). The average of the highest rating per category reached

by the sampled ventures is 2.22 for *Suppliers*, 2.54 for *People*, 2.51 for *Customers*, and 2.03 for *Financiers*.

Two more variables were added to the four transaction relation category variables to complete the set of **input variables** used in this research. First, the ventures' technological propositions were determined by capturing the status of their patenting strategy as described in the business plans. With the *Patent* variable, five major cases were differentiated: (1) no attempt to patent, (2) option to patent, (3) applied for a patent, (4) holds a patent, and (5) held a patent and applied for at least one further patent. Most of the ventures, 176, showed no patenting activities while 55 applied for or held a patent, and only 11 followed a multiple-patenting strategy.

Second, we assumed that participating in the business plan award aimed at gaining publicity in the State of Baden-Württemberg's venture capital community. Combining desk research with interviewing one of the most active venture capital (VC) investors in the period sampled, we created the *Risk Capital* variable based on the *Financier* transaction relation variable and adding the values 4 or 5 if the ventures were able to acquire risk capital (confirmed VC funding) post submission of the business plan. Thus, for 27 ventures with a relatively low rating in the *Financier* variable, the *Risk Capital* variable expresses a higher level of capital acquisition since financing activities after business plan submission are taken into account.

To collect the secondary data used to build the performance indicators and thus the **output variable** of this research, we tested different economic data providers to enrich our own data collection results and finally chose Bisnode Deutschland GmbH. Bisnode provided the most comprehensive financial data in comparison to other data providers. A pre-specified data collection process served to improve data quality further. It was conducted by three independent researchers and included checking the official registers, venture activity on the company website, and any online publication of news.

Based on the results, the 242 ventures were classified into failed (n=118), survived (n=64), or successful (n=60) after five years following a purely economic definition, i.e., growth in turnover and staff (Trailer, Hill and Murphy, 1996; Petersen and Ahmad, 2007). The definition of a failed and survived venture was based on the company information given in the trade register. A successful venture was defined as a company that still needs to be officially registered five years after the submission of the business plan and has a turnover of at least 300,000 euros and has tripled the turnover if it was initially between 100,000 and 500,000 euros or has doubled if it was initially above 500,000 euros. In the case of an unclear turnover, the increase in the number of employees was used as a second indicator. We specified that a company with 3 to 15 people initially must have tripled its staff within the 5 years, while ventures employing more than 15 people when submitting the business plan needed to have doubled their staff to be classified as a successful venture. Figure 3 provides a summary of the variables used in this research.

3.4 Methodology

Due to the exploratory nature of our research and the discussions on specific data distribution in entrepreneurship research (Crawford *et al.*, 2015), we decided to use a combination of PCA and RST. In particular, RST is a methodology that does not follow the idea of any distribution and so allows exploring rules in any kind of data (Nagamachi, 2006). We applied the data exploration approach illustrated in Figure 4 following two steps: data reduction and classification of patterns. The data exploration leads to a reduced set of primarily consistent deterministic rules.

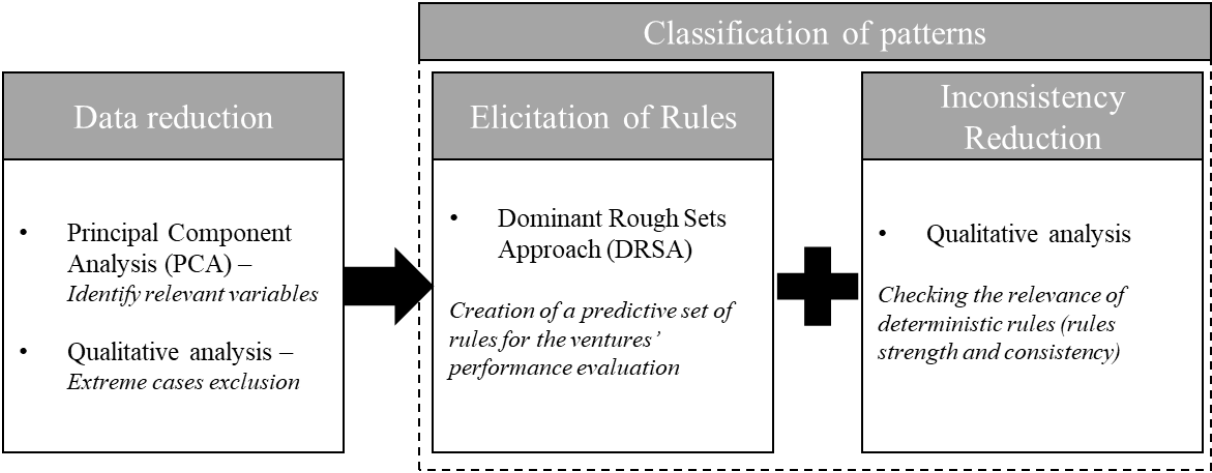


Figure 4: Methodological steps

The data reduction step aims to improve the current database by identifying the core variables for the predictive model. The core represents the set of features that contain all reduced data necessary to obtain the best multidimensional predictive power (Podsiadlo and Rybinski, 2016). Data reduction is a way to prevent decision conflict resolution and to reduce inconsistencies in the decision system (Rissino and Lambert-torres, 2009; Podsiadlo and Rybinski, 2016). For this purpose, it is necessary to identify the relevant variables of the decision system. We explored how the input variables from our research instrument relate to venture performance. To further define the core of the information system, we depend on the data reduction with a qualitative analysis to exclude inconclusive cases (Rissino and Lambert-torres, 2009).

PCA delivers graphical representations of a sample according to two principal axes defined for the different variables (Syms, 2008). Each variable is represented by a vector shown in a three-dimensional (3D) space and then brought back to a two-dimensional (2D) plane constructed by two main axes: the principal components. The axes represent the two virtual dimensions showing the larger amount of data from the 3D space in a plane. These two axes (the two principal components) do not have a specific meaning in themselves but are considered as the most representative dimensions to exploit the data. If two variables are represented in the same direction, they are positively correlated. If they are represented in opposite directions, they are negatively correlated. Finally, if the vectors of two variables are orthogonal, there is no correlation between them. (Lever, Krzywinski and Altman, 2017)

The second phase of our methodology concerns the elicitation of rules from the core database, leading to a set of rules based on empirical patterns of venture performance. The rules were designed to translate certain redundant empirical situations in the database into performance predictions for the ventures they are associated with. Thus, the objective was to identify patterns within the database that reflect the failure, survival, or potential success of ventures with these characteristics. We used the dominance-based rough set approach (DRSA) to create a predictive set of rules.

The DRSA is an extension of RST dedicated to multicriteria decision analysis (Greco, Matarazzo and Slowinski, 2001). The main difference compared to the classical RST is the substitution of the indiscernibility relation by a dominance relation. In this way, inconsistencies related to the consideration of criteria and a preference-ordered decision can be dealt with. This approach could be used to obtain a set of rules underlying common patterns of venture performance based on preference-ordered performance criteria.

These rules are formulated according to the following structure: **IF** *venture X shows 'these characteristics of measurement instruments' (input variables)* **THEN** *it could be 'Failed', 'Survived', or 'Successful' (output variable).*

The RST approach relies on a subdivision of the decision classes into a number of elementary sets. These elementary sets describe specific features of the classes (here, the classes are: Failed, Survived and Successful). If an object belongs to a set that is completely included in class X, it could be classified without any ambiguity. However, if an object belongs to an elementary set partially but not entirely included in class X, its classification needs to be approximated. In the specific case of a dominant-based rough set approach, the classification of these objects relies on the relation of domination between objects. The classes are preference-ordered, such that an object belonging to the lower class cannot dominate an object belonging to the upper class. (Greco, Matarazzo and Slowinski, 2001).

The classification of these objects leads to the generation of predictive rules. Two quantitative measures, called absolute and relative strength, characterize the importance and reliability of the generated rules and define their claimed relevance. The absolute strength of the rule defines the number of objects in the global sample that are consistent with the rule (supporting cases). The relative strength is the relationship between the supporting cases of the rule and the number of objects that constitute the lower approximation of the considered union of classes (cf. Tables 1 to 4). Finally, the reliability of the set of patterns that have been elicited through the rough set approach needs to be considered to create deterministic rules. (Podsiadlo and Rybinski, 2016)

4. Results

4.1. Data reduction

We applied the PCA to the global sample of 242 ventures (including digital and non-digital ventures). We used the performance variable (Failed, Survived, and Successful) as the output variable and the variables *Suppliers*, *People*, *Customers*, *Financiers*, *Risk Capital*, and *Patent* as input variables. The two principal component axes accounted for 49.55% and 16.48% of the data. Although we cannot assume normally distributed variables in the context of early-stage entrepreneurship, we consider this analysis as meaningful given the percentage of data representation compared to the number of variables and individuals.

Based on the results of the PCA (Figure 5), the *Supplier* variable does not appear relevant to our model, indicating a very weak correlation with the success variable. These two variables are indeed almost orthogonal. By contrast, the *Customers*, *Finance*, and *People* variables show a strong correlation with success. We decided to remove the *Supplier* variable from the model. This also reflects the results of prior related research in which the *Supplier* variable did not turn out to be meaningful for explaining survival or growth in the total sample (König, Ungerer and Baltes, 2018).

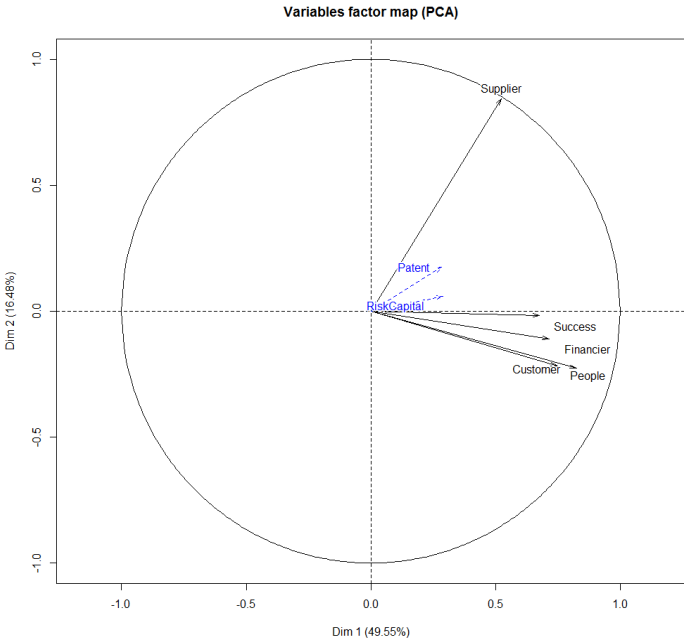


Figure 5: PCA loading plot – global sample

The *Patent* and *Risk Capital* variables in the loading plot were not well represented. These variables are far from the boundary of the PCA circle, thus no conclusion is possible through this representation. Further analysis was carried out by adding a third and then a fourth dimension to the principal component space, but despite this, it was not possible to interpret these two variables with certainty concerning the venture performance. However, earlier research indicated the relevance of the *Risk Capital* and *Patent* variables in the data set (König *et al.*, 2019). In particular, from a cluster analysis based on transaction relations, we saw that certain groups could be created, indicating a relation between *Risk Capital* and *Patents* in the context of performance. We decided to keep these variables in the model.

The PCA analysis results demonstrate strong correlations between the success of the venture (performance variable) and the three transaction relation variables: *Financiers*, *People*, and *Customers*, which is supporting Hypothesis 1. As such, it seems that “**performance-related business model variables**” could be identified in business plans of tech ventures.

We deepened the data reduction phase with a qualitative analysis of the 242 business plans in the sample. Following the principles of RST, we searched for inconclusive venture cases that could not be clearly allocated to one of the performance/output classes (Rissino and Lambert-torres, 2009). The objective of the data reduction is to reduce the uncertainty of the future deterministic rules (Yao, 2009). We finally removed 23 inconclusive cases as they showed contradicting results in specific patterns (contradicting cases) or were inconsistent with a larger number in a decision class and at the same time disagreed with the general reasoning concept (outliers).

The consolidated database after the reduction phase consisted of 219 cases in the core of our information system. In the group of 166 digital ventures, 83 failed, 45 survived, and 38 were successful, whereas the non-digital venture group contained a total of 53 ventures, with 25 successful, 13 survived, and only 15 failed ventures.

4.2 Classification of Patterns

From the corrected set of input variables (namely *People*, *Customers*, *Financiers*, *Risk Capital*, and *Patent*), we elicited decision rules using the dominance-based rough set approach (DRSA) based on the 4Emka software, developed at the Laboratory of Intelligent Decision Support Systems of the Institute of Computing Science (Poznan University of Technology) (Gatnar *et al.*, 2005). We first calculated these performance patterns for the entire sample and then for digital and non-digital ventures separately. Only relevant rules with a relative strength above 50% were considered.

4.2.1 Global sample analysis

Regarding the global sample, specific patterns could be defined for each performance group. For each rule, Table 1 to Table 4 show a description according to the five variables considered: three transaction relations (*Customers*, *People*, and *Financiers*) and two additional variables (*Patent* and *Risk Capital*), resulting in *performance* after 5 years as the output variable (*Failure*, *Survival*, or *Success*), the number of cases in the sample that support this rule, and the relative strength, represented by the number of supporting cases among cases from the lower approximation of the decision class (defined by the performance variable: *Failure*, *Survival*, *Success*).

Table 1: Framework of rules: Global Sample – five variables (*People*, *Customer*, *Financier*, *Risk Capital*, and *Patent*)

Rule no.	Description of rule	Performance	Supporting cases	Relative Strength (%)
1	(Customer ≤ 1)	Failure	2	66.67
2	(Customer ≤ 2) & (Risk Capital ≤ 2) & (Patent ≤ 1)	At most survival	62	72.94
3	(Customer ≤ 1) & (Risk Capital ≤ 3)	At most survival	66	77.65
4	(Customer ≥ 4) & (Patent ≥ 4)	Success	14	73.68
5	(Risk Capital ≥ 4) & (Patent ≥ 4)	Success	15	78.95
6	(People ≥ 3) & (Customer ≥ 2) & (Patent ≥ 4)	At least survival	15	65.22

As a first observation, only rule 1 describes the *Failure* decision class. The high relative strength of rule 1 (66%) and the small number of supporting cases (two ventures) show that few ventures could be classified unhesitatingly as a *Failure*. Despite many ventures in the *Failure* decision class (98 ventures in the global sample), it seems that the few supporting cases (only 2) highlight a high degree of uncertainty around putting ventures into this class.

The most relevant rules are numbers 2 and 3, separating ventures with low survival and growth probabilities. According to our measurement instrument (Figure 3), rule number 2 states that ventures with only interviewed customers, no follow-up risk capital acquisition, and in some cases, no intention to create patents are most likely to survive. In general, we can argue that this rule applies to more than one-third of the sample. Although rules 1 to 3 apply to 130 cases in total, we assumed that a cross-section exists in-between the cases.

Comparing rule 6 with the previous rules, the existence of a functional team, at least customer feedback, and a patent are relevant indicators of survival and success in 15 cases. This rule is supported by the success rules 4 and 5, adding the relevant notion of external investments and a solid existing customer base.

The *Customer* category seems to be particularly discriminating in the core of the global sample. We identify an interval between a *Customer* variable rating of less than or equal to 2 for “At most survival” and a *Customer* variable rating greater than or equal to 2 for “At least survival”. In general, the *Customer* variable seems to be an essential indicator that separates the sample into failure or survival and survival or success.

4.2.2 Digital Venture sample analysis

Looking at the **digital ventures**’ subset in Table 2, 6 rules were identified.

Table 2: Framework of rules: Digital ventures – five variables (People, Customer, Financier, Risk Capital, Patent)

Rule no.	Description of rule	Performance	Supporting cases	Relative Strength (%)
1	(Financier <=1)	Failure	1	50.00
2	(Risk Capital <=1)	Failure	1	50.00
3	(Customer <=1)	Failure	1	50.00
4	(Customer <=1) & (Risk Capital <=2) & (Patent<=1)	At most survival	59	79.73
5	(Customers <=1) & (Risk Capital <=3)	At most survival	55	74.32
6	(People >=5)	Success	6	66.67

The relevance of customers is further supported by rules 3 to 5, offering clear evidence that ventures with weak customer relations failed, and even if these weak customer relations are combined with medium financing relations (*Risk Capital*), ventures survive at most. However, the results show no evidence for “At least survival” or “Success” linked to this *Customer* category. Only one rule (rule 6: already an existing organization), supported by 6 specific cases, seems to be an indicator of success. This could mean that these six digital venture businesses were scaled through their headcount, and thus the existence of an organization gives an indication of future growth potential. In these six cases, the strength of each transaction relation is at level 5 in the *Customer* category, which is not represented in the rules.

We assumed that behind rule number 6, there should be further potential success rules, and we, therefore, decided to take these six cases out of the core sample of digital ventures. Looking at the results in Table 3, we see that the rules of failure or at most survival stay the same, but new rules appear for at least survival and at least success. However, these new rules, from 6 to 11 in Table 3, are pretty weak, as they are only supported by two to three cases. For the most part, they describe a combination of existing *Patents* and *Risk Capital*, but according to rules 8 and 10, they also include strong customer relations. In total, this subset of rules now accounts for a large proportion of the 19 surviving ventures.

Table 3: Framework of rules: Digital ventures – five variables (People, Customer, Financier, Risk Capital, and Patent) - six cases taken out

Rule no.	Description of rule	Performance	Supporting cases	Relative Strength (%)
1	(Financier <=1)	Failure	1	50.00
2	(Risk Capital <=1)	Failure	1	50.00
3	(Customer <=1)	Failure	1	50.00
4	(Customer <=2) & (Risk Capital <=1) & (Patent <=1)	At most survival	59	79.73
5	(Customer <=1) & (Risk Capital <=3)	At most survival	55	74.32
6	(Financier >=3) & (Patent >=4)	Success	2	66.67
7	(Risk Capital >=4) & (Patent >=4)	Success	3	100.00
8	(Customer >=4) & (Patent >=4)	Success	2	66.67
9	(Financier >=2) & (Patent >=5)	At least survival	2	50.00
10	(Customer >=3) & (Patent >=5)	At least survival	2	50.00
11	(Risk Capital >=2) & (Patent >=5)	At least survival	2	50.00

Interestingly, for the digital venture sample, the small number of supporting cases in the failure class also highlights a high degree of uncertainty for classifying ventures in this class. Indeed, rules 1, 2, and 3 show a high relative strength value (50%) but only one supporting case. Thus, only two digital ventures can be classified unhesitatingly in the “*Failure*” class. The other failed ventures are classified under uncertainty.

4.2.3 Non-Digital Ventures sample analysis

Looking at the **non-digital ventures’** subset, we computed a total of 17 rules (Table 4).

Table 4: Non-Digital ventures –five variables (People, Customer, Financier, Risk Capital, Patent)

Rule no.	Description of rule	Performance	Supporting cases	Relative Strength (%)
1	(Financier <=1) & (Customer <=1)	Failure	5	83.33
2	(Customer <=1) & (Risk Capital <=1)	Failure	5	83.33
3	(Customer <=1) & (Patent <=2)	Failure	5	83.33
4	(Customer <=3) & (Risk Capital <=2) & (Patent <=3)	At most survival	17	70.83
5	(Customer <=2) & (Risk Capital <=2)	At most survival	16	66.67
6	(Customer <=2) & (Risk Capital <=3)	At most survival	17	70.83
7	(Risk Capital >=4)	Success	19	86.36
8	(Customer >=4) & (Patent >=4)	Success	12	54.55
9	(People >=3) & (Customer >=3)	At least survival	22	73.33
10	(Financier >=3)	At least survival	15	50.00
11	(Risk Capital >=3)	At least survival	24	80.00
12	(Customer >=4)	At least survival	19	63.33
13	(Customer >=4) & (Risk Capital <=3) & (Patent <=3)	At least survival	4	57.14
14	(People >=3) & (Financier <=3) & (Customer >=4) & (Patent <=3)	At least survival	4	57.14
15	(People <=2) & (Financier >=2) & (Risk Capital <=2) & (Patent >=3)	At most survival	9	52.94
16	(People <=2) & (Risk Capital =2) & (Patent >=3)	At most survival	9	52.94
17	(Risk Capital <=2) & (Patent =3)	At most survival	9	52.94

The rules in the non-digital venture subset are more diverse in differentiating between *Failure*, *Survival*, and *Success* of the business activity than those in the digital venture subset. The “*Failure*” and “*At most survival*” cases imply that *Customers* and *Risk Capital* are again relevant. However, in rule 4, the *Patent* representation is also of high relevance. In this rule, the prospect of only having the intention to file a patent is not a sufficient indicator of growth.

In contrast to the “*At least survived*” and “*Success*” rules, we see much stronger rules than in the previous digital venture core sample. We see that *Risk Capital* (rule 7) and also strong customer relations, together with a granted patent (rule 8), lead to “*Success*” or, in combination with a management team (rule 9), they lead to “*At least survival*”. For “*survival*” as well, only a solid existing customer base leads to a high probability of survival. Further consideration should be given to rules 13 and 14 and to rules 15 to 17, which create a boundary between more interesting ventures (*At least survival*) and less interesting ones (*At most survival*).

4.2.4 Inconsistency reduction

Creating a predictive model based on the classification rules for different performance groups of ventures requires sorting the relevant deterministic rules by voting characteristics such as rule strength or rule similarity to classified objects (Podsiadlo and Rybinski, 2016). We analyse the initial set of rules to categorise them for classification rules of business models. Figure 6 proposes three different core rules for each performance category from a life cycle perspective.

Failure Rules	Survival Rules	Success Rules
<p>At most: (Customer ≤ 3) & (RiskCapital ≤ 2) & (Patent ≤ 0)</p> <p><i>No sold products to customers & no professional investment from at least business angels & no intention to file a patent.</i></p>	<p>At most: (Financial ≥ 3) OR (Customer ≥ 4) OR (Patent ≥ 4)</p> <p><i>At least an investment from a professional source OR paying customers OR granted patent</i></p> <p>At Least: (People ≥ 3) & (Customer ≥ 2) & /OR (Patent ≥ 4)</p> <p><i>At least functional management team & at least feedback from customers & /OR at least a granted patent</i></p>	<p>General 1: (RiskCapital ≥ 4) & (Patent ≥ 4)</p> <p><i>Professional seed capital & granted patent</i></p> <p>General 1: (Customer ≥ 4) & (Patent ≥ 4)</p> <p><i>Paying Customers & granted patent</i></p> <p>Digital: (People ≥ 5)</p> <p>Business scale-up organization</p> <p>Non-Digital: (RiskCapital ≥ 4)</p> <p>Professional Seed Investment</p>

Figure 6: Classification rules for tech venture performance

These observations confirm our second hypothesis: **“Relevant patterns of explaining variables form classification rules that relate to ventures’ performance in terms of failure, survival, and success.”** Reflecting on the initial research question, we find that based on the textual description of ventures’ business models in business plans, patterns in variables can be identified that allow for a performance-oriented classification. The rules follow the ideas of the business life cycle and allow predictions on venture performance by sorting cases according to the rules into the performance classes.

5. Discussion

5.1 Implications

We used business plans to explore performance-related classification rules for the evolving business model. Although activities in the early days of tech ventures are dynamic, the explored rules approach predicts performance with a five-year perspective. For this purpose, we adapted a PCA/RST mixed methodology inspired by applications in innovation research (Du *et al.*, 2018) and applied it to tech ventures’ evolving business models.

Next to this methodological contribution, the rules add to the literature on predicting venture performance from business plan texts (Baglioni *et al.*, 2008; Fernández-Guerrero, Revuelto-Taboada and Simón-Moya, 2012; Simon, 2012; McKenzie and Sansone, 2019) by taking an evolving business model perspective. The rules confirm the business life cycle literature based on the variables of the ventures' value networks and the technological proposition applied to the heterogeneous data sample. The results confirm that an increasing interrelation with reality reduces the risk of failure, increases the chance of survival, and opens the potential for success. In the context of the business life cycle, the research adds to the longitudinal perspective on business model evolution described by Cavalcante et al. (Cavalcante, Kesting and Ulhøi, 2011) and Fritscher and Pigneur (Fritscher and Pigneur, 2014) with a quantitative approach. In this respect, the ruleset represents a general logic for stress-testing core assumptions in business models of digital and non-digital tech ventures alongside the business life cycle according to entrepreneurial management concepts (e.g., the lean start-up approach). The main contribution accordingly represents a predictive model for venture performance based on the evolving business model described in the text of business plans.

Regarding the implications of each relevant variable, the *Customer* category plays a critical role in bringing a venture to life. The venture has to prove right at the start whether the business is considering customers' needs - an explorative idea represented in the literature on adaptive learning strategies (Mcgrath and Macmillan, 1995; Sykes and Dunham, 1995; Hart, 2012). Hence, the explorative skill of testing and initially selling products is a crucial factor at the beginning of the venturing activity.

External professional money seems to be a success indicator in many cases. At least from a business angel, investment demands and brings in the professionalism needed to earn a return on investment. According to the results of our success rules, this investment can also stem from professional customer relations that are financing the business out of cash flows in digital

venture cases with already an organization exists (Carpenter and Guariglia, 2008; König *et al.*, 2019). It thus seems that external confidence from either the investor or the customer side is relevant for bringing cash into the venture to finance people.

A technological proposition also plays a role in the growth of digital and non-digital ventures. Patents seem to be more relevant for the non-digital ventures due to their relatively stronger representation in the sub-sample. This result is also supported by the Berkeley Patent Study that concludes that non-digital ventures tend towards initial patenting and thus build on a more tangible strategic benefit, while for digital ventures, the go-to-market is a dominating success strategy (Graham *et al.*, 2009). Apart from patents, it can be speculated that digital ventures follow a different strategy to gain strategic value based on customer relations, create a unique and secret data asset, or build a specialized ability on the part of the organization to deliver a product or service.

Practitioners could analyze tech ventures' business cases by comparing the patterns from the business model at hand with the rulesets resulting from our research to categorizing ventures into performance groups. Entrepreneurs and innovation intermediaries could set standard strategies for each performance group and actively manage their tech venture(s) based on objective patterns derived from the textually described business models. Since a venture that shows failure patterns does not necessarily fail (e.g., weak success patterns and inconclusive cases), practitioners need to be capable of executing strategies that help individual venture cases evince survival or success patterns. Practitioners who do not have the relevant support capabilities should instead focus on engaging with tech-ventures in later stages.

5.2 Limitations & Further Research

A limitation arises from the number and distribution of cases in the sample. Ventures in the very early stage are overrepresented. As a result, we obtained relevant but weak success rules due to relatively fewer ventures in later life cycle stages. Longitudinal argumentation over the

life cycle is limited, given that the data only describe the classification of business models snapshots. The relatively heterogeneous distribution of the cases over the early stage enabled us to explore patterns with the RST suggested by the life cycle theory.

The previous limitations relate to the issue of sampling bias. The sampling of business plan award submissions excludes ventures that have not written a business plan and those that may not be connected to the network. Besides, the region and the innovation system itself may have biased the results by their ability to support new ventures. Due to the number of 242 cases, there is still uncertainty in the rules obtained related to the variable number of supported cases and their relative strength.

Further research is needed to generalize the results for the innovation system in southwest Germany and other innovation systems. Research should continue to validate the results in other innovation ecosystems and with broader samples. A larger sample and further relevant variables could also allow us better to understand the 23 inconclusive cases in the sample. Due to other new research on business plans (Hanák and Grežo, 2020) and the organizational learning capabilities in terms of the shift from exploration towards exploitation (March, 1991; Baumbach *et al.*, 2020), the management team's experience be one such variable in future research. The progress of the different tech ventures also needs more investigations from a longitudinal perspective to explain the existing and new variables and patterns.

References:

- Asir, D. *et al.* (2016) 'Feature Selection Using Rough Set For Improving the Performance of the Supervised Learner', *International Journal of Advanced Science and Technology*, 87, pp. 1–8. doi: 10.14257/ijast.2016.87.01.
- Baglioni, M. *et al.* (2008) 'Ontology-based business plan classification', in *Proceedings - 12th IEEE International Enterprise Distributed Object Computing Conference, EDOC 2008*, pp. 365–371. doi: 10.1109/EDOC.2008.30.
- Bailey, A., Johnson, G. and Daniels, K. (2000) 'Validation of a multi-dimensional measure of strategy development processes', *British Journal of Management*, 11(2), pp. 151–162. doi: 10.1111/1467-8551.t01-1-00157.
- Bajwa, S. S. *et al.* (2017) "'Failures" to be celebrated: an analysis of major pivots of software

- startups', *Empirical Software Engineering*, 22(5), pp. 2373–2408. doi: 10.1007/s10664-016-9458-0.
- Baumbach, S. *et al.* (2020) 'Dynamic capabilities for opportunity exploration: Insights from an explorative case study', *International Journal of Entrepreneurial Venturing*, 12(6), pp. 575–616. doi: 10.1504/IJEV.2020.112232.
- Brinckmann, J., Grichnik, D. and Kapsa, D. (2010) 'Should entrepreneurs plan or just storm the castle? A meta-analysis on contextual factors impacting the business planning–performance relationship in small firms', *Journal of Business Venturing*, 25(1), pp. 24–40. doi: 10.1016/j.jbusvent.2008.10.007.
- Burke, A., Fraser, S. and Greene, F. J. (2010) 'The multiple effects of business planning on new venture performance', *Journal of Management Studies*, 47(3), pp. 391–415. doi: 10.1111/j.1467-6486.2009.00857.x.
- Carnovale, S. and Yenyurt, S. (2015) 'The role of ego network structure in facilitating ego network innovations', *Journal of Supply Chain Management*, 51(2), pp. 22–46. doi: 10.1111/jscm.12075.
- Carpenter, R. E. and Guariglia, A. (2008) 'Cash flow, investment, and investment opportunities: New tests using UK panel data', *Journal of Banking and Finance*, 32(9), pp. 1894–1906. doi: 10.1016/j.jbankfin.2007.12.014.
- Cavalcante, S., Kesting, P. and Ulhøi, J. (2011) 'Business model dynamics and innovation: (re)establishing the missing linkages', *Management Decision*, 49(8), pp. 1327–1342. doi: 10.1108/00251741111163142.
- Clarysse, B., Brunell, J. and Wright, M. (2011) 'Explaining growth paths of young technology-based firms: structuring resource portfolios in different competitive environments', *Strategic Entrepreneurship Journal*, 15(5), pp. 137–157. doi: 10.1002/sej.
- Crawford, G. C. *et al.* (2015) 'Power law distributions in entrepreneurship: Implications for theory and research ☆', *Journal of Business Venturing*, 30, pp. 696–713. doi: 10.1016/j.jbusvent.2015.01.001.
- Doganova, L. and Eyquem-Renault, M. (2009) 'What do business models do?', *Research Policy*, 38(10), pp. 1559–1570. doi: 10.1016/j.respol.2009.08.002.
- Du, J. *et al.* (2018) 'Looking Deeper into the Factors Regulating Global Innovation with PCA and Rough Sets', *SAR Journal*, 1(3), pp. 95–106. doi: 10.18421/SAR13-04.
- Egeln, J. *et al.* (2012) *Gründungsaktivitäten im Hightech-Bereich in Baden- Württemberg*. Mannheim.
- Fernández-Guerrero, R., Revuelto-Taboada, L. and Simón-Moya, V. (2012) 'The business plan as a project: an evaluation of its predictive capability for business success', *The Service Industries Journal*, 32(15), pp. 2399–2420. doi: 10.1080/02642069.2012.677830.
- Fritscher, B. and Pigneur, Y. (2014) 'Visualizing Business Model Evolution with the Business Model Canvas: Concept and Tool', in *2014 IEEE 16th Conference on Business Informatics*. IEEE, pp. 151–158. doi: 10.1109/CBI.2014.9.
- Gatnar, E. *et al.* (2005) 'Data Mining - The Polish Experience', in *Innovations in Classification, Data Science, and Information Systems. Proceedings of the 27th Annual Conference of the Gesellschaft für Klassifikation e.V., Brandenburg University of Technology, Cottbus, March 12-14, 2003*. Springer, Berlin, Heidelberg (Studies in Classification, Data Analysis, and Knowledge Organization), pp. 217–223.
- Gay, B. (2014) 'Open innovation, networking, and business model dynamics: the two sides', *Journal of Innovation and Entrepreneurship*, 3(1). doi: 10.1186/2192-5372-3-2.
- George, G. and Bock, A. J. (2011) 'The Business Model in Practice and its Implications for Entrepreneurship Research', *Entrepreneurship Theory and Practice*, 35(1), pp. 83–111. doi: 10.1111/j.1540-6520.2010.00424.x.
- Graham, S. J. H. *et al.* (2009) 'High Technology Entrepreneurs and the Patent System: Results of the 2008 Berkeley Patent Survey.', *Berkeley Technology Law Journal*, 24(4), pp. 1255–1327. doi: 10.2139/ssrn.1429049.
- Greco, S., Matarazzo, B. and Slowinski, R. (2001) 'Rough sets theory for multicriteria decision analysis', *European Journal of Operational Research*, 129(1), pp. 1–47. doi: 10.1016/S0377-2217(00)00167-3.
- Greiner, L. E. (1998) 'Evolution and revolution as organizations grow. 1972.', *Harvard business review*, 76(3).
- Hanák, R. and Grežo, M. (2020) 'The effect of entrepreneurial experience on the quality of a business

- plan proposal in applying for angel investment', *International Journal of Entrepreneurial Venturing*, 12(6), pp. 617–647. doi: 10.1504/IJEV.2020.112239.
- Hart, M. A. (2012) 'The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses', *Journal of Product Innovation Management*, 29(3), pp. 508–509. doi: 10.1111/j.1540-5885.2012.00920_2.x.
- Hite, J. M. and Hesterly, W. S. (2001) 'The evolution of firm networks: From emergence to early growth of the firm', *Strategic Management Journal*, 22(3), pp. 275–286. doi: 10.1002/smj.156.
- Honig, B. and Karlsson, T. (2004) 'Institutional forces and the written business plan', *Journal of Management*, 30(1), pp. 29–48. doi: 10.1016/j.jm.2002.11.002.
- Johnston, L. and Sabin, K. (2010) 'Sampling hard-to-reach populations with respondent driven sampling', *Methodological Innovations Online*, 5, pp. 38–48. doi: 10.4256/mio.2010.0017.
- Kakati, M. (2003) 'Success criteria in high-tech new ventures', *Technovation*, 23(5), pp. 447–457. doi: 10.1016/S0166-4972(02)00014-7.
- Kazanjian, R. K. (2018) 'Relation of dominant problems to stages of growth in technology-based new ventures', *Academy of Management Journal*, 31(2), pp. 257–279. doi: 10.5465/256548.
- Kemal Avkiran, N. (1994) 'Developing an Instrument to Measure Customer Service Quality in Branch Banking', *International Journal of Bank Marketing*, 12(6), pp. 10–18. doi: 10.1108/02652329410063223.
- Kilkenny, M. and Love, N. F. (2014) 'Network analysis and business networks', *International Journal of Entrepreneurship and Small Business*, 21(3), p. 303. doi: 10.1504/IJESB.2014.060894.
- Konig, M. et al. (2016) 'Agreement on the Venture's Reality Presented in Business Plans Purifying a Multi-Dimensional Measurement Instrument to Improve Validity and Reliability', in *2016 International Conference on Engineering, Technology and Innovation/IEEE International Technology Management Conference (ICE/ITMC)*. Trondheim: IEEE, pp. 1–10. doi: 10.1109/ICE/ITMC39735.2016.9026148.
- Konig, M. et al. (2017) 'Business model validity in early-stage technology ventures' business plans testing agreement between text and reality', in *2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC)*. IEEE, pp. 930–937. doi: 10.1109/ICE.2017.8279982.
- König, M. et al. (2019) 'Different patterns in the evolution of digital and non-digital ventures' business models', *Technological Forecasting and Social Change*, 146(Special Issue on Digital Entrepreneurship), pp. 844–852. doi: 10.1016/j.techfore.2018.05.006.
- Konig, M., Baltes, G. and Katzy, B. (2015) 'On the role of value-network strength as an indicator of technology-based venture's survival and growth: Increasing innovation system efficiency by leveraging transaction relations to prioritize venture support', in *2015 IEEE International Conference on Engineering, Technology and Innovation/ International Technology Management Conference (ICE/ITMC)*. Belfast: IEEE, pp. 1–9. doi: 10.1109/ICE.2015.7438682.
- König, M., Ungerer, C. and Baltes, G. (2018) 'The Semantics of Entrepreneurial Learning in New Technology-Based Firms', in Presse, A. and Terzidis, O. (eds) *Technology Entrepreneurship, Insights in New Technology-Based Firms, Research Spin-Offs and Corporate Environments*. Springer, pp. 3–20. doi: 10.1007/978-3-319-73509-2_1.
- Lever, J., Krzywinski, M. and Altman, N. (2017) 'Principal component analysis', *Nature Methods*, 14(7), pp. 641–642. doi: 10.1038/nmeth.4346.
- Lussier, R. N. and Pfeifer, S. (2000) 'A Comparison of Business Success versus Failure Variables between U.S. and Central Eastern Europe Croatian Entrepreneurs', *Entrepreneurship: Theory & Practice*, 24(4), p. 59.
- Mainela, T. and Puhakka, V. J. (2013) 'Role of networks in emergence of international new ventures', *Int. J. Entrepreneurial Venturing*, 3(1), pp. 5–25. doi: 10.1504/IJEV.2011.037855.
- Maiya, A. S. and Berger-wolf, T. Y. (2011) 'Benefits of Bias: Towards Better Characterization of Network Sampling', *KDD 2011: 17th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 105–113. Available at: <http://dl.acm.org/citation.cfm?doid=2020408.2020431>.
- March, J. G. (1991) 'Exploration and Exploitation in Organizational Learning', *Organization Science*, 2(1), pp. 71–87. doi: 10.1287/orsc.2.1.71.
- Mcgrath, R. G. and Macmillan, I. C. (1995) 'Discovery driven planning: Turning conventional planning on its head', *Harvard Business Review*, 73, pp. 44–54.
- McKenzie, D. and Sansone, D. (2019) 'Predicting entrepreneurial success is hard: Evidence from a business plan competition in Nigeria', *Journal of Development Economics*, 141. doi:

- 10.1016/j.jdeveco.2019.07.002.
- Mitter, C. and Kraus, S. (2011) 'Entrepreneurial finance – issues and evidence, revisited', *International Journal of Entrepreneurship and Innovation Management*, 14(2/3), p. 132. doi: 10.1504/IJEIM.2011.041728.
- Mohaghar, A., Monawarian, A. and Raassed, H. (2010) 'Evaluation of technology transfer strategy of petrochemical process', *The Journal of Technology Transfer*, 37(4), pp. 563–576. doi: 10.1007/s10961-010-9180-9.
- Nagamachi, M. (2006) 'Kansei engineering and rough sets model', in *Rough Sets and Current Trends in Computing: 5th International Conference*, pp. 27–37. doi: 10.1007/11908029_4.
- Nguyen-Duc, A., Shah, S. M. A. and Amrahamsson, P. (2016) 'Towards an Early Stage Software Startups Evolution Model', in *IEEE*, pp. 120–127. doi: 10.1109/SEAA.2016.21.
- Nyström, A.-G. and Mustonen, M. (2017) 'The dynamic approach to business models', *AMS Review*, 7(3–4), pp. 123–137. doi: 10.1007/s13162-017-0103-x.
- Oksanen, P., Hallikas, J. and Sissonen, H. (2010) 'The evolution of value networks', *International Journal of Networking and Virtual Organisations*, 7(4), p. 381. doi: 10.1504/IJNVO.2010.032914.
- Osterwalder, A. et al. (2010) *Business Model Generation : A Handbook for Visionaries, Game Changers, and Challengers* by Alexander Osterwalder. doi: 10.3406/antiqu.2003.2508.
- Petersen, D. R. and Ahmad, N. (2007) 'High-Growth Enterprises and Gazelles - Preliminary and Summary Sensivity Analysis', pp. 1–16.
- Podsiadlo, M. and Rybinski, H. (2016) 'Financial time series forecasting using rough sets with time-weighted rule voting', *Expert Systems with Applications*, 66, pp. 219–233. doi: 10.1016/j.eswa.2016.08.066.
- Ries, E. (2011) *The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses*, Crown Business. doi: 23.
- Rissino, S. and Lambert-torres, G. (2009) 'Rough Set Theory – Fundamental Concepts , Principals , Data Extraction , and Applications', *Data Mining and Knowledge Discovery in Real Life Applications*, (February), pp. 35–58. doi: 10.5772/6440.
- Sahlman, W. A. (1997) 'How to Write a Great Business Plan', *Harvard Business Review*.
- Samuelson, P. (2010) 'Why do software startups patent (or not)?', *Communications of the ACM*, 53(11), p. 30. doi: 10.1145/1839676.1839687.
- Shane, S. and Delmar, F. (2004) 'Planning for the market: business planning before marketing and the continuation of organizing efforts', *Journal of Business Venturing*, 19(6), pp. 767–785.
- Shi, Y. and Li, X. (2019) 'A bibliometric study on intelligent techniques of bankruptcy prediction for corporate firms', *Heliyon*. Elsevier Ltd, p. e02997. doi: 10.1016/j.heliyon.2019.e02997.
- Simon, P. (2012) *Frühindikatoren der wirtschaftlichen Entwicklung von Jungunternehmen: eine empirische Untersuchung von Businessplänen*. Coperate L. Edited by K. Nathusius. Lohmar - Köln: EUL Verlag. Available at: http://books.google.de/books/about/Frühindikatoren_der_wirtschaftlichen_En.html?id=iB75TOq8CL0C&pgis=1 (Accessed: 14 December 2014).
- Stachowiak, H. (1973) *Allgemeine Modelltheorie*, Library. Vienna: Springer Vienna. doi: 10.1007/978-3-7091-8327-4.
- Succurro, M., Arcuri, G. and Costanzo, G. D. (2019) 'A combined approach based on robust PCA to improve bankruptcy forecasting', *Review of Accounting and Finance*, 18(2), pp. 296–320. doi: 10.1108/RAF-04-2018-0077.
- Sullivan, D. M. and Ford, C. M. (2014) 'How Entrepreneurs Use Networks to Address Changing Resource Requirements During Early Venture Development', *Entrepreneurship Theory and Practice*, 38(3), pp. 551–574. doi: 10.1111/etap.12009.
- Sykes, H. B. and Dunham, D. (1995) 'Critical assumption planning: A practical tool for managing business development risk', *Journal of Business Venturing*, 10(6), pp. 413–424. doi: 10.1016/0883-9026(95)00085-M.
- Syms, C. (2008) 'Principal Components Analysis', in Jørgensen, S. E. and Fath, B. D. (eds) *Encyclopedia of Ecology*. Oxford: Academic Press, pp. 2940–2949. doi: 10.1016/B978-008045405-4.00538-3.
- Tam, S. and Gray, D. E. (2016) 'Organisational learning and the organisational life cycle: The differential aspects of an integrated relationship in SMEs', *European Journal of Training and*

- Development*, 40(1), pp. 2–20. doi: 10.1108/EJTD-07-2015-0052.
- Trailer, J. W., Hill, R. C. and Murphy, G. B. (1996) ‘Measuring performance in entrepreneurship research’, *Journal of Business Research*, 36(1), pp. 15–23. doi: 10.1016/0148-2963(95)00159-X.
- Yao, Y. (2009) ‘Three-way decision: An interpretation of rules in rough set theory’, in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Springer, Berlin, Heidelberg, pp. 642–649. doi: 10.1007/978-3-642-02962-2_81.