Four Essays on the Complexity of Entrepreneurial Ecosystems

Doctoral Dissertation

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by

Tim Haarhaus, M.Sc.
Email: tim.haarhaus@tu-dortmund.de

Reviewers:

Prof. Dr. Andreas Liening
Chair of Entrepreneurship and Economic Education
TU Dortmund University

Prof. Dr. Andreas Hoffjan
Chair of Management Accounting and Controlling
TU Dortmund University

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To Patricia

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A Introduction

“As we begin to understand complex systems, we begin to understand that we're part of an ever-changing, interlocking, non-linear, kaleidoscopic world.”
W. Brian Arthur (1992)

1 Motivation

Entrepreneurship is considered as an important driving force for economic growth (Schumpeter, 1947; Davidsson et al., 2006). Most entrepreneurship research has concentrated on the traits and behaviors of individual entrepreneurs or ventures (Wiklund, 1999; Shane and Venkataraman, 2000; Baker and Welter, 2020). While this still holds true, a growing number of scholars calls for a stronger emphasis on the systemic and contextual nature of entrepreneurship (Szerb et al., 2013; Roundy et al., 2018), because observers “have a tendency to underestimate the influence of external factors and overestimate the influence of internal or personal factors when making judgements about the behavior of other individuals” (Gartner, 1995, p. 70).

Accordingly, a novel stream of research has emerged in the field of entrepreneurship that investigates the contextual factors of entrepreneurial activity and how entrepreneurial regions evolve (Welter and Baker, 2020). This shift in perspective is reflected by the entrepreneurial ecosystem approach, which has received heightened attention from scholars, policy-makers and practitioners over the last decade (Wurth et al., 2021; Roundy et al., 2018). The concept of entrepreneurial ecosystems refers to “dynamic local social, institutional, and cultural processes and actors that encourage and enhance new firm formation and growth” (Malecki, 2018, p. 1) and originated from different related literatures, such as business ecosystems (Moore, 1993), industrial districts (Asheim, 1996), clusters (Rocha, 2004; Delgado et al., 2010), innovation systems (Cooke, 2007) and entrepreneurial environments (Van de Ven, 1993). However, what distinguishes the concept of entrepreneurial ecosystems from these other approaches is its specific focus on the role of entrepreneurs and start-up ventures (Stam and Spigel, 2017).

The notion of entrepreneurial ecosystems quickly gained traction among governmental and non-governmental actors, such as the World Economic Forum (Foster et al., 2013) and the OECD (Mason and Brown, 2014). Its popularity in academic and policy circles facilitated the recent implementation of several ecosystem policies that aimed at initiating or enhancing place-based entrepreneurial ecosystems (Wurth et al., 2021), e.g., *Expanding Entrepreneurial Ecosystems* as part of the European Union's Horizon Europe program, *Startup Estonia* in Estonia and *Startup Delta/TechLeap.NL* in the Netherlands.

Generally, the entrepreneurial ecosystem framework provides a deeper understanding of the essential ingredients of established ecosystems, including universities, investors, incumbent firms, support organizations, and entrepreneurial actors (among other factors), as well as insights into the key relationships between these stakeholders (Malecki, 2018; Roundy et al., 2018). Furthermore, by synthesizing previously disconnected literatures in the areas of business strategy and regional development, the concept of entrepreneurial ecosystems offers a new perspective for analyzing how entrepreneurial activity might transform regions or countries (Wurth et al., 2021; Malecki, 2018; O'Connor et al., 2018).

However, in spite of these important advances in research on entrepreneurial ecosystems, it has been noted that existing research applies a predominantly static, mechanistic framework to study entrepreneurial ecosystems (Roundy et al., 2018; Welter and Baker, 2020; Kuckertz, 2019). Moreover, current examinations mostly ignore the dynamic combinations of sets of factors, as well as the nonlinear interdependencies between ecosystem actors, that drive the evolution of entrepreneurial ecosystems (Malecki, 2018; Roundy et al., 2018).

In order to address these research gaps, this thesis serves the following purposes. First, it aims to enhance our understanding concerning the dynamic evolution of entrepreneurial ecosystems by investigating the self-organizing mechanisms that facilitate ecosystem emergence. In this regard, this work also intends to provide quantitative empirical evidence on the hypothesized complex dynamics of entrepreneurial ecosystems. Second, this thesis aims to explore how digitalization affects the broader entrepreneurial landscape by examining the topological characteristics of digital entrepreneurial ecosystems as well as the sets of digital technologies and infrastructures that in combination facilitate new venture formation in regional entrepreneurial ecosystems. Given the aforementioned gaps in the literature, this thesis uses a complex systems approach to study the dynamic processes and interdependencies within entrepreneurial ecosystems, because entrepreneurial ecosystems "emerge from nonlinear and dynamic combinations of sets of variables" (Roundy et al., 2018, p. 7).

Since it is still unclear how entrepreneurial ecosystems evolve over time and which combinations of factors drive the emergence of ecosystems, the findings of this thesis offer new insights for researchers, managers and policy-makers. Extending previous work on the development of entrepreneurial ecosystems, this research identifies the evolution of entrepreneurial ecosystems as a chaotic process. Furthermore, this thesis provides a holistic view on the digital framework conditions that promote the creation of new start-up ventures and establishes a network representation of a digital entrepreneurial ecosystem. The results of this thesis demonstrate that entrepreneurs, managers as well as policy-makers should expect complex, nonlinear dynamics throughout the evolution of entrepreneurial ecosystems. This finding has far-reaching implications for the governance of entrepreneurial ecosystems and stakeholder relationships therein.

2 Overview and summary of contributions

As illustrated in Figure 1, this thesis consists of four distinct essays which, in combination, aim to enhance the understanding of the complexity of entrepreneurial ecosystems.

Essay	**1**	**2**	**3**	**4**
Research issue	Assessing the complex dynamics of entrepreneurial ecosystems	Analyzing the factors of digitalization that enable new venture creation in entrepreneurial ecosystems	Generating a harmonized understanding of ecosystem conceptualizations	Exploring the structure of digital entrepreneurial ecosystems
Data	Monthly new business formation in Singapore between 1970 and 2018	Data on 35 regional entrepreneurial ecosystems across 19 countries in Europe	71 articles for in-depth literature review	111 application programming interfaces (APIs) and 150 API mashups in the healthcare domain
Methodology	Pointwise D2, Brock-Dechert-Scheinkman test, Local Largest Lyapunov Exponents	Fuzzy-set qualitative comparative analysis	Structured literature review and cluster analysis	Network analysis

Fig. 1. Dissertation structure.

Subsequent to the introduction (*part A)*, essay 1 (*part B*) applies three methods from chaos theory to study the nonlinear dynamics of the Singapore entrepreneurial ecosystem. In essay 2 (*part C*), we examine the combinations of digital technologies and infrastructures that lead to high or low to medium levels of new venture formation in regional entrepreneurial ecosystems. In essay 3 (*part D*), we analyze existing ecosystem conceptualizations and develop a typology of ecosystems based on the derivation of generic ecosystem characteristics. In essay 4 (*part E*), we use data-driven visualizations of application programming interfaces (APIs) and API mashups to investigate the topological characteristics of a digital entrepreneurial ecosystem. Finally, the conclusion (*part F*) summarizes the key findings of the four essays and discusses the theoretical as well as practical implications of this thesis. The related literature is discussed within the respective essays. The following section outlines the main contributions of the individual essays.

Essay 1

In essay 1 (*part B*), we apply three methods from chaos theory to analyze the complex dynamics of entrepreneurial ecosystems. While extant research has conceptualized the evolution of entrepreneurial ecosystems as a dynamic and emergent process, quantitative empirical evidence on the hypothesized complex dynamics of entrepreneurial ecosystems is still lacking. Thus, we apply three techniques from complexity theory, namely the Pointwise D2 (PD2), the Brock-Dechert-Scheinkman (BDS) test and Local Largest Lyapunov Exponents (LLLE), to investigate the development of the Singapore entrepreneurial ecosystem from 1970 to 1980. Our findings suggest that the evolution of entrepreneurial ecosystems can be considered as a chaotic process in which an initial period of critical instability is followed by an enduring phase of order generation which is characterized by recurring chaotic fluctuations.

Essay 2

Essay 2 (*part C*) explores the combinations of digital technologies and infrastructures that facilitate new venture formation in regional entrepreneurial ecosystems. Whereas recent literature emphasizes the role of digitalization as a crucial enabler of entrepreneurial activity, it is still unclear how digitalization affects the broader entrepreneurial landscape. Furthermore, extant research on the intersection between digitalization and entrepreneurial ecosystems did not incorporate the increasing complexity infused by digital technologies. Hence, we employ fuzzy-set qualitative comparative analysis (fsQCA), a configurational approach to understand complex phenomena, in order to identify the sets of digital framework conditions that lead to high or low to medium levels of entrepreneurial activity. We draw on data from 35 regional entrepreneurial ecosystems across 19 countries in Europe. Our results indicate that two specific configurations of digital framework conditions are conducive to relatively high start-up activity in entrepreneurial ecosystems, and four configurations may lead to relatively low to medium start-up activity in entrepreneurial ecosystems. In addition, we find that digitally skilled human capital, advanced digital government and an appropriate digital market are particularly important factors for facilitating new venture formation in entrepreneurial ecosystems.

Essay 3

In essay 3 (*part D*), we analyze differing ecosystem conceptualizations, derive generic ecosystem characteristics and propose five idealized types of ecosystems. While the popularity of the ecosystem approach gave rise to a multitude of ecosystem conceptualizations, such concepts are often characterized by conceptual blurring and overlap. Thus, in order to allow for a clear delimitation and differentiability between existing ecosystem concepts, we develop a generic ecosystem typology that is based on a structured literature review and the derivation of generic ecosystem characteristics. Our initial literature search included 6.308 scanned articles and further selection of the core literature resulted in 71 articles relevant for in-depth analysis. The literature review identified five overarching ecosystem characteristics, namely population, purpose, relationship structure, system configuration and system dynamics. Furthermore, derived from the analysis of ecosystem characteristics, we outline five distinct ecosystem types, which include sociocentric ecosystems, symbiotic collective ecosystems, centrally balanced ecosystems, orchestrating actor ecosystems, as well as structured resource sharing ecosystems.

Essay 4

In essay 4 (*part E*), we analyze the topological characteristics of digital entrepreneurial ecosystems utilizing data-driven visualizations of APIs and mashups. While the concept of digital entrepreneurial ecosystems is rapidly emerging in the literature, rigorous empirical studies on the structure of such systems and interfirm relationships therein are still lacking. In order to uncover the underlying structure of digital entrepreneurial ecosystems, we use APIs as distinct types of boundary resources and mashups to create a network representation of an exemplary case, i.e., the global digital health ecosystem. The established network contains 261 nodes consisting of 111 APIs, 150 mashups and 271 edges. The findings from the network analysis suggest that prominent APIs from incumbent companies represent key resources for health start-ups that operate in the digital entrepreneurial ecosystem. Furthermore, through generating clusters, we structure the existing landscape of applications in the digital health ecosystem and identify four dominant types of services. Lastly, we present the geographical distribution of APIs and mashups in the digital health ecosystem.

3 Publication history

This doctoral dissertation represents the composition of four different research articles. All four research articles were substantially authored by the doctoral student. Each of the articles has been submitted to research conferences and/or peer-reviewed scientific journals. The following paragraph outlines the publication history of the four research articles included in this doctoral dissertation.

Essay 1: "Assessing the Complex Dynamics of Entrepreneurial Ecosystems: A Nonstationary Approach"

Keywords:

Entrepreneurial ecosystems, new venture creation, complexity, chaos theory, nonlinearity.

A short version of this manuscript was originally published in the *Journal of Business Venturing Insights*:

- Haarhaus, T., Strunk, G., & Liening, A. (2020). Assessing the complex dynamics of entrepreneurial ecosystems – a nonstationary approach. *Journal of Business Venturing Insights*, 14. https://doi.org/10.1016/j.jbvi.2020.e00194.

Presentations:

- 2nd Annual Conference on the Geography of Innovation and Complexity, Utrecht, Netherlands. September 04, 2019.
- 39th Babson College Entrepreneurship Research Conference (BCERC), Wellesley, USA. June 06, 2019.

Essay 2: "Digital Framework Conditions of Entrepreneurial Activity in Cities: A fsQCA Approach"

Keywords:

Digitalization, digital entrepreneurship, entrepreneurial ecosystems, fsQCA.

A short version of this manuscript was originally published in *Proceedings of the 39th International Conference on Information Systems (ICIS)*:

- Haarhaus, T., Geiger, J. M., & Liening, A. (2018). The influence of digitalization on emergent processes of entrepreneurial ecosystems – a complexity science perspective (Short Paper). *Proceedings of the 39th International Conference on Information Systems (ICIS)*.

Presentations:

- 39th International Conference on Information Systems (ICIS), San Francisco, USA. December 14, 2018.

Essay 3: "Ecosystem Types in Information Systems"

Keywords:

Ecosystems, typology, ideal types, literature review.

This manuscript was originally published in *Proceedings of the 28th European Conference on Information Systems (ECIS)*:

- Guggenberger, T. M., Möller, F., Haarhaus, T., Gür, I., & Otto, B. (2020). Ecosystem Types in Information Systems. *Proceedings of the 28th European Conference on Information Systems (ECIS)*.

Presentations:

- 28th European Conference on Information Systems (ECIS), online edition due to pandemic.

Essay 4: "APIs as Boundary Resources of Digital Entrepreneurial Ecosystems: The Case of Digital Health Start-ups"

Keywords:

Digital entrepreneurial ecosystems, boundary resources, application programming interfaces, digital health, network analysis.

A short version of this manuscript was originally published in *Frontiers of Entrepreneurship Research (FER) 2020*:

- Haarhaus, T., Stachon, M., Möller, F., Geiger, J. M., Liening, A., & Otto, B. (2020). APIs as boundary resources of digital entrepreneurial ecosystems: the case of digital health startups (Summary). *Frontiers of Entrepreneurship Research (FER) 2020*.

Presentations:

- 40th Babson College Entrepreneurship Research Conference (BCERC), online edition due to pandemic.

B Essay 1: Assessing the Complex Dynamics of Entrepreneurial Ecosystems: A Nonstationary Approach

The following is based on Haarhaus et al. (2020):

Haarhaus, T., Strunk, G., & Liening, A. (2020). Assessing the complex dynamics of entrepreneurial ecosystems – a nonstationary approach. *Journal of Business Venturing Insights*, 14. https://doi.org/10.1016/j.jbvi.2020.e00194.

Abstract

The notion of entrepreneurial ecosystems has received growing interest from scientists, practitioners and policy-makers over the past decade. Whereas previous research has predominantly focused on identifying the main components and attributes of different ecosystems, the understanding of how entrepreneurial ecosystems evolve over time is still limited. In this study, we build on recent conceptualizations of entrepreneurial ecosystems as complex adaptive systems and apply three methods from chaos theory, the Pointwise D2 (PD2), the Brock-Dechert-Scheinkman (BDS) test and Local Largest Lyapunov Exponents (LLLE), to study the nonlinear dynamics of entrepreneurial ecosystems. To illustrate our ideas, we analyze the development of the Singapore entrepreneurial ecosystem from 1970 to 2018, using time series data on the monthly creation of new ventures. Our results suggest that the evolution of an entrepreneurial ecosystem can be considered as a nonlinear chaotic process that changes over time. Implications for theory and practice, as well as limitations and future research directions, are discussed.

Keywords:

Entrepreneurial ecosystems, new venture creation, complexity, chaos theory, nonlinearity.

1 Introduction

The concept of entrepreneurial ecosystems represents a burgeoning research field that has received increased interest from academics, practitioners and policy-makers over the recent decade (Roundy et al., 2018; Spigel and Harrison, 2018). Entrepreneurial ecosystems are perceived as combinations of interconnected organizations, institutions, actors and actions which are arranged in such a way that they facilitate and perpetuate entrepreneurial activity within regional environments (Auerswald, 2015; Mason and Brown, 2014; Roundy et al., 2017). Until today, research on entrepreneurial ecosystems has mainly focused on the description of the main components of different ecosystems (Roundy et al., 2018). A variety of investigations has concentrated on examining established ecosystems, thereby providing a comprehensive overview of the core elements and characteristics of entrepreneurial ecosystems (Isenberg, 2010; Spigel, 2017). Essential components comprise a culture that supports entrepreneurs and start-up ventures, strong networks which connect entrepreneurs with key resources, and organizations as well as institutions that promote entrepreneurial activity, such as universities, incubators, investors and policy (Spigel and Harrison, 2018).

While these conceptions are important to understand the composition of entrepreneurial ecosystems, it has been noted that extant research applies a predominantly static framework to investigate entrepreneurial ecosystems, thus neglecting that ecosystems constantly evolve (Alvedalen and Boschma, 2017; Sussan and Acs, 2017; Kuckertz, 2019). In addition, literature had a tendency to depict entrepreneurial ecosystems as structures that consist of entirely or partly separate parts and as marked by causal or linear interrelations between actors (Roundy et al., 2018), whereas entrepreneurial ecosystems actually "emerge from nonlinear and dynamic combinations of sets of variables" (Roundy et al., 2018, p. 7). Hence, there is growing consent among researchers that evolutionary, longitudinal perspectives are required to explain the emergent and complex dynamics of entrepreneurial ecosystems (Auerswald and Dani, 2017; Autio et al., 2018a; Kuckertz, 2019).

In fact, scholars are increasingly considering the complex and evolutionary nature of entrepreneurial ecosystems in order to adequately conceptualize its evolution (Colombelli et al., 2019; Roundy et al., 2018; Auerswald and Dani, 2017; Mack and Mayer, 2016; Spigel, 2017). However, quantitative empirical evidence on the hypothesized complex dynamics of entrepreneurial ecosystems is still missing. We believe the time is ripe to advance the debates about applying techniques from complexity theory to the phenomenon of entrepreneurial ecosystems (e.g., Roundy et al., 2018) and begin utilizing quantitative methods to analyze entrepreneurial ecosystem dynamics. Thus, this paper aims to empirically assess the evolution of entrepreneurial ecosystems. We apply three methods from chaos theory, the Pointwise D2 (PD2) which describes changes in a system's complexity over time (Skinner et al., 1994), the Brock-Dechert-Scheinkman (BDS) test that identifies nonlinear serial dependence in a time series (Brock et al., 1996), and Local Largest Lyapunov Exponents (LLLE) which indicate variations in the chaoticity of the examined system dynamics (Kowalik et al., 1997), to the empirical case of the Singapore entrepreneurial ecosystem. Our study substantiates the notion of a complex and nonlinear evolution of entrepreneurial ecosystems and answers the calls for further empirical investigations in this area (Kuckertz, 2019; Roundy et al., 2018). In the following paragraph, we review recent literature on the evolution of entrepreneurial ecosystems. Then, we explain the methods employed for assessing the complex dynamics of entrepreneurial ecosystems. Lastly, we discuss the implications for theory and practice, as well as future research directions.

2 Dynamics of entrepreneurial ecosystems – a brief review

2.1 Evolution of entrepreneurial ecosystems

The notion of entrepreneurial ecosystems as regional agglomerations of entrepreneurial activity has garnered increasing interest from scholars and policy-makers (Kuckertz, 2019; Roundy et al., 2018). The recent rise of the concept is evidenced by a shift in entrepreneurship research, where the use of the term entrepreneurial ecosystem has surpassed related and preceding concepts dealing with the entrepreneurial context, such as systems, infrastructures or environments for entrepreneurship (Malecki, 2018). Despite the concept's popularity, current literature on entrepreneurial ecosystems has frequently been criticized for applying a rather static framework that concentrates on the essential components of the system, while neglecting its evolution over time (Alvedalen and Boschma, 2017; Stam, 2015; Brown and Mason, 2017; Spigel, 2017; Malecki, 2018; Mack and Mayer, 2016). Thus, we share the view of Malecki (2018, p. 10) that "in order to understand the emergence and evolution of an entrepreneurial ecosystem, we have to go beyond the lists of factors/components/elements approach."

The few existing conceptualizations of entrepreneurial ecosystem development are largely based on evolutionary approaches to life cycle dynamics in social and natural systems (Colombelli et al., 2019; Auerswald and Dani, 2017; Brown and Mason, 2017; Mack and Mayer, 2016). According to this evolutionary perspective, entrepreneurial ecosystems emerge from self-reinforcing interactions between the systems' elements which, in turn, initiate feedback mechanisms that enable the self-organization of the structures and behaviors of entrepreneurial ecosystems (Roundy et al., 2018; Auerswald and Dani, 2017). Additionally, several scholars have pointed out the nonlinear, dynamic nature of entrepreneurial ecosystems, meaning that the evolution of entrepreneurial ecosystems involves fundamental changes that potentially result in multiple outcomes (Brown and Mason, 2017; Colombelli et al., 2019). In this context, Auerswald and Dani (2017, p. 105) found that the life cycle of entrepreneurial ecosystems is best characterized by “the evolutionary dynamics of complex adaptive systems”, as opposed to traditional industry life cycle frameworks that follow rather linear developmental trajectories. Therefore, we share the opinion of Brown and Mason (2017, p. 26) who suggest that scholars studying entrepreneurial ecosystems should “appreciate the full complexity of the dynamics of entrepreneurial activity”.

2.2 Complex dynamics of entrepreneurial ecosystems

Generally, entrepreneurship is considered as “a complex social phenomenon in a particular spatial and temporal context” and defined “by complex, dynamic and emergent processes, and the interplay between actors, processes, and contexts” (Karatas-Ozkan et al., 2014, p. 590). More recently, entrepreneurship scholars have begun to apply complexity theory to entrepreneurial ecosystems and conceptualize them as complex adaptive systems (Han et al., 2019; Aeeni and Saeedikiya, 2019; Roundy et al., 2018; Arikan, 2010), i.e., systems in which the interactions between complex elements on the system’s micro-level generate novel behaviors on the macro-level (Dooley, 1997; Levin, 2005; Haken, 1979; Liening, 2014; Strunk et al., 2004). As suggested by several researchers, entrepreneurial ecosystems exhibit the preconditions necessary for the development of complex system dynamics (Roundy et al., 2018; Han et al., 2019).

For instance, entrepreneurial ecosystems consist of numerous heterogeneous components (e.g., individual entrepreneurs, investors, governments or accelerators) that have multiple roles and operate at different levels (Spigel, 2017; Lichtenstein, 2011). Complexity then arises from the interactive relationships between various ecosystem agents; furthermore, entrepreneurial ecosystems have open-but-distinct boundaries which enable the system to exchange resources and information with its environment (Spigel and Harrison, 2018; Roundy et al., 2018). The dissipation of specific types of entrepreneurial resources (e.g., human or financial capital) throughout the ecosystem subsequently may result in complex system dynamics; entrepreneurial ecosystems also exhibit both positive and negative feedback loops which occur when entrepreneurial activities feed back on themselves (Roundy et al., 2018; Cilliers, 1998). Whereas positive feedback between two elements leads to a self-reinforcing, indefinite growth of certain system behaviors and negative feedback loop results in steady-state equilibria (Senge, 1990), 'mixed' feedback is required to develop complex system dynamics (an der Heiden and Mackey, 1987); in addition, interactions among the agents in an entrepreneurial ecosystem are often of nonlinear nature, meaning that relatively small inputs can lead to disproportionally large outputs (Brown and Mason, 2017; Han et al., 2019; Roundy et al., 2018). This nonlinearity generates a characteristic feature of complex systems which is also shared by entrepreneurial ecosystems, namely sensitivity to starting conditions (Roundy et al., 2018; McKelvey, 2004): slight changes in the initial configurations of entrepreneurial ecosystems potentially result in significant and unforeseen consequences over time (Roundy et al., 2018; Han et al., 2019). Importantly, such ecosystem dynamics and behaviors are not controlled by a single agent or organization, but emerge from the micro-interactions between the system's elements in a process of self-organization (Isenberg, 2010; Roundy et al., 2018).

Taken together, recent conceptualizations suggest that the evolution of entrepreneurial ecosystems can be identified as a complex and dynamic process that changes over time (Roundy et al., 2018; Han et al., 2019). Whereas these conceptions represent an important contribution to a better understanding of the dynamic and emergent processes inherent in entrepreneurial ecosystems, it has been noted that "the empirical analysis of the dynamics of networks in entrepreneurship studies is still rare" (Alvedalen and Boschma, 2017, p. 9). Hence, in this study, we empirically assess the complex dynamics of entrepreneurial ecosystems by applying three methods from chaos theory.

3 Methodology

In general, the term chaos refers to "erratic or apparently random time-dependent behavior in deterministic systems" (Kanters et al., 1994, p. 591). Chaos theory is thus concerned with the behavior of deterministic nonlinear dynamical systems which are highly sensitive to initial conditions (Azar and Vaidyanathan, 2016). This sensitivity to initial conditions is also referred to as the 'butterfly effect' where small variations in the initial conditions can lead to unexpected, large changes in the system over time (Gleick, 1987; Farazmand, 2014). Chaos theory is often considered as a subdivision of complexity theory (Bloom, 2000). However, while chaos theory focuses on the manner in which simple systems generate complicated patterns of behavior that cannot be predicted, complexity theory investigates how systems composed of many systems can produce ordered and predictable behavior (Bloom, 2000).

Chaos theory offers several powerful tools for examining the dynamics of natural and social systems (Krasner, 1990; Wagner et al., 1996). Being based on the mathematics of nonlinear dynamics, i.e., "the study of the temporal evolution of nonlinear systems" (Kiel and Elliott, 1996, p. 1), chaos theory goes beyond metaphorical descriptions of the evolutionary change processes that characterize complex systems (Hung and Tu, 2014). Consequently, methods from chaos theory have been frequently applied to analyze the temporal dynamics of various social phenomena and systems, such as the innovation process (Cheng and Van de Ven, 1996), technological change processes (Hung and Tu, 2014), career pathways (Strunk, 2009), industry environments (Ndofor et al., 2018) and tourism systems (Baggio and Sainaghi, 2011). While there exists a variety of methods from chaos theory, we apply three techniques, the Pointwise D2 (PD2), the Brock-Dechert-Scheinkman (BDS) test and Local Largest Lyapunov Exponents (LLLE), to evaluate the complex dynamics of entrepreneurial ecosystems. We focus on these three measures because they allow us to test for the main features of chaotic systems, namely dimensional complexity (PD2), the existence of nonlinearity (BDS test), and sensitive dependence on initial conditions (LLLE) (Cheng and Van de Ven, 1996; Ndofor et al., 2018). Each of these methods has been widely used to test for chaos in nonstationary time series data (see, e.g., Kowalik et al., 1997; Lim and Hooy, 2013). In combination, the three measures provide a robust and relatively precise identification of changes in the system dynamics over time.

3.1 Data and measurement

In this study, we examine the evolution of the Singapore entrepreneurial ecosystem from January 1970 to May 2018, using archival time series data on the monthly creation of new ventures obtained from the Singapore Department of Statistics (Singapore Department of Statistics, 2019). The period of analysis was chosen due to the availability of data. Our 48-year study period is appropriate because it covers almost the entire evolution of the Singapore entrepreneurial ecosystem, including the very early stages of ecosystem development with only 80 new companies formed in January 1970 (Singapore Department of Statistics, 2019). Hence, analysis of the period from 1970 to 2018 provides insight into the transformation of the Singapore entrepreneurial ecosystem from a small domestic market with high dependence on foreign investment to one of the world's leading hubs for high-tech entrepreneurship (UNESCAP, 2018). We utilize new venture creation as a proxy to measure ecosystem dynamics, because new venture creation is considered as the outcome of the interaction between various stakeholders and elements (Cavallo et al., 2019; Gartner, 1985), thus adequately representing the overall entrepreneurial activity within regional agglomerations.

Several earlier studies have conceptualized the Singapore entrepreneurial ecosystem as a single, country-level entrepreneurial ecosystem (see, e.g., Berger and Kuckertz, 2016; Nylund and Cohen, 2017). The case of Singapore provides an appropriate context for studying the complex dynamics of entrepreneurial ecosystems for three main reasons: first, Singapore has one of the world’s strongest entrepreneurial ecosystems, featuring three ‘unicorns’ (i.e., start-up ventures that are valued at over one billion dollars), a highly qualified workforce, high availability of early-stage funding and a leading role in the development of new technologies, such as Blockchain and Fintech (Startup Genome, 2018; CB Insights, 2019). Second, Singapore’s rapid transformation from a third world country to a first world country in a single generation is characterized by several periods of dynamic economic and social change (UNESCAP, 2018). Since our goal is to examine the patterns of dynamic change and chaotic behavior, the Singapore entrepreneurial ecosystem provides a fitting context for our study. Third, Singapore’s city-state character makes it a suitable case for investigating system-level entrepreneurial dynamics, because entrepreneurial activity is primarily concentrated in cities or regions (O’Connor et al., 2018). As illustrated in Fig. 2, we captured 581 sample months (hence, data points) of new venture creation during the study period. Regarding other studies that focused on analyzing complex phenomena, our sample size is comparable to those of Thietart and Forgues (1997) (445 data points), Hung and Tu (2014) (420 data points), Cheng and Van de Ven (1996) (two samples of 96 and 152 data points) and Jayanthi and Sinha (1998) (125 data points).

Fig. 2. Raw time series of new venture creation, 1970/1 to 2018/5.

3.2 Analytical strategy

Conventional nonlinear methods, such as the correlation dimension (D2) (Grassberger and Procaccia, 1983) and Largest Lyapunov Exponents (LLE) (Wolf et al., 1985; Rosenstein et al., 1993), suppose that attractors, i.e., the specific territories around which the system trajectory moves and that set the boundaries of the system's long-term behaviors (Ruelle and Takens, 1971; Ikiugu, 2005; Hung and Tu, 2014), remain stable throughout the measurement of the examined process (Kowalik et al., 1997). In light of current conceptualizations of the evolution of entrepreneurial ecosystem as a dynamic and nonlinear process, this stationarity assumption might not be appropriate for entrepreneurial ecosystems. Thus, it could be more accurate to assume nonstationarity of the examined time series, meaning that the statistical properties of the time series could change considerably over the observation period (Hively et al., 2000). Critical transitions should typically be expected in the case of long observation periods, e.g., in the study of business cycles and economic dynamics (Chen, 1996; Hamilton, 1989). Consequently, we apply tools from chaos theory which do not require stationarity of the underlying time series in order to uncover the temporal dynamics of entrepreneurial ecosystems. Before applying the three measures described below, the raw times series data was transformed into logarithmic returns (see Fig. 3) to obtain a realistic representation of the system's internal dynamics and to eliminate strong seasonality or trend effects (Baggio, 2008; Baggio and Sainaghi, 2011). Using logarithmic transformations instead of the raw time series is a common procedure in the analysis of economic and financial time series, because seasonality or trend effects in the original time series data could positively bias the detection of chaotic patterns in a time series (Cheng and Van de Ven, 1996).

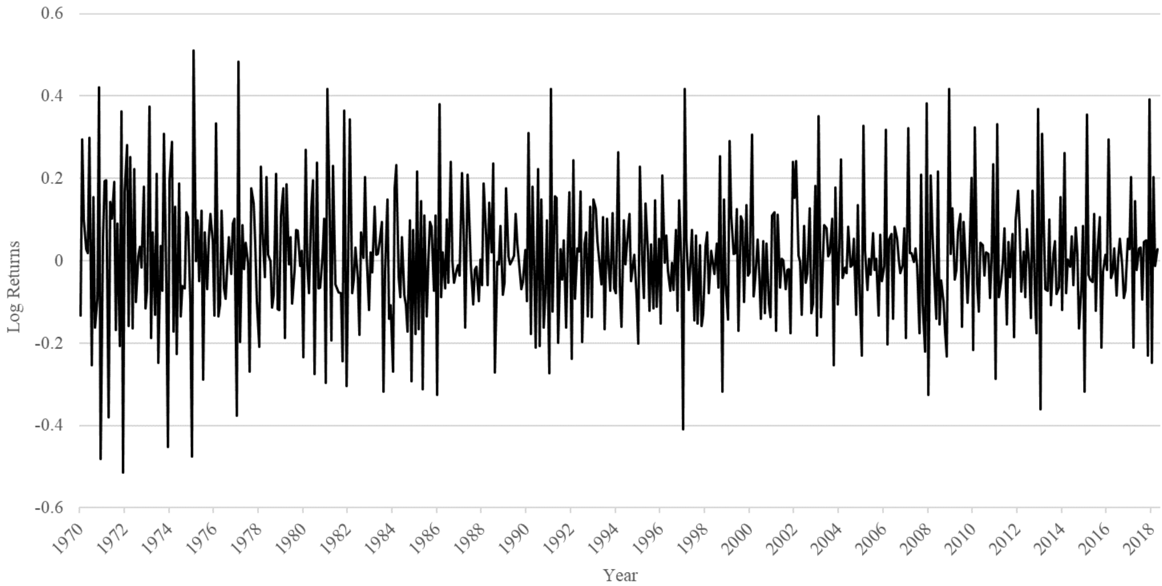

Fig. 3. Time series of logarithmic returns.

The PD2 is a modification of the correlation dimension D2 and indicates pointwise variations in the dimensional complexity of a system (Skinner et al., 1994; Kowalik et al., 1997). The D2 provides estimates of how many independent system elements influence the system dynamics and how many independent behaviors a system can exhibit, thus quantifying the number of degrees of freedom needed to describe a system (Grassberger and Procaccia, 1983; Schiepek et al., 2016). The determination of the D2 requires the reconstruction of a phase space (i.e., a set of coordinates that specifically determine the state of the system) of a time series and its attractor (Grassberger and Procaccia, 1983). The D2 is then estimated by calculating the relative number of pairs of arbitrarily chosen points close to an attractor that are separated by a distance less than a predefined value, hence indicating the density of points in the phase space (Grassberger and Procaccia, 1983).

Whereas the D2 is concentrated on the static structure of the underlying data and estimates the complexity of the whole process, the PD2 represents the changes of complexity over time (Skinner, 1992; Schiepek et al., 2016). Relatively high values of the PD2 indicate a temporarily high amount of the system's degrees of freedom, therefore suggesting the presence of complex system dynamics (Grassberger and Procaccia, 1983; Schiepek et al., 2016). The PD2 algorithm employed in this study was developed by one of the authors and has been applied in various studies to identify changes of dimensional complexity over time (see, e.g., Schiepek et al., 2016). Crucial for running the PD2 algorithm is the setting of the embedding dimension (m) which is defined as "the number of phase space co-ordinates to correctly embed the attractor in the phase space" (Fichera et al., 2001, p. 186). Since the correct embedding dimension is initially unknown for any empirical data, the correlation dimension is calculated for different embedding dimensions. If the investigated system is chaotic, the correlation dimension increases with increasing the embedding dimension m, but will then start to stabilize at a certain value (i.e., the correlation dimension saturates as the structure of the system's attractor has been unfolded) (Ndofor et al., 2018). In order to avoid including unnecessary and too small embedding dimensions during the calculation of the PD2, we consider only those embedding dimensions for which the D2 of the embedded dynamics remains constant (i.e., the embedding is shifted to the saturation range). Applying the procedure described above, we use embedding dimensions (m) in the range of 19 to 33 for running the PD2 algorithm (with $m = 19$ representing the minimum dimension of the phase space in which the attractor is correctly embedded and $m = 33$ representing the embedding dimension at which the saturation of the correlation dimension occurs).

In addition, Theiler (1986) proposed that the calculation of the correlation dimension should exclude temporally adjacent pairs of data points, because the correlation between such data points could distort the calculation of the correlation dimension. Therefore, only pairs of data points which are at least w time cycles apart are included in the calculation of the correlation dimension. Accordingly, the size of the so-called Theiler window w was set to one (Theiler, 1986). The PD2 calculation delivers valid results for 100% of the 534 data points that can be effectively used for analysis, thereby surpassing the recommended threshold of 75% (Skinner, 1992).

In order to assess whether the investigated time series is nonlinear, which is considered a characteristic feature of a complex system, we employ the BDS test statistic devised by Brock et al. (1996). The BDS test statistic is based on the algorithm by Grassberger and Procaccia (1983) which was originally developed to calculate the correlation dimension D2. The BDS test identifies nonlinear serial dependence in a time series and has been widely used in the economics and finance literature (Ndofor et al., 2018). In this study, we test the null hypothesis that the logarithmic returns of the observed time series are independent and identically distributed (i.i.d.), i.e., random (Carpenter et al., 2011). At the 5% level of significance, the two-tailed critical value for the BDS test is ±1.96, meaning that the null is rejected in case the BDS statistic is greater than 1.96 or less than -1.96. In case the i.i.d. hypothesis is rejected we can assume that there is ordered structure (i.e., serial dependence) instead of pure randomness in the time series. Since the linear dependence of the original time series has already been removed by taking the first difference of the logarithms of monthly new venture creation, the observed serial dependence hints at nonlinear dependence in the logarithmic returns of the series (Dakos et al., 2012; Chu, 2003). However, it should be noted that nonlinearity represents a necessary condition, but not a sufficient condition for the existence of chaos. As we are particularly interested in capturing time variations in nonlinear dynamics to track the evolution of the entrepreneurial ecosystem, we apply the BDS test within a moving window of 80 data points (Lim and Hooy, 2013). We estimate the BDS statistic for an embedding dimension (m) of four and a metric bound (ε) (i.e., the maximum distance between pairs of data points) that equals 0.75 times the standard deviation of the logarithmic return series (Urquhart and McGroarty, 2016).

The LLLE is a variation of the Largest Lyapunov Exponent (LLE) and measures changes in the chaoticity of the investigated system dynamics (Kowalik et al., 1997). Generally, Lyapunov exponents represent the mean rate of divergence or convergence of two initially nearby trajectories in the same phase space (Wolf et al., 1985). A positive Lyapunov exponent indicates the divergence of the two trajectories which implies the system's sensitive dependence on initial conditions and, thus, deterministic chaos (Hibbert and Wilkinson, 1994; Hung and Tu, 2014). Whereas the LLE is utilized to examine chaoticity on a global or macroscopic level and requires data stationarity, the LLLE allows the local, microscopic detection of transient process dynamics in particular periods, even if the system is nonstationary (Kowalik et al., 1997; Hung and Tu, 2014). By partitioning the entire time series into several quasi-stationary sub-epochs, it is possible to estimate the LLLE for each of these sub-epochs, hence providing an appropriate measure of the local chaoticity of the analyzed system (Kowalik et al., 1997; Hung and Tu, 2014). In this study, we use an algorithm developed by one of the authors that extends the algorithm presented by Rosenstein et al. (1993) to account for changes in the LLE. In order to calculate the LLLEs, the embedding dimension (m) was set to ten and the size of the Theiler window was set to three (Theiler, 1986). All calculations were performed with GChaos statistical software, a nonlinear time series analysis program (version 28.7, www.complexity-research.com).

4 Results

Since the PD2 calculation delivers valid results for 100% of the 534 data points that can be effectively used for analysis, all of the investigated processes are suitable for being interpreted as ordered dynamics, rather than representing stochastic processes (Schiepek et al., 2016). The PD2 has an arithmetic mean of 5.46 (± 0.95), indicating chaos in the time series data (Ruelle and Takens, 1971). Fig. 4 illustrates the evolution of PD2 dimensionalities over time, showing the changes in the complexity of the Singapore entrepreneurial ecosystem. The evolution of the Singapore entrepreneurial ecosystem realizes profound nonstationarities and can be divided into different time periods. In the beginning of the measurement period (1971–1974), the dimensional complexity peaks at a PD2 value of 9.7, hinting at the critical instability of the system. Then, from 1974 to 1995, the PD2 decreases until it reaches a minimum of 4.1. In the following years, the PD2 ranges between relatively low values of 4.3–6.2. Interestingly, while the system's overall complexity diminishes over time and stabilizes at moderate levels, we observe several abrupt increases in the PD2 measure throughout its evolution. Such local peaks of the system's dimensional complexity can be seen at PD2 values of 6.6 (December 1981), 6.2 (June 1991), 5.6 (June 1998) and 6.2 (December 2007).

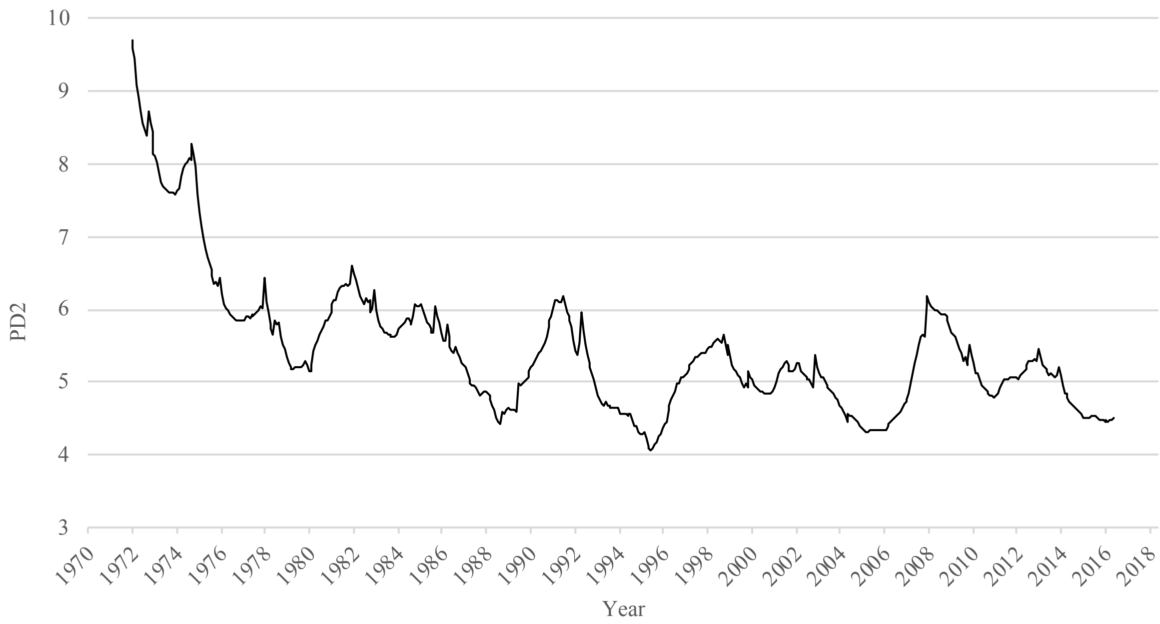

Fig. 4. Evolution of PD2 with time.

Applying the BDS test to logarithmic returns within moving windows, we find strong evidence of nonlinear dynamics during the evolution of the Singapore entrepreneurial ecosystem. As can be seen in Fig. 5, the null hypothesis of logarithmic returns being i.i.d. is rejected at the 5% level for most periods of system development, because the BDS test statistic is greater than the critical value of 1.96 during almost all periods of system development. Since the results suggest the existence of nonlinear structure in the data, we can assume that the observed time series exhibits persistent and significant nonlinear dependence, hence deviating from a random walk supposition. The time variations in nonlinear dynamics captured by the BDS test are relatively consistent with the findings of the PD2 calculation, thus adding robustness to our results. Fig. 5 shows that the nonlinearity is particularly evident in the beginning of the measurement period (1973–1974). Furthermore, the BDS test identifies the sequences from March 1988 to June 1988 (four months), November 1992 to December 1995 (38 months), June 1998 to March 1999 (10 months) and July 2009 to November 2012 (41 months) as periods of sharply increased nonlinearity.

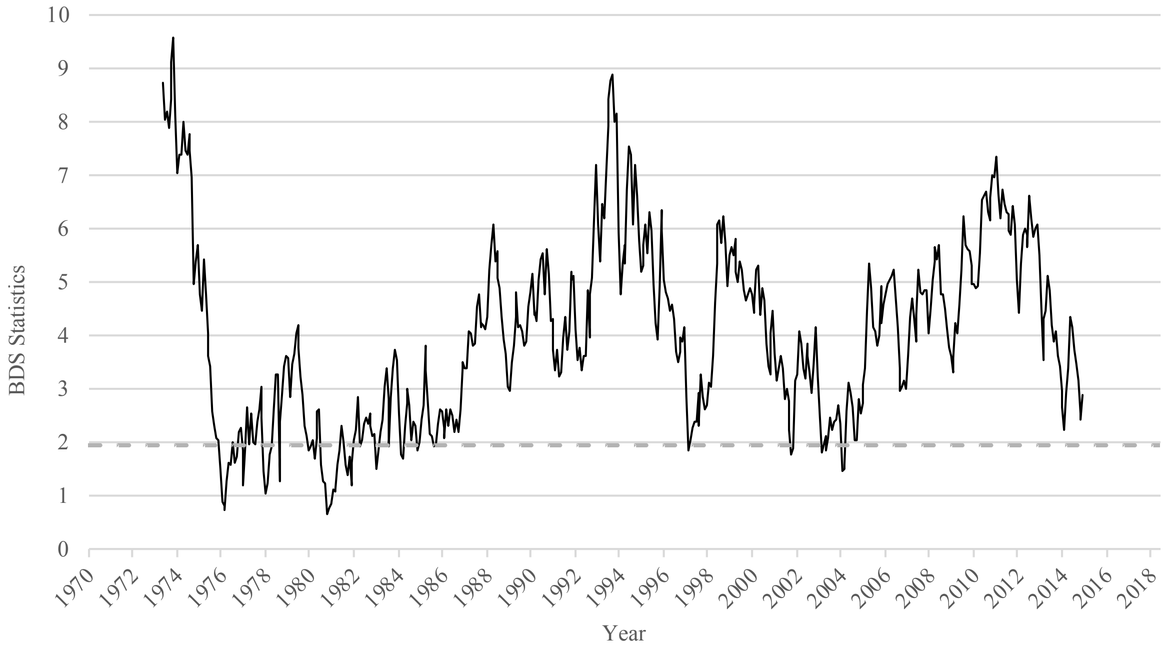

Fig. 5. Results of the BDS test within moving windows. Note: The BDS test statistic is computed for a window of 80 measurement points. The calculation window is shifted by one data point after each calculation, resulting in a BDS test time series that is shorter than the original time series (it starts 40 data points later and ends 41 data points earlier. This procedure is repeated until the last measurement point is used. The dotted horizontal line indicates the two-tailed critical value for normal distribution at the 5% level of significance.

In addition, our analysis identifies dynamical jumps in the development of the LLLEs, representing distinct changes in the chaoticity of the Singapore entrepreneurial ecosystem (see Fig. 6). Overall, the detected positive LLLEs provide good evidence that the evolution of the Singapore entrepreneurial ecosystem can be considered as a chaotic process. We observe a total of four short periods of considerably increased chaoticity. Each of these periods is marked by an abrupt growth and decline of chaotic dynamics. As shown in Fig. 6, the periods from July 1978 to January 1980 (19 months), June 2000 to June 2001 (13 months) and September 2007 to May 2011 (45 months) appear as local peaks of the chaoticity measure based on LLLEs. The corresponding highest positive LLLE values are 0.062 (August 1979), 0.063 (August 2000) and 0.080 (November 2009), respectively.

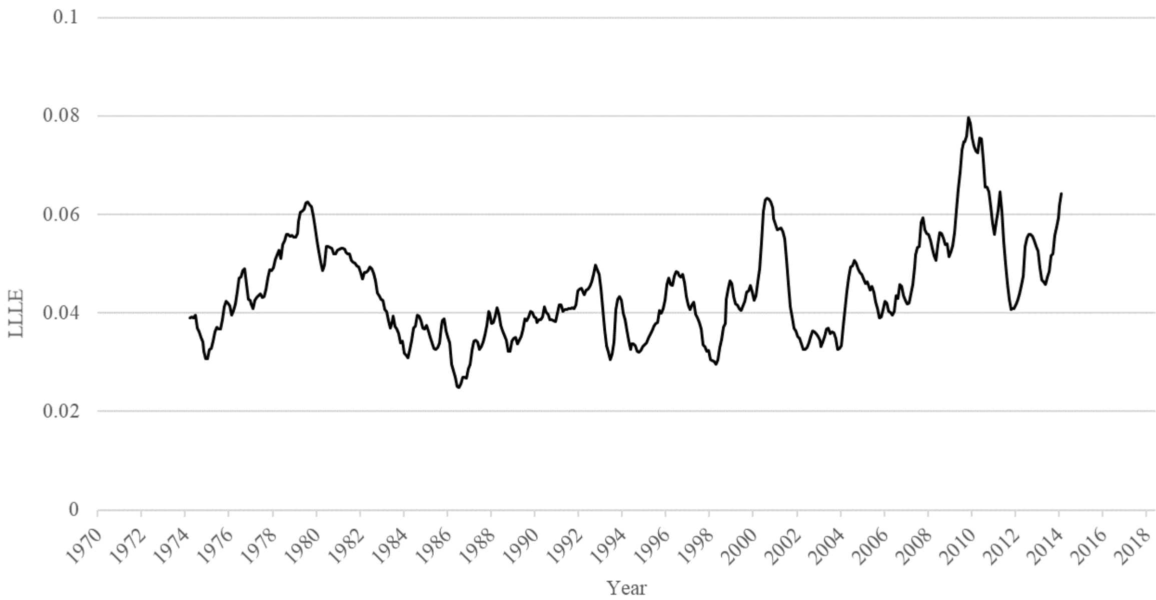

Fig. 6. Changes of LLLEs with time. Note: The LLLE is computed for a window of 100 measurement points. The calculation window is shifted by one data point after each calculation, resulting in a LLLE time series that is shorter than the original time series (it starts 50 data points later and ends 51 data points earlier). This procedure is repeated until the last measurement point is used. Positive LLLEs indicate chaotic system behavior.

5 Discussion and conclusion

The question of how entrepreneurial ecosystems evolve is of great interest to scholars, practitioners and public policy (Auerswald and Dani, 2017). Whereas existing research has conceptualized the evolution of entrepreneurial ecosystems as a dynamic and emergent process, quantitative empirical evidence on the expected complex dynamics of entrepreneurial ecosystems is still lacking. In this study, we applied three methods from chaos theory, the PD2, the BDS test and LLLEs, to examine the complex dynamics of entrepreneurial ecosystems. The analysis of the Singapore entrepreneurial ecosystem substantiates previous assumptions concerning the complex and nonlinear evolution of entrepreneurial ecosystems. Our results indicate that chaotic discontinuities are rather the rule than the exception throughout ecosystem development. More specifically, we found that the evolution of entrepreneurial ecosystems can be characterized as a chaotic process in which an initial period of critical instability is followed by a continuing phase of order generation which, in turn, is marked by repeated chaotic fluctuations.

When looking at the historical development of the Singapore entrepreneurial ecosystem, one can find several events that coincide with periods of considerably increased complexity/chaoticity (as evidenced by relatively high values of the PD2/LLLE) of the Singapore entrepreneurial ecosystem: during the initial period of critical instability from 1971 to 1974, Singapore's transition from a strong dependency on technology transfer and diffusion from foreign multinational corporations to a focus on local technological development was initiated (UNESCAP, 2018). This economic shift was accompanied by high government investment in the development of local technological infrastructure and science parks (Koh, 2006). Hence, this strategic reorientation might be considered as the foundation of the Singapore entrepreneurial ecosystem and explain the complex dynamics during this period. It is likely that the critical instability from 1971 to 1974 was further enhanced by the impact of the first oil crisis in 1973.

Moreover, it is noticeable that subsequent periods of enhanced complexity/chaoticity of the Singapore entrepreneurial ecosystem frequently coincide with economic crises and ensuing local policy initiatives by the Singapore government. In 1979, just after the second oil crisis, the Singapore government launched an economic restructuring program to strengthen the local research and development capacity with a focus on high-value-added technologies (UNESCAP, 2018); a subsequent local peak of the entrepreneurial ecosystem's complexity can be observed in 1981, whereas a local peak of the entrepreneurial ecosystem's chaoticity can be observed in 1980. From 1997 to 2000, Singapore experienced two major economic crises, namely the 1997 Asian financial crisis and the tech-bubble burst in 2000 (UNESCAP, 2018). It was also during this period that the Singapore government started a range of new policy initiatives to facilitate entrepreneurship (Koh, 2006). Examples of such initiatives include the launch of the Technopreneurship 21 program in 1998 to nurture and invest in high-tech start-up ventures, as well as the establishment of the One-North science park in 2000 as a new hub for entrepreneurial activity (Koh, 2006); a local peak of the entrepreneurial ecosystem's complexity can be observed in 1998, whereas a local peak of the entrepreneurial ecosystem's chaoticity can be observed in 2000. In addition, the most recent period of sharply enhanced complexity/chaoticity of the Singapore entrepreneurial ecosystem between 2007 and 2009 might be associated with the impact of the Great Recession that occurred during the same time period. Although far from definitive proof, these observations show that relevant events internal or external to the Singapore entrepreneurial ecosystem might explain periods of considerably increased system complexity/chaoticity which, in turn, signal major system transformations.

5.1 Theoretical implications

Our empirical finding that the evolution of entrepreneurial ecosystems exhibits features of deterministic chaos has important theoretical implications.

First, our work highlights that, if the evolution of entrepreneurial ecosystems is indeed chaotic, then the long-term behavior and development of entrepreneurial ecosystems is unpredictable. Whereas the question of how entrepreneurial ecosystems react to specific conditions (e.g., availability of venture capital) or influences (e.g., policy interventions to promote entrepreneurship) is intensively discussed among entrepreneurship scholars, the complex dynamics of entrepreneurial ecosystems severely limit the accuracy of extrapolations and long-term predictions. Given the nonlinearity of ecosystem evolution, marginal changes in the initial configurations of entrepreneurial ecosystems can lead to unexpected, disproportionate outcomes. Just as near-perfect modeling and understanding of initial system conditions do not allow precise long-term weather forecasts (Lorenz, 1963), detailed knowledge of entrepreneurial ecosystem conditions does not enable accurate predictions about ecosystem behavior in the long run. However, since our results imply the existence of deterministic chaos within the Singapore ecosystem time series, it can be assumed that the evolution of entrepreneurial ecosystems is not characterized by erratic randomness, but possesses inner structure and order (Kowalik et al., 1997). Consequently, the development of entrepreneurial ecosystems does not follow a random walk. Instead, the ecosystem's initial conditions fully determine its development trajectory and set the boundaries of its future behavior. We therefore argue that, whereas long-term ecosystem development is unpredictable, observation of underlying evolutionary patterns and anticipation of potential ranges of future system behaviors might be possible (Benbya et al., 2020).

Second, our work highlights that, under the conditions of nonlinearity, a linear notion of causation is limited and inappropriate for examining entrepreneurial ecosystems. Conventional entrepreneurship and entrepreneurial ecosystem research predominantly rely on linear cause-and-effect models that investigate entrepreneurial components separately from each other (Anderson et al., 2012). However, such fragmented, mechanistic input-output approaches might be inadequate to grasp the wholeness of entrepreneurial phenomena, including the complex dynamics of entrepreneurial ecosystems (Roundy et al., 2018). Building on our findings, we propose that entrepreneurship scholars need to take into consideration the complex causalities inherent in the evolution of entrepreneurial ecosystems. For instance, unidirectional causation is inappropriate to explain how order emerges in entrepreneurial ecosystems, since ecosystem emergence involves (self-reinforcing) feedback loops as well as co-evolutionary dynamics between the systems' elements, and, thus, multi-directional causality (Benbya et al., 2020). Furthermore, additive and unifinal conceptions of causality are ill-suited to capture the complex interactions among ecosystem stakeholders that ultimately create the nonlinear dynamics of entrepreneurial ecosystems. Hence, the appreciation of complexity provides new ways to enhance our understanding of the nature of causality in entrepreneurial ecosystems, as complexity theory accounts for the equifinality, conjunction and asymmetry of interdependencies between entrepreneurial actors (Benbya et al., 2020; Muñoz and Dimov, 2015).

Third, our findings provide empirical evidence to previous conceptualizations (Colombelli et al., 2019; Auerswald and Dani, 2017) suggesting that the ‘birth’ and early growth phases of entrepreneurial ecosystems are marked by extreme instability (as evidenced by high degrees of complexity), potentially because many relationships are not yet defined and the system can develop in many different directions (i.e., the system exhibits high degrees of freedom). As hypothesized by prior research (Colombelli et al., 2019), the system then enters an ongoing consolidation phase during which order emerges from the interactions between the stakeholders (as evidenced by comparatively low degrees of complexity). However, this period of relative stability is repeatedly interrupted by short periods of significantly increased chaoticity, hinting at radical change processes during the evolution of entrepreneurial ecosystems. These chaotic dynamics could be induced by events that are internal or external to the entrepreneurial ecosystem. In the case of the Singapore entrepreneurial ecosystem, internal events that might explain increased ecosystem dynamics could be major policy initiatives to promote entrepreneurial activity (e.g., the liberalization of business regulations since 1998; the establishment of a governmental venture capital fund in 1999). External events that may explain increased ecosystem dynamics could be severe economic crises (e.g., the oil shock of 1973; the Asian financial crisis beginning in 1997; the tech-bubble burst in 2000; the Great Recession between 2007 and 2009) (Koh, 2006; UNESCAP, 2018).

Furthermore, we contribute to the broader entrepreneurial ecosystem literature by answering the urgent call for a change of perspective, from the current, rather static framework to an evolutionary, longitudinal approach towards entrepreneurial ecosystems (Roundy et al., 2018; Auerswald and Dani, 2017). Whereas theory and methodologies from complexity science have been utilized to study the dynamic patterns of entrepreneurial activity before (Lichtenstein et al., 2007; Liening et al., 2016; McKelvey, 2004), this paper, to our knowledge, reports the first application of techniques from complexity/chaos theory to the phenomenon of entrepreneurial ecosystems.

5.2 Managerial and policy implications

Generally, our study shows that entrepreneurs, managers and policy-makers should expect nonlinear chaotic dynamics during the evolution of entrepreneurial ecosystems. Hence, as outlined above, efforts to predict entrepreneurial ecosystem's long-term behavior as well as its specific responses to changing conditions or interventions are in vain. Instead, our findings suggest that navigation in such complex environments requires precise monitoring of the actual ecosystem dynamics (Strunk and Lichtwarck-Aschoff, 2019). The methods presented in this paper can be applied to closely observe changes in the system dynamics, therefore enabling ecosystem stakeholders to detect undesirable developments and to tailor situation-specific interventions (Strunk and Lichtwarck-Aschoff, 2019). Since the ecosystem's development trajectory is constrained by its initial conditions and its overall behavior patterns can be observed, decision-makers also have the opportunity to anticipate the spectrum of possible ecosystem behaviors, thereby enabling adaptation to changing ecosystem conditions (Benbya et al., 2020).

However, given that entrepreneurial ecosystems are characterized by nonlinearity, we recommend ecosystem stakeholders to carefully evaluate potential interventions. As small inputs or changes to the configuration of an entrepreneurial ecosystem could lead to large and unexpected consequences over time (Levy, 1994), possibly involving multi-directional feedback loops, directed evolution and steering of entrepreneurial ecosystems towards predefined long-term targets are impossible. This finding has far-reaching implications for the governance of entrepreneurial ecosystems. Rather than adopting a rigid planning and control approach that aims to achieve specific outcomes, we suggest that policy-makers should focus on establishing favorable framework conditions that enable the self-organization of entrepreneurial activity within ecosystems (Arikan, 2010). For instance, an improved (digital) infrastructure could increase the interconnectedness between entrepreneurs and other ecosystem stakeholders, thereby facilitating interactions within the entrepreneurial ecosystem. Moreover, the access to a workforce with diverse skill sets might enhance a region's creative potential. Importantly, such initiatives require an adaptive, iterative and experimental attitude towards ecosystem governance, thereby allowing flexible improvisation and quick reactions to changes within the ecosystem or in its external environment (Hung and Tu, 2011; Baggio and Sainaghi, 2011).

In this context, our work also highlights the fundamental individuality of the development process of entrepreneurial ecosystems. Under conditions of nonlinearity and sensitivity to initial ecosystem configurations, it can be assumed that the development trajectory of each entrepreneurial ecosystem is unique. In addition, each entrepreneurial ecosystem responds differently to a specific policy intervention (Arikan, 2010). Hence, whereas it might be possible that certain overall behavior patterns emerge across different ecosystems, we propose that policy-makers should not concentrate on imitating the success stories of other prominent entrepreneurial ecosystems. On the contrary, we suggest that policy-makers should first and foremost examine the path-dependent history of their own entrepreneurial ecosystems (Arikan, 2010). In-depth knowledge about the respective ecosystem's initial conditions and fundamental structures that emerged over time can then be used to develop ecosystem-specific policy measures.

5.3 Limitations and future research

Our study focused on the analysis of complex dynamics inherent in the evolution of the Singapore entrepreneurial ecosystem, utilizing the PD2, the BDS test and LLLEs. Like other methods from chaos theory, these three methods require an accurate data sequence over a long period of time (Richards, 1990). Consequently, our choice of proxy for measuring ecosystem dynamics was limited. While we believe that new venture creation adequately represents the overall entrepreneurial activity within regional agglomerations, future research can investigate alternative measures that reflect the evolution of entrepreneurial ecosystems.

Furthermore, the generalizability of our findings might be limited, because the present study used only the case of the Singapore entrepreneurial ecosystem. In this context, it should be noted that the Singapore entrepreneurial ecosystem differs in several important aspects from other entrepreneurial ecosystems. First, Singapore's economic development features extensive government intervention and planning (Huff, 1995). Hence, it might be that focused policy interventions, such as the establishment of venture capital funds or major investments in research and development infrastructure, trigger some of the chaotic fluctuations observed in the Singapore entrepreneurial ecosystem. Other entrepreneurial ecosystems that are not subject to extensive government interventions may not evidence such complex dynamics. Second, the Singapore entrepreneurial ecosystem evolved very rapidly and changed profoundly. Therefore, it could be that other entrepreneurial ecosystems which developed less drastically and over a longer period of time do not exhibit chaotic behavior. However, the aim of this study was not to prove that the evolution of each entrepreneurial ecosystem features chaotic fluctuations, but rather to demonstrate that the possibility of chaos in the evolution of entrepreneurial ecosystems should at least be considered. Further studies can apply the methods outlined in this paper to other entrepreneurial ecosystems and compare their findings with the results of our study.

This study offers several additional directions for future research. On a more general level, our finding that the evolution of entrepreneurial ecosystems features chaotic behavior suggests that conventional methods, which rely on linear cause-and-effect models, do not seem appropriate for studying the complex dynamics of entrepreneurial ecosystems (Roundy et al., 2018; Berger and Kuckertz, 2016). Hence, future entrepreneurial ecosystem research should employ methods that explicitly account for the nonlinearity and complexity exhibited by entrepreneurial ecosystems. Whereas our paper represents an important step towards emphasizing the complex dynamics of entrepreneurial ecosystems by employing three methods from nonlinear time series analysis, we encourage researchers to apply other methods from complexity science to further investigate entrepreneurial ecosystems. For instance, future studies might use qualitative comparative analysis (QCA) to examine the complex interrelationships between entrepreneurial components, as such a configurational approach accounts for the complex causality inherent in entrepreneurial processes (Roundy et al., 2018). Moreover, due to its focus on the interactions that are the main drivers of a system's complexity, dynamic network modeling represents a promising methodology to study the emergent processes of entrepreneurial ecosystems (Benbya et al., 2020).

However, apart from examining what (configurations of) factors trigger the complex dynamics and major transitions throughout the evolution of entrepreneurial ecosystems, future research should also explore the question of when entrepreneurial ecosystems are susceptible to change. Under conditions of nonlinearity and, thus, sensitivity to small perturbations, the timing of an intervention might determine whether an entrepreneurial ecosystem transitions into an ordered or chaotic state.

C Essay 2: Digital Framework Conditions of Entrepreneurial Activity in Cities: A fsQCA Approach

Abstract

Recent literature conceptualizes digitalization as an important enabler of entrepreneurial activity. However, the understanding of how digitalization influences the broader entrepreneurial landscape remains limited. In this context, there have been approaches lately that suggest investigating potential effects of digital technologies and infrastructures on entrepreneurial ecosystems. Despite growing research on the intersection between digitalization and entrepreneurial ecosystems, the vast majority of extant work in the literature is of conceptual nature. This study provides empirical evidence on how the availability of different sets of digital technologies and infrastructures facilitates emergent processes of entrepreneurial ecosystems. Based on data from 35 regional entrepreneurial ecosystems, we investigate the causal configurations that lead to high or low to medium levels of new venture formation using fuzzy-set qualitative comparative analysis (fsQCA). Our analysis reveals that two distinct configurations are conducive to relatively high start-up activity in entrepreneurial ecosystems, whereas four different paths explain relatively low to medium start-up activity in entrepreneurial ecosystems.

Keywords:

Digitalization, digital entrepreneurship, entrepreneurial ecosystems, fsQCA.

1 Introduction

Recent literature conceptualizes digitalization, i.e., “the sociotechnical process of applying digitizing techniques to broader social and institutional contexts that render digital technologies infrastructural” (Tilson et al., 2010, p. 749), as an important enabler of entrepreneurial activity (Nambisan, 2017; von Briel et al., 2018; Autio et al., 2018a). As an example, digital technologies and infrastructures provide start-ups with new methods to shape their processes of value creation, delivery, and capture (Nambisan et al., 2017), thus facilitating business model innovation (Prahalad and Ramaswamy, 2003). Moreover, digitalization affects venture creation processes in that it allows for more fluid boundaries and more dispersed agency (Nambisan, 2017). However, while existing literature acknowledges the role of digitalization as an enabler of new venture creation processes (von Briel et al., 2018), the understanding of how digitalization influences the broader entrepreneurial landscape remains limited (von Briel et al., 2018; Autio et al., 2018a; Sussan and Acs, 2017).

In this context, there have been approaches lately that suggest investigating potential effects of digital technologies and infrastructures on entrepreneurial ecosystems (Autio et al., 2018a; von Briel et al., 2018). The concept of entrepreneurial ecosystems has drawn considerable attention from researchers, policy and practitioners in recent years (Spigel and Harrison, 2018). Following the complexity-based conceptualization by Roundy et al. (2018, p. 5), an entrepreneurial ecosystem can be defined as “a self-organized, adaptive, and geographically bounded community of complex agents operating at multiple, aggregated levels, whose nonlinear interactions result in the patterns of activities through which new ventures form and dissolve over time.” More recently, entrepreneurial ecosystems have been conceptualized as a form of cluster that specializes in exploiting the technological potential afforded by digitalization to facilitate new venture creation (Autio et al., 2018a). In addition, scholars highlight the centrality of digital technologies and infrastructures in the conception of entrepreneurial ecosystems and call for further investigations into the influences of digitalization on the processes and structures that shape entrepreneurial ecosystems (von Briel et al., 2018; Autio et al., 2018a).

Although research on the intersection between digitalization and entrepreneurial ecosystems is growing, the vast majority of extant work in the literature is of conceptual nature. Moreover, current literature provides only limited guidance with respect to the issue that, with digitalization, entrepreneurial initiatives become less bounded and entrepreneurial agency becomes less predefined, resulting in more complex and dynamic dependencies between entrepreneurial processes and outcomes (Nambisan, 2017). Since traditional theories and concepts in entrepreneurship have assumed rather stable boundaries around entrepreneurial initiatives (e.g., Honig and Karlsson, 2004) as well as predefined sets of founders (e.g., Eckhardt and Shane, 2003), alternative conceptualizations of entrepreneurship are required that incorporate the increasing complexity infused by digital technologies (Nambisan, 2017) in order to develop more accurate explanations of the influence of digitalization on entrepreneurial ecosystems.

As pointed out above, it is suggested that digital technologies and infrastructures create technological affordances that shape the processes and structures comprising entrepreneurial ecosystems (Autio et al., 2018a). However, the complex and emergent phenomena underlying entrepreneurship in a digitalized world are yet to be explained, and scholars propose to examine how the availability of different sets of digital technologies influences the evolution of entrepreneurial ecosystems (von Briel et al., 2018). Thus, we seek to address the following research question:

Which combinations of factors of digitalization enable the emergent processes of entrepreneurial ecosystems?

To answer this research question, we examine the influence of digitalization on entrepreneurial ecosystem emergence using a configurational approach, with emergence being defined as “the arising of novel and coherent structures, patterns and properties during the process of self-organization in complex systems” (Goldstein, 1999, p. 49). We will address our research question through performing fsQCA, representing a configurational approach to comprehend complex phenomena (Ragin, 2000). This methodology is appropriate for our research project because it implies nonlinear interrelations and complex causality instead of assuming linear relationships and singular causation (Fiss, 2007). Building on the concept of digital affordances by Autio et al. (2018a), we inductively elaborate the complexities of the causal relationships inherent in theories on the intersection between digitalization and entrepreneurial ecosystems. We assemble a sample of 35 effective entrepreneurial ecosystems across 19 countries in Europe. This data-rich research design allows us to reveal under which conditions and circumstances digitalization influences emergent processes of entrepreneurial ecosystems.

In the next section we elaborate on the influence of digital technologies and infrastructures on entrepreneurial ecosystem emergence and the role of several digital framework conditions. We then outline the methodology and present our empirical findings. We conclude by discussing the theoretical as well as practical implications of our results and offer guidance for future research.

2 Theoretical background

2.1 Existing research on the interplay between digitalization and entrepreneurial ecosystems

Digitalization is increasingly viewed as an objective, actor-independent factor that enables entrepreneurial activity (Nambisan, 2017). Nambisan’s initial call to begin “theorizing the role of specific aspects of digital technologies in shaping entrepreneurial opportunities, decisions, actions, and outcomes" (2017, p. 2) was answered by several studies at the nexus of digitalization and entrepreneurship research. For instance, von Briel et al. (2018) describe digital technologies as external enablers of venture creation. Sussan and Acs (2017) developed a digital entrepreneurial ecosystem framework to conceptualize entrepreneurship in the digital age. Autio et al. (2018a, p. 74) perceive entrepreneurial ecosystems "as a digital economy phenomenon that harnesses technological affordances to facilitate entrepreneurial opportunity pursuit by new ventures through radical business model innovation."

To describe digitalization and illustrate its impact on the emergent processes of entrepreneurial ecosystems, we build on the concept of digital affordances proposed by Autio et al. (2018a). Following Autio et al. (2018a), digitalization supports entrepreneurial ecosystems in facilitating entrepreneurial opportunity pursuit by providing three key affordances, with the noun "affordance" indicating the potentiality to execute existing or novel functions more efficiently. First, the inherent flexibility of digital technology, which is due to a digital technology's re-programmability and reducibility to the form of bits, allows for a *decoupling* between form and function (Autio et al., 2018a). In consequence, preexisting assets can be transformed for alternative applications and by different users (De Vita et al., 2011), while the local resource dependency decreases (Autio et al., 2018a). Second, digitalization drives *disintermediation*, referring to the capacity of the internet to enable direct interactions among end users and service providers (Bakos, 1998), thereby diminishing the dependency of start-ups on local intermediaries and increasing the flexibility to adjust and align the capabilities that are needed to deliver ventures' products or services (Autio et al., 2018a). Lastly, digitalization promotes *generativity*, i.e., "a function of a technology's capacity for leverage across a range of tasks, adaptability to a range of different tasks, ease of mastery, and accessibility" (Zittrain, 2006, p. 1981). For instance, the internet enables a new venture to generate spontaneous, innovative feedback from enormous, uncoordinated audiences that are situated outside the venture's original local cluster, thus facilitating the dynamic emergence of entrepreneurial opportunities (Autio et al., 2018a; Nambisan, 2017). Taken together, digitalization creates digital affordances that promote a new form of emergent and dynamic processes in entrepreneurial ecosystems, which is due to a reduced dependency of start-ups on their local environment as well as more opportunities for business model experimentation and innovation (Autio et al., 2018a).

However, whereas digitalization enables more dispersed agency and more fluid boundaries in entrepreneurial processes, it also increases the nonlinearity and unpredictability of how such processes evolve (Nambisan, 2017; Huang et al., 2017). While higher degrees of nonlinearity and unpredictability of entrepreneurial processes could also result in unfavorable outcomes or a loss of control, it should be noted that in this study we concentrate on the positive effects of digitalization, i.e., its enabling mechanisms. More specifically, new forms of digital infrastructures, including social media platforms and crowdfunding systems, facilitate the involvement of a broader, evolving set of actors in the entrepreneurial process, thus shifting the locus of entrepreneurial agency from a predefined agent to a vibrant collection of actors, such as customers or investors, who are now able to interact and form social ties with peer entrepreneurs (Nambisan, 2017). Furthermore, the utilization of digital tools and corresponding processes in product design was found to enable the connection of previously disassociated actors, resulting in unintended design outcomes and higher variability in entrepreneurial processes (Bailey et al., 2012; Nambisan, 2017). Summarizing the above arguments, we propose that the availability of digital technologies and infrastructures, on the basis of their function as a platform for bottom-up emergence of innovations and a catalyst of self-organizing system behavior (Zorina and Karanasios, 2017), is crucial for facilitating the emergence of entrepreneurial ecosystems. Hence, in this study, we introduce digitalization as a specific type of injection of resources that promotes emergent processes of entrepreneurial ecosystems

(Roundy et al., 2018). This notion is in line with the recent conception of digital technologies as external enablers of entrepreneurial processes (Davidsson, 2015; von Briel et al., 2018).

Having discussed the key affordances as well as enabling mechanisms provided by digitalization, it is important to outline the theoretical foundation of entrepreneurial ecosystems in order to build a clear understanding of the concept. To date, literature on entrepreneurial ecosystems has concentrated primarily on the identification of the core elements of established ecosystems (Roundy et al., 2018). In this context, a range of studies has focused on examining prominent ecosystems resulting in a profound understanding of essential elements and attributes of entrepreneurial ecosystems. For instance, Isenberg (2010) proposes six specific domains of entrepreneurial ecosystems, namely human capital, markets, finance, policy, culture and support. Stam (2015) develops an entrepreneurial ecosystem framework consisting of ten elements, including formal institutions, culture, networks, physical infrastructure, leadership, finance, knowledge, demand, talent and intermediate services. Foster et al. (2013) present eight different components of entrepreneurial ecosystem pillars.

Although these findings are crucial for the understanding of entrepreneurial ecosystem structure, current literature has been criticized for focusing too much on the key components of entrepreneurial ecosystems, hence ignoring the sets of combinations of elements that foster sustainable entrepreneurial activity in regions (Malecki, 2018). Moreover, research tended to describe entrepreneurial ecosystems as being composed of completely or partially disconnected elements and as characterized by causal or linear interactions among agents (Roundy et al., 2018), while in fact entrepreneurial ecosystems "emerge from nonlinear and dynamic combinations of sets of variables" (Roundy et al., 2018, p. 7). Thus, there is growing consensus among scholars that future research should investigate the complex interactions among the system's elements in order to shed light on the facilitating mechanisms and emergent processes of entrepreneurial ecosystems (Stam, 2015; Autio et al., 2018a). As we strive to comprehend which combinations of digital technologies and infrastructures enable the emergence of entrepreneurial ecosystems, we next review the literature to identify a set of factors of digitalization that are essential in this process.

2.2 Digital framework conditions of entrepreneurial ecosystem emergence

As previously mentioned, a plethora of research has examined the key ingredients of entrepreneurial ecosystems (Stam and Van de Ven, 2019; Spigel, 2017; Foster et al., 2013; Stam, 2015; Isenberg, 2011). Building on these ecosystem models and frameworks, we concentrate on accessible markets, funding and finance, human capital, an entrepreneurial culture, government and regulatory framework, knowledge spillovers and the physical infrastructure as core elements of entrepreneurial ecosystems (see, e.g., Stam and van de Ven, 2019; Foster et al., 2013; Isenberg, 2010). Since this study aims to determine the combinations of digital technologies and infrastructures that facilitate the emergent processes of entrepreneurial ecosystems, we develop a digital counterpart of each of the identified core elements of entrepreneurial ecosystems. These digital proxies represent the digital framework conditions of entrepreneurial ecosystem emergence. This approach follows the methodology applied by Autio et al. (2018b). We illustrate the derived digital framework conditions in Fig. 7. Each of these conditions is described in more detail below.

One of the digital framework conditions that plays an important role in the development of entrepreneurial ecosystems is the *digital market* (Sussan and Acs, 2017). This factor refers to the exploitation of online market channels (in the form of e-commerce) by consumers and businesses at the regional level (Autio et al., 2018b). Access to markets is considered as one of the most important determinants of new venture growth (Foster et al., 2013; Stam and Van de Ven, 2019). Digital markets provide start-ups with a wider access to consumers and businesses, offer the opportunity to increase interaction with business partners and customers, and reduce the transaction costs of start-up companies (Kraus et al., 2018; Autio et al., 2018b). Hence, a thriving digital market is crucial for the development of a sustainable entrepreneurial ecosystem (Sussan and Acs, 2017).

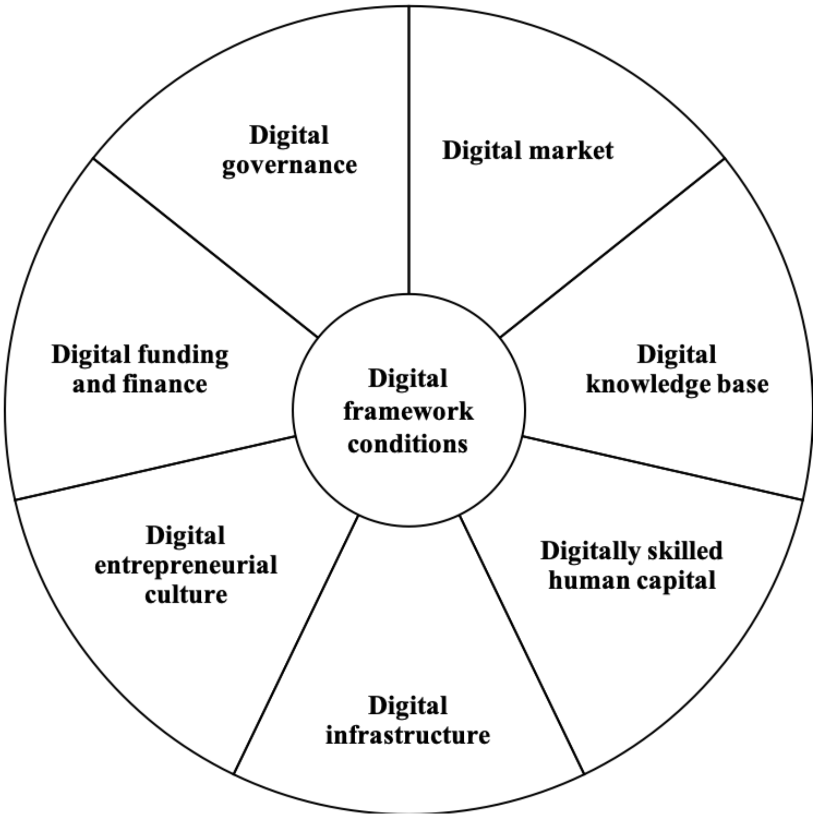

Fig. 7. Visual representation of digital framework conditions.

The availability of *digital funding and finance* is another factor that facilitates the evolution of entrepreneurial ecosystems (Lehner and Harrer, 2017). Generally, funding and finance relate to the amount of funding that start-up ventures have access to (Autio et al., 2018b). The amount and accessibility of finance is commonly seen as a key condition for the success and development of entrepreneurial ecosystems (Stam and Van de Ven, 2019). With regard to the digital context, crowdfunding platforms enable start-ups to attract funding from a wide public, thereby reducing entrepreneurs' dependence upon traditional forms of venture capital acquisition (Sahut et al., 2019; Mollick, 2014). Consequently, the access to digital funding and finance and the emergence of entrepreneurial ecosystems are closely linked (Cicchiello, 2019).

The development of entrepreneurial ecosystems also depends on the availability of *digitally skilled human capital* (Autio and Cao, 2019). It refers to the access to employees skilled in information and communication technologies, as well as the individual citizens' digital skills (Autio et al., 2018b). Whereas researchers agree that human capital is one of the key domains of entrepreneurial ecosystems (Isenberg, 2010; Foster et al., 2013; Stam, 2015), digitally skilled human capital plays a particularly important role in the development of entrepreneurial ecosystems, since "a vibrant community of digitally skilled workforce enhances the possibility to create high-quality digital start-ups" (Autio and Cao, 2019, p. 5433).

Another determinant of the emergence of entrepreneurial ecosystems captures the level of *digital entrepreneurial culture*. This factor reflects people's engagement with the digital start-up ecosystem (Bannerjee et al., 2016). In general, a strong entrepreneurial culture is considered a crucial component for creating a sustainable entrepreneurial ecosystem (Mack and Mayer, 2016). Digital entrepreneurial culture constitutes an essential condition for strengthening entrepreneurial ecosystems because it promotes an open and collaborative attitude towards entrepreneurial learning and experimentation (Autio and Cao, 2019).

Furthermore, entrepreneurial ecosystems are influenced by the quality of *digital government*, also referred to as e-government (Klapper and Delgado, 2007). Digital government is defined as "the initiative taken by governmental agencies and organizations to use the Internet technology in increasing their working effectiveness and efficiency" (Chen et al., 2007, p. 45) and reflects the digitalization of public services (Autio et al., 2018b). Digital government contributes to the emergent processes of entrepreneurial ecosystems, as it provides efficiency gains and enables a more conducive business environment for start-up ventures (Autio et al., 2018b).

An additional condition for the development of entrepreneurial ecosystems is the *digital knowledge base*. It refers to the regional research and development intensity in digital technologies and the newly generated knowledge in the form of high-tech patent applications (Bannerjee et al., 2016). The access to new and valuable knowledge is commonly seen as an important element of entrepreneurial ecosystems and a crucial source of entrepreneurial opportunities (Stam and Van de Ven, 2019; Autio et al., 2018b). Hence, the digital knowledge base acts as a key resource for the creation of digital start-ups within the entrepreneurial ecosystem.

Lastly, the emergent processes of entrepreneurial ecosystems are affected by the quality of the *digital infrastructure* (Autio and Cao, 2019). Digital infrastructure reflects the connectivity and accessibility of urban systems and comprises elements such as internet speed and penetration (Autio et al., 2018b). High connectivity and accessibility enabled by digital infrastructures support firms and start-up ventures to identify and pursue business opportunities (Autio et al., 2018b). Furthermore, digital infrastructure plays a crucial role in supporting business operations, and thus, entrepreneurial activity (Autio et al., 2018b). Consequently, digital infrastructure is an important condition for strengthening entrepreneurial ecosystems (Sussan and Acs, 2017). Based on the literature, the present study proposes:

Different combinations of the digital market, digital funding and finance, digitally skilled human capital, digital entrepreneurial culture, digital government, digital knowledge base, and digital infrastructure explain a high level of new venture creation in entrepreneurial ecosystems.

3 Methodology

Following Ketchen Jr. et al. (2008), the empirical verification of new theories often needs new methodologies. This is particularly true for the investigation of complex phenomena such as entrepreneurial ecosystems, since traditional research methods, which are typically based on a linearity supposition, are not suitable to study the emergent and nonlinear processes inherent in complex systems (Liening, 2017; Berger and Kuckertz, 2016). Thus, methodologies are required which are able to take into account the complexity-related properties of entrepreneurial ecosystems, as well as the increasing complexity infused by digital technologies. FsQCA represents a configurational approach to comprehend complex phenomena (Ragin, 2000) which can be characterized "as clusters of interconnected structures and practices, rather than as modular or loosely coupled entities whose components can be understood in isolation" (Fiss, 2007, p. 1180). FsQCA implies nonlinear interrelations and complex causality, instead of assuming linear relationships and singular causation (Fiss, 2007). It investigates the combinations of causal conditions that explain the outcome under investigation and acknowledges that the same outcome could result from different combinations of conditions (Ragin, 2000; Muñoz and Dimov, 2015). Hence, we follow the recommendation of Roundy et al. (2018) to apply the method of fsQCA to the study of entrepreneurial ecosystems. Since qualitative comparative analysis (QCA) perceives cases as specific configurations of causal conditions and allows to systematically compare cases (Misangyi et al., 2017), this research method is particularly well suited to identify the specific features of different entrepreneurial ecosystems. As von Briel et al. (2018) state, configurational approaches are appropriate for examining how digitalization gives rise to start-up activity. Adopting a configurational approach also corresponds with the call for "theoretical concepts and methodological approaches that reflect the incremental and nonlinear paths that digital artifacts and platforms facilitate in entrepreneurial initiatives" (Nambisan, 2017, p. 14). By using fsQCA, we aim to investigate which combinations of digital framework conditions facilitate the emergent processes of entrepreneurial ecosystems.

QCA is focused on "examining complexity through the intensity of in-depth investigation of a moderate number of cases, while maintaining rigor, replicable procedures and the use of formal logic" (Ceric and Krivokapic-Skoko, 2016, p. 351) and can be utilized to investigate small to medium numbers of cases (Misangyi et al., 2017). This empirical study analyzed the data from 35 regional entrepreneurial ecosystems across 19 countries in Europe. Fig. 8 shows the map of the 35 investigated regional entrepreneurial ecosystems. These regional entrepreneurial ecosystems were chosen due to the availability of data.

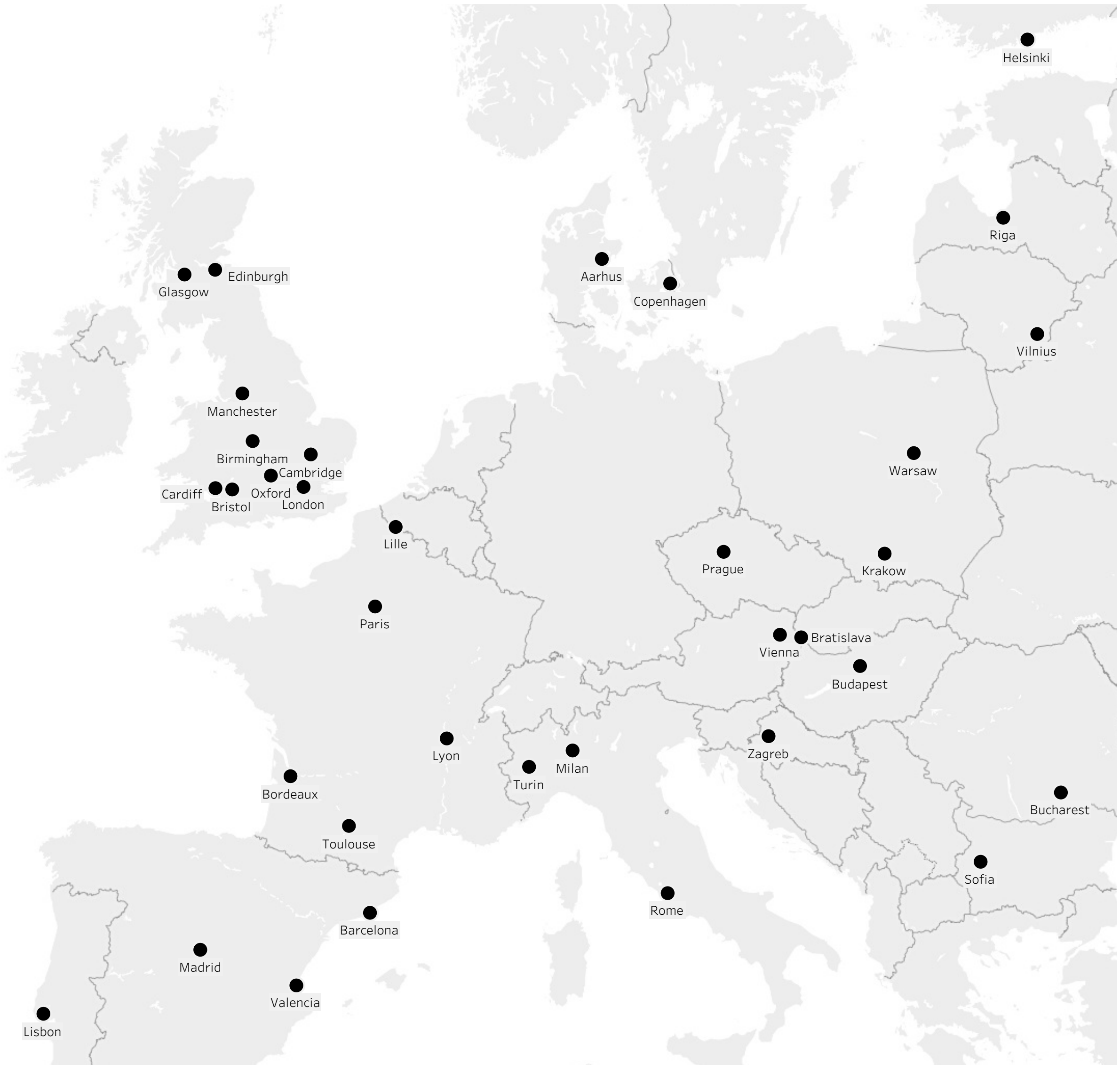

Fig. 8. Map of the 35 investigated regional entrepreneurial ecosystems.

The data were retrieved from five databases: the European Digital City Index (Bannerjee et al., 2016) indicates how well major cities across Europe support digital entrepreneurship and integrates ten different themes. The Digital Economy and Society Index (European Commission, 2019) measures the progress of European Union member states towards a digital economy as well as a digital society and is based on five components. Dealroom is a database that provides business information on start-up ventures, funding and investors (Dealroom, 2020). Eurostat is a database launched by the European Commission and offers statistical information on nine different themes, such as general and regional statistics, economy and finance, as well as science, technology and digital society (Eurostat, 2020). Finally, the Office for National Statistics is the national statistical institute of the United Kingdom and provides data on the economy, population and society, also including business demography statistics (ONS, 2020).

As outlined above, this study considers seven different digital framework conditions of each entrepreneurial ecosystem. The *digital market* framework condition includes local online transactions, growth in local online transactions and a country-level indicator of the digital market size (Bannerjee et al., 2016). The study captures *digital funding and finance* by assessing the availability of crowdfunding at the city-level (Bannerjee et al., 2016) and the amount of total venture capital investment at the city-level (Dealroom, 2020). *Digitally skilled human capital* includes the local access to information and communication technology (ICT) specialists (Bannerjee et al., 2016) and a country-level indicator of individuals' level of digital skills (Eurostat, 2020). The *digital entrepreneurial culture* framework condition comprises three city-level measures that indicate the local degree of online collaboration, local digital engagement with the entrepreneurial ecosystem and the local history of highly successful digital start-ups (Bannerjee et al., 2016). We capture *digital government* by assessing five country-level indicators, including the percentage of e-government users, availability of pre-filled online forms, availability of online service completion, availability of digital public services for businesses and the extent of open data (European Commission, 2019). The *digital knowledge base* framework condition includes the regional research and development intensity in digital technologies (Bannerjee et al., 2016) and the newly generated knowledge in the form of regional high-tech patent applications (Eurostat, 2020). Finally, this study captures the *digital infrastructure* by assessing three city-level indicators, namely the speed of broadband and mobile internet (Bannerjee et al., 2016) as well as the proportion of households with broadband access (Eurostat, 2020).

The outcome variable, *start-up activity*, is captured by the enterprise birth rate in the respective entrepreneurial ecosystems, with the enterprise birth rate representing the number of newly-created ventures as a proportion of the total number of active enterprises (Eurostat, 2020; ONS, 2020). In order to differentiate between the digital framework conditions of entrepreneurial ecosystems with a relatively high start-up activity and a relatively low to medium start-up activity, we also investigate the non-outcome of relatively low to medium start-up activity in an entrepreneurial ecosystem.

Since the selected indicators used different orders of magnitude and measurement units, each indicator was normalized into the (0 – 1) spectrum, with higher values indicating better outcomes (Khedhaouria and Thurik, 2017). We performed normalization in accordance with the min-max method (Khedhaouria and Thurik, 2017).

In the next step, to investigate how the digital framework conditions outlined above causally combine and contribute to the outcome of entrepreneurial activity, the data needs to be calibrated. The data was transformed into fuzzy sets employing the well-established procedure proposed by Ragin et al. (2006). Using the fsQCA 3.0 software, the original measures were rescaled into scores ranging between 0.0 and 1.0 (Ragin et al., 2006). We set three different anchor points to calibrate the data and determine the degree of membership of each variable, with scores above 0.9 representing full membership, scores below 0.1 representing full non-membership and a score of 0.5 representing the cross-over anchor (Curado et al., 2016). Table 1 provides the descriptive statistics and the thresholds for calibration.

After the raw data was transformed into sets, we constructed a data matrix (also referred to as truth table) that includes the various combinations of causal conditions which are logically possible in conjunction with the cases that are consistent with each combination. A truth table contains 2^k rows, with k indicating the amount of conditions ($2^7 = 128$ rows in this analysis).

We set the solution frequency threshold at one, which is recommendable if the amount of investigated cases is relatively small (Ragin et al., 2006; Muñoz and Dimov, 2015). The lowest acceptable consistency threshold was established at 0.9, which is above the minimum threshold of 0.75 that was recommended by Ragin et al. (2006).

Lastly, the fsQCA proceeds by applying an algorithm on the basis of Boolean algebra, thereby diminishing the rows of the truth table to combinations of conditions (Ragin et al., 2006). FsQCA was applied to investigate the digital framework conditions which are conducive to high or low to medium start-up activity.

Table 1.
Descriptive statistics (not calibrated) and calibration criteria.

	Descriptive statistics		Calibration criteria		
	Mean	SD	Full member	Cross-over	Non-member
Outcome					
High start-up activity	0.28	0.23	0.57	0.23	0.06
Conditions					
Digital market	1.37	0.68	2.38	1.22	0.57
Digital funding and finance	0.41	0.53	0.97	0.23	0.05
Digitally skilled human capital	1.02	0.38	1.55	0.94	0.59
Digital entrepreneurial culture	0.68	0.59	1.42	0.48	0.24
Digital government	0.54	0.27	0.84	0.55	0.08
Digital knowledge base	0.48	0.46	1.21	0.29	0.09
Digital infrastructure	1.48	0.47	1.99	1.49	0.77

Notes: N = 35; Mean = arithmetic mean; SD = standard deviation.

4 Results

Before constructing the truth table, we conducted fsQCA to identify potential necessary conditions. A condition is considered necessary in case it must be present to reach the outcome (Ragin et al., 2006). Since no condition surpassed the consistency threshold of 0.9 (Schneider and Wagemann, 2010), we concluded that none of the digital framework conditions is necessary for high or low to medium start-up activity. Hence, we performed the truth table procedure in order to check for sufficient conditions. A condition is sufficient if its presence always produces the outcome, despite alternative conditions that could also be conducive to this outcome (Ragin et al., 2006). As recommended by Ragin et al. (2006), we concentrate our analysis on the causal conditions that are included in the intermediate solution, which integrates logical remainders on the basis of theoretical knowledge (Ragin, 2008). The results of the fsQCA for sufficient conditions that are conducive to high start-up activity are presented in Table 2.

Table 2.
Configurations leading to *high* start-up activity.

	Intermediate solution	
	A1	A2
Digital market	●	●
Digital funding and finance	●	⊗
Digitally skilled human capital	●	●
Digital entrepreneurial culture	●	⊗
Digital government	●	●
Digital knowledge base		⊗
Digital infrastructure	⊗	⊗
Consistency	0.92	0.96
Raw coverage	0.28	0.17
Unique coverage	0.17	0.07
Overall solution consistency	0.93	
Overall solution coverage	0.35	

Notes: Black circles indicate the presence of a condition, and circles with an "X" indicate their absence. Blank spaces indicate irrelevant conditions (Ragin and Fiss, 2008).

The intermediate solution provides two substitutable configurations that exhibit a high overall solution consistency (i.e., the degree to which the configurations are subsets of the solution) of 0.93, hence exceeding the suggested threshold of 0.75 that was recommended by Woodside (2013). The overall solution coverage indicates that the causal conditions that are part of the two configurations account for 34.6% of membership in the solution, which is above the recommended threshold of 0.2 (Woodside, 2013). Both configurations have a unique coverage greater than the suggested threshold of 0.01 (Rigtering et al., 2017).

Configuration A1 indicates that the presence of digitally skilled human capital, strong digital entrepreneurial culture, digital funding and finance, an appropriate digital market and advanced digital government combined with the absence of an advanced digital infrastructure is sufficient for leading to high start-up activity in entrepreneurial ecosystems. Configuration A1 has a consistency level of 0.92.

Configuration A2 shows that the presence of digitally skilled human capital, an appropriate digital market and an advanced digital government combined with the absence of high levels of digital funding and finance, digital entrepreneurial culture, digital infrastructure and digital knowledge base is sufficient for resulting in high start-up activity in entrepreneurial ecosystems. Configuration A2 has a consistency level of 0.96.

Since fsQCA is not symmetric (Cervelló-Royo et al., 2020), it could be interesting to also investigate the combinations of digital framework conditions that result in low to medium start-up activity in entrepreneurial ecosystems. Hence, the results of the fsQCA for sufficient conditions resulting in low to medium start-up activity are presented in Table 3.

The intermediate solution provides four substitutable configurations that exhibit a high solution consistency of 0.95. The overall solution coverage indicates that the causal conditions that are part of the four configurations account for 43.1% of membership in the solution. All four configurations have a unique coverage greater than the suggested threshold of 0.01 (Rigtering et al., 2017).

Configuration B1 indicates that the presence of digitally skilled human capital, an advanced digital infrastructure and an appropriate digital knowledge base combined with low values for digital funding and finance, digital market and digital government is sufficient for leading to low to medium start-up activity in entrepreneurial ecosystems. Configuration B1 has a consistency level of 0.92.

Configuration B2 shows that the presence of a strong digital knowledge base alone is sufficient for leading to low to medium entrepreneurial activity, given the absence of the other six digital framework conditions. This configuration has a consistency level of 0.92.

Table 3.
Configurations leading to *low to medium* start-up activity.

	Intermediate solution			
	B1	B2	B3	B4
Digital market	⊗	⊗	●	●
Digital funding and finance	⊗	⊗	⊗	●
Digitally skilled human capital	●	⊗	⊗	●
Digital entrepreneurial culture		⊗	⊗	⊗
Digital government	⊗	⊗	⊗	●
Digital knowledge base	●	●	●	●
Digital infrastructure	●	⊗	●	●
Consistency	0.92	0.92	0.90	0.92
Raw coverage	0.16	0.17	0.18	0.17
Unique coverage	0.07	0.07	0.06	0.10
Overall solution consistency	0.95			
Overall solution coverage	0.43			

Notes: Black circles indicate the presence of a condition, and circles with an "X" indicate their absence. Blank spaces indicate irrelevant conditions (Ragin and Fiss, 2008).

Configuration B3 indicates that the presence of an advanced digital infrastructure, strong digital knowledge base and an appropriate digital market combined with low values for digital funding and finance, digital entrepreneurial culture, digitally skilled human capital and digital governance is sufficient for leading to low to medium start-up activity in entrepreneurial ecosystems. Configuration B3 has a consistency level of 0.90.

Configuration B4 shows that the presence of digital funding and finance, digitally skilled human capital, an advanced digital infrastructure, a strong digital knowledge base, an appropriate digital market and an advanced digital government combined with the absence of a digital entrepreneurial culture is sufficient for leading to low to medium entrepreneurial activity. This configuration has a consistency level of 0.92.

Finally, as recommended by Ragin et al. (2006), we tested the robustness of our results and the appropriateness of the calibration procedure. This was done by repeating the fsQCA procedure with slightly differing raw consistency limit values and small changes in the data calibration process. These methods suggested that the findings were relatively robust. Whereas the specific number of configurations could be slightly changed in some instances, the overall interpretation of our results remained essentially unchanged.

5 Discussion

This study investigates how different combinations of digital framework conditions explain start-up activity in entrepreneurial ecosystems. Applying fsQCA, our study shows that two configurations may lead to relatively high start-up activity in entrepreneurial ecosystems, and four configurations may lead to relatively low to medium start-up activity in entrepreneurial ecosystems.

With respect to high start-up activity, our results highlight the crucial importance of an appropriate digital market, digitally skilled human capital and advanced digital government for promoting entrepreneurial activity in entrepreneurial ecosystems. These three digital framework conditions are present (i.e., high) in both configurations (A1, A2) which are sufficient for leading to high start-up activity. Our findings suggest that an appropriate digital market, digitally skilled human capital and advanced digital government are conducive to high start-up activity with the presence of digital funding and finance as well as digital entrepreneurial culture, combined with the absence of digital infrastructure (configuration A1). In addition, an appropriate digital market, digitally skilled human capital and advanced digital government may lead to high start-up activity combined with the absence of digital infrastructure, digital funding and finance, digital entrepreneurial culture and digital knowledge base (configuration A2). Interestingly, the digital infrastructure framework condition is absent (i.e., low) in both configurations (A1, A2) which are sufficient for leading to high start-up activity. Furthermore, the digital knowledge base framework condition is not present in any of the two configurations (A1, A2) that lead to high start-up activity in entrepreneurial ecosystems.

Regarding low to medium start-up activity (i.e., not high start-up activity), our results highlight the distinctive role of the digital knowledge base because it is present in all four configurations (B1, B2, B3, and B4) which are sufficient for leading to low to medium start-up activity. In addition, digital infrastructure is present in three out of four configurations (B1, B3, and B4) that are sufficient for leading to low to medium start-up activity. If digital infrastructure is absent, low to medium start-up activity may only occur in the presence of the digital knowledge base framework condition (configuration B2). Moreover, three digital framework conditions are absent in three out of four configurations that lead to low to medium start-up activity in entrepreneurial ecosystems (both digital government as well as digital funding and finance are absent in configurations B1, B2, and B3; digital entrepreneurial culture is absent in configurations B2, B3, and B4).

Hence, our findings show that no singular combination of digital framework conditions is sufficient for leading to high or low to medium start-up activity. As proposed above, there exist different combinations of digital framework conditions that explain high or low to medium levels of venture creation in entrepreneurial ecosystems.

5.1 Implications

This paper offers valuable contributions to the entrepreneurship literature by connecting the stream of research on entrepreneurial ecosystems with that on digitalization. It provides a holistic view on digital framework conditions that facilitate the creation of new ventures. Our study shows how different digital framework conditions can be combined and lead to high or low to medium levels of entrepreneurial activity in entrepreneurial ecosystems. Whereas previous studies emphasized the important role of digital technologies and infrastructures as enablers of entrepreneurial activity (von Briel et al., 2018, Autio et al., 2018a), existing literature offered only limited insights with regard to the influence of digitalization on the broader entrepreneurial landscape.

Furthermore, research on the intersection between digitalization and entrepreneurship did not account for the enhanced complexity of entrepreneurial processes enabled by digital technologies and infrastructures. Our holistic, configurational approach enables researchers to grasp the complex and dynamic phenomena underlying entrepreneurship in a digitalized world by incorporating the increasing complexity infused by digitalization (Nambisan, 2017). The fsQCA method allows us to move beyond traditional methods of data analysis relying on variance-based tests (Ragin, 2006; Khedhaouria and Cucchi, 2019) and highlights the equifinal and conjunctural character of causal relationships in the emergent processes of entrepreneurial ecosystems.

Moreover, our results point out the crucial importance of three digital framework conditions for facilitating new venture creation in entrepreneurial ecosystems, namely digitally skilled human capital, advanced digital government and an appropriate digital market. Hence, our findings confirm previous assumptions that a workforce that is skilled in information and communication technologies increases the chances to develop successful start-ups (Autio and Cao, 2019). Furthermore, our results support earlier suggestions that the use of digital technologies and infrastructures by governmental agencies and organizations promotes a more conducive business environment for start-ups (Autio et al., 2018b), as well as the supposition that the access to a thriving digital market is crucial for new venture growth (Sussan and Acs, 2017). Interestingly, and contradictory to previous assumptions, our study also identifies two digital framework conditions which are not present in any of the configurations leading to relatively high start-up activity in entrepreneurial ecosystems, namely digital infrastructure and the digital knowledge base. Instead, these digital framework conditions are present in all configurations (digital knowledge base) or all but one configuration (digital infrastructure) resulting in low to medium start-up activity. Consequently, our results suggest that both the digital knowledge base and digital infrastructure do not appear to be decisive factors for the creation of high start-up activity in entrepreneurial ecosystems.

The findings of our study offer several opportunities for decision makers aiming to employ digital technologies and infrastructures to promote entrepreneurial activity in their respective local context. Whereas this configurational approach does not provide linear cause-and-effect models that indicate the exact influence of a specific digital framework condition on new venture formation, we believe that our results offer policy-makers a range of interesting combinations of digital framework conditions. Policy-makers can tailor these configurations to the specific local conditions of their particular city or region in order to enhance entrepreneurial activity. With regard to the two configurations that may lead to relatively high start-up activity in entrepreneurial ecosystems, the development of digitally skilled human capital, strengthening of digital government and support of the digital market appear to be the most promising ways for policy-makers to facilitate entrepreneurial activity in their cities.

Furthermore, our results suggest that decision makers should not focus too strongly on the development of the digital knowledge base and the digital infrastructure because these digital framework conditions are not present in any configuration leading to relatively high start-up activity. In fact, these two conditions are present in almost all configurations that result in low to medium entrepreneurial activity. Hence, our findings indicate that policies which concentrate too strongly on establishing an appropriate digital knowledge base and digital infrastructure might neglect other factors which are more important for creating a vibrant entrepreneurial ecosystem.

5.2 Limitations and future research

This study is subject to several limitations that can provide opportunities for future research. First, given the data availability of the utilized databases, the number of entrepreneurial ecosystems included in this study was limited. Furthermore, as all of the cases are based in Europe, the generalizability of our findings might be limited. Hence, future research could include a larger number of entrepreneurial ecosystems that are not only based in Europe, but cover cities in other continents, in order to examine whether our results hold for different geographical contexts. Second, while this study incorporates a relatively broad range of seven digital framework conditions and, in our view, represents an appropriate starting point for investigating how digitalization influences the broader entrepreneurial landscape, it could be possible that additional digital framework conditions impact the level of new venture formation in cities. We therefore suggest that future research should explore the effect of other digital framework conditions, such as digital collaboration or the digital business environment (Autio et al., 2018b; Bannerjee et al., 2016), on entrepreneurial activity. In this context, further studies could also examine the influence of digital framework conditions on additional outcome variables, such as survival rates of start-ups, the employment share of newly formed ventures or the productivity contribution of start-ups. Such analyses could offer a more fine-grained understanding of how digitalization influences different levels of entrepreneurial activity. Third, whereas the fsQCA approach enabled us to identify several configurations of digital framework conditions that might lead to high or low to medium levels of entrepreneurial activity, the fsQCA method does not allow to identify potential causal sequences between the digital framework conditions which may lead to relevant outcomes. Thus, future research could explore in greater detail the particular antecedent conditions which are conducive to high or low to medium levels of new venture formation in entrepreneurial ecosystems and if there exists a specific causal ordering between the antecedent conditions (Bonomi et al., 2020; Khedhaouria and Cucchi, 2019).

In spite of the limitations outlined above, this study represents an important contribution to closing the gap in the literature on the intersection between digitalization and entrepreneurial ecosystems. By adopting a fsQCA approach, our study is one of the first to reveal the configurations of digital technologies and infrastructures that lead to high or low to medium levels of new venture formation in entrepreneurial ecosystems.

D Essay 3: Ecosystem Types in Information Systems

Abstract

As of now, the academic community puts increasing attention on the ecosystem concept. Subsequently, a plethora of ecosystem conceptualizations has emerged, blurring the concept and making accurate utilization increasingly difficult. To address that issue, this study reports on an in-depth structured literature review following established, rigorous guidelines, with the goal in mind to structure and analyze the differing ecosystem conceptualizations and to produce a harmonized understanding of them. Based on the identified literature, we inductively derive mandatory and differentiating characteristics that are suitable to explain ecosystem configurations. Next, we use established clustering procedures to identify groups of ecosystems from the literature. From that, we propose five idealized types of ecosystems. The goal of the study is to provide the research community and practitioners with a conceptually sound understanding of different ecosystem types and, thus, giving them a tool to develop their own ecosystem approaches.

Keywords:

Ecosystems, typology, ideal types, literature review.

1 Introduction

Sciences and society are currently witnessing a paradigm change that entails a fundamental shift from a mechanistic towards a systemic worldview (Capra and Luisi, 2014). This systemic worldview emphasizes the interdependence and interconnectedness of the phenomena under study, with a particular focus on contextual and relational factors (Koskela-Huotari et al., 2016). In this connection, companies from various industries have transformed their previously hierarchical, linear supply chains into flexible networks of strategic alliances with external stakeholders during the last few decades (Bitran et al., 2007). Furthermore, as a result of the increasingly disaggregated character of technology development and specialist knowledge, firms are moving their locus of innovation from their own, internal research and development (R&D) facilities towards outside their firm boundaries, thus enabling collaborative innovation and R&D (Ritala et al., 2013; Baldwin and Hippel, 2011). This trend in the direction of more interconnected and collaborative business processes is further enhanced by digitally enabled networks, which provide new opportunities for less predefined and more dispersed organizational processes (Pagani, 2013).

In this context, the concept of ecosystems has recently gained traction among researchers, practitioners, and policymakers, since this approach allows to investigate the interdependencies and interactions between various actors (Ritala et al., 2013). Recent calls for papers of top information systems (IS) journals (e.g., see MIS Quarterly (2019), Electronic Markets (2019)), and conferences (e.g., ECIS, 2020; ICIS, 2020), also highlight the significance of ecosystems for the scientific community. Generally, from an economic perspective, ecosystems are perceived "as evolutionary self-organizing cross-industrial systems of independent economic actors that are connected by value-added chains and behave similarly to naturalistic systems" (Benedict, 2018, p. 453).

Multiple authors have highlighted the abundance of ecosystem conceptualizations existing in the literature. For example, Seppänen et al. (2017) find ecosystem concepts with varying prefixes, including platform, mobile, innovation, or business ecosystems, and Benedict (2018) identifies seven dominant ecosystem types discussed in IS research. These concepts, rather than being clearly delimitable, are characterized by conceptual blurring and overlap (Hyrynsalmi and Hyrynsalmi, 2019). Resulting from this definitional and conceptual ambiguity is the overutilization of the term *ecosystem* and the associated risk of the creation of just another "buzzword" (Fuller et al., 2019). More recent papers have introduced yet more concepts, for example, that of *data ecosystems* (Oliveira and Lóscio, 2018). Thus, scholars find it challenging to identify, distill, and investigate the specific ecosystem concepts which are relevant for their particular field of research (Tsujimoto et al., 2018).

Our paper addresses precisely this issue and develops a comprehensive theoretical synthesis of the respective concepts. Thus, we conduct an in-depth analysis of existing ecosystem approaches and create a sound conceptual basis for understanding and delimiting ecosystems. Firstly, we identify relevant literature and concepts through conducting a structured literature review, following the well-established and rigorous recommendations of Webster and Watson (2002) and Vom Brocke et al. (2009). Next, in order to tackle the problem of blurriness between ecosystem terminology and its utilization, we develop a typology of ecosystems based on the derivation of generic characteristics from the literature. The merit of this approach is the decoupling from detail and the focus on the larger picture, which, we argue, is required presently because of the aforementioned vast landscape of ecosystem conceptualizations and their utilization (Weber, 1949; Watkins, 1952). Hence, our research question is as follows:

Which generic ecosystem types can be derived from the literature in order to generate a harmonized understanding of ecosystem conceptualizations?

In order to achieve the goal of demarcation and creation of differentiability between the ecosystem concepts, we draw from the notion of *ideal types,* which represent a unique combination of the generic characteristics (Doty and Glick, 1994). We chose to draw from *ideal types* since these represent a suitable conceptual framework to codify conceptual knowledge, which has been abstracted and generalized. With the help of clustering methods, we derive idealized ecosystem types, as these are a suitable tool to create differentiability of ecosystem concepts. Once we identify the major concepts and their interrelations, the need for a clear demarcation of the field becomes distinct. Building on our first contribution, we are subsequently investigating the characteristics of the different ecosystem types.

The paper is structured as follows. First, we provide conceptual and theoretical fundamentals in ecosystem theory, beginning with the origin of the concept in ecology. Subsequently, we investigate the change and adaption of the term in IS literature. Following, we outline our approach to building the literature corpus, which, in section 4, is then used to derive general characteristics. Also, we detail our types, and discuss the typology in section 5. Lastly, in section 6, we discuss the significant contributions of our work, as well as limitations.

2 Ecosystems

2.1 Origin, definition, and utilization

There is widespread agreement that the initial concept of *ecosystems* in the field of *ecology* was coined by Tansley (1935, p. 299), who proposed the following definition: ”But the more fundamental conception is, as it seems to me, the whole *system*, including not only the organism-complex, but also the whole complex of physical factors in the widest sense” (Lindeman, 1942; Willis, 1997; Richter and Billings, 2015). Nevertheless, as with many other concepts, there is no incontrovertible definition (see Table 4 for exemplary, selected definitions), but rather a multitude of more or less varying definitional approaches (Blew, 1996). Tansley (1935) introduced the term *ecosystem* to replace the then-used terminology *complex organism* or *biotic community.* He argued that a system-based approach is more meaningful than strict limitations onto the organism-based view. Then, Tansley's (1935) conceptualization of ecosystems built on the compositional understanding of *ecology* as proposed by Haeckel (1866) and systems in the physics sense (Tansley, 1935; Weigmann, 2007). In that regard, ecosystems define the logic of the coexistence of living and non-living things under their environmental habitat (Evans, 1956). In the advent and throughout most of the 20th century, the ecosystem concept was predominantly used in the context of ecology (Willis, 1997; Jacobides et al., 2018), which is "the branch of biology that deals with the relations of organisms to one another and to their physical surroundings" (Stevenson, 2010, p. 557). Thus, the notion explicates ecosystems as the understanding of organisms living together (ecology) in delimited borders inhabited by interrelated and interdependent parts and elements (system) (Kast and Rosenzweig, 1972).

Table 4.
Selected biological definitions of the ecosystem concept throughout history.

Definition	Reference
"But the more fundamental conception is, as it seems to me, the whole *system* (in the sense of physics), including not only the organism-complex, but also the whole complex of physical factors in the widest sense."	(Tansley, 1935, p. 299)
"The *ecosystem* may be formally defined as the system composed of physical-chemical-biological processes active within a space-time unit of any magnitude, i.e., the biotic community *plus* its abiotic environment."	(Lindeman, 1942, p. 400)
"A biological community of interacting organisms and their physical environment."	(Stevenson, 2010, p. 557)

Since then, we can find multiple transfers of the ecological ecosystem concept onto additional domains, thus attracting scientific attention from outside the field of biology and establishing the concept as a central object of discussion in IS and management research (Adner and Kapoor, 2010; Jacobides et al., 2018). Furthermore, many studies draw from the biology analogy to explain the meaning of ecosystems within different contexts (see, e.g., Nischak and Hanelt (2019) or Nischak et al. (2017)). Probably the most prominent ecosystem analogy, at least in IS literature, is the conceptualization of various businesses that together form value creation networks, termed *business ecosystems* by Moore (1993). Business ecosystems, at that time introduced as a strategic management concept (Adner, 2017; Iansiti and Levien, 2004a), adopt an ecological approach to explain the underlying logic of the dynamics in platform-based cooperative networks (Moore, 1993). Moore (1993) considers ecosystems to be inherently shaped by *coopetition*, in which actors in the ecosystem both engage in friendly (cooperative) and hostile (competitive) relationships simultaneously (Bengtsson and Kock, 2000; Nalebuff and Brandenburger, 1997).

Ecosystems can be described as "a set of actors with varying degrees of multilateral, non-generic complementarities that are not fully hierarchically controlled" (Jacobides et al., 2018, p. 2255). The roots of business ecosystems trace back to the advent of the automotive industry at the beginning of the 20th century, with the automobile as the central platform for complementary goods and services (Moore, 2006). Other domains to which the concept of ecosystems has been transferred to are, among others, *platform ecosystems* (e.g., Huang et al., 2009; Tiwana et al., 2010), *innovation ecosystems* (e.g., Adner, 2006; Adner and Kapoor, 2010), or *software ecosystems* (e.g., Jansen et al., 2009; Plakidas et al., 2016).

2.2 Ecosystem types

According to Bailey (1994, p. 4), classification is the "(…) general process of grouping entities by similarity". Classifications can be dichotomously divided into two approaches, one focusing on the empirical derivation of *taxa* (taxonomies) and one referring to conceptually derived *types* (typology) (Lambert, 2006, 2015; Baden-Fuller and Morgan, 2010). Both terms are frequently used interchangeably, which results in a conceptual blurring (Szopinski et al., 2019; Gregor, 2006; Nickerson et al., 2013). Lambert (2006) and Lambert (2015) provide a productive juxtaposition of both terms by summarizing characteristic features of both approaches, which positions the present work as a *typology* rather than a *taxonomy* since we strive to construct general types relying on deductively derived characteristics. This understanding mostly corresponds with finding *ideal types* (or "Gedankenbild" (Weber, 1949, p. 90)), which are appropriate as they enable to not only explain reality through models but, more so, are a tool to explain deviations from them (Doty et al., 1993; Blalock, 1969; McKinney, 1966). This perception also corresponds with the typology understanding of Doty and Glick (1994, p. 232), which is as follows: "(…) typology, refers to conceptually derived interrelated sets of ideal types." Thus, a taxonomy might be more helpful when classifying real-world objects, yet it lacks in assisting the goal of the study outlined above, which aims to demarcate conceptual boundaries of ecosystem approaches and, naturally, requires idealized types to make distinction possible. To achieve this goal, the types need to be general by design, rather than specific, meaning, that the underlying characteristics derived from the literature require stark generalization and abstraction (McKinney, 1966).

Table 5.
A summary of selected studies analyzing ecosystem types.

Source	Short description	Types
Hyrynsalmi and Hyrynsalmi (2019)	The study identifies 23 types of non-biological ecosystems based on a literature review (LR), for example, business ecosystems, data ecosystems, innovation ecosystems, and platform ecosystems.	23
Faber et al. (2019)	The study identifies 12 types of business ecosystems based on a LR.	12
Seppänen et al. (2017)	The study identifies 11 research communities based on a LR.	11
Benedict (2018)	The study identifies seven types of ecosystems based on a LR classified alongside two dimensions, firstly, the nature of the systems and, secondly, its platform focus.	7
Knodel and Manikas (2015)	The study identifies 4 types of software ecosystems based on a LR.	4
Jacobides et al. (2018)	The study identifies 3 major types of ecosystems based on a LR.	3

To date, there exists a plethora of ecosystem concepts, with some authors listing more than ten different types. Table 5 provides a summary of selected studies that identify different ecosystem concepts and the corresponding number of identified ecosystem types. In the following section, we will explicate selective ecosystem conceptualizations that we have identified as the most dominant ones for IS research. The selection bases on the analysis of the keyword frequency within the Scopus Database, where we searched for "Ecosystems" in sources whose title contains "Information AND Systems". We added “Innovation Ecosystems” as a significant concept within management research (Jacobides et al., 2018) to additionally account for adjacent fields. We did not include “Digital Ecosystem(s)”, although it is the most frequent ecosystem keyword, since the articles are subsumable under the other concepts (e.g., Karhu et al., 2009; Briscoe and Wilde, 2006). Instead, the digital ecosystem can refer to any digitized ecosystem (Razavi et al., 2010; Nachira, 2002). Based on the reasoning above, we consider *business, platform, service, innovation,* and *software ecosystems* as most important from an IS research perspective.

Business ecosystems were introduced by Moore (1993) and apply ecosystem thinking to business relationships. Contrary to the more fundamental definitions stemming from *ecology* (see Table 4), the business ecosystem concept highlights the notion of a range of various interdependent and co-evolving actors complementing, through cooperation and competition, each other’s capabilities to satisfy customer needs (Teece, 2016; Basole et al., 2015). While the notion of ecological ecosystems indicates self-organization, business ecosystems may both be dynamic or steered through a pivotal actor, for example, a platform (Teece, 2016).

Platform ecosystems are novel in IS research, which becomes apparent by the increasing amount of discussions and scientific interest in the field of digitally-enabled ecosystems, such as app stores. Through app stores, developers might offer their products and services in the form of applications provided to the platform through *boundary resources,* such as *application programming interfaces* (API), *software development kits* (SDK), or *integrated development environments* (IDE) (Ghazawneh and Mansour, 2015; Ghazawneh and Henfridsson, 2013). These *boundary resources* empower developers with the technological equipment to contribute to applications and, in vibrant ecosystems, provide a consistent stock of external innovations (Tiwana, 2015). More generally, the notion of external innovation and third-party contributions represents a core principle of platform ecosystems. Thus, the platform is the technological infrastructure consisting of various modules to enable external innovation, whereas the corresponding, evolving ecosystem consists of users, vendors, and so on (Huang et al., 2009; Qiu et al., 2017; Tiwana et al., 2010).

Service ecosystems are composed of service providers, consumers, and composition developers that collaboratively create new services, thereby adding value to the service ecosystem (Barros and Dumas, 2006; Papazoglou and van den Heuvel, 2006; Huang et al., 2014). The system's service-oriented architecture enables the continuous integration of various resources and the exchange of services between the different interconnected actors (Benedict, 2018; Huang et al., 2014). Due to the ongoing change in the service offering and dynamic interactions between the system's stakeholders, the service ecosystem is continuously evolving (Huang et al., 2014).

Innovation ecosystems draw upon the concept of business ecosystems introduced by Moore (1993). Similar to the business ecosystem concept, the innovation ecosystem approach is also based on the notion of interconnected network actors (Gomes et al., 2018). Various stakeholders, such as focal companies, suppliers, customers, policymakers, and additional innovators, share sets of knowledge and skills to jointly co-create innovative products and services (Iansiti and Levien, 2004a; Gomes et al., 2018; Carayannis and Campbell, 2009). However, despite the analogies between the business ecosystem and innovation ecosystem concepts, several researchers point to the differences between both approaches, with the main difference being that innovation ecosystems are related to value creation. In contrast, business ecosystems primarily refer to value capturing processes (Gomes et al., 2018).

Software ecosystems integrate combinations of interacting actors upon a shared technological platform that generates new software and services (Manikas and Hansen, 2013). While there exist several different definitions of software ecosystems (e.g., Messerschmitt and Szyperski, 2003; Lungu et al., 2010; Jansen et al., 2009), the majority of definitions consider a standard software, the interdependent relationships between ecosystem stakeholders as well as business-related aspects, such as user satisfaction or revenue models, to be integral parts of the software ecosystem concept (Jansen et al., 2009; Bosch, 2009; Bosch and Bosch-Sijtsema, 2010; Manikas and Hansen, 2013).

3 Literature review

Even though the scientific disciplines differ in their perception of knowledge and the means of creating it, they share the commonality of leveraging existing research published by scholars (Boell and Cecez-Kecmanovic, 2014; Schryen et al., 2015), which often employs the famous metaphor by Newton (1675), that describes scientific progress as "standing on the shoulders of giants". Our literature review follows established guidelines within the IS community (Webster and Watson, 2002; Vom Brocke et al., 2009). While there is a wide variety of different literature review types, which differ in their respective orientation and purpose (see Cooper, 1988), our focus lies on the attributes that the individual authors assign to the ecosystem concepts. Our approach can be described as a mapping study (Paré et al., 2015), which we conduct to identify the characteristics of the individual concepts and determine generic types of ecosystems.

We first select databases that cover the essential IS journals and conference proceedings (Peffers and Ya, 2003; Ferratt et al., 2007) and filter for peer-reviewed articles (Levy and Ellis, 2006; Webster and Watson, 2002). As these databases meet the outline requirements, we choose the AISeL, ACM, and Scopus databases. To determine the most important ecosystem types and in addition to that, a scope for further investigation, we perform an initial search for "ecosystems" (following Vom Brocke et al., 2015) within IS journals and conferences (see section 2.2). Based on the findings from that first, preliminary analysis (Okoli and Schabram, 2010), we conduct a second search iteration concentrating on business, platform, service, innovation, and software ecosystems. Although there exist other concepts, such as entrepreneurial or Internet of Things (IoT) ecosystems (e.g., Seppänen et al., 2017; Hyrynsalmi and Hyrynsalmi, 2019), we identify those five ecosystem types to be the key concepts within IS research. Fig. 9 depicts and quantifies the summarized search process. After we made an initial reduction within the databases themselves, for example, by excluding biological and psychological contributions, we manually screened the remaining publications. Based on the manual selection, we only considered articles that deal with our research objectives in a non-trivial and non-marginal way (Okoli and Schabram, 2010; Vom Brocke et al., 2015). Finally, we conduct a short citation analysis of our literature core and a forward search of the most cited articles to include promising contributions to our research. The adjustment is made to include journal versions of conference papers if available.

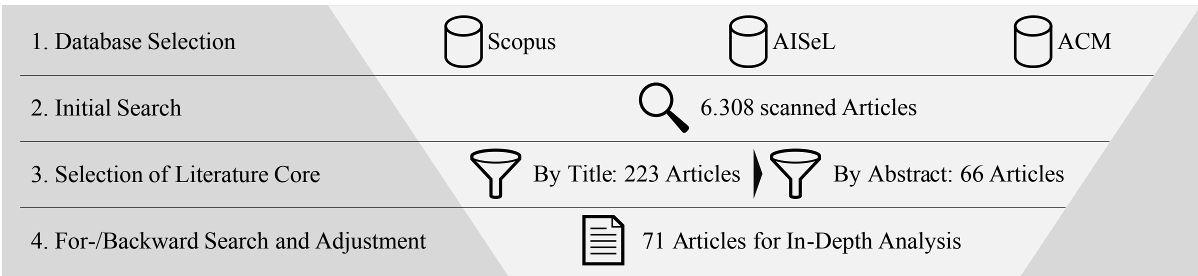

Fig. 9. Visualization of the literature search process.

4 Ecosystem types

4.1 Construction

The design of the ecosystem types is based on the literature review outlined in section 3. We have identified 71 papers relevant to the present study and analyzed them to identify attributed ecosystem characteristics decoupled from their respective prefix (e.g., business ecosystems or innovation ecosystems). Table 6 shows the corpus of literature and the corresponding characteristics. Our analysis uses a dichotomous assessment logic, in that we differentiate between addressed and non-addressed characteristics. The former is visualized by full circles, the latter by hyphens. To improve the clarity and to structure our analysis, the discussion, and

Table 6.
Overview of generic characteristics of ecosystems and corresponding sources.

Sources	Population				Purpose			Relationship Structure							Sys. Config.				Sys. Dynamic				
	Distinct roles	Specialization	Loose coupling	Overlapping industries	Innovation	Value creation	Niche creation	Interaction	Collective intention	Resource sharing	Symbiosis	Centralized power	Balanced power	Orchestration	Structuredness	Centricity	Coordinating mech.	Stability	Adaptive behavior	Self-organization	Lifecycle pattern	Co-evolution	Timing relevance
Adner (2006)	-	●	-	-	●	●	-	-	●	●	-	●	-	●	-	●	-	-	-	-	-	●	●
Adner (2017)	●	●	-	●	●	●	-	●	●	●	-	-	-	-	●	-	-	-	-	-	-	-	●
Adner and Kapoor (2010)	●	●	-	-	●	●	-	●	●	●	●	●	-	-	●	-	-	-	-	-	-	-	-
Alves et al. (2017)	●	-	●	-	-	●	-	●	●	-	-	-	●	●	-	●	●	-	●	-	-	●	-
Amorim et al. (2013)	●	-	●	-	●	-	-	●	●	●	●	-	-	-	●	●	-	-	-	-	-	-	-
Barrett et al. (2015)	●	●	-	-	●	●	-	●	-	●	●	-	-	-	-	-	●	-	-	●	-	-	-
Basole (2009)	●	●	-	●	●	●	-	●	●	-	●	-	-	●	-	●	-	-	-	-	-	●	-
Basole and Karla (2011)	●	●	●	●	-	●	-	●	●	-	●	●	-	-	-	-	-	-	●	●	-	●	-
Basole et al. (2015)	●	-	●	-	-	-	-	-	-	-	●	-	-	-	-	-	-	-	●	-	-	●	-
Basole et al. (2018)	●	-	-	-	●	-	-	-	●	●	●	●	-	●	-	●	-	-	-	-	-	●	-
Bosch (2009)	●	-	●	-	●	●	-	●	●	●	-	-	-	-	-	●	-	-	-	-	-	●	-
Briscoe (2010)	●	-	●	-	-	-	-	●	-	-	-	●	-	-	-	-	-	●	●	-	-	●	-
Briscoe and Wilde (2006)	●	-	-	-	●	-	-	●	●	●	-	●	-	-	-	●	●	-	-	●	-	-	-
Burden et al. (2019)	●	●	●	-	-	●	-	●	-	●	-	●	-	-	-	●	-	●	-	-	-	-	-
Burkard et al. (2012)	●	-	●	-	●	●	-	●	●	-	-	-	-	●	-	●	-	-	-	-	-	●	-
Ceccagnoli et al. (2012)	●	-	-	-	●	-	-	●	-	●	-	-	-	-	-	-	-	-	-	-	-	●	-
Chae (2019)	●	●	-	-	-	●	●	-	●	●	-	-	-	-	-	●	-	●	-	-	-	-	-
den Hartigh et al. (2006)	●	-	●	-	●	-	-	●	-	-	●	●	-	●	●	-	-	●	●	-	-	●	-
Dhanaraj and Parkhe (2006)	●	-	-	-	-	●	-	●	●	●	●	-	-	-	-	●	●	-	●	-	●	●	-
Dhungana et al. (2010)	●	●	●	-	●	●	-	-	●	●	-	●	-	-	●	●	-	-	●	-	-	●	-
Gawer and Cusumano (2013)	●	-	●	-	●	●	-	●	-	-	-	●	-	-	-	-	-	-	●	-	-	-	-
Goldbach et al. (2018)	●	-	-	-	●	●	-	●	-	●	-	-	-	-	●	●	-	●	-	-	-	●	-
Handoyo et al. (2013)	●	●	●	-	●	-	-	●	●	●	●	●	-	-	-	●	-	-	-	-	-	-	-
Huang et al. (2009)	●	●	●	-	●	●	-	●	-	●	●	-	-	-	-	-	-	-	-	-	-	-	●
Huhtamäki and Rubens (2016)	●	●	●	●	●	●	●	●	●	-	●	●	●	-	-	●	-	●	-	-	-	-	-
Iansiti and Levien (2004a)	●	●	●	-	●	●	-	●	-	-	●	-	-	-	-	●	-	●	-	-	-	●	-
Isckia et al. (2018)	●	●	-	-	●	●	-	●	-	-	-	●	-	●	-	●	-	-	-	-	-	●	-
Iyer et al. (2007)	●	●	-	●	●	●	-	●	●	-	●	●	-	-	-	●	●	-	-	-	-	-	-
Jacobides et al. (2018)	●	-	●	-	-	-	-	●	●	●	-	●	-	●	-	●	●	-	-	-	-	-	-
Jansen et al. (2009)	●	-	-	-	●	●	-	-	-	-	-	-	-	-	●	-	-	●	-	●	-	●	-
Karhu et al. (2009)	●	●	-	-	-	●	-	●	-	-	-	-	-	-	-	●	-	-	-	-	●	-	-
Khadka et al. (2011)	●	●	-	-	-	-	-	●	●	●	●	-	-	-	-	●	-	-	-	-	-	●	-
Kim et al. (2008)	●	●	●	-	●	●	-	●	-	-	-	-	-	-	-	●	-	-	-	-	●	-	-
Kim et al. (2016)	●	-	●	●	-	●	-	●	●	-	●	●	-	-	-	-	-	-	-	-	-	-	-
Kim et al. (2017)	●	●	-	-	-	-	-	●	-	-	-	-	-	●	●	●	●	-	●	-	-	●	-
Knodel and Manikas (2016)	●	-	-	-	●	●	-	●	-	-	-	-	-	●	●	-	●	-	-	●	-	●	-
Koskela-Huotari et al. (2016)	●	●	●	-	●	-	-	-	●	●	-	●	-	-	●	●	●	-	-	-	-	-	-
Lettner et al. (2014)	●	●	●	●	●	●	-	●	●	-	●	●	-	-	-	●	-	-	●	-	●	●	-
Lihua et al. (2009)	●	-	-	-	●	●	-	-	●	●	●	-	-	-	●	-	-	-	●	●	-	●	-
Liu et al. (2010)	●	●	●	-	-	-	-	●	●	●	●	-	-	-	-	-	-	-	●	●	-	●	-
Lurgi and Estanyol (2010)	●	-	●	-	-	●	-	●	-	●	-	-	-	-	●	-	●	-	●	●	-	●	-
Lusch and Nambisan (2015)	●	-	●	-	-	-	-	-	●	●	-	-	-	-	●	●	●	-	-	-	-	●	-
Manikas (2016)	●	●	-	-	-	●	-	●	●	●	-	-	-	-	●	-	●	-	-	●	-	-	-
Mele et al. (2018)	●	●	-	-	-	●	-	-	●	-	●	-	-	-	-	-	-	-	-	-	-	-	-
Messerschmitt and Szyperski (2003)	●	●	●	●	●	-	-	●	●	-	-	●	-	-	●	-	-	●	●	-	●	●	-
Moore (1993)	●	●	●	-	●	-	-	●	●	●	-	-	-	-	●	●	●	-	-	-	-	-	-
Nambisan (2013)	●	-	-	-	-	●	-	-	-	●	-	-	-	-	●	-	●	-	●	●	-	●	●
Nenonen et al. (2018)	●	●	-	-	-	●	-	●	-	●	●	-	-	-	-	-	-	-	●	-	-	●	-
Ojuri et al. (2018)	●	●	●	-	●	●	-	●	●	●	●	●	-	●	●	●	-	-	-	-	-	-	-
Parker et al. (2017)	●	-	●	-	●	-	●	●	●	-	●	●	-	-	-	-	-	●	●	-	-	●	-
Peltoniemi (2006)	●	-	●	-	●	●	-	●	●	-	●	-	-	-	●	●	●	-	-	-	-	-	-
Plakidas et al. (2016)	●	-	-	-	●	-	-	-	●	-	●	-	-	-	-	●	-	-	-	-	-	-	-
Qiu et al. (2017)	●	●	●	-	-	-	-	-	-	-	●	-	●	-	-	-	-	-	-	●	-	-	-
Razavi et al. (2010)	●	●	-	-	-	-	-	●	-	-	-	-	-	-	-	●	-	-	-	-	-	-	-
Riedl et al. (2009)	●	-	-	-	●	●	-	-	●	●	-	-	-	●	●	-	●	●	-	-	●	-	-
Ritala et al. (2013)	-	●	-	-	●	●	-	●	●	-	●	-	-	-	●	-	-	-	●	●	●	●	-
Rong and Shi (2009)	●	●	●	-	●	●	-	●	●	●	-	-	-	-	●	●	-	-	-	-	-	●	-
Rong et al. (2018)	●	-	-	-	●	●	-	●	-	●	-	-	●	-	-	-	-	-	-	-	-	●	-
Saarikko (2016)	●	●	●	-	●	●	●	●	●	●	●	●	-	●	●	●	-	-	-	-	-	●	-
Schettino et al. (2017)	●	●	-	●	●	●	-	●	●	●	-	-	-	-	●	●	●	-	-	-	-	●	-
Selander et al. (2010)	●	●	-	-	-	-	-	●	-	-	●	-	-	-	●	●	●	●	-	-	-	●	-
Serebrenik and Mens (2015)	●	●	-	-	●	●	-	●	●	●	-	-	-	-	-	●	●	-	-	-	-	-	-
Smith et al. (2016)	●	-	-	-	●	●	-	●	-	-	●	●	-	●	-	●	-	-	-	-	-	●	-
Song et al. (2018)	●	●	●	-	●	●	-	●	●	-	-	●	-	-	●	-	-	●	-	-	-	-	-
Tan et al. (2009)	●	-	-	-	-	●	-	●	●	-	●	-	-	-	●	●	-	-	-	-	●	●	-
Tian et al. (2008)	●	-	●	-	●	-	-	●	-	-	●	●	-	-	●	●	-	●	●	-	-	●	-
Tiwana (2015)	●	-	-	-	●	-	-	●	●	-	●	●	-	-	-	-	-	-	-	-	-	-	-
Tiwana et al. (2010)	●	-	●	-	-	●	●	●	-	●	●	●	-	●	-	-	●	●	-	-	-	-	-
van den Berk et al. (2010)	●	●	●	-	●	●	-	●	●	●	●	-	-	-	-	-	●	-	-	●	-	●	-
Vargo et al. (2015)	●	●	-	-	-	●	-	●	●	●	●	●	-	-	-	-	●	●	-	●	-	●	-
Wang et al. (2019)	-	●	-	-	●	●	-	-	●	●	-	●	-	●	-	●	-	-	-	-	-	●	●

presentation, we grouped the characteristics utilizing a hybrid inductive-deductive thematic analysis (see Fereday and Muir-Cochrane, 2006). While we mainly use inductive grouping, the process is influenced by the theories of social systems (Parsons, 1972), complex systems (Gao et al., 2012; Koskela-Huotari et al., 2016), and complex adaptive systems (Holland, 1992; Briscoe, 2010; Peltoniemi and Vuori, 2008). In the following, we discuss the groups of characteristics as derived from the literature study (see Table 6). Additionally, we present mandatory and differentiating characteristics (see Table 7) within the groups. A more detailed explanation of all identified characteristics can be found in Table 8.

The *population* is central to every type of system since the specific quantity of individuals (or actors) form a community (Parsons, 1972). The population's heterogeneity is essential and valid for all types of ecosystems (Gao et al., 2012), which is often expressed in *distinct roles* that actors can take (Barrett et al., 2015). *Specialization* (Adner and Kapoor, 2010) means the uniqueness of the actors' value propositions (Liu et al., 2010), and *loose coupling* refers to their openness (Rong et al., 2018). Both characteristics are essential to differentiate between the ecosystem types.

Table 7.
Overview of mandatory and differentiating ecosystem characteristics.

Type	Explanation	Characteristics
Mandatory	Distinct across all clusters and not appropriate for differentiation.	Distinct roles, innovation, value creation, interaction, co-evolution.
Differentiating	High variance between the clusters and used for distinction.	Specialization, loose coupling, collective intention, resource sharing, symbiosis, centralized power, orchestration, structuredness, centricity, coordinating mechanisms, stability, adaptive behavior, self-organizing.
Others	Neither characterizing for the clusters nor suitable for differentiation.	See Table 8 for the remaining characteristics.

The *ecosystem purpose* is essential as a decision-making maxim for participation and behavior in ecosystems (Smith and Stacey, 1997; Lurgi and Estanyol, 2010; Parsons, 1972). Parsons (1972) points out that a social system comprises a value system, which possibly entails social goals. For the case of the analyzed ecosystem types, we identify *innovation*, and generally *value creation* as fundamental goals for those communities (Adner, 2017; Adner and Kapoor, 2010). In platform ecosystems, the latter is often a result of the utilization of network effects (Song et al., 2018).

The *relationship structure* represents the social layer of the ecosystem and is the largest group of characteristics, which underpins its importance. Just as social systems emerge from the interactions between human actors and a respective "sense of 'belonging'" (Parsons, 1972, p. 254), the ecosystem's population forms from the actors' *interactions*, which represents the fundamental relationship type. Differentiating characteristics for the ecosystem types are the *collective intention*, representing a decentral decision making (Knodel and Manikas, 2016), *resource sharing,* and *symbiosis*, representing specific interactions (Iansiti and Levien, 2004a; Vargo et al., 2015), *centralized power,* and *orchestration*, which both imply social centrality (Ritala et al., 2012; Dhanaraj and Parkhe, 2006).

System configuration defines the static structure of an ecosystem, which mainly consists of tangible, physical characteristics (Briscoe, 2010). We identify four characteristics to differentiate between the ecosystem types. First, *structuredness* refers to decentral interaction-enabling technologies (Amorim et al., 2013), second, a *centricity* that can relate, e.g., to products, innovations, platforms, or value propositions (Adner, 2017; Jansen et al., 2009). *Coordinating mechanisms*, as the third characteristic, refer to explicit or implicit rules that steer the coordination of the ecosystems (Tiwana et al., 2010; Vargo and Lusch, 2016). Fourth, the *stability* of an ecosystem refers to the robustness against external stimuli (den Hartigh et al., 2006).

System dynamics entail characteristics referring to the system behavior concerning environmental changes and variations over time. Some authors describe ecosystems as being, in general, dynamic (e.g., Basole et al., 2015), while others describe ecosystems as *complex adaptive systems* (e.g., Briscoe and Wilde, 2006; Liu et al., 2010). These are time-variant due to their differentiating *adaptive behavior* and *self-organization* of the actors and structures (Holland, 1992; Peltoniemi and Vuori, 2008; Briscoe, 2010). Additionally, *co-evolution* (Iansiti and Levien, 2004a) is an essential characteristic of all types.

Given the structure of our documentation (see section 3), we consider the individual papers and the respective ecosystem conceptualization as vectors. Thus, to find groups of conceptualizations that are more similar amongst each other than to other groups, we use cluster analysis. The cluster analysis was performed using the statistical programming language *R* and the package *"cluster"* (Maechler et al., 2018). In *R*, we performed *Agglomerative Hierarchical Clustering* (AHC) based on *Ward's Method* (Ward, 1963), distance matrices generated using Gower's (1971) coefficient, and comparison of clusters (e.g., for n = 4, 5, or 6). In the first iteration, the cluster analysis used all characteristics. Given our dichotomous classification of characteristics into optional and mandatory characteristics, we excluded the mandatory characteristics, as they were defined to be valid for all ecosystem concepts and thus do not provide meaningful grounds for differentiation. Therefore, we repeated the cluster analysis with the optional characteristics. We identified five clusters to be a valid solution by the visual analysis of the plotted dendrograms and the resulting clusters. In line with our understanding of *ideal types,* we then interpreted the clusters alongside their dominant characteristics, which also serve as the basis for naming them, and interpreted their idealized variation.

Table 8.
Complete description of ecosystem characteristics.

Characteristic	Definition
Mandatory Characteristics	
Distinct roles	Actors take on different roles to operate an ecosystem (Khadka et al., 2011). Roles can be, e.g., the platform providers (Saarikko, 2016), keystones, and niche players (Iansiti and Levien, 2004a).
Innovation	Innovation is fundamental for gaining competitive advantages and can be achieved through the development of, e.g., technology (Adner and Kapoor, 2010), services (Lusch and Nambisan, 2015; Nambisan, 2013) or business models (Chesbrough, 2010).
Value creation	This characteristic focusses on the (collective) creation of value, though, e.g., different types of complementary propositions (Jacobides et al., 2018). Value can consist of, e.g., products, services, and content (Handoyo et al., 2013). Network effects are elementary for value creation in ecosystems (Katz and Shapiro, 1985; Parker et al., 2017).

Interaction	The relationship network bases on interactions between interdependent actors (Basole et al., 2015; Lusch and Nambisan, 2015). Those interactions can be specified, e.g., as transactions (Tian et al., 2008).
Co-evolution	Co-evolution can be described as an emergent process of continuous, interdependent advancement of two or more actors (Moore, 1993) and, e.g., their capabilities (Jacobides et al., 2018). Briscoe (2010) speaks of mutual “selection pressure” (p. 42).
Differentiating Characteristics	
Specialization	Refers to any contribution to an ecosystem (Knodel and Manikas, 2016), which is in most cases an individual offering (Adner, 2006) or value propositions (Vargo et al., 2015).
Loose coupling	This refers to the openness of a system, as the actors have the option to leave the ecosystem and/or join another system (Lusch and Nambisan, 2015). From a systems theory point of view, this can be described as openness (Parker et al., 2017).
Collective intention	This refers to an intrinsic motivation to participate and contribute in an ecosystem (Knodel and Manikas, 2016; Dhungana et al., 2010). It can become manifest, e.g., through coopetition (see Nalebuff and Brandenburger, 1997) or collaboration (Hamel et al., 1989).
Resource sharing	Specifies the base of interactions as the integration of resources, knowledge, and/or capabilities to create value collaboratively (Vargo et al., 2015; Basole, 2009).
Symbiosis	Symbiosis can be defined as a special form of interaction between, at least, two actors that gain mutual advantages from the relationship (Iansiti and Levien, 2004a).
Centralized power	Centralized power refers to a certain degree of centricity within the social subsystem, which can lead to “aristocratic patterns” (Basole et al., 2015, p. 24).
Orchestration	Refers to centralized decision making to create and capture value within a network (Dhanaraj and Parkhe, 2006) through “coordination by enabling” (Ritala et al., 2012, p. 325).
Structuredness	The technical base that allows the relationship network to interact (Amorim et al., 2013; Gawer and Cusumano, 2013) and therewith to exchange (in)tangible resources to reach its objectives (Briscoe and Wilde, 2006; Nambisan, 2013). Does not have to be platform-central, rather it can be decentralized (Lusch and Nambisan, 2015).
Centricity	Refers to a manifest central hub, which might be a (software) platform (Gawer and Cusumano, 2013; Plakidas et al., 2016), innovation (Burden et al., 2019), products (Jacobides et al., 2018), or more generally a value proposition (Adner, 2017).
Coordinating mechanism	Refers to decision making and control in ecosystems. Encompasses, e.g., governance (Tiwana et al., 2010) or institutions (Vargo et al., 2015) that refer to, e.g., norms and rules, which are the most important aspects of actor configurations (Vargo and Lusch, 2016).
Stability	Important for establishing a coopetition equilibrium within ecosystems (Wang et al., 2019) and is closely related to the ecosystem’s health (Handoyo et al., 2013).
Adaptive behavior	Refers to the system’s ability to react to external influences and environmental stimuli with internal changes (Holland, 1992; Lusch and Nambisan, 2015). This happens either through self-organization or central players and correlates with timing (Lusch, 2011).
Self-organization	Implies decentralized decision making in a system without central power (Peltoniemi, 2006) to react on external stimuli by changing the system (Holland, 1992).
Other Characteristics	
Overlapping industries	One of the fundamental premises of ecosystems is the transition from traditional perspectives (Moore, 1993) to the notion of economic communities “beyond the boundaries of a single industry” (Jacobides et al., 2018, p. 2257).
Niche creation	Iansiti and Levien (2004a) introduced this characteristic as elementary for measuring the ecosystem's diversity and its health. Niche players create value for themselves (van den Berk et al., 2010), influencing the systems evolution (Schettino et al., 2017), as their niches act as innovation clusters for the ecosystem (den Hartigh et al., 2006).
Balanced power	This refers to a healthy balance between control of the orchestrator and autonomy of the other participants (Alves et al., 2017) to create sustainability (Razavi et al., 2010).
Lifecycle pattern	Moore (1993) introduced the business ecosystem as an evolving, lifecycle-based economic system that implies the existence of development phases (Khadka et al., 2011).
Timing relevance	This characteristic refers to the dynamic capability (Nenonen et al., 2018) of the timing of decisions within an ecosystem, e.g., the launch of an innovation (Adner, 2006).

4.2 Generic ecosystem typology

Derived from the analysis above, we present five generic ecosystem types, as displayed in Table 9. In the following section, we describe the individual types, their dominant characteristics, and their interrelationships. Additionally, we showcase illustrative examples to make each type more tangible.

Table 9.
Overview of ecosystem types.

#	Name	Dominant Characteristics	Description
(1)	*Sociocentric ecosystems*	- Centralized power - Adaptive behavior - Stability - Loose coupling	*Open communities that are organized around a social power, e.g., a keystone player, and evolve through adaptation to external stimuli.*
(2)	*Symbiotic collective ecosystems*	- Symbiotic relationships - Collective intention - Self-organizing - Specialization	*Closed communities focussing on symbiotic relationships to evolve their individual specializations.*
(3)	*Centrally balanced ecosystems*	- Centricity - Collective intention - Loose coupling - Specialization	*Open communities sharing their resources and specialization on a central object, which is controlled by collective intentions.*
(4)	*Orchestrating actor ecosystems*	- Centricity - Centralized power - Specialization - Collective intention	*Communities controlled by a central power and a central object used to orchestrate the individual specializations.*
(5)	*Structured resource sharing ecosystems*	- Resource sharing - Structuredness - Self-organizing - Coordinating mechanism	*Closed community sharing its resources through technical structures to co-evolve, steered by coordination mechanisms.*

Sociocentric ecosystems (1) are centrally organized and focus on the social layer. Centrality is implicated by an actor whose advantage is an imbalance of power within the social system. The main emphasis is on the adaptive steering of the ecosystem in order to pursue stability and co-evolution. The system is open, and the actors enter the system for the purpose of creating symbiotic relationships and thus generate collective expectations towards the central actor. As an example, for the first type (see Fig. 10: Type 1**)**, we point to the case of ABB Canada in the mid-'90s (see Moore, 1996). To overcome stagnating sales volumes, they took the innovative path to foster the regional economy instead of traditional cost-cutting. ABB formulated a strategy independent of specific technology that was dedicated to establishing a stable, long-term oriented partnership network, which is adaptive towards environmental changes. Their principal value proposition was to build an open network of partners around ABB and to relate their capabilities to the partners' activities for advancing their respective competitive advantages.

Symbiotic collective ecosystems (2) are characterized by an existing power equilibrium due to the absence of a central actor. The priority of this type is on the social level. At the heart of the decentralized decision-making lies the creation of symbiotic relationships, which, by using the unique abilities of the actors, are to enable co-evolution and value creation. Due to this decentralized system configuration, self-organization occurs. An example of *symbiotic collective ecosystems* (see Fig. 10: Type 2) is the open innovation platform DEMOLA, which is presented by Huhtamäki et al. (2013). Its purpose is the solution of entrepreneurial problems by students who bring in the unique expertise of their discipline symbiotically. DEMOLA does not provide technical infrastructure, but brings together the user groups and organizes the offline innovation workshops.

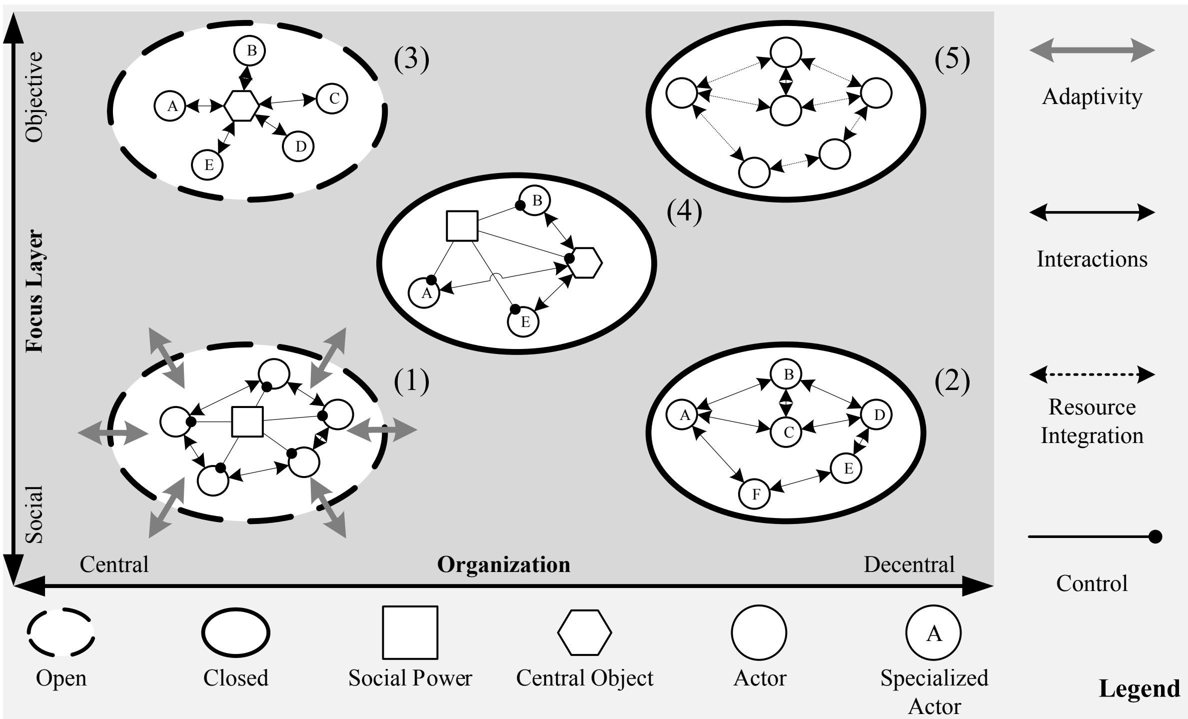

Fig. 10. Typology of ecosystems.

Centrally balanced ecosystems (3) represent ecosystems that organize around a central object and have a balance of power. These ecosystems are controlled by coordinating mechanisms, which are integrated into the platforms or structures based on collective intention. The loosely coupled actors contribute their respective specialized capabilities and resources. Woodard (2016) describes the Ag-Analytics platform, which we propose as a representative example of *centrally balanced ecosystems* (see Fig. 10: Type 3). The platform collects and aggregates data from a wide variety of sources so that researchers can use a single repository for research projects. The vision of the platform operators is to build an active community, which contributes to the further development of the platform.

Orchestrating actor ecosystems (4) are shown at the centre of Figure 10 and are based on a sound balance between central organization and decentralized structures. A focus is placed both on the social and technical dimension, which is shown by the presence of a central object and an orchestrating actor. In such ecosystems, the orchestrator implements the collective will, thereby integrating the specialized capabilities of each actor in the direction of the common objectives. The SAP development partner ecosystem (Rickmann et al., 2014) is exemplary for the *orchestrating actor ecosystem* (see Fig. 10: Type 4), as it demonstrates how a platform provider can foster a community by orchestrating the relationships. By restricting the access to the platform and guiding the development of its complementarities, SAP holds a central place in the ecosystem at all dimensions.

Structured resource sharing ecosystems (5) are decentralized ecosystems with a focus on a shared objective. The integration of resources between actors is made possible by technical *structures* that contain coordinating mechanisms. The latter is based on collective intent and leads to self-organization of the ecosystem. An illustrative example of the *structured resource sharing ecosystem* (see Fig. 10: Type 5) is the API ecosystem as described by Evans and Basole (2016). Without central hubs or keystones, ecosystem actors can provide their resources amongst each other, which makes efficient resource integration possible. The technical infrastructure of digital technologies allows borderless interactions between participants of these self-organizing ecosystems.

5 Discussion of the typology

Although our results consist of both a typology and five corresponding *ideal types,* we use the five subjective conditions by Nickerson et al. (2013) for a useful taxonomy as the existing knowledge base (as they argue that both terms are synonyms) to argumentatively discuss the quality of our typology (Hevner et al., 2004).

The criterion of *conciseness* refers to the typology being manageable, yet meaningful. Our typology proposes ecosystem types alongside two central dimensions, namely the *organization* and the *focus.* Additionally, we introduce visual, conceptual dimensions in the shape of icons (see Fig. 10). Using these visual aids (e.g., canvases such as the Business Model Canvas), both assist in sharpening the comprehensibility, communicability, and delimitability of the conceptual content (Chandra Kruse and Nickerson, 2018). Thus, by summarizing all dimensions (including actors, interconnections between them, and systems borders), we reach five dimensions to which Nickerson et al. (2013) point to Miller's (1956) "magical number seven" and give a span of plus or minus two dimensions for being adequately comprehensible and utilizable.

Next, the typology needs to be *robust*, meaning that the dimensions sufficiently and meaningfully provide differentiation between the types. We argue that our dominant differentiating dimensions, such as the juxtaposition of central and decentral ecosystems, lie at the heart of the concept. Thus, it provides both the opportunity to find polar opposite ecosystem configurations (e.g., centralized ecosystems versus decentralized ecosystems), as well as to identify "shades of grey" in-between, as expressed by the visualization of the five types (see Fig. 10).

The *comprehensiveness* refers to the ability of the typology to subsume all of the underlying objects or a relevant sub-sample. The typology builds on a structured literature review and identifies 71 papers relevant to our study (see Table 6). The types build on a clustering of the conceptualization of all 71 papers without the exclusion of any. Thus, all conceptualizations can be classified through these types, as each of them was used to derive it.

The typology needs to be *extendible*, i.e., it must be possible to append additional dimensions easily. As we chose to explicate the types through a visualization based on multiple dimensional metrics, we believe that it should be relatively easy to introduce additional elements. One could, e.g., introduce another dimension through filling the objects with colours, which would be easily executable.

Lastly, the typology needs to be *explanatory*, in that the chosen dimensions need to explain *enough* about an object to make it understandable. Similar to the point of robustness, we argue that the types are explanatory as they comprise relevant dimensions spanning across various ecosystem conceptualizations and make them differentiable.

6 Contributions, limitations and outlook

This paper provides two central contributions. Firstly, we develop generic characteristics of ecosystems and categorize them as either fundamental, i.e., mandatory for every ecosystem, or as optional characteristics. Second, we have identified generic types, thereby detaching the scientific discourse from the established concepts (e.g., business ecosystems, platform ecosystems, and innovation ecosystems) and concentrate on the essential characteristics of generic ecosystem types. Finally, our research allows existing concepts to be aligned with our typology so that specific instances can be distinguished.

The scientific contributions are twofold. On the one hand, we develop generic ecosystem characteristics, which may act as conceptual bedrocks for other researchers to build their concepts of ecosystems. Moreover, we differentiate dichotomously between mandatory and differentiating characteristics. Thus, researchers may find inspiration in identifying necessary elements of ecosystems they need to include if they were to design or conceptualize one. For example, we have already provided a visual representation of the types. Hence, it provides fertile soil for additional visual tools for ecosystem design, i.e., through innovating new design canvases, workshop concepts, or modeling tools. On the other hand, sound definitions of terms are the basis for conducting successful research (Belnap, 1993). We argue that the proposed types resemble definitions of specific ecosystem configurations, which give other researchers a structure while working with the concept.

The transformation of traditional supply chain networks to ecosystems is prevalent, also in practice. Thus, our work also produces managerial contributions as each type represents a possible strategic option for managers to either identify their current position in an ecosystem or strategize about their desired position. Hence, our work strengthens the clarity of the ecosystem concept, which thus provides managers with a more distinct basis for aligning intra-organizational decisions with the ecosystem direction.

The typology and corresponding types that we propose are, naturally, subject to limitations. Firstly, we derive the types solely from the literature, which offers opportunities for incorporating practice-oriented findings, such as one would acquire in, e.g., case studies. Moreover, even though the typology builds on the quantitative analysis of data gathered through a literature review, the data collection itself is open to interpretation, which is why other researchers might find deviating characteristics. Given the inherent nature of idealized types, it is both an advantage as well as a limitation, as it demands to look at the bigger picture rather than each and all of the details. Thus, even though the types give ample conceptual assistance for conceptualizing and differentiating ecosystems, there is a need for tools that provide more in-depth details, e.g., in the form of an empirical taxonomy.

Derived from our findings, we identify three promising research avenues. First, to form a holistic theoretical grounding of the generic types, it would be promising to merge the existing knowledge of the ecosystem concepts via, e.g., a content analysis. Second, adding practice-oriented literature, such as case reports or strategic studies, to our approach would be an advancement, as we look forward to bridging the gap between our theoretical findings and business practice. Third, to address managerial issues, we propose to explicit the theoretical foundations of the alignment above of intra-organizational decisions within ecosystems.

E Essay 4: APIs as Boundary Resources of Digital Entrepreneurial Ecosystems: The Case of Digital Health Start-ups

Abstract

Among researchers as well as practitioners there is currently a growing interest in the digital entrepreneurial ecosystem approach. However, systemic insight into the structure of digital entrepreneurial ecosystems and the nature of interfirm relationships therein remains limited. Drawing on the concept of platform boundary resources, this study offers a deeper understanding of the topological characteristics of digital entrepreneurial ecosystems. Specifically, we employ application programming interfaces (APIs) and API mashups to establish a network representation of an exemplary case, namely the global digital health ecosystem. Our findings indicate that prominent APIs from incumbent firms act as key resources for health start-ups in the digital entrepreneurial ecosystem.

Keywords:

Digital entrepreneurial ecosystems, boundary resources, application programming interfaces, digital health, network analysis.

1 Introduction

Based on the strand of research on the intersection between entrepreneurial ecosystems and digitalization, the new concept of digital entrepreneurial ecosystems is rapidly emerging in the literature (Sussan and Acs, 2017). The digital entrepreneurial ecosystem, i.e., "the matching of digital customers (users and agents) on platforms in digital space through the creative use of digital ecosystem governance and business ecosystem management to create matchmaker value and social utility by reducing transactions cost" (Sussan and Acs, 2017, p. 63), is based on the principles of open-source digital architecture, user-participatory governance and content creation, as well as co-creation among various partners in the virtual space, hence differing from entrepreneurial activity in the past which was primarily performed loosely-connected and segregated within clusters (Sussan and Acs, 2017; Autio et al., 2018a).

Recently, there has been growing consensus among scholars that entrepreneurial actors within a separate organization can no longer generate the necessary level of innovative capacity, but have to harness the potential for open innovation and intellectual capital from the external environment in order to adapt to market demands (O'Connor et al., 2018; Chesbrough, 2011). However, systemic insight into the structure of digital entrepreneurial ecosystems and the nature of interfirm relationships in such systems is still limited (Chinta and Sussan, 2018).

In order to better understand the complex interrelationships and the structure of co-creation between the different stakeholders, we draw on the notion of platform boundary resources (Ghazawneh and Henfridsson, 2013; Eaton et al., 2015). Platform boundary resources are "software tools and regulations that serve as the interface for the arm's-length relationship between the platform owner and the application developer" (Ghazawneh and Henfridsson, 2013, p. 174). More precisely, platform boundary resources enable platform owners to transfer design capabilities to external users, hence supporting the generation of complementary functions and services in the form of applications (Huhtamäki et al., 2017; Ghazawneh and Henfridsson, 2013).

In this study, we focus on one specific type of boundary resources, namely APIs. An API represents “the contract of one piece of computer software with another” (Huhtamäki et al., 2017, p. 5306) and enables companies to collaborate and exchange information with external actors (Iyer and Subramaniam, 2015). Moreover, it is possible to create combinations of APIs, which are also termed mashups, in order to develop entirely new digital services (Basole et al., 2018). Since rigorous empirical studies on the structure of digital entrepreneurial ecosystems are lacking, this paper aims to uncover the topological characteristics of digital entrepreneurial ecosystems utilizing a data-driven approach. Specifically, we employ APIs as particular types of boundary resources and mashups to establish a network representation of an exemplary case, i.e., the global digital health ecosystem, thus illustrating the collaborative relationships between healthcare start-ups in the digital space.

2 Theoretical development and hypotheses

2.1 Digital entrepreneurial ecosystems

The recent call to start “theorizing the role of specific aspects of digital technologies in shaping entrepreneurial opportunities, decisions, actions, and outcomes” (Nambisan, 2017, p. 2) was answered by various investigations at the intersection of entrepreneurship and digitalization research. As an example, von Briel et al. (2018) perceive digital technologies as external enablers of start-up creation. Autio et al. (2018, p. 74) describe entrepreneurial ecosystems “as a digital economy phenomenon that harnesses technological affordances to facilitate entrepreneurial opportunity pursuit by new ventures through radical business model innovation”. Furthermore, the concept of digital entrepreneurial ecosystems was introduced to enhance the comprehension of entrepreneurial activity in the digital economy (Sussan and Acs, 2017).

The digital entrepreneurial ecosystem incorporates two extant ecosystem literatures, namely the digital ecosystem, i.e., "...a self-organizing, scalable and sustainable system composed of heterogeneous digital entities and their interrelations focusing on interactions among entities to increase system utility, gain benefits, and promote information sharing, inner and inter cooperation and system innovation" (Li et al., 2012, p. 119) and the entrepreneurial ecosystem with its emphasis on the interactions between heterogenous stakeholders that aim at strengthening the entrepreneurial activity within a distinct region (Stam and Spigel, 2017).

Building on the conceptual framework developed by Sussan and Acs (2017), a digital entrepreneurial ecosystem comprises four interrelated core elements: *digital infrastructure* refers to the combination of networks, systems, human and technological features as well as processes which together form a socially integrated technical system (Henfridsson and Bygstad, 2013; Sussan and Acs, 2017). Since digital infrastructure represents an open system without strict boundaries, participants are able to freely develop and enhance such systems (Tilson et al., 2010; Sussan and Acs, 2017). In consequence, entrepreneurs can utilize the diverse sets of digital technologies that build the digital infrastructure, which in turn acts as a platform for innovation (Zittrain, 2006). *Users* are described as individuals with access to digital technologies such as the Internet or mobile phones and are increasingly perceived as co-creators of new products and services (Sussan and Acs, 2017). Due to the open-source architecture of the Internet, users can interact with firms and other users within the digital ecosystem and participate in value creation activities, thus representing a potential source of companies' intellectual capital (Sussan and Acs, 2017; Sussan, 2012). *Institutions* determine the rules that ecosystem stakeholders have to follow and influence how economic incentives are shaped and perceived (Sussan and Acs, 2017). Moreover, institutions affect the allocation of entrepreneurial talent, as entrepreneurial talent concentrates on those activities which promise the highest private return (Baumol, 1996; Sussan and Acs, 2017). *Agents* originate from the entrepreneurial ecosystem and can be considered as entrepreneurs that concentrate on making decisions concerning the deployment of scarce resource in situations where no standard procedures or routines exist to guide them, such as in high-growth entrepreneurship (Sussan and Acs, 2017; Casson, 1982). Taken together, digital entrepreneurial ecosystems comprise "the space where agents and users interact on multisided platforms created by Schumpeterian entrepreneurs using a broad array of digital and other technologies" (Sussan and Acs, 2017, p. 62).

A fundamental theoretical construct underlying the study of digital entrepreneurial ecosystems is represented by the concept of ecosystems. Adapted from the biological sciences, the ecosystem concept is based on the principle that a heterogenous, interrelated and constantly evolving set of living and nonliving components forms a network within which the stakeholders interact in order to generate system performance (Acs et al., 2014; Iansiti and Levien, 2004b). Interestingly, collaborative innovation approaches that include value co-creation, interfirm cooperation and network formation appear to be vital strategies to operate successfully in ecosystems, as such concepts enable stakeholders to harness synergistic knowledge, enhance organizational learning and improve innovative capacity (Eisenhardt and Schoonhoven, 1996; Basole and Patel, 2018). However, despite the importance of these key underpinnings of ecosystemic thinking for system performance, the understanding of the underlying processes of interfirm cooperation and information exchange within and between digital entrepreneurial ecosystems is still in its infancy.

While existing studies primarily focus on knowledge management within individual organizations, scholars call for novel approaches that are capable of fully capturing the complexities and dynamics of knowledge transfer between interacting stakeholders on digital platforms and surrounding ecosystems (Baggio and Cooper, 2010; de Reuver et al., 2018). In this context, network analysis of ecosystem dynamics as well as broader data-driven analysis and visualization procedures have been identified as suitable approaches (Karhu et al., 2014; de Reuver et al., 2018). In the next section we conceptualize APIs as crucial boundary resources that enable knowledge transfer between interacting users and agents within digital entrepreneurial ecosystems.

2.2 APIs as boundary resources of digital entrepreneurial ecosystems

Companies are increasingly relying on loosely coupled third-party actors to develop new innovative products and services (Mohagheghzadeh and Svahn, 2016). In particular, firms attempt to harness the creative potential of external actors by participating in digital ecosystems (Tiwana et al., 2010; Um et al., 2013). Such digital ecosystems comprise, on the one hand, a digital platform that is designed and managed by a focal company, and, on the other hand, a range of complementary products and functions created by third-party developers (Um et al., 2013). Since digital platforms are characterized by a collaborative and open infrastructure, they enable value-creating interactions between the platform owners and external developers (Huhtamäki et al., 2017).

As stated above, we draw on the notion of platform boundary resources (Ghazawneh and Henfridsson, 2013; Eaton et al., 2015) to investigate the complex interactions and processes of knowledge transfer among the different stakeholders. We concentrate on one particular type of boundary resources, namely APIs. APIs allow third-party developers to innovate on top of digital platforms established by focal firms, thereby providing platform owners with substantial benefits from the emerging ecosystem of digital platforms (Iyer, 2016; Huhtamäki et al., 2017). Most notably, APIs support companies in scaling their operations, tapping into new markets and developing new services (Basole et al., 2018). In addition, APIs can be combined (in the form of mashups) to develop completely new digital services (Basole et al., 2018). Regarding the crucial impact of APIs on future interfirm partnerships, it is not surprising that researchers perceive APIs to be among the most important factors of digital transformation (Jacobson et al., 2011; Iyer and Subramaniam, 2015). The significance of APIs also becomes apparent when considering the success of several leading companies that implement open API strategies, including *Google*, *Facebook*, *Uber*, *Amazon* and *Expedia* (DuVander, 2012; Iyer and Subramaniam, 2015; Basole, 2016).

Because APIs were found to promote the information exchange between different stakeholders and to facilitate the inbound flow of creative capital to the focal organizations (Aitamurto and Lewis, 2013), we conceptualize APIs as a boundary resource that enables knowledge transfer in digital entrepreneurial ecosystems. Interestingly, recent analyses of the global distribution of APIs reveal that these are primarily concentrated in prominent entrepreneurial regions (Huhtamäki et al., 2017). Hence, we argue that APIs allow users and agents within digital entrepreneurial ecosystems to cooperatively (re)combine elements of the digital infrastructure (i.e., extant software code modules), which ultimately facilitates the exchange of informational assets and the creation of novel digital services. The (re)combination of APIs and other boundary resources connects complementary functions and services and eventually leads to the emergence of a network structure within the digital ecosystem (Um et al., 2013). Consequently, we apply a network analytic approach in order to investigate the topological characteristics of an exemplary digital entrepreneurial ecosystem, i.e., the global digital health ecosystem, and to examine the processes of knowledge transfer in digital entrepreneurial ecosystems.

Since digital health implies pervasive change throughout the existing healthcare system, as well as an extension and redefinition of longstanding barriers between consumers, patients, healthcare professionals, organizations and entrepreneurs (Herselman et al., 2016), we believe that the digital health ecosystem represents a suitable exemplary case for analyzing the topological characteristics of digital entrepreneurial ecosystems. Generally, digital health can be defined as "applying the most advanced information and communication technologies to the collection, sharing and use of information that can improve health and healthcare" (World Economic Forum, 2012).

Building on the findings of previous examinations of the topological characteristics of various digital ecosystems, such as the microservices ecosystem (Basole, 2019), the global API ecosystem (Huhtamäki et al., 2017) and the FinTech ecosystem (Basole and Patel, 2018) we propose that (1) the digital health ecosystem is characterized by a core-periphery structure with several incumbent firms acting as core software vendors, (2) several subcommunities exist within the overall digital health ecosystem, and that (3) the geographical distribution of digital health activities is highly skewed.

3 Research design

The research approach follows the five-step method of Basole (2019) that is explicitly designed to construct, visualize, and analyze data-based ecosystems as networks. Step 1 (Data Identification & Curation) is to identify and select appropriate data that are suitable to answer the research question. We draw from the database *ProgrammableWeb*, as it provides detailed information on APIs and mashups (Huang et al., 2012). To concentrate on healthcare and closely related themes, we have identified and used the keywords "Medical", "Medicine", "Health", "Healthcare", "Fitness", and "Emergency" to search for suitable data. Each mashup is a combination of one or multiple APIs (Yu and Woodard, 2008) in the healthcare domain. Step 2 (Ecosystem Network Construction) is to construct the network and to visualize it. We use the open-source tool Gephi 0.9.2 (Bastian et al., 2009) to visualize the network using directed graphs, which consist of nodes (mashups and APIs) and edges (connections). Step 3 (Ecosystem Metric Computation) is the analysis of the ecosystem using typical metrics from graph theory, such as the *InDegree* or *PageRank* (Cherven, 2013). The *InDegree* describes incoming intersections of one node with other nodes, indicating how many mashups use data or capabilities from an API. Using typical metrics from graph theory enables the mathematical analysis and derivation of meaning for either individual components of the network or the network as a whole (Zaheer et al., 2010; Basole and Patel, 2018). Subsequently, in Step 4 (Design & Implementation of Visualization), the constructed graph may be visualized more effectively by using standard layouts, in our case, the *Yifan-Hu* algorithm (Hu, 2005), and filters, such as *NoOverlap* (Basole, 2019). Additionally, the mapping of the locations enables geographical analysis and visualization of the network and, thus, the derivation of knowledge regarding the globally distributed structure of the ecosystem. Lastly, in Step 5 (Ecosystem Sensemaking), the data, i.e., both the metrics and the visual structure of the network, are the basis for interpretation and ultimately enable us to derive meaning and general conclusions about the nature of the ecosystem.

4 Results

4.1 Network construction

Our study provides new insights into the topology of the digital health ecosystem utilizing data-driven visualizations of APIs and mashups. The complete network contains 261 nodes consisting of 111 APIs, 150 mashups and 271 edges. However, one can quickly identify structures in the system. Firstly, one can observe a more extensive network that interconnects most of the nodes, which are linked through edges, and, secondly, the smaller, cloud-like structures that mostly consist of only one node or very few interconnected nodes. By using the filter *Giant Component*, we remove all nodes that do not belong to the largest network structure (Cherven, 2015). As there was no perceivable merit in analyzing cloud-like structures of minimal pairs (e.g., one node and one API) that hover around the network, we delimit our inquiry to the most extensive network structure.

Table 10.
Number of nodes and iterative reduction of the network.

Filters/Measures	Nodes	Edges
No filters applied	261	271
Removing doubles	259	269
Giant Component	191	229
Geographical Data	135	140
Geographical Data + Giant Component	99	120

After the iterative reduction through applying filters, the final subset of 191 nodes and 229 edges was reached (see Table 10). The final subset was analyzed using the modularity class, a metric computable in *Gephi*, which calculates clusters mathematically. The results are taken as a basis and consequently enriched with visual analysis and qualitative interpretation, which lead us to the four larger-scale clusters described in Fig. 11. We chose to use the node-centric network metric *InDegree* for sensemaking. Based on the logic of how the network was constructed, the metric enables easy and intuitive computation of the most used and central APIs (Cherven, 2013).

The initial computation of typical network metrics stemming from graph theory underlines the importance of prominent APIs, such as *Google Maps*, *Twitter*, or *FitBit*. Additionally, our visual analysis reveals that the three APIs mentioned above represent central nodes in clusters, around which connected nodes are created from mashups. An example is the mashup *MyFitnessPal*, which accesses data from the *FitBit* API and thus, visually, orbits around the node. The clusters were generated using the *Yifan-Hu* algorithm (Hu, 2005). For a better visual presentation, we applied the filters *NoOverlap* (prevents overlap of nodes), *expansion* (enlarges the network), *rotate* (rotates the network), and *Bezeichner-Justierung* (prevents overlap of labels). Moreover, some nodes were moved manually to enhance the clearness of the clusters.

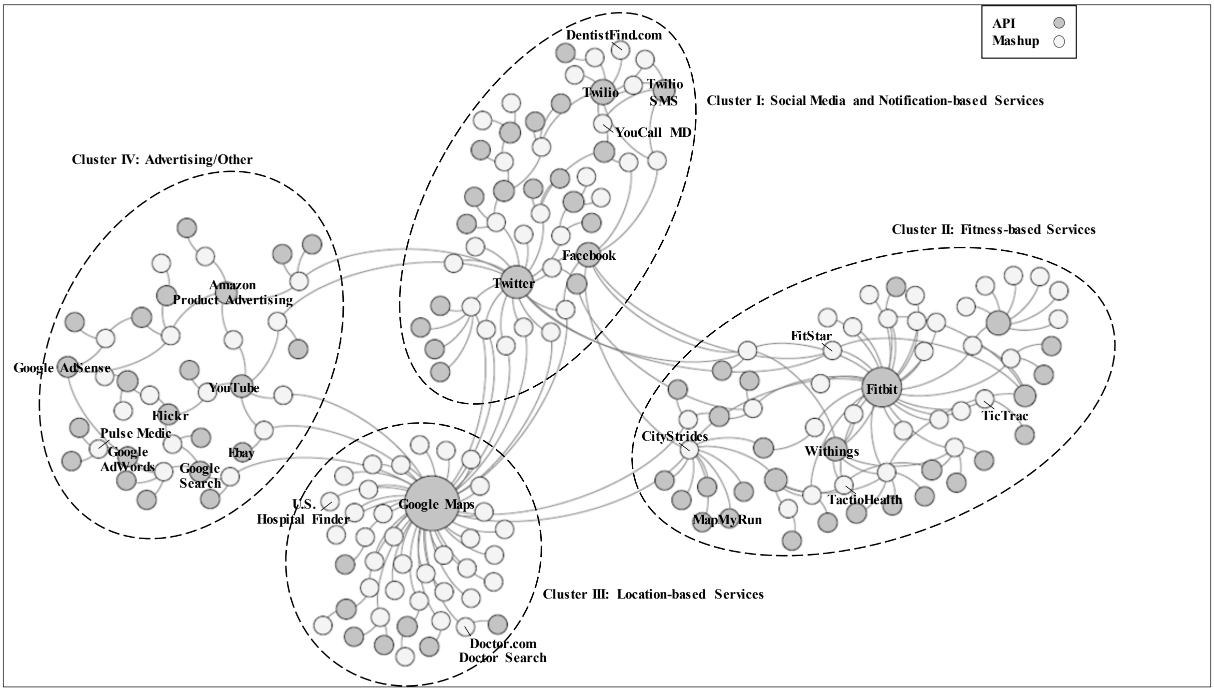

Fig. 11. Visualization of the API network.

4.2 Interpretation

The following interpretation of the data is divided dichotomously. First, we will outline clusters in the data and provide them with qualitative labels to give them meaning (see Fig. 11). The *InDegree* metric is indicated by brackets following the API that it is attested to. Second, through enriching the data with geographical data, we interpret it geographically.

The first cluster mainly includes APIs that offer communication or social media services and, respectively, mashups that use them (e.g., the *Facebook* API (7)). For example, the mashup *SleepingTime* integrates the *Twitter* API to determine sleeping schedules based on the first and last daily activities of users on *Twitter* (17). The *Twilio* API (8) provides users with communication infrastructure (Voice and SMS), enabling them to integrate communication capabilities into their applications. For example, *YouCall MD* gives nurses a single point of contact to reach physicians, and *TextWeight* helps users track their weight by texting it.

The second cluster is centered around the API of *FitBit* (25), which enables access to user data originating in the *FitBit* ecosystem. Usually, mashups built around *FitBit* (25) offer fitness-linked services, e.g., through building workout communities (e.g., *FitStar*), tracking of daily workout activity (e.g., *TicTrac*), or motivational applications that encourage activity through gamification (e.g., *Wokamon*). Other central APIs in this cluster include *Withings* (6), which is an API providing data from internet-enabled medical devices to measure body metrics, such as blood pressure or weight, which are used, e.g., by health management mashups like *TactioHealth*.

The hub and central API of the third cluster is *Google Maps* (43), which chiefly includes location-based services. With regard to healthcare, the applications usually offer some service that assists customers in finding the necessary healthcare-related service, e.g., the doctor who is geographically closest (e.g., *Doctor.com*). Another functionality includes the integration of mapping services, which communicate emergencies geographically (e.g., *LiveMap UK Medical Emergency* or *KPBS San Diego Fires*).

The fourth cluster differs from the other three clusters, as there is no identifiable, clearly dominating API that provides the cluster with a specific, delimitable set of services. However, it is evident that there is some convergence on the topics of advertising (e.g., through the APIs *Amazon Product Advertising* (4) and *Google AdSense* (3)). The cluster includes APIs that could also be allocated to other clusters (e.g., *Yahoo Maps* (3)), which makes a clear distinction hardly possible. We regard this cluster as being a collection of lower-threshold clusters which are not easily identifiable and outliers that could belong to other clusters.

Gephi offers the integration of user-created plug-ins. Using the two plug-ins *MapOfCountries* and *GeoLayout* enables the enrichment of each node with geographical information, such as longitudes and latitudes (Cherven, 2015). The geographic locations were gathered with *Google Search* and from *ProgrammableWeb*. Finding the data for each node was not possible, which is why the total number of nodes in the analysis is reduced to 135 (see Table 10). As most nodes are located on the US west coast, specifically, in the Silicon Valley, the nodes had to be spread manually to improve readability.

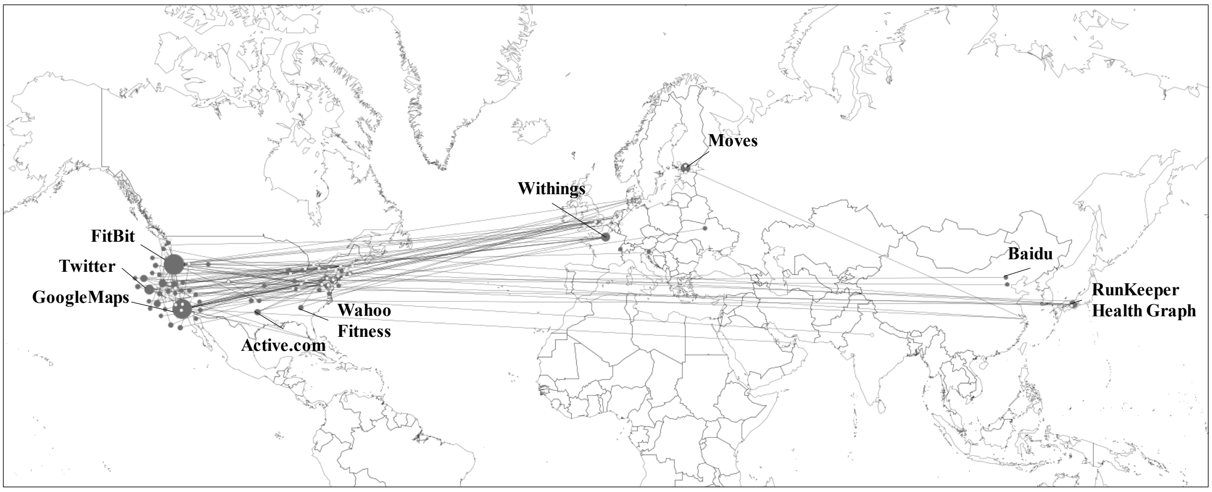

Fig. 12. Geographical distribution of mashups and APIs (most APIs are located in Silicon Valley; for visualization purposes, they were uncluttered manually).

Fig. 12 visualizes the geographical distribution of mashups and APIs. As stated above, there are some APIs that take on dominant roles and influence multiple mashups, such as *Google Maps* or *FitBit*. The geographical distribution of the nodes visualizes the US dominance with regard to APIs that provide data for value creation. Thus, at least in the data supplied by *ProgrammableWeb*, there is a strong dependency on US data providers, especially for location-based services. The size of the nodes indicates the number of incoming edges, i.e., the number of mashups that use an API. Using that logic enables us to depict the dominant sources for data resources.

5 Conclusion, limitations and outlook

Our study analyzed the global digital health ecosystem with data on APIs and mashups provided by *ProgrammableWeb*. The study offers three significant contributions. First, it visually highlights the interconnectedness of APIs that enable knowledge transfer between ecosystem stakeholders and provide data resources for applications which, in turn, generate new value for customers. Second, through generating clusters, we both structure the existing landscape of applications in healthcare and explain the dominant, fundamental services. Lastly, through geographical analysis, our research highlights the dominance of data and digital capabilities originating from the US.

Regarding the broader implications of this study, our findings indicate that APIs which originate from incumbent firms act as key resources for health start-ups in the digital entrepreneurial ecosystem. APIs that track and analyze the fitness activity of users (e.g., *FitBit*) or provide mapping services (e.g., *Google Maps*) are among the most important APIs for the observed mashups. As originally proposed, several established companies, such as *Google*, *Facebook* and *Twitter*, act as core software vendors and shape the core-periphery structure of the digital health ecosystem. Furthermore, our analysis confirms the assumption that the digital health ecosystem consists of several distinct subcommunities, with each of the four identified clusters focusing on different kinds of services.

Theoretically, our study provides novel insights into interfirm relations in digital entrepreneurial ecosystems (specifically in the healthcare context) and demonstrates the crucial role of APIs as boundary resources for value co-creation. Hence, we argue that APIs represent boundary resources that enable locally unbound entrepreneurial activity within digital entrepreneurial ecosystems. Managerially, our findings offer guidance for developing partnership strategies that include both incumbent firms as well as digital health start-ups in the observed digital entrepreneurial ecosystem. For example, entrepreneurs can draw from clusters and identify purposes for location data provided by *Google Maps* and learn how to build services around that data, or how to incorporate this data into existing business models. From a methodological point of view, we show that a network analytic and visualization approach can support various ecosystem stakeholders in identifying the structural characteristics of digital entrepreneurial ecosystems and key relationships within such systems.

Naturally, our work is subject to several limitations. Primarily, our data are collected from *ProgrammableWeb*. While this database is extensive, it is unlikely to be complete, i.e., to contain all APIs and mashups in healthcare (and adjacent fields). Thus, our work is a snapshot in time, based on the point of data collection from *ProgrammabeWeb*. Also, as explained above, some APIs have since gone inactive or split into multiple lower-threshold APIs (e.g., *Google Maps* was split into multiple APIs) which were not reflected in the structure of the database. It was, therefore, necessary to utilize the original APIs to generate the network. Lastly, based on the findings in the database, it should be noted that not all APIs and mashups used in this study represent start-up ventures, but also incumbent firms.

Our research offers a framework for further research into the structure of digital entrepreneurial ecosystems. For instance, the data utilized in this study could be cross-matched with data that indicates the success of start-up ventures (e.g., by using data provided by *CrunchBase*). Doing so could enable the identification of the most promising interfirm relationships within digital entrepreneurial ecosystems. Furthermore, it might be an interesting avenue for future research to validate this study's findings by using alternative data sources (which might focus on alternative industries) or applying other research methods, such as expert interviews with healthcare professionals, or surveys of entrepreneurs that operate in the domain of digital health. A potential starting point for such research endeavors could be the investigation of specific entrepreneurial ecosystems that rely heavily on digitally-enabled interactions, thereby offering rich insights into the relationships between ecosystem stakeholders.

F Conclusion

Over the course of the last decade, the concept of entrepreneurial ecosystems has emerged as a popular approach to examine entrepreneurial activity within regional agglomerations and the relationships between the stakeholders of such systems. Building on the growing body of literature on entrepreneurial ecosystems, this doctoral dissertation aimed to improve the understanding of how entrepreneurial ecosystems evolve and how digitalization influences the broader entrepreneurial landscape.

In order to answer these guiding research questions, a range of methodological approaches was employed, including nonlinear time series analysis, fuzzy-set qualitative comparative analysis (fsQCA), literature reviews and network analysis. Essentially, it can be concluded that (1) the evolution of entrepreneurial ecosystems exhibits features of deterministic chaos, (2) specific combinations of digital technologies and infrastructures are conducive to high or low to medium levels of start-up activity in entrepreneurial ecosystems, (3) ecosystems can be categorized by five overarching ecosystem characteristics and five generic ecosystem types, and (4) prominent APIs from incumbent companies represent crucial resources for health start-ups that operate in the digital entrepreneurial ecosystem (see Fig. 13).

Essay	**1**	**2**	**3**	**4**
Contribution	Applying three methods from chaos theory, we find that the evolution of an entrepreneurial ecosystem can be considered as a nonlinear chaotic process that changes over time	Using fsQCA, we identify the configurations of digital framework conditions that lead to relatively high or relatively low to medium start-up activity in entrepreneurial ecosystems	Conducting a literature review and cluster analysis, we identify five distinct ecosystem characteristics and derive five generic ecosystem types	By establishing a network representation of the global digital health ecosystem, we show that APIs from incumbent firms act as key resources for digital health start-ups

Fig. 13. Major contributions.

Whereas the limitations and avenues for future research are outlined in the individual essays of this doctoral dissertation, the following sections summarize the main results and contributions of this thesis.

In essay 1, we investigate the development of the Singapore entrepreneurial ecosystem from 1970 to 2018. We assess the nonlinear dynamics of the entrepreneurial ecosystem by applying three methods from chaos theory, i.e., the Brock-Dechert-Scheinkman (BDS) test, the Pointwise D2 (PD2), and Local Largest Lyapunov Exponents (LLLE). Our results provide quantitative empirical evidence on the previously hypothesized complex dynamics of entrepreneurial ecosystems. We show that the evolution of an entrepreneurial ecosystem can be viewed as a chaotic process in which a first phase of critical instability is succeeded by an enduring phase of order generation which, in turn, is characterized by repeated chaotic fluctuations. Our finding that the development of entrepreneurial ecosystems shows features of deterministic chaos contributes to the entrepreneurial ecosystem literature in several ways. Our study answers the urgent call for evolutionary, longitudinal approaches towards entrepreneurial ecosystems (Roundy et al., 2018; Auerswald and Dani, 2017) and substantiates previous conceptualizations of the different stages of ecosystem evolution (Colombelli et al., 2019). Moreover, our findings highlight that, if the evolution of entrepreneurial ecosystems is indeed nonlinear and chaotic, then the long-term behavior of entrepreneurial ecosystems is unpredictable and a linear notion of causation is limited for investigating entrepreneurial ecosystems. With regard to implications for entrepreneurs, managers and policy-makers, our results suggest that stakeholders should precisely monitor the actual system dynamics, carefully evaluate possible interventions and acknowledge the path-dependent history of the respective system in order to operate successfully in entrepreneurial ecosystems. In summary, our investigation confirms the notion of a complex, nonlinear evolution of entrepreneurial ecosystems and answers the calls for further empirical studies in this emerging field of research (Kuckertz, 2019; Roundy et al., 2018).

In essay 2, we explore how the availability of different combinations of digital technologies and infrastructures enables new venture formation in entrepreneurial ecosystems. Drawing on data from 35 regional entrepreneurial ecosystems across 19 countries in Europe, we use fuzzy-set qualitative comparative analysis (fsQCA) to identify the causal configurations of digital framework conditions that lead to high or low to medium levels of entrepreneurial activity. Our results indicate that two configurations are conducive to relatively high start-up activity in entrepreneurial ecosystems, whereas four configurations explain relatively low to medium start-up activity in entrepreneurial ecosystems. More precisely, we find that an appropriate digital market, advanced digital government as well as digitally skilled human capital are especially important elements for enabling entrepreneurial activity in regional ecosystems, since these three digital framework conditions are present in all configurations that are sufficient for leading to high levels of new venture formation. Hence, we contribute to entrepreneurship literature by addressing the research gap at the intersection of digitalization and entrepreneurial ecosystems (Autio et al., 2018a; von Briel et al., 2018) and provide first empirical evidence on how different combinations of digital framework conditions affect the broader entrepreneurial landscape. In addition, the fsQCA approach allows to move beyond rather traditional methods of data analysis that rest upon variance-based tests (Khedhaouria and Cucchi, 2019; Ragin, 2006) and emphasizes the complexity as well as equifinality of relationships within entrepreneurial ecosystems. Our findings also inform decision makers about promising approaches for fostering new venture formation in their respective cities (e.g., by developing digitally skilled human capital, promoting the digital market, strengthening the digital government) and point out factors which should not be prioritized when aiming at creating a vibrant entrepreneurial ecosystem (e.g., the digital knowledge base and digital infrastructure). In conclusion, our configurational approach enables scholars as well as practitioners to better comprehend the impact of digital technologies and infrastructures on entrepreneurial ecosystems by accounting for the digitalization-induced complexity.

In essay 3, we investigate which generic ecosystem types can be derived from the literature in order to develop a harmonized understanding of different ecosystem conceptualizations. Based on a structured literature review of 71 articles relevant for this topic, we identify five overarching ecosystem characteristics and propose a generic ecosystem typology. More specifically, the overarching ecosystem characteristics comprise the system configuration, system dynamics, relationship structure, population and purpose. Furthermore, the generic ecosystem types include centrally balanced ecosystems, symbiotic collective ecosystems, sociocentric ecosystems, structured resource sharing ecosystems and orchestrating actor ecosystems. Generally, our findings enable a clear delimitation and differentiability between the multitude of existing ecosystem concepts. The identified ecosystem characteristics provide orientation for researchers who aim to establish own ecosystem conceptualizations. Furthermore, the proposed ecosystem typology offers an overview of specific ecosystem configurations, thereby addressing the issue of blurriness between ecosystem terminology and its utilization. With respect to potential implications for managers, entrepreneurs and policy-makers, the presented ecosystem types can support practitioners in assessing their respective position in an ecosystem or assist them in developing novel strategies for attaining the desired position. In summary, our study enhances the conceptual clarity of the ecosystem concept and offers orientation for scholars as well as practitioners dealing with different types of ecosystems.

In essay 4, we examine the topological characteristics of digital entrepreneurial ecosystems and the nature of interfirm relationships in such systems. Specifically, we use application programming interfaces (APIs) and API mashups to develop a network representation of a paradigmatic case, namely the global digital health ecosystem. The created network consists of 261 nodes which include 111 APIs, 150 mashups and 271 edges. Our findings provide systemic insights into the structure of digital entrepreneurial ecosystems and suggest that APIs originating from incumbent companies act as key resources for digital health start-ups. Hence, our results highlight the important role of boundary resources such as APIs for enabling collaboration as well as knowledge exchange between ecosystem stakeholders. Furthermore, our findings help to disentangle the variety of applications in the digital health domain by identifying several major API clusters that indicate the dominant, fundamental services (i.e., communication or social media services, fitness-linked services and location-based services). In addition, the analysis of the geographical distribution of nodes points out the dominance of US data providers with regard to APIs that provide data for value creation. Concerning the implications for entrepreneurs and managers, our results offer guidance for establishing interfirm alliances in the digital health ecosystem and help to identify the key actors as well as relationships therein. We therefore contribute to the nascent literature on digital entrepreneurial ecosystems (Sussan and Acs, 2017) and provide first empirical insights into the structure of such systems.

Finally, it can be concluded that the four essays presented in this thesis enhance our understanding of the complexity of entrepreneurial ecosystems by outlining the nonlinear dynamics inherent in the evolution of entrepreneurial ecosystems and demonstrating the impact of digitalization on the broader entrepreneurial landscape. Accordingly, future research can use the insights offered by this doctoral dissertation to further investigate the dynamic relationships between ecosystem stakeholders and nonlinear interdependencies that facilitate the evolution of entrepreneurial ecosystems. Entrepreneurs, managers and policy-makers might integrate the findings of this thesis into the development of new strategies for navigating the chaotic dynamics of entrepreneurial ecosystems.

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