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Innovation performance: The effect of knowledge-based dynamic capabilities in cross-country innovation ecosystems

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ABSTRACT

This study operationalizes the knowledge-based dynamic capabilities (KBDC) that act as drivers of innovation performance in innovation ecosystems, across different market economies. Innovation ecosystems facilitate the flow of resources to transform ideas into reality. In turn, KBDC provide a means to create and share expertise, which contributes to the diversification of the economy, and allow businesses to reach beyond their own boundaries to create value for customers in new ways. Employing partial least squares path analysis, four constructs, namely knowledge creation, knowledge diffusion, knowledge absorption and knowledge impact, are comparatively analyzed. Across all four constructs, knowledge creation is the biggest driver of innovation performance, and the strongest predictor of innovation performance in developed and developing market economies. Knowledge absorption is the strongest predictor of innovation performance in transition economies. A KBDC-centered innovation ecosystem framework is proposed to highlight the innovation performance and competitive advantage inherent in each knowledge-related capability.

1. Introduction

Innovation is a critical driver in the enhanced performance and economic growth of firms and the wealth of countries (Tellis et al. 2012). Due to its association with economic growth, innovation performance in particular, has long been a topic of interest in contemporary business fields (Charterina et al. 2016; Chen & Huang, 2009; Chiu, 2009; Cordero, 1990; Dekoulou & Trivellas, 2017; Prajogo & Sohal, 2003; Wagner, 2010). Defined as the ability to transform innovation resources and capabilities into outputs that result in innovative market success (Abdulai, 2019), innovation performance underscores the notion that achieving market success is reliant on the efforts of other innovators in one's environment (Aarikka-Stenroos and Ritala, 2017). This, in turn, reflects the systems view of innovation, highlighting that it is an interactive process that requires a cooperative network (Radicic et al., 2020). For innovation to be useful, literature is increasingly asserting that it must involve the sharing and application of knowledge (Kaur, 2019; Manniche & Testa, 2018), specifically from an innovation ecosystem perspective (Carayannis & Campbell, 2009).

The concept of innovation ecosystems has increasingly drawn the attention of industrial marketing and management scholars (Aarikka-Stenroos & Ritala, 2017; Adner & Kapoor, 2010; Autio & Thomas, 2014; Möller & Halinen, 2018; Valkokari et al. 2017). Innovative ecosystems are described as "the evolving set of actors, activities, and artifacts, and the institutions and relations, including complementary and substitute relations, that are important for the innovative performance of an actor or a population of actors" (Granstrand and Holgersson, 2020, p.1). These innovation ecosystems underscore the dynamic nature of innovation to achieve innovation outcomes (Bacon, Williams, & Davies, 2020) and innovation performance (Carayannis & Campbell, 2009; Malerba, 2004). In contrast to the traditional industry organization framework approach, an innovation ecosystem considers the business environment as a mutually interdependent system, not limited to any single industry or organization (Teece, 2007). Successful innovation ecosystems provide value by facilitating the flow of information and providing access to resources, which assists with business cooperation and strategic innovation development beyond one's firm and industry borders (Klimas & Czakon, 2021). In turn, the information flow and resource infrastructure serve as catalysts for opportunities to connect stakeholders with ideas for competitive advantage (Granstrand & Holgersson, 2020).

The successful performance of economies increasingly depends on

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knowledge (Carayannis & Campbell, 2009). Innovation ecosystems are constituent systems of innovation meta-networks (networks of innovation networks and knowledge clusters) and knowledge meta-clusters (clusters of innovation networks and knowledge clusters) that act as building blocks to create the knowledge and innovation architecture (Carayannis, 2001). Innovation ecosystems further also vary in terms of knowledge configurations, entity specializations, innovative capacity and spatial distribution – with no panacea for success (Kamaşak and Bulutlar, 2010; Manniche et al. 2017). Although not regarded as interchangeable concepts, there are areas where knowledge and innovation co-exist to express mutual interaction, referred to as knowledge-based innovation (Carayannis & Campbell, 2009). Research indicates that capabilities to innovate faster, better and smarter, and to transform and adapt to new contexts through managing knowledge, provides competitive advantage (Peris-Ortiz et al. 2019). In light of the knowledge-economy where knowledge can thus be gainfully leveraged to produce superior capabilities and dynamism, the advanced paradigm of Knowledge-Based Dynamic Capabilities (KBDC) has emerged as an edifice to existing business and management literature (Kaur, 2019). Building on the theoretical premise of the Resource-Based View (RBV) (Barney, 1991) and dynamic capabilities (Teece et al., 1997), KBDC emphasize knowledge and knowledge-related practices as fundamental to positive innovation performance (Kazadi et al. 2016), especially where interconnected and interdependent networks are at play (Galati & Bigliardi, 2017; Martín-de Castro, 2015).

Knowledge does not exist in a vacuum (Paavola et al. 2004), and similarly, innovation seldom exists in isolation (Rybnicek & Königsgruber, 2019). Both knowledge and innovation are embedded within a bigger innovation context with evolving, recursive interactions between multi-level network members contained within the ecosystem (Acemoglu et al. 2016; De Vasconcelos et al. 2018; Valkokari, 2015). KBDC enable the exploration of abilities to generate, combine, and acquire knowledge resources to deal with environmental dynamics for innovative market success (Beuter et al. 2019; Denford, 2013). However, the link between KBDC and innovation performance remains unidentified in the existing literature and is a major gap in the present body of knowledge (Beuter et al. 2019; Cheng et al. 2016; Han & Li, 2015; Kaur, 2019; Zheng et al. 2011). In addition, little is known about what the drivers of innovation performance are (Adner & Kapoor, 2010; Autio & Thomas, 2014; Oh et al. 2016; Zahra & Nambisan, 2011), or how KBDC impact innovation performance in the context of innovation ecosystems (Andreeva & Kianto, 2011; Malerba & McKelvey, 2020; Nunn, 2019).

Therefore, the overarching research question of this study seeks to assess the effect of KBDC on innovation performance in innovation ecosystems. Two research objectives guide the enquiry. The first seeks to identify the knowledge-related constructs that encompass KBDC in an innovation ecosystem. The second seeks to determine the role that the identified KBDC constructs play as drivers of innovation performance across diverse economic markets. Building on the work of Nelson (1993) on National Systems of Innovation, this study approaches country-level innovation, institutions and policies from a structural perspective and works off the premise that structure, rather than individual processes, determines the innovation performance of economic markets (Acs et al. 2018). Furthermore, we also align to the proposed viewpoint of Carayannis and Campbell (2009, p.223) in asserting that "the competitiveness and superiority of a knowledge system is highly determined by its adaptive capacity to combine and integrate different knowledge and innovation modes via co-evolution, co-specialization and co-opetition knowledge stock and flow dynamics."

The purpose of the study is to add to the theories and concepts of the RBV and dynamic capabilities, by focusing on knowledge and its linkage to innovation performance on an ecosystem level. From an industrial marketing and management perspective, a more comprehensive understanding of KBDC and its impact on innovation performance within innovation ecosystems is important for the following four considerations:

1 An understanding of the links between the various building blocks of KBDC and innovation performance within an innovation ecosystem would facilitate and expedite learning between actors within the ecosystem to accelerate the innovation process.
2 Leveraging the expertise of actors and network members across the ecosystem could improve the overall know-how and flow of information within the innovation ecosystem.
3 Awareness of the diverse and complementary knowledge capabilities within the interconnected and co-dependent members of the innovation ecosystem, may heighten the potential of ecosystem members to sense and shape new innovation opportunities.
4 Closely linked to the previous, an appreciation of the knowledge dynamics in an ecosystem may stimulate the proliferation of new product, service, technology, platform or process developments.

To achieve these objectives, the paper commences by first reviewing the extant literature pertaining to innovation performance and the role of knowledge and KBDC. Building on the RBV and dynamic capabilities frameworks as theoretical underpinning, it proceeds to conceptualize KBDC as consisting of four dimensions and proposes hypotheses linking these to innovation performance in an innovation ecosystem context. Secondary data is collected and analyzed using a partial least squares approach. The results, which show that knowledge creation is the strongest driver of innovation performance is then discussed, implications are presented, limitations are noted and areas for future research are indicated.

2. Literature Review

2.1. Innovation performance

Over the years, the concept of innovation has been strongly linked to economic ideology, with countries embracing innovation as a source of international competitiveness and a solution to meet economic challenges (Drejer, 2004). Innovation can occur in products or processes, component or design technologies, via platforms, or through business models (Tellis et al. 2012). As an instrument that accelerates productivity, innovation is conducive to industrial leadership (Adner & Kapoor, 2010). It represents a "process of industrial mutation … that incessantly revolutionizes the economic structure from within" (Schumpeter, 1942, p. 83).

A key outcome of innovation is innovation performance. An ideal definition of innovation performance would include both linear and holistic approaches (Edquist et al. 2018), and include all determinants of the development and diffusion of innovations which lead to superior innovative firm performance or market success. Innovation performance is a result of multiple influencing factors and represents all achievements and results derived from innovation. Extant conceptions rely on input-output relationships to describe innovation performance (Linton, 2009), defining it as the outcome resulting from an innovation process comprising the development and implementation of innovation activities (Chen & Huang, 2009). The successful transformation of innovation resources and capabilities, into innovation activities, leads to innovative market success (Abdulai, 2019; Edquist et al. 2018). To gain an edge in the hypercompetitive business landscape, innovative capabilities aid in differentiating a firm from its competitors (Kaur & Mehta, 2017). Firms with higher innovative capabilities outperform competitors, are more profitable, and report higher survival probabilities (Adeniran & Johnston, 2012).

Research suggests that innovation performance is impacted by the ability to interact with one's environment (Chiu, 2009) and its knowledge-sharing routines (Charterina et al. 2016). Innovation capability has been identified as a driver of innovation performance that acts to enable the development and application of resources to transform knowledge into innovative outcomes (Rajapathirana & Hui, 2018). In terms of outcomes, increased innovation performance stimulates enhanced customer value relationships and positive financial outcomes (Dekoulou & Trivellas, 2017). Innovation performance is also reported to be positively correlated with absorptive capacity (Chen et al. 2009). Moreover, with the accelerated change in the business environment, organizations increasingly realign their structures to keep pace (Teece, 1998), remain competitive (Teece, 2007), and create capabilities (Narayanan et al. 2009) that will enable them to seize opportunities linked to innovation performance (Guerrero et al. 2019). However, Autio and Thomas (2014, p. 20) assert that little is known about how to "proactively create, steer, and leverage innovation ecosystems for enhanced innovation performance."

As competition in the marketplace steadily evolves from between firms to between ecosystems (Teece, 2014), the heterogeneity of innovation ecosystem members provides complementary resources and capabilities for the shared benefit of the whole ecosystem (Peltier et al. 2020). Such an example would be the sharing of strategic industry knowledge and marketing skills between ecosystem members (Sun et al. 2019; Zahra & Nambisan, 2011). From an industrial marketing perspective, the move away from an industry-only focused strategic approach towards broader strategizing within and around ecosystems (Iansiti & Levien, 2004), highlights the interdependencies of ecosystem members. This interdependence leads to new perspectives as to how to co-create value to facilitate positive innovation performance (Adner & Kapoor, 2010). Ecosystem members vary, but often encompass startups, universities, public and private sector entities, government, small businesses, brands, and multinational corporations (Talmar et al. 2018). In the context of ecosystems, the interaction between members within the ecosystem is dependent on knowledge. Indeed, knowledge has gained currency as a medium to share and enhance the innovative performance of all in its ecosystem (Jarzabkowski & Wilson, 2006; Van der Borgh et al. 2012).

2.2. Knowledge and knowledge-based dynamic capabilities

Successful innovation necessitates knowledge integration across a broad set of competencies within the innovation environment, with collaborators exchanging and combining different combinations of knowledge to foster innovation (Grant, 1996; Möller & Rajala, 2007). In a rapidly changing world where markets, products, and technology are in constant flux, the dynamics of knowledge as a valuable, and irreplaceable resource (Barney, 1991), have increasingly gained prominence as a driver of innovation performance (Darroch & McNaughton, 2003; Gupta et al. 2016; Hunt & Morgan, 1996; Lancioni & Chandran, 2009; Tsai & Hsu, 2014). Carayannis and Campbell (2009) propose a "Mode 3" innovation ecosystems approach for knowledge creation and diffusion, which encompasses a multi-system approach to conceptualize and manage knowledge-stock and knowledge-flow. This perspective ascribes to a system-theoretic perspective of, among other factors, socio-economic conditions, that shape the co-evolution of knowledge with the "knowledge-based and knowledge-driven, global/local economy and society" (Kaur, 2009, p.vi)

Hansen and Birkinshaw (2007) propose that the innovation process consists of a three-stage innovation value chain, closely linked to knowledge-related capabilities. Stage one consists of efforts to source the different types of knowledge necessary for innovation (Hansen & Birkinshaw, 2007; Roper et al. 2008). For example, building internal knowledge creation within the firm through R&D to substitute or complement external knowledge (Pittaway et al. 2004). Stage two involves the transformation of this knowledge into new services or business processes. This is an encoding activity that combines the internal and external knowledge resources (Love et al. 2011). The final stage in the innovation value chain entails the exploitation of innovations, for example in product creation and commercialization (Grant and Baden-Fuller, 2004). Each stage in the innovation value chain requires a variety of knowledge types and partners (Hansen & Birkinshaw, 2007; Rosenkopf & Nerkar, 2001; Rothaermel & Deeds, 2004).

Frenz and Ietto-Gillies (2009) argue that knowledge is difficult to conceptually measure through directly quantifiable measures, and suggest that it is easier to identify and capture the presence of, and the access to, different sources of knowledge. There is agreement in the literature that knowledge-based capabilities are closely related to long-term competitive advantage (Argote & Ingram, 2000; Carneiro, 2000; Cavusgil et al. 2003; Peris-Ortiz et al. 2019; Tzokas & Saren, 2004), and innovation outcomes (Andreeva & Kianto, 2011; Basadur & Gelade, 2006; Darroch, 2005; Goh, 2005; Leiponen, 2006). As such, the concept of KBDC emerged. KBDC are based on a synthesis of the knowledge-based theory of the firm (Grant, 1996), with its roots in the RBV (Barney, 1991), and the dynamic capabilities view (Teece et al. 1997). The knowledge-based view of the firm suggests that the capability to learn faster than a competitor yields a source of competitiveness, while the dynamic capabilities view posits that competitive advantage is dependent on dynamic capabilities that enable one to adapt to changes in the business environment (Kaur, 2019). The two views are in essence complementary. Knowledge-based processes are dynamic in nature as they help to renew and reconfigure resources, while, on the other hand, dynamic capabilities are inherently knowledge-based, as changes in the business environment are sensed and seized with the help of knowledge processes and capabilities (Kaur, 2019).

Zheng et al. (2011, p. 1037) define KBDC as the "ability to acquire, generate and combine knowledge resources to sense, explore and address environment dynamics". In turn, Han and Li (2015, p. 43) define it as the "potential to systematically solve problems through more dynamic applications and adjustments of [the firm's] knowledge base, formed by knowledge sensing capacity, knowledge seizing capacity and knowledge reconfiguring capacity". A limited number of studies have been published on the subject of 'Knowledge-Based Dynamic Capabilities', and as such, conflicts on the true meaning and application of the term exist (Denford, 2013; Kaur, 2019). Table 1 provides an overview of these studies, as well as identified areas for future research.

Perusal of the future research sections in these papers, indicate three main gaps in the theory and literature of KBDC. First, a number of KBDC conceptualizations are presented in the literature, yet, with the exception of a few studies, the empirical testing of links between the conceptual constructs and specific innovation outcomes is scarce (Denford, 2013). In addition, most of the studies tend to focus on two or three of the knowledge-based constructs and overlook the possibility of mediated relationships (Han and Li, 2015). Second, the concrete operationalization of KBDC still seems elusive as extant studies operationalize the concept differently (Bendig, Strese, Flatten, da Costa, & Brettel, 2018). Finally, since KBDC research is still in its infancy, it is uncertain what the impact of the various KBDC dimensions are on innovation performance across different contexts (Khaksar et al. 2020). There is therefore a clear call for comparative studies that review the relationships of the various KBDC in differing contexts and configurations with set boundary conditions.

2.3. Resource-based view and dynamic capabilities

The RBV (Barney, 1991; Penrose, 1959; Wernerfelt, 1984) emphasizes the critical role of knowledge and knowledge-related practices for business performance (Kazadi et al. 2016). The work by Eisenhardt and Martin (2000), Nonaka (1994) and Teece et al. (1997), have advanced theory development and management practice regarding the dynamics of knowledge management. These authors gave considerable currency to the relevance of the concept of dynamic capabilities in organizations that provide the capacity to flex tangible and intangible assets, such as knowledge, for competitiveness. Dynamic capabilities are defined as an organization's ability to "integrate, build and reconfigure internal and external competencies in response to rapid environmental changes" (Teece et al. 1997, p. 516). Over the years knowledge has materialized as

Table 1
Overview of previous research articles relating to KBDC.

Author	Purpose of study	Recommendations based on findings
Khaksar et al. (2020)	To assess the relationship between KBDC and knowledge worker productivity, while examining the moderating effect of organizational culture on the two factors.	Future cross-border research on the relationship between KBDC and knowledge worker productivity is proposed.
Beuter et al. (2019)	To identify how KBDC influences the process of developing sustainable innovations.	Future studies on this topic should analyze the economic impact of KBDC on company performance.
Yan et al. (2019)	This research proposes a knowledge-based management decision support system (KMDSS), using System Dynamics modelling and computer simulations, to analyze project performance, strategic management decisions, and dynamic capability of an e-commerce case study.	The case study results demonstrate the usefulness of the KMDSS and show that it can be used for evaluation during the dynamic decision-making process. Application in different contexts to validate the findings is suggested.
Faccin et al. (2019)	The identification of dynamic capabilities in joint R&D projects that enable them to successfully achieve knowledge creation throughout the life cycle of a collaborative project.	Further quantitative research on other emerging categories to develop and validate the construction of KBDC scales.
Alonso et al. (2019)	The identification of mechanisms that support family firms' adaptation to changing environments, using dynamic capabilities and knowledge-based strategies.	Use the proposed theoretical framework to theoretically and empirically test the validity of the framework, using other firms that have adapted to adversity, overcoming major disruptions and/or have adapted to the rapid changes of a globalized business environment.
Bednig et al. (2018)	Presenting an in-depth perspective on the antecedents of dynamic capabilities, by integrating managerial and organizational micro-foundations, using the personality of Chief Executive Officers, manifested through their core self-evaluation, represents an individual-level micro-foundation which influences	Study proposes that three types of a firm's knowledge-based capital, i.e., human, social, and organizational capital, are organization-level micro-foundations that enable the development of a firm's dynamic capabilities. Future research on micro-foundations could go beyond self-evaluation dimensions of this study and include social capital dimensions, using a different sample design and hierarchy levels.
Laasonen and Kolehmainen (2017)	This paper introduces a capability framework to reveal the multi-layered and dynamic nature of capabilities in knowledge-based regional development.	More comprehensive and comparative case studies across diverse regions and a wide range of organizations to verify the applicability and consistency of the framework. In addition, an examination of the links between capabilities and the performance of specific regions would also provide more depth regarding which areas to further develop for competitive advantage.
Cheng et al. (2016)	Building on KBDC, this paper examines how knowledge capabilities influence the effectiveness of open innovation inbound and outbound activities on radical innovation performance.	Based on a survey of 213 Chinese firms, the results indicate that the effectiveness of open innovation inbound and outbound activities is contingent on the presence of knowledge acquisition capabilities and knowledge sharing capabilities. Future research could expand and replicate the study in different environments.
Monferrer et al. (2015)	To assess the influence of a network market orientation on Spanish born globals' adaptation, absorption and innovation dynamic capabilities, and its influence on the performance achieved by these companies.	Further consideration of other variables that could explain dynamic capabilities. Study was solely based on Spanish born globals, thus other international contexts could be taken into account when testing exploration/ exploitation interrelationships.
Han and Li (2015)	An assessment of the relationship between intellectual capital and innovative performance, from a knowledge-based dynamic capability perspective.	Intellectual capital positively affects innovative performance, and KBDC is a partial mediator of the relationship between intellectual capital and innovative performance. Further empirical testing in other contexts.
Denford (2013)	A KBDC typology, based on a review of the existing resource-based and knowledge-based views literature.	Further testing of the developed framework to determine if particular knowledge-based dynamic capabilities are more or less strongly linked to a performance construct, such as innovation output.
Zheng et al. (2011)	Creating a synthesized construct bridging dynamic capabilities and the knowledge-based perspective – KBDC – and investigating its influence on innovation performance in networked environments.	Further empirical examination and verification of the knowledge-based dynamic capabilities construct.

one of the most significant organizational resources to respond to environmental changes (Tzokas & Saren, 2004). Grant (1996) developed the knowledge-based theory of the firm to explore the organizational aspects that focus on the role of knowledge as a factor of production. Originating from the strategic management literature and building on the RBV (Barney, 1991), the knowledge-based theory of the firm proposes that knowledge-based resources are usually socially complex and difficult to imitate. Moreover, heterogeneous knowledge bases and capabilities are major drivers of competitive advantage and superior organizational performance. The RBV and dynamic capabilities theories serve as a theoretical framework for the development of the hypotheses of this study. Building on these theories, the section to follow conceptualizes KBDC as drivers of innovation performance in innovation ecosystems, and the hypothesized relationships between the KBDC constructs and innovation performance in an innovation ecosystem context are developed.

3. Theoretical background and hypotheses

3.1. Conceptualizing KBDC as drivers of innovation performance in innovation ecosystems

The role of knowledge capabilities to gain competitive advantage through innovation performance across innovation ecosystems, has gained prominence as a subject for deeper enquiry in recent years (Bacon et al., 2020; Crespo & Crespo, 2016; Malerba & McKelvey, 2020; Menna et al. 2019; Najafi-Tavani et al. 2018; Valkokari et al. 2017). In line with this development, and to address the identified gaps, this research seeks to better conceptualize KBDC. In essence, KBDC are underpinned by embedded networks of internal and external knowledge-related activities (Khaksar et al. 2020), and expands on the role of knowledge as a unique source of competitive advantage, promoting a knowledge-based perspective of dynamic capabilities (Zheng et al. 2011).

The evolving relationships between the wide range of innovation partners in an innovation ecosystem highlights the degree to which their interaction contributes to knowledge creation, rate of knowledge diffusion, and transformation of knowledge into innovative performance outcomes within their organizational environment (Mercan & Goktas, 2011; Romano et al. 2014). From a performance perspective, the impact of the acquired knowledge-in-use may also be of value to assess and gauge its replicability for broader deployment across the innovation ecosystem (Eisenhardt & Martin, 2000). Even though there is agreement that KBDC may facilitate competitive advantage (Denford, 2013; Laasonen & Kolehmainen, 2017), confusion exists as to the conceptual dimensions that KBDC encompass. Table 2 provides an overview of the different conceptualized KBDC dimensions that have been put forward in the literature.

Looking for commonalities in the nomenclature and definitions of previously proposed dimensions as per Table 2, lead to the identification of four dimensions that most closely align to the knowledge management and process capabilities that facilitate performance outcomes, as per the knowledge-based theory of the firm (Grant, 1996) and dynamic capabilities (Teece et al. 1997). As such, we propose that KBDC encompass the dimensions of knowledge creation, knowledge diffusion, knowledge absorption, and knowledge impact. These dimensions are defined in more detail in the sections to follow.

3.1.1. Knowledge creation and its impact on innovation performance

Knowledge creation, also referred to as knowledge generation or knowledge exploration, is widely acknowledged as a key construct of KBDC (Eisenhardt & Martin, 2000; Faccin et al. 2019; Khaksar et al. 2020), with close ties to innovative performance outcomes. Andreeva and Kianto (2011, p. 1010) define knowledge creation as the “ability to develop new and useful ideas and solutions”, relating to organizational activities, new products or services, technological processes and managerial procedures (Nonaka, 1991; Un & Cuervo-Cazurra, 2004). As a focal part of the innovation process (Nonaka et al. 2014; Quintane et al. 2011), thriving innovation ecosystems are characterized by knowledge creation (Bramwell et al. 2012). Nonaka and Takeuchi (1995) describe knowledge creation as a spiral that flows between tacit and explicit knowledge. Knowledge creation is a complex process that involves interaction between multiple actors in the innovation ecosystem (Faccin et al. 2019), by optimizing different types of tacit or explicit knowledge at differing knowledge levels (Tzokas & Saren, 2004).

As a dynamic capability, knowledge creation competencies promote new thinking and capabilities within networked environments (Nonaka et al. 2000), including innovation ecosystems (Kazadi et al. 2016).

Table 2
Previous conceptualizations of KBDC in literature.

Author(s)	Conceptualized Dimensions
Khaksar et al. (2020)	knowledge acquisition, knowledge generation, knowledge combination
Monferrer et al. (2015)	adaptive capability, absorptive capability, innovative capability
Han and Li (2015)	knowledge sensing capacity, knowledge seizing capacity, knowledge reconfiguring capacity
Denford (2013)	knowledge creation, knowledge integration, knowledge reconfiguration, knowledge replication, knowledge development, knowledge assimilation, knowledge synthesis, knowledge imitation
Zheng et al. (2011)	knowledge acquisition, knowledge generation, knowledge combination

Knowledge creation reflects the ability to introduce new knowledge into the ecosystem by either facilitating the flow of knowledge from outside the boundaries of the ecosystem to build an internal knowledge repository (Robertson, 2020), or employing existing knowledge in an innovative and improved manner internally (Alrubaiee et al. 2015). Processes to create or acquire new knowledge are a necessity for sustained competitive advantage, as entities cannot develop all the required knowledge within their own boundaries (Kaur, 2019). The performance value of knowledge created or acquired is however only fully realized when combined with other knowledge-related capabilities, as Carayannis and Campbell (2009) explicitly identify knowledge creation, knowledge diffusion, and knowledge-in-use as dynamic processes that act as driving forces behind the formation of innovation ecosystems. Furthermore, knowledge creation has been shown to be closely linked with an organization’s competitive advantage (Gupta et al. 2016), and is regarded as an output indicator of innovation performance (Andreeva & Kianto, 2011). In light of the above, the following hypothesis is presented:

H1. There is a positive relationship between knowledge creation and innovation performance in an innovation ecosystem.

3.1.2. Knowledge diffusion and its impact on innovation performance

In line with the diffusion of innovation theory (Rogers, 1962), knowledge diffusion refers to the rate at which newly created technological content and intellectual property spreads for eventual adoption (Klarl, 2014). Within an innovation ecosystem, a clear understanding of the diffusion of knowledge is fundamentally important from an economic perspective, as the ease with which diffusion occurs directly affects economic growth (Grossman & Helpman, 1991). Knowledge diffusion also holds implications for regional and national technology strategies, technology transfer policies, as well as incoming and outgoing investment (Singh, 2008). In a multi-level analysis of innovation processes, Manniche and Testa (2018) show that innovation outcomes in innovation systems are directly affected by the diffusion of created knowledge across all levels of analysis.

The diffusion of knowledge is however not a homogeneously distributed process across all potential adopters (Klarl, 2014). Research shows that induced knowledge spillovers in certain specialized sectors, markets and countries lead to enhanced capabilities for knowledge diffusion in those environments (Boschma & Frenken, 2011; Lundvall, 2007). Capello and Varga (2013) assert that proximity-related advantages between innovating partners, as can often be found in innovation ecosystems, would contribute to the increased creation and diffusion of knowledge, and lead to enhanced innovation performance. Knowledge diffusion acts as a vital component in the development of a sustainable competitive advantage, suggesting that the diffusion of knowledge has become a critical factor to enhance the rate of innovation and remain competitive (Tang et al. 2020). Following the adaptive capabilities assertion by Day (2014), knowledge diffusion is proposed to represent an inside-out strategic approach, which focuses and relies on internal efficiencies to sense and address market shifts (Day, 2020).

It is posited that to attain superior innovation performance, the actors in an innovation ecosystem should possess the ability to create or generate new knowledge, diffuse it through its ecosystem, and expediently transform the newly acquired knowledge into new technologies or processes for competitive advantage. Therefore, innovation performance is thus regarded as an outcome of knowledge diffusion, and the following is hypothesized:

H2. There is a positive relationship between knowledge diffusion and innovation performance in an innovation ecosystem.

3.1.3. Knowledge absorption and its impact on innovation performance

The process of knowledge absorption involves the assessment, organization, interpretation, synthesis, integration, and ultimately exploitation of varied sources and types of knowledge (Gold et al. 2001).

Closely-linked with knowledge diffusion, knowledge absorption thus supports the assimilation and application of newly created knowledge for commercial purposes, thus increasing the capacity for innovation (Cohen & Levinthal, 1990; Faccin et al. 2019). Knowledge absorption also often leads to new knowledge creation, which in turn improves the ability to gain and sustain competitive advantage (Zahra & George, 2002). As an absorptive capability, knowledge absorption is concerned with the consolidation of the newly created knowledge with existing knowledge stocks, as well as with the experimentation of past knowledge bases for innovative applications (Zheng et al. 2011).

Knowledge absorption entails first looking outside of the boundaries and constraints of the ecosystem to sense changes, and then aligning the internal dynamic capabilities accordingly to address shifting market needs (Day, 2020). For its part, knowledge absorption is thus regarded as an outside-in strategic approach, based on the adaptive capabilities view by Day (2014). Knowledge absorption is dependent on the ability of innovation ecosystem members to acquire, absorb and apply, often external knowledge from outside the boundaries of its own entities. These activities make it possible for the ecosystem to redeploy resources as new products, services, processes or systems. Knowledge absorption also facilitates the capability to collect and comprehend new knowledge gained through collaboration, which then enhances the working skills that accompany the appropriation of the new knowledge – a critical necessity in collaborative innovation ecosystems (Carayannis & Campbell, 2009). The approach implies an agile innovation process to assimilate internal and external knowledge and technologies through collaborative relationships, in open innovation (Chesbrough, 2003; Najafi-Tavani et al. 2018).

Previous research has identified that a positive correlation exists between knowledge absorption and innovation capabilities, which ultimately results in the development of a sustainable competitive advantage (Pai and Chang, 2013). In light of the above, the following hypothesis is suggested:

H3. There is a positive relationship between knowledge absorption and innovation performance in an innovation ecosystem.

3.1.4. Knowledge impact and its impact on innovation performance

Knowledge impact and use implies collaborative effort and inclusion of entities both internal and external to an organization (Nonaka et al. 2014). For knowledge to have an impact, it has to go through a process of integration, synthesis, refinement, management, and importantly - market implementation. Knowledge impact represents the effect that the integration and combination of knowledge-based innovation activities have at both a micro- and macro-economic level. From an innovation ecosystem perspective, the accurate measurement of knowledge impact is a budding area of research which the academic literature has identified as not yet sufficiently investigated (Faccin et al. 2019; Santoro et al. 2018).

From an ecosystem perspective, knowledge impact would thus be concerned with the transformation of knowledge into a cohesive knowledge base that is of use to the whole innovation ecosystem. When knowledge is applied to commercial ends, the sustainability of its competitive advantage within the innovation ecosystem will depend on the degree to which it is of use to various actors within the ecosystem. As an output indicator, the relationship between knowledge impact and innovation performance seems intuitively connected. Therefore:

H4. There is a positive relationship between knowledge impact and innovation performance in an innovation ecosystem.

The impact of knowledge is inextricably reliant on new knowledge being created (Santoro et al. 2018) and the different types of knowledge are known to be interlinked. Therefore, we further hypothesize the following mediated relationships:

H5a. The relationship between knowledge diffusion and innovation performance is mediated by knowledge creation.

H5b. The relationship between knowledge absorption and innovation performance is mediated by knowledge diffusion.

H5c. The relationship between knowledge impact and innovation performance is mediated by knowledge creation.

The hypotheses described above are represented in the research model in Fig. 1.

Eisenhardt and Martin (2000) assert that although there are some commonalities in how dynamic capabilities are flexed across different organizations, they are mostly idiosyncratically developed and deployed. Zheng et al. (2011) also propose that since the level and form of dynamic capabilities can be quite different across different environments, it would be prudent to consider how this may lead to different levels of innovation performance. We posit that this would be similar across different innovation ecosystems. Therefore, the relationships can be comparatively tested across developed, transition and developing economies. Accordingly, we ask which of the four capabilities are the most important driver of innovation performance within the respective market economy innovation ecosystems?

4. Methodology

To test the research hypotheses and model, and the research question set above, a descriptive research design is employed using a quantitative secondary data analysis. Secondary data pertains to any data that has been previously collected by a researcher for another purpose and is freely available (Kothari, 2004). The benefits of using secondary data include a significantly lower level of resources required to obtain the data (Malhotra, 2010). However, a potential limitation to using secondary data, may relate to its usefulness to address a specific research problem that the data was not originally collected to address. This therefore, necessitates an evaluation of the reliability of the data (Malhotra, 2010).

4.1. Data and sample

The data source for this research is the publicly available Global Innovation Index (GII) 2019 dataset. The GII is a collaborative research effort between Cornell University, INSEAD and the World Intellectual Property Organization. The reasons for selecting the GII 2019 as the primary data source for the current research are two-fold. First, the magnitude of the dataset offers a near complete examination of countries across the globe representing a significant proportion of the global population. The dataset spans 129 countries, representing 91.8 % of the world's population, accounting for 96.8 % of the world's GDP (Dutta et al. 2019). Second, the GII employs a broad operationalization of innovation that allows for the data to reflect improvements made to outcomes (Dutta et al. 2019).

In evaluating the usefulness of secondary data, one needs to ensure the reliability of the data, in particular by examining the recency of the data, the method of collection and the possible presence of bias (Kothari, 2004). The GII 2019 dataset is the most recent global innovation dataset at the time of writing this article with a record of dependable publication. Furthermore, the dataset is subject to a number of consistency and reliability assessments, including an examination of conceptual consistency, data checks, statistical coherence and a qualitative review (Dutta et al. 2019). As such, "the GII 2019 ranks are reliable and for most economies the simulated 90 % confidence intervals are narrow enough for meaningful inferences to be drawn" (Dutta et al. 2019, p. 381).

4.2. Measures

Effective economies are those that succeed in translating innovation inputs into innovation outputs, thus yielding a higher innovation performance score (Dutta et al. 2019). The GII provides innovation input and output sub-indices together with innovation performance scores.

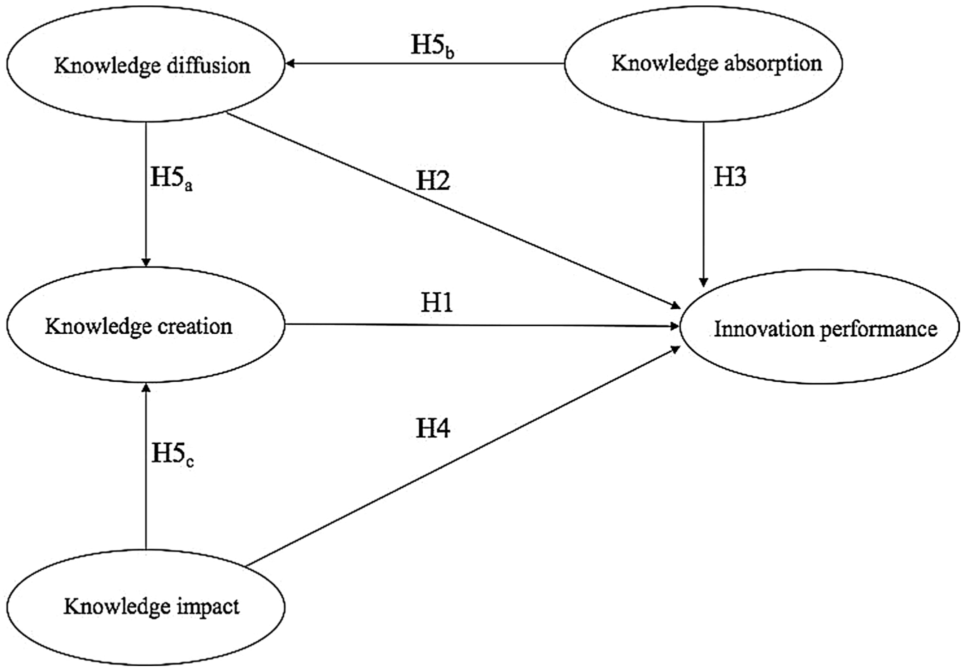

Fig. 1. Research model and hypotheses.

The innovation input sub-index comprises areas within national economies that enable innovation activities in a country. The innovation output sub-index encompasses information about outputs as a result of innovative activities within economies. The innovation performance is the average of both the input and output sub-indices for the particular country. The GII dataset also provides a country-level innovation efficiency score that captures innovation performance, based on the output and input sub-index scores.

Given the focus of the research model on the role of KBDC in driving innovation performance, the components of the GII dataset relating to the conceptualized KBDC constructs were identified for use as data. Knowledge creation, diffusion, and impact are regarded as output indicators of innovation performance. Operationally, knowledge creation is a result of both inventive and innovative activities, while knowledge diffusion reflects the outputs achieved based on the knowledge that has been absorbed. Knowledge impact represents elements that reflect the impact of innovative activities at both a micro- and macro-economic level post market implementation. Conversely, knowledge absorption is regarded as an input indicator of innovation performance, and encompasses elements that are connected to economic sectors with high-tech content or those that are key to innovation-directed activities. The specific indicators used to measure each dimension are presented in Appendix A. All data for the KBDC constructs consist of composite variables that range from 0–100.

4.3. Data analysis

A variance-based structural equation modelling (SEM) technique, using the partial least squares (PLS) approach (Ringle et al. 2015) was used. SmartPLS was selected as the most appropriate software for this analysis for three reasons. First, as a predictive technique, PLS does not require as large a sample size as covariance-based SEM (Anaza et al. 2015; Hair et al. 2019). Second, when working with secondary data, Hair et al. (2019) note that PLS-SEM is especially suitable in offering flexible interaction between theory and data. Third, PLS-SEM allows the research focus to move from strictly confirmatory to predictive and causal-predictive modeling (Hair et al. 2019).

PLS data analysis necessitates assessing the measurement model as well as the structural model (Chin, 1998; Hair et al. 2011). First, the psychometric properties of the measurement model were analyzed and tested for common method bias, followed by the evaluation of the structural model. To test relationships by economic level of development, the dataset was split according to the 2019 United Nations published country classification of economic development (United Nations Department of Economic & Social Affairs, 2019). Appendix B provides an overview of the different countries, grouped as developed, transition or developing economy. The results are reported next.

5. Results

Descriptive statistics for the four types of knowledge and innovation performance appear in Table 3. To confirm the convergent validity of the measurement model, all indicator items should load significantly on their latent construct (Anderson & Gerbing, 1988). With the use of secondary data from the GII 2019 dataset, only composite variables were available for analysis. This is often expected from industry reports where measures are not usually created and refined over time for confirmatory analyses (Sarstedt and Mooi, 2019). The results section first uses SmartPLS to test the hypotheses and research model of this study and then proceeds to investigate these relationships across three categories of countries according to their economic level of development.

5.1. Assessing the measurement model

The GII 2019 report confirms reliable aggregates and provides Cronbach's alpha values that are well above the 0.7 threshold for all aggregate sub-index scores (Dutta et al. 2019). Although the use of the dataset does not allow an opportunity to revise or refine the

Table 3
Descriptive statistics and discriminant validity using the HTMT criterion.

Latent Variable	Mean	SD	IP	KC	KD	KA
Innovation performance (IP)	36.31	12.01				
Knowledge creation (KC)	19.26	19.10	0.88			
Knowledge diffusion (KD)	22.56	16.40	0.80	0.70		
Knowledge absorption (KA)	35.47	11.84	0.76	0.65	0.83	
Knowledge impact (KI)	24.76	14.18	0.70	0.58	0.55	0.58

measurement model to achieve fit, the variance inflation factor (VIF) was assessed to evaluate collinearity (Hair et al. 2019) and test for common method bias (Kock, 2015). Ideally, the VIF values should be close to 3.3 and less or equal to 5 (Becker et al. 2015). Results confirmed that all VIF values were below the 3.3 threshold, with the exception of knowledge absorption (VIF = 3.41) and knowledge diffusion (VIF = 3.65), that are well within the accepted range.

The discriminant validity of the measurement model was assessed by examining the heterotrait-monotrait (HTMT) matrix of correlations (Henseler et al. 2015). HTMT values of 1 indicate a lack of discriminant validity, and values < 0.90 are deemed acceptable (Gold et al. 2001). All HTMT values are below the threshold, thus meeting the criterion for discriminant validity – Table 3.

5.2. Analyzing the structural model

PLS was further employed to estimate the path relationships in the research model. To evaluate the structural model, particularly the statistical significance of all parameter estimates (Chin, 1998), the bootstrapping procedure (139 cases, 1,000 samples, no sign changes option) was adopted. The analysis requires the evaluation of R^2 values, f^2 effect size, and the path analysis results (Chin, 1998; Hair et al. 2014). First, the PLS results for direct effects and R^2 values, as shown in Fig. 2, are investigated. Chin (1998) characterizes R^2 values of 0.67 as substantial, 0.33 as moderate and 0.19 as weak. The model explains 88 % (R^2 = 0.88) of the variance in innovation performance, 68 % of the variance in knowledge diffusion (R^2 = 0.68), and 54 % in knowledge creation (R^2 = 0.54). Therefore, the results confirm substantial effects for innovation performance and knowledge diffusion, and moderate effects for knowledge creation. Second, in order to estimate how large a proportion of unexplained variance is accounted for by a change in R^2 (Hair et al. 2014), the f^2 effect sizes were also evaluated. Cohen (1988) respectively classifies effect sizes of 0.02, 0.15, and 0.35 as small, medium, and high. The results indicate that knowledge impact (f^2 = 0.20) has a moderate effect on innovation performance, and knowledge creation (f^2 = 1.09) has a very strong effect on innovation performance. In addition, knowledge diffusion (f^2 = 0.45) has a strong effect on knowledge creation, and knowledge absorption (f^2 = 2.14) has a very strong effect on knowledge diffusion. All other f^2 effect sizes are < 0.1 and thus small.

An additional part of the analysis assesses the significance of the hypothesized paths. With the exception of H3, all path coefficients yielded statistically significant results (p < 0.00) – Table 4. The results suggest that three of the KBDC, namely knowledge creation, knowledge diffusion and knowledge impact are significant drivers of innovation

Table 4
Results of PLS analysis.

Hypothesis	Path	β	t-statistic	Significance	Results
H1	Knowledge creation → □ Innovation performance	0.54	11.65	0.00**	Supported
H2	Knowledge diffusion → □ Innovation performance	0.20	2.84	0.00**	Supported
H3	Knowledge absorption → □ Innovation performance	0.13	1.57	0.12ns	Not supported
H4	Knowledge impact → □ Innovation performance	0.20	5.00	0.00**	Supported
$H5_a$	Knowledge diffusion → □ Knowledge creation	0.55	7.02	0.00**	Supported
$H5_b$	Knowledge absorption → □ Knowledge diffusion	0.83	29.20	0.00**	Supported
$H5_c$	Knowledge impact → □ Knowledge creation	0.28	4.49	0.00**	Supported

ns = not significant.
** Significant at 1% level of significance.

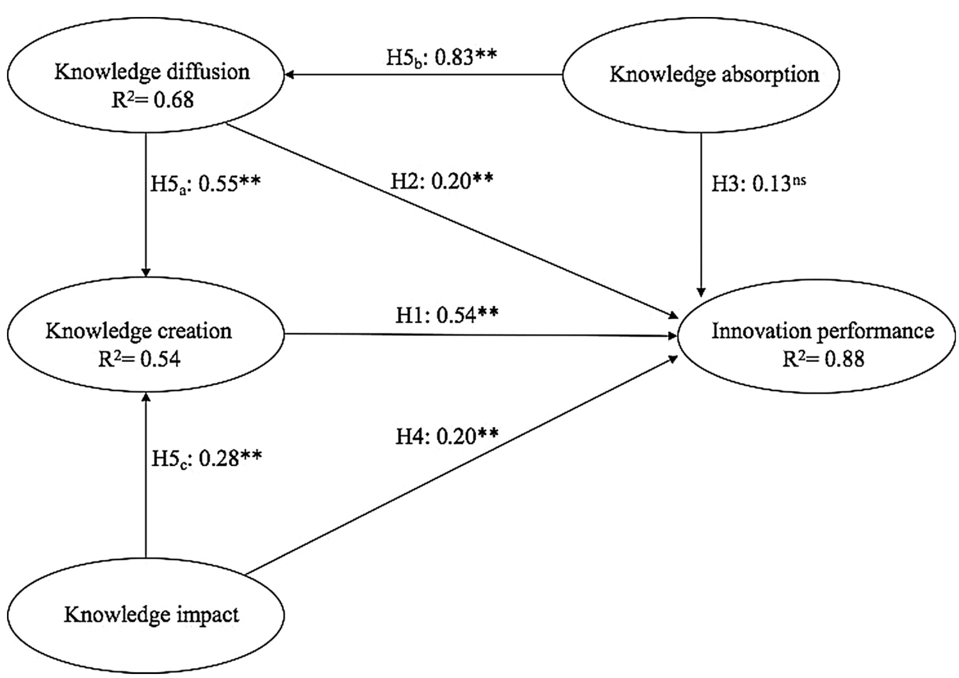

Fig. 2. Path model and PLS estimates.
**Significant at 1 % level of significance.
ns = not significant.

performance. In terms of mediating relationships, knowledge diffusion fully mediates the relationship between knowledge absorption and innovation performance, while knowledge creation is found to be a partial mediator of the relationship between knowledge diffusion and innovation performance, as well as knowledge impact and innovation performance. An examination of the standardized β coefficients provides insight into the strongest driver of innovation performance allowing for the indicators to be ranked. Knowledge creation is the strongest driver of innovation performance, followed by knowledge diffusion and knowledge impact, which are of equal importance.

5.3. Differences according to economic level of development

Table 5 provides a summary of the descriptive statistics for the 129 different market economies considered. To assess the impact of the respective KBDC components on innovation performance in innovation ecosystems at different stages of economic development, the SmartPLS path analysis was run again. This time, path analyses were independently run for the three categories, namely: countries that either fall within developed, transition or developing economies. In this analysis, no mediating relationships were included. As expected, the overall innovation performance is greatest for developed economies and least for developing economies.

One-way ANOVA shows a statistically significant difference in innovation performance for the three stages of economic development ($F_{(2, 126)} = 74.26$; $p < 0.00$; $eta^2 = 0.54$). The effect size, calculated using eta squared indicates a large effect (Cohen, 1988). Post-hoc comparisons using Tukey's HSD test indicate that differences between developed and transition economies, as well as differences between developed and developing economies are significant ($p < 0.00$). No significant differences are noted between the overall innovation performance for transition and developing economies. Similarly, one-way ANOVA indicates statistically significant differences between the means for each of the four variables – knowledge creation ($F_{(2, 126)} = 46.58$; $p < 0.00$; $eta^2 = 0.43$), knowledge diffusion ($F_{(2, 126)} = 26.64$; $p < 0.00$; $eta^2 = 0.30$), knowledge absorption ($F_{(2, 126)} = 24.66$; $p < 0.00$; $eta^2 = 0.28$) and knowledge impact ($F_{(2, 126)} = 25.61$; $p < 0.00$; $eta^2 = 0.29$). All effect sizes indicate a large effect (Cohen, 1988). Using the Tukey HSD post-hoc test, statistically significant differences are noted between knowledge creation, knowledge diffusion, knowledge absorption, and knowledge impact for developed and transition economies as well as developed and developing economies ($p < 0.00$). No significant differences are noted in the knowledge creation, knowledge diffusion, knowledge absorption and knowledge impact between transition and developing economies.

Table 6 provides an overview of the PLS results for each KBDC component across the market economies in the different countries. The results shown enable a comparative determination as to which of the knowledge capabilities have the strongest predictor effect on innovation performance across developed, transition and developing economies. The examination of the impact of KBDC on innovation performance in developed, transition and developing economies, shows that the overall model was significant - developed economies ($F = 79.76$, $p = 0.00$; $R^2 =$ 91.1 %; adjusted $R^2 = 90$ %); transition economies ($F = 5.76$; $p = 0.01$, $R^2 = 69.7$ %; adjusted $R^2 = 57.6$ %); developing economies ($F = 66.19$; $p = 0.00$; $R^2 = 78.4$ %; adjusted $R^2 = 77.2$ %). The magnitude of R^2 is indicative of a large effect size across all three stages of economic development (Cohen et al. 2003).

The results reported above suggest that in developed economies, knowledge creation is the strongest predictor of innovation performance, while in transition economies, knowledge absorption is the strongest predictor of innovation performance, followed by knowledge impact. In developing economies, knowledge creation is the strongest predictor of innovation performance, followed by knowledge diffusion and knowledge impact.

Table 5
Summary descriptive statistics.

Variable	Developed (n = 36) Mean	Developed (n = 36) SD	Transition (n = 15) Mean	Transition (n = 15) SD	Developing (n = 78) Mean	Developing (n = 78) SD
Innovation performance	50.43	7.78	33.33	3.63	30.37	9.00
Knowledge creation	38.98	19.25	17.31	11.25	10.53	12.64
Knowledge diffusion	36.92	18.50	15.95	3.59	17.21	12.60
Knowledge absorption	45.45	10.29	29.03	5.81	32.11	10.70
Knowledge impact	46.79	6.69	33.92	6.19	29.37	14.56

Mean range 0–100.

Table 6
Results of the PLS analysis according to economic stage of development.

Economic stage of development	KBDC	Standardized β coefficient	t-statistic	p-value
Developed economy	Knowledge creation	0.76	11.65	0.00**
	Knowledge absorption	0.11	0.91	0.36
	Knowledge diffusion	0.18	1.47	0.14
	Knowledge impact	−0.01	0.08	0.93
Transition economy	Knowledge creation	0.08	0.06	0.96
	Knowledge absorption	0.61	3.06	0.00**
	Knowledge diffusion	0.07	0.35	0.72
	Knowledge impact	0.46	1.94	0.05*
Developing economy	Knowledge creation	0.45	6.50	0.00**
	Knowledge absorption	0.08	0.66	0.51
	Knowledge diffusion	0.35	3.35	0.00**
	Knowledge impact	0.20	3.13	0.00**

* Significant at a 5 % level of significance.
** Significant at a 1 % level of significance.

6. Discussion

Increased economic importance is put on the innovation ecosystems of markets to expedite and improve their innovation performance and gain competitive advantage. Drawing from the RBV, Teece et al. (1997) proposed a framework of dynamic capabilities to focus the attention on how firms can dynamically renew their resource-based competitive advantage. The theoretical principles of competitive advantage show that knowledge-based resources play an important role in gaining and sustaining innovation outcomes (Nonaka et al. 2014; Srivastava et al., 2001). At the same time, the concept of innovation ecosystems, their performance, and the dynamics of their knowledge infrastructure from a multi-level perspective, have gained traction in the industrial marketing and management literature in recent years (Pattinson et al. 2018). The emergence of KBDC as an extension of extant dynamic capabilities research, provides a promising lens through which to assess the knowledge infrastructure of innovation ecosystems, and to assess how it contributes towards innovation performance.

To gain a deeper understanding of KBDC and its link with innovation performance in innovation ecosystems, this study first assessed the knowledge-related constructs that encompass KBDC in an innovation ecosystem; and, second, determined the role that these identified KBDC constructs comparatively play as drivers of innovation performance in diverse economic markets. A discussion of the major findings follows.

6.1. Operationalizing KBDC in innovation ecosystems

To operationalize KBDC, innovation performance is first conceptualized as the transformation of innovation inputs or resources into implemented innovative outputs, which contribute to economic growth and market success. Four knowledge-related capabilities, namely knowledge creation, knowledge diffusion, knowledge absorption, and knowledge impact, are respectively identified as input-output indicators of innovation performance in innovation ecosystems. Aligned to the extant understanding of the RBV and dynamic capabilities, these components represent knowledge-based capabilities which would serve to enable innovation activities, provide competitive advantage, and lead to enhanced innovation performance when leveraged within innovation ecosystems. Operationally, the four components comprise knowledge dimensions that span both discrete innovation outcomes (e.g., product, service, scientific publication), as well as process-based innovative capabilities (e.g., improved high-tech or operational processes) that lead to economic market success. Innovation ecosystems are presumed to possess heterogeneous knowledge bases and differ by context (Autio & Thomas, 2014), thereby necessitating comparative analysis.

6.2. The comparative importance of KBDC for innovation performance in innovation ecosystems

Using the ecosystem categorization approach for B2B-research (Aarikka-Stenroos & Ritala, 2017), it is proposed that KBDC drives innovation performance and competitive advantage goals by aligning to a particular focused approach. An *interaction focus* concentrates on interactions between customers, stakeholders and other actors in the ecosystem. These are fundamental components that facilitate market structure and organizing for value creation through innovation. A *system dynamics focus* is concerned with the structural dynamics of the ecosystem to either encourage change and renewal for market disruption, or create stability and symbiosis through a process of institutionalization. Fig. 3 provides an illustrative representation of how this applies to KBDC in an innovation context, highlighting its pertinence to innovation performance and competitive advantage.

Knowledge creation relates to the development of new solutions and capabilities within the innovation ecosystem that allows the transformation of knowledge into innovation outcomes or processes for commercial gain. It is seen as a strategic and dynamic resource capability, that is closely linked to competitive advantage. Based on the results of this research, knowledge creation has the strongest impact on innovation performance across all KBDC. Knowledge creation is also the strongest predictor of innovation performance in developed and developing economies. In relation to all components of KBDC, knowledge creation also acts as a partial mediator and conduit to facilitate the diffusion and impact of knowledge for overall innovation performance in the innovation ecosystem.

As inferred from the literature, knowledge diffusion is markedly connected with the pursuit of economic growth, as evidenced by the fact that it is only a strong predictor of innovation performance in developing economies. From a dynamic capabilities viewpoint, it refers to the rate at which new, created knowledge disperses through the greater ecosystem from the inside-out, and is seen as a significant indicator of innovation performance. In an innovation ecosystem, knowledge diffusion would facilitate the flow and absorption of knowledge and knowledge spillovers, which advances innovation exports and affects competitive advantage.

The capability to sense and seize knowledge for competitive advantage, is represented by knowledge absorption. It necessitates a high level of interaction and networked engagement within an innovation ecosystem, as it entails the assimilation of both internal and external knowledge, from the outside-in. Although the results indicate that knowledge absorption is not a significant indicator of innovation performance, it indirectly determines innovation performance through knowledge diffusion, in a fully mediated relationship. It is the strongest predictor of innovation performance in transition economies, which may indicate that these economies dynamically require external input in order to transform content into innovation outcomes.

Knowledge impact symbolizes the ripple effect of utilized knowledge for innovation activities in the micro- and macro-economic environment. As a KBDC it has been found to be a significant indicator of innovation performance, but is posited to be heavily reliant on newly created knowledge in the ecosystem, in order to transform and exploit this knowledge for commercial purposes. It is surprising that the results indicate that knowledge impact does not act as a strong driver of innovation performance in developed economies. However, although not the strongest driver, knowledge impact is identified as an important driver of innovation performance in transition and developing economies.

7. Managerial and theoretical implications

From a managerial perspective, the work contributes to innovation system and ecosystem research in that it presents a comparative approach which researchers and practitioners can use to gauge the knowledge capabilities of particular ecosystems. The Front Runner, Challenger, Caretaker, and Borrower categories can be flexed beyond knowledge-related capabilities to further explore other dynamic capabilities within innovation ecosystems. By integrating research in the field of knowledge-related resources with the literature on dynamic capabilities, the study attempts to provide a deeper understanding of its impact on competitive advantage in the context of innovation ecosystems. This study also addresses a lacuna in the literature regarding the role and impact of KBDC on innovation performance, especially for firms

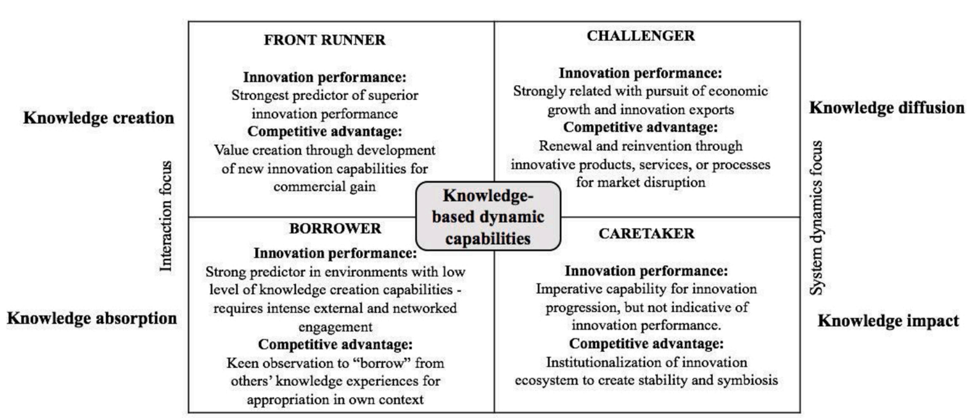

Fig. 3. Innovation ecosystem framework centered around a knowledge-based dynamic capabilities' approach.

operating in radically-changing and cross-border market environments. As far as can be ascertained, this current study is the first to operationalize KBDC in an innovation ecosystem environment. The comparison of competitive advantage gained through strategically flexing various KBDC in the innovation ecosystem framework, provides an opportunity to gauge what impact changes in the ecosystem would have on innovation performance over time. The research further offers a practical understanding of the factors influencing innovation performance in differing economic contexts.

Innovation policy and development could similarly also use the classification to assess knowledge capabilities and associated innovation performance from an ecosystem-based perspective. These could be addressed by an interaction or system dynamics focus. Innovation ecosystems are defined by their ability to adapt and evolve (Basole, 2009), and as such, a clear articulation and empirical examination of the knowledge-related capabilities in the ecosystem, may act as a starting point to actuate change. This research could better inform cross-country collaboration, particularly when collaboration includes countries at differing stages of economic development. A clearer understanding of the determinants of innovation performance, both at a firm-level and a country-level, will impact how innovation is best able to penetrate sector, industry and national boundaries. As such it is vital to gain an understanding of how best to enhance innovation performance locally, regionally, nationally and trans-nationally.

As theoretical contribution, the research advances knowledge about the role of KBDC on innovation performance and its application to achieve competitive advantage. Rather than applying the dynamic capabilities, knowledge-, or resource-based views in isolation, the combined capabilities are leveraged to form higher-order KBDC, offering additional potential to generate competitive advantage for a firm by considering its market economy and the innovation ecosystem in which it operates. Moreover, the operationalization and empirical testing of links between KBDC dimensions and innovation outcomes adds depth in our understanding of the innovation process. From a knowledge perspective, this research has enhanced the understanding of the relationship between knowledge and innovation and has taken the first step in terms of operationalizing the variables that comprise KBDC.

Furthermore, the cross-country comparative approach also provides a yardstick against which one can gauge what impact a high or low level of knowledge-related capabilities have on countries within a particular market economy stage. Without comparisons, it would be difficult to identify optimal or ideal innovation systems or knowledge intensity. Contextually, little is known about the knowledge architecture in innovation ecosystems, and, as innovation ecosystems mostly function as market networks (Aarikka-Stenroos & Ritala, 2017), a holistic view of the dynamics at play would serve to better create and provide value for all stakeholders.

8. Limitations and future research

As with all research, this study is not without its limitations. First, using secondary data constrains the researcher to analyze dimensions and variables measured with predetermined items. The GII dataset does however provide measures for consistency and reliability, yet, future research could in particular seek to validate the internal structure between the knowledge capability constructs and seek to contextually validate all measurement items. As a KBDC variable, knowledge impact, in particular, could be further probed and empirically studied. Second, when operationalizing KBDC, human resources or knowledge workers were not included as constructs. Although people are central to the creation, diffusion, absorption and impact of knowledge, the exclusion was driven by a focus that was more nuanced towards the inherent and diverse knowledge abilities present in the people within the ecosystem. As such, from a unit of analysis perspective, the particularities of the people within the ecosystem fell outside the scope of this study. Third, the study provides a snapshot representation within a particular context, and future research could take an in-depth look at member-specific aspects within an innovation ecosystem. The results indicate that efficient innovation performance, based on innovation inputs and outputs, are concentrated in specific market economies, possibly pointing to an innovation divide between innovation ecosystems.

A comparative longitudinal study would provide a more detailed perspective regarding changes over time, and how this affects innovation performance. Fourth, the use of secondary data meant that the study adopted a linear approach to measuring innovation performance (input-output relationship). Finally, while the conceptual model focused on the role of KBDC in driving innovation performance, this is not to suggest that the model provides an exhaustive list of factors that could influence innovation performance. As such, it is recommended that future researchers seek to provide a more holistic inclusion of the factors, influences and determinants of innovation performance within an innovation ecosystem context. In addition, this analysis could be further deconstructed to the firm-level in order to offer insight into KBDC and their impact on innovation performance at a micro-level.

9. Conclusion

Once regarded as a safeguard for the most advanced economies, innovation is now considered imperative for all economies (Carayannis et al. 2018; Vargo et al. 2015; Youtie & Shapira, 2008; Zahra & Nambisan, 2011). Yet, for many, the formula for successful innovation remains obscure. This study set out to build on extant literature and add to the theoretical understanding of knowledge-related capabilities in dynamic innovation environments. Using the concept of KBDC as drivers of innovation performance in innovation ecosystems, four constructs are operationalized and hypothesized to have an impact on the innovation performance of 129 countries at different stages of economic development. Results indicate that three of these constructs – knowledge creation, knowledge diffusion, and knowledge impact – have a significant impact on innovation performance in different market economies. Aligned to the evolving innovation ecosystem approach to understand business networks and market dynamics, the findings suggest that innovation performance is context dependent and driven by diverse factors with varied influence on the innovation outcomes. The categorization of innovation ecosystems based on the prevailing KBDC acts as a point of reference on how to achieve competitive advantage in a particular market environment.

Appendix A. Indicators used as measures for each KBDC composite variable

KBDC composite variable	Indicators
Knowledge creation	Patent applications by origin (regional or national patent office), patent cooperation treaty applications by origin (filed by residents), utility models by origin (filed by residents at the national patent office), scientific and technical publications, citable documents H-index
Knowledge diffusion	Intellectual property receipts, high-tech exports, ICT services exports, foreign direct investment net outflows
Knowledge absorption	Intellectual property payments, high-tech imports, ICT services imports, foreign direct investment net inflows, research talent in business enterprise
Knowledge impact	Growth rate of GDP per person engaged, new business density, total computer software spending, ISO 9001 quality certificates, high-tech and medium-high-tech output

Source of items: GII 2019 report.

Appendix B. Country classifications based on stage of economic development

Developed economies		Economies in transition	Developing economies		
Australia	Poland	Albania	Algeria	Honduras	Pakistan
Austria	Portugal	Armenia	Argentina	Hong Kong, China	Panama
Belgium	Romania	Azerbaijan	Bahrain	India	Paraguay
Bulgaria	Slovakia	Belarus	Bangladesh	Indonesia	Peru
Canada	Slovenia	Bosnia and Herzegovina	Benin	Iran	Philippines
Croatia	Spain	Georgia	Bolivia	Israel	Qatar
Cyprus	Sweden	Kazakhstan	Botswana	Jamaica	Republic of Korea
Czech Republic	Switzerland	Kyrgyzstan	Brazil	Jordan	Rwanda
Denmark	United Kingdom	Montenegro	Brunei Darussalam	Kenya	Saudi Arabia
Estonia	United States of America	North Macedonia	Burkina Faso	Kuwait	Senegal
Finland		Republic of Moldova	Burundi	Lebanon	Singapore
France		Russian Federation	Cambodia	Madagascar	South Africa
Germany		Serbia	Cameroon	Malawi	Sri Lanka
Greece		Tajikistan	Chile	Malaysia	Thailand
Hungary		Ukraine	China	Mali	Togo
Iceland			Colombia	Mauritius	Trinidad and Tobago
Ireland			Costa Rica	Mexico	Tunisia
Italy			Cote d'Ivoire	Mongolia	Turkey
Japan			Dominican Republic	Morocco	Uganda
Latvia			Ecuador	Mozambique	United Arab Emirates
Lithuania			Egypt	Namibia	United Republic of Tanzania
Luxembourg			El Salvador	Nepal	Uruguay
Malta			Ethiopia	Nicaragua	Viet Nam
Netherlands			Ghana	Niger	Yemen
New Zealand			Guatemala	Nigeria	Zambia
Norway			Guinea	Oman	Zimbabwe

References

Aarikka-Stenroos, L., & Ritala, P. (2017). Network management in the era of ecosystems-Systematic review and management framework. *Industrial Marketing Management, 67*, 23–36.

Abdulai, A. F. (2019). Social capital and innovation performance in firms. In B. Thomas, & L. Murphy (Eds.), *Innovation and social capital in organizational ecosystems* (pp. 81–97). Hershey, PA: IGI Global.

Acemoglu, D., Akcigit, U., & Kerr, W. R. (2016). Innovation network. *Proceedings of the National Academy of Sciences, 113*(41), 11483–11488.

Acs, Z. J., Estrin, S., Mickiewicz, T., & Szerb, L. (2018). Entrepreneurship, institutional economics, and economic growth: An ecosystem perspective. *Small Business Economics, 51*(2), 501–514.

Adeniran, T. V., & Johnston, K. A. (2012). Investigating the dynamic capabilities and competitive advantage of South African SMEs. *African Journal of Business Management, 6*(11), 4088–4099.

Adner, R., & Kapoor, R. (2010). Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic Management Journal, 31*(3), 306–333.

Alonso, A. D., Kok, S., & O'Shea, M. (2019). The family business, adversity and change: A dynamic capabilities and knowledge-based approach. *Journal of General Management, 44*(2), 96–109.

Alrubaiee, P., Alzubi, H. M., Hanandeh, R., & Ali, R. A. (2015). Investigating the relationship between knowledge management processes and organizational performance the mediating effect of organizational innovation. *International Review of Management and Business Research, 4*(4), 989–1009.

Anaza, N. A., Rutherford, B., Rollins, M., & Nickell, D. (2015). Ethical climate and job satisfaction among organizational buyers: An empirical study. *The Journal of Business & Industrial Marketing, 30*(8), 962–972.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411–423.

Andreeva, T., & Kianto, A. (2011). Knowledge processes, knowledge-intensity and innovation- a moderated mediation analysis. *Journal of Knowledge Management, 15* (6), 1016–1034.

Argote, L., & Ingram, P. (2000). Knowledge transfer: A basis for competitive advantage in firms. *Organizational Behavior and Human Decision Processes, 82*(1), 150–169.

Autio, E., & Thomas, L. (2014). Innovation ecosystems: Implications for innovation management. In M. Dodgson, N. Philips, & D. M. Gann (Eds.), *The Oxford handbook of innovation management* (pp. 204–228). Oxford: Oxford University Press.

Bacon, E., Williams, M. D., & Davies, G. (2020). Coopetition in innovation ecosystems: A comparative analysis of knowledge transfer configurations. *Journal of Business Research, 115*, 307–316.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Basadur, M., & Gelade, G. A. (2006). The role of knowledge management in the innovation process. *Creativity and Innovation Management, 15*(1), 45–62.

Basole, R. C. (2009). Visualization of interfirm relations in a converging mobile ecosystem. *Journal of Information Technology, 24*(2), 144–159.

Becker, J.-M., Ringle, C. M., Sarstedt, M., & Völckner, F. (2015). How collinearity affects mixture regression results. *Marketing Letters, 26*(4), 643–659.

Bendig, D., Strese, S., Flatten, T. C., da Costa, M. E. S., & Brettel, M. (2018). On micro-foundations of dynamic capabilities- a multi-level perspective based on CEO personality and knowledge-based capital. *Long Range Planning, 51*(6), 797–814.

Beuter Júnior, N., Faccin, K., Volkmer Martins, B., & Balestrin, A. (2019). Knowledge-based dynamic capabilities for sustainable innovation: The case of the green plastic project. *Sustainability, 11*(8), 2392.

Boschma, R., & Frenken, K. (2011). Technological relatedness and regional branching. In H. Bathelt, M. Feldman, & D. Kogler (Eds.), *Beyond territory: Dynamic geographies of knowledge creation, diffusion and innovation* (pp. 64–81). Abingdon: Routledge.

Bramwell, A., Hepburn, N., & Wolfe, D. A. (2012). *Growing innovation ecosystems: University-industry knowledge transfer and regional economic development in Canada*. Final Report to the Social Sciences and Humanities Research Council of Canada, No. 62.

Capello, R., & Varga, A. (2013). Knowledge creation and knowledge diffusion in space and regional innovation performance: Introductory remarks. *The Annals of Regional Science, 51*(1), 113–118.

Carayannis, E. G. (2001). *The strategic management of technological learning*. Boca Raton, Florida: CRC Press.

Carayannis, E. G., & Campbell, D. F. J. (2009). "Mode 3" and "Quadruple Helix": Toward a 21st century fractal innovation ecosystem. *International Journal of Technology Management, 46*(3–4), 201–234.

Carayannis, E. G., Grigoroudis, E., Campbell, D. F., Meissner, D., & Stamati, D. (2018). The ecosystem as helix: an exploratory theory-building study of regional co-opetitive entrepreneurial ecosystems as Quadruple/Quintuple Helix Innovation Models. *R&D Management, 48*(1), 148–162.

Carneiro, A. (2000). How does knowledge management influence innovation and competitiveness? *Journal of Knowledge Management, 4*(2), 87–98.

Cavusgil, S. T., Calantone, R. J., & Zhao, Y. (2003). Tacit knowledge transfer and firm innovation capability. *Journal of Business & Industrial Marketing, 18*(1), 6–21.

Charterina, J., Basterretxea, I., & Landeta, J. (2016). Types of embedded ties in buyer-supplier relationships and their combined effects on innovation performance. *Journal of Business & Industrial Marketing, 31*(2), 152–163.

Chen, C. J., & Huang, J. W. (2009). Strategic human resource practices and innovation performance: The mediating role of knowledge management capacity. *Journal of Business Research, 62*(1), 104–114.

Chen, Y. S., Lin, M. J. J., & Chang, C. H. (2009). The positive effects of relationship learning and absorptive capacity on innovation performance and competitive advantage in industrial markets. *Industrial Marketing Management, 38*(2), 152–158.
Cheng, C. C. J., Yang, C., & Sheu, C. (2016). Effects of open innovation and knowledge-based dynamic capabilities on radical innovation: An empirical study. *Journal of Engineering and Technology, 41*, 79–91.
Chesbrough, H. W. (2003). *Open innovation: The new imperative for creating and profiting from technology*. Boston, MA: Harvard Business School Press.
Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–358). Mahwah: Erlbaum.
Chiu, Y. T. H. (2009). How network competence and network location influence innovation performance. *Journal of Business & Industrial Marketing, 24*(1), 46–55.
Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Lawrence Erlbaum Associates.
Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152.
Cohen, J., Cohen, P., West, S., & Aiken, L. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). New Jersey: Lawrence Erlbaum Associates.
Cordero, R. (1990). The measurement of innovation performance in the firm: An overview. *Research Policy, 19*(2), 185–192.
Crespo, N. F., & Crespo, C. F. (2016). Global innovation index: Moving beyond the absolute value of ranking with a fuzzy-set analysis. *Journal of Business Research, 69*(11), 5265–5271.
Darroch, J. (2005). Knowledge management, innovation and firm performance. *Journal of Knowledge Management, 9*(3), 101–115.
Darroch, J., & McNaughton, R. (2003). Beyond market orientation. *European Journal of Marketing, 37*(3/4), 572–593.
Day, G. S. (2014). An outside-in approach to resource-based theories. *Journal of the Academy of Marketing Science, 42*(1), 27–28.
Day, G. S. (2020). The yin and yang of outside-in thinking. *Industrial Marketing Management, 88*, 84–86.
De Vasconcelos Gomes, L. A., Facin, A. L. F., Salerno, M. S., & Ikenami, R. K. (2018). Unpacking the innovation ecosystem construct: Evolution, gaps and trends. *Technological Forecasting and Social Change, 136*, 30–48.
Dekoulou, P., & Trivellas, P. (2017). Organizational structure, innovation performance and customer relationship value in the Greek advertising and media industry. *Journal of Business & Industrial Marketing, 32*(3), 385–397.
Denford, J. S. (2013). Building knowledge: Developing a knowledge-based dynamic capabilities typology. *Journal of Knowledge Management, 17*(2), 175–194.
Drejer, I. (2004). Identifying innovation in surveys of services: A Schumpeterian perspective. *Research Policy, 33*(3), 551–562.
Dutta, S., Lanvin, B., & Wunsch-Vincent, S. (2019). *The global innovation index. Creating healthy lives: The future of medical innovation* (12th edition).
Edquist, C., Zabala-Iturriagagoitia, J. M., Barbero, J., & Zoño, J. L. (2018). On the meaning of innovation performance: Is the synthetic indicator of the Innovation Union Scoreboard flawed? *Research Evaluation, 27*(3), 196–211.
Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal, 21*(10/11), 1105–1121.
Faccin, K., Balestrin, A., Martins, B. V., & Bitencourt, C. C. (2019). Knowledge-based dynamic capabilities: A joint R&D project in the French semiconductor industry. *Journal of Knowledge Management, 23*(3), 439–465.
Frenz, M., & Ietto-Gillies, G. (2009). The impact on innovation performance of different sources of knowledge: Evidence from the UK Community Innovation Survey. *Research Policy, 38*(7), 1125–1135.
Galati, F., & Bigliardi, B. (2017). Does different NPD project's characteristics lead to the establishment of different NPD networks? A knowledge perspective. *Technology Analysis & Strategic Management, 29*(10), 1196–1209.
Goh, A. (2005). Harnessing knowledge for innovation: An integrated management framework. *Journal of Knowledge Management, 9*(4), 6–18.
Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. *Journal of Management Information Systems, 18*(1), 185–214.
Granstrand, O., & Holgersson, M. (2020). Innovation ecosystems: A conceptual review and a new definition. *Technovation, 90*, 102098.
Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal, 17*(S2), 109–122.
Grant, R. M., & Baden-Fuller, C. (2004). A knowledge accessing theory of strategic alliances. *Journal of Management Studies, 41*(1), 61–84.
Grossman, G. M., & Helpman, E. (1991). Trade, knowledge spillovers, and growth. *European Economic Review, 35*(2/3), 517–526.
Guerrero, M., Urbano, D., & Herrera, F. (2019). Innovation practices in emerging economies: Do university partnerships matter? *The Journal of Technology Transfer, 44*(2), 615–646.
Gupta, H., & Barua, M. K. (2016). Identifying enablers of technological innovation for Indian MSMEs using best–worst multi criteria decision making method. *Technological Forecasting and Social Change, 107*, 69–79.
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 139–151.
Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24.
Hair, J., Black, W., Babin, B., & Anderson, R. (2014). *Multivariate data analysis* (7th ed.). Essex, England: Pearson Education Limited.
Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review, 26*(2), 106–121.
Han, Y., & Li, D. (2015). Effects of intellectual capital on innovative performance: The role of knowledge-based dynamic capability. *Management Decision, 53*(1), 40–56.
Hansen, M. T., & Birkinshaw, J. (2007). The innovation value chain. *Harvard Business Review, 85*(6), 121–130.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.
Hunt, S. D., & Morgan, R. M. (1996). The resource-advantage theory of competition: Dynamics, path dependencies, and evolutionary dimensions. *Journal of Marketing, 60*(4), 107–114.
Iansiti, M., & Levien, R. (2004). Strategy as ecology. *Harvard Business Review, 82*(3), 68–78.
Jarzabkowski, P., & Wilson, D. C. (2006). Actionable strategy knowledge: A practice perspective. *European Management Journal, 24*(5), 348–367.
Kamaşak, R., & Bulutlar, F. (2010). The influence of knowledge sharing on innovation. *European Business Review, 22*(3), 306–317.
Kaur, V. (2019). *Knowledge-based dynamic capabilities: The road ahead in gaining organisational competitiveness* (1st ed.). Switzerland: Springer International Publishing.
Kaur, V., & Mehta, V. (2017). Dynamic capabilities for competitive advantage: A comparative study of IT multinationals in India. *Paradigm, 21*(1), 31–51.
Kazadi, K., Lievens, A., & Mahr, D. (2016). Stakeholder co-creation during the innovation process: Identifying capabilities for knowledge creation among multiple stakeholders. *Journal of Business Research, 69*(2), 525–540.
Khaksar, S. M. S., Chu, M. T., Rozario, S., & Slade, B. (2020). Knowledge-based dynamic capabilities and knowledge worker productivity in professional service firms: The moderating role of organisational culture. *Knowledge Management Research & Practice*, 1–18.
Klarl, T. (2014). Knowledge diffusion and knowledge transfer revisited: Two sides of the medal. *Journal of Evolutionary Economics, 24*(4), 737–760.
Klimas, P., & Czakon, W. (2021). Species in the wild: A typology of innovation ecosystems. *Review of Managerial Science*, 1–34.
Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec), 11*(4), 1–10.
Kothari, C. (2004). *Research methodology – methods and techniques*. New Delhi: New Age International Limited Publishers.
Laasonen, V., & Kolehmainen, J. (2017). Capabilities in knowledge-based regional development–towards a dynamic framework. *European Planning Studies, 25*(10), 1673–1692.
Lancioni, R. A., & Chandran, R. (2009). Managing knowledge in industrial markets: New dimensions and challenges. *Industrial Marketing Management, 38*(2), 148–151.
Leiponen, A. (2006). Managing knowledge for innovation: The case of business-to-business services. *Journal of Product Innovation Management, 23*(3), 238–258.
Linton, J. D. (2009). De-babelizing the language of innovation. *Technovation, 29*(11), 729–737.
Love, J. H., Roper, S., & Bryson, J. R. (2011). Openness, knowledge, innovation and growth in UK business service. *Research Policy, 40*(10), 1438–1452.
Lundvall, B.Å. (2007). National innovation systems: Analytical concept and development tool. *Industry and Innovation, 14*(1), 95–119.
Malerba, F. (2004). *Sectoral systems of innovation, concepts, issues and analyses of six major sectors in Europe*. Cambridge: Cambridge University Press.
Malerba, F., & McKelvey, M. (2020). Knowledge-intensive innovative entrepreneurship integrating Schumpeter, evolutionary economics, and innovation systems. *Small Business Economics, 54*, 503–522.
Malhotra, N. (2010). *Marketing research – An applied orientation* (6th ed.). New Jersey: Pearson Education.
Manniche, J., & Testa, S. (2018). Towards a multi-levelled social process perspective on firm innovation: Integrating micro, meso and macro concepts of knowledge creation. *Industry and Innovation, 25*(4), 365–388.
Manniche, J., Moodysson, J., & Testa, S. (2017). Combinatorial knowledge bases: An integrative and dynamic approach to innovation studies. *Economic Geography, 93*(5), 480–499.
Martín-de Castro, G. (2015). Knowledge management and innovation in knowledge-based and high-tech industrial markets: The role of openness and absorptive capacity. *Industrial Marketing Management, 47*, 143–146.
Menna, A., Walsh, P. R., & Ekhtari, H. (2019). Identifying enablers of innovation in developed economies: A National Innovation Systems approach. *Journal of Innovation Management, 7*(1), 108–128.
Mercan, B., & Goktas, D. (2011). Components of innovation ecosystems: A cross-country study. *International Research Journal of Finance and Economics, 76*(16), 102–112.
Möller, K., & Halinen, A. (2018). IMP thinking and IMM: Co-creating value for business marketing. *Industrial Marketing Management, 69*, 18–31.
Möller, K., & Rajala, A. (2007). Rise of strategic nets: New modes of value creation. *Industrial Marketing Management, 36*(7), 895–908.
Monferrer, D., Blesa, A., & Ripollés, M. (2015). Born globals trough knowledge-based dynamic capabilities and network market orientation. *Business Research Quarterly, 18*(1), 18–36.
Najafi-Tavani, S., Najafi-Tavani, Z., Naudé, P., Oghazi, P., & Zeynaloo, E. (2018). How collaborative innovation networks affect new product performance: Product innovation capability, process innovation capability, and absorptive capacity. *Industrial Marketing Management, 73*, 193–205.

Narayanan, V. K., Colwell, K., & Douglas, F. L. (2009). Building organizational and scientific platforms in the pharmaceutical industry: A process perspective on the development of dynamic capabilities. *British Journal of Management, 20*, S25–S40.
Nelson, R. R. (1993). *National innovation systems: A comparative analysis*. New York: Oxford University Press.
Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization science, 5*(1), 14–37.
Nonaka, I. (1991). Managing the firm as an information creation process. *Advances in Information Processing in Organizations, 4*, 239–275.
Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. USA: Oxford University Press.
Nonaka, I., Kodama, M., Hirose, A., & Kohlbacher, F. (2014). Dynamic fractal organizations for promoting knowledge-based transformation: A new paradigm for organizational theory. *European Management Journal, 32*(1), 137–146.
Nonaka, I., Toyama, R., & Nagata, A. (2000). A firm as a knowledge-creating entity: A new perspective on the theory of the firm. *Industrial and Corporate Change, 9*(1), 1–20.
Nunn, R. (2019). Innovation ecosystem and knowledge management: A practitioners view. *Business Information Review, 36*(2), 70–74.
Oh, D. S., Phillips, F., Park, S., & Lee, E. (2016). Innovation ecosystems: A critical examination. *Technovation, 54*, 1–6.
Paavola, S., Lipponen, L., & Hakkarainen, K. (2004). Models of innovative knowledge communities and three metaphors of learning. *Review of Educational Research, 74*(4), 557–576.
Pai, F., & Chang, H. (2013). The effects of knowledge sharing and absorption on organizational innovation performance – A Dynamic Capabilities perspective. *Interdisciplinary Journal of Information, Knowledge and Management, 8*, 83–97.
Pattinson, S., Nicholson, J., & Lindgreen, A. (2018). Emergent coopetition from a sensemaking perspective: A multi-level analysis. *Industrial Marketing Management, 68*, 25–35.
Peltier, J. W., Dahl, A. J., & Swan, E. L. (2020). Digital information flows across a B2C/C2C continuum and technological innovations in service ecosystems: A service-dominant logic perspective. *Journal of Business Research, 121*, 724–734.
Penrose, E. T. (1959). *The theory of the growth of the firm*. Oxford, England: Oxford University Press.
Peris-Ortiz, M., Ferreira, J. J., & Lindahl, J. M. M. (2019). *Knowledge, innovation and sustainable development in organizations*. Cham: Springer.
Pittaway, L., Robertson, M., Munir, K., Denyer, D., & Neely, A. (2004). Networking and innovation: A systematic review of the evidence. *International Journal of Management Reviews, 5*(3/4), 137–168.
Prajogo, D. I., & Sohal, A. S. (2003). The relationship between TQM practices, quality performance, and innovation performance. *International Journal of Quality & Reliability Management, 20*(8), 901–918.
Quintane, E., Casselman, R. M., Reiche, B. S., & Nylund, P. A. (2011). Innovation as a knowledge-based outcome. *Journal of Knowledge Management, 15*(6), 928–947.
Radicic, D., Pugh, G., & Douglas, D. (2020). Promoting cooperation in innovation ecosystems: Evidence from European traditional manufacturing SMEs. *Small Business Economics, 54*(1), 257–283.
Rajapathirana, R. J., & Hui, Y. (2018). Relationship between innovation capability, innovation type, and firm performance. *Journal of Innovation & Knowledge, 3*(1), 44–55.
Ringle, C., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. Bönningstedt: Smartpls. Available at: http://www.smartpls.com (accessed 1 June 2020).
Robertson, J. (2020). Competition in knowledge ecosystems: A theory elaboration approach using a case study. *Sustainability, 12*(18), 7372.
Rogers, E. (1962). *Diffusion of innovations*. New York: Free Press.
Romano, A., Passiante, G., Del Vecchio, P., & Secundo, G. (2014). The innovation ecosystem as booster for the innovative entrepreneurship in the smart specialization strategy. *International Journal of Knowledge-Based Development, 5*(3), 271–288.
Roper, S., Du, J., & Love, J. H. (2008). Modelling the innovation value chain. *Research Policy, 37*, 961–977.
Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal, 22*(4), 287–306.
Rothaermel, F. T., & Deeds, D. L. (2004). Exploration and exploitation alliances in biotechnology: A system of new product development. *Strategic Management Journal, 25*(3), 201–221.
Rybnicek, R., & Königsgruber, R. (2019). What makes industry–university collaboration succeed? A systematic review of the literature. *Journal of Business Economics, 89*(2), 221–250.
Santoro, G., Vrontis, D., Thrassou, A., & Dezi, L. (2018). The Internet of Things: Building a knowledge management system for open innovation and knowledge management capacity. *Technological Forecasting and Social Change, 136*, 347–354.
Sarstedt, M., & Mooi, E. A. (2019). *A concise guide to market research: The process, data, and methods using IBM SPSS statistics*. Heidelberg: Springer.
Schumpeter, J. (1942). *Creative destruction: Capitalism, socialism and democracy*. New York City, NY: Harper and Brothers.
Singh, J. (2008). Distributed R&D, cross-regional knowledge integration and quality of innovative output. *Research Policy, 37*(1), 77–96.
Srivastava, R. K., Fahey, L., & Christensen, H. K. (2001). The resource-based view and marketing: The role of market-based assets in gaining competitive advantage. *Journal of Management, 27*(6), 777–802.
Sun, S. L., Zhang, Y., Cao, Y., Dong, J., & Cantwell, J. (2019). Enriching innovation ecosystems: The role of government in a university science park. *Global Transitions, 1*, 104–119.
Talmar, M., Walrave, B., Podoynitsyna, K. S., Holmström, J., & Romme, A. G. L. (2018). Mapping, analyzing and designing innovation ecosystems: The ecosystem pie model. *Long Range Planning*, 101850.
Tang, H., Ma, Z., Xiao, J., & Xiao, L. (2020). Toward a more efficient knowledge network in innovation ecosystems: A simulated study on knowledge management. *Sustainability, 12*(6328), 1–18.
Teece, D. J. (1998). Capturing value from knowledge assets: The new economy, markets for know-how, and intangible assets. *California Management Review, 40*(3), 55–79.
Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319–1350.
Teece, D. J. (2014). A dynamic capabilities-based entrepreneurial theory of the multinational enterprise. *Journal of International Business Studies, 45*(1), 8–37.
Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533.
Tellis, G. J., Chandy, R. K., & Prabhu, J. C. (2012). Key questions on innovation in the B2B context. In G. L. Lilien, & R. Grewal (Eds.), *Handbook of business-to-business marketing* (pp. 582–595). Cheltenham, UK: Edward Elgar Publishing.
Tsai, K. H., & Hsu, T. T. (2014). Cross-Functional collaboration, competitive intensity, knowledge integration mechanisms, and new product performance: A mediated moderation model. *Industrial Marketing Management, 43*(2), 293–303.
Tzokas, N., & Saren, M. (2004). Competitive advantage, knowledge and relationship marketing: Where, what and how? *Journal of Business & Industrial Marketing, 19*(2), 124–135.
Un, C. A., & Cuervo-Cazurra, A. (2004). Strategies for knowledge creation in firms. *British Journal of Management, 15*(S1), 27–41.
United Nations Department of Economic and Social Affairs. (2019). *World economic situation and prospects 2019*. Available at: https://www.un.org/development/desa/dpad/wpcontent/uploads/sites/45/WESP2019_BOOK-web.pdf (Accessed 12 May 2020).
Valkokari, K. (2015). Business, innovation, and knowledge ecosystems: How they differ and how to survive and thrive within them. *Technology Innovation Management Review, 5*(8), 17–27.
Valkokari, K., Seppänen, M., Mäntylä, M., & Jylhä-Ollila, S. (2017). Orchestrating innovation ecosystems: A qualitative analysis of ecosystem positioning strategies. *Technology Innovation Management Review, 7*(3), 12–24.
Van der Borgh, M., Cloodt, M., & Romme, A. G. L. (2012). Value creation by knowledge-based ecosystems – evidence from a field study. *R&D Management, 42*(2), 150–169.
Vargo, S. L., Wieland, H., & Akaka, M. A. (2015). Innovation through institutionalization: A service ecosystems perspective. *Industrial Marketing Management, 44*, 63–72.
Wagner, S. M. (2010). Supplier traits for better customer firm innovation performance. *Industrial Marketing Management, 39*(7), 1139–1149.
Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171–180.
Yan, M. R., Tran-Danh, N., & Hong, L. Y. (2019). Knowledge-based decision support system for improving e-business innovations and dynamic capability of IT project management. *Knowledge Management Research & Practice, 17*(2), 125–136.
Youtie, J., & Shapira, P. (2008). Building an innovation hub: A case study of the transformation of university roles in regional technological and economic development. *Research Policy, 37*(8), 1188–1204.
Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review, 27*(2), 185–203.
Zahra, S. A., & Nambisan, S. (2011). Entrepreneurship in global innovation ecosystems. *Academy of Marketing Science Review, 1*(1), 4–17.
Zheng, S., Zhang, W., Wu, X., & Du, J. (2011). Knowledge-based dynamic capabilities and innovation in networked environments. *Journal of Knowledge Management, 15*(8), 1035–1051.