

Organizational Learning for Innovation Performance of Ventures: The Mediating Role of Entrepreneurial Orientation

벤처기업의 조직학습과 혁신성과: 기업가적 지향성의 매개역할

서리빈 (Ribin Seo)

Pohang University of Science and Technology¹⁾

박지훈 (Ji-Hoon Park)

Hanyang University²⁾

〈 Abstract 〉

While organizational learning (OL) is vital for ventures to build knowledge bases necessary for successful innovation, less attention has been paid to how learning organizations leverage it for performance improvement. We investigate entrepreneurial orientation's (EO) role in performance-by-learning mechanisms underpinning ventures' innovative initiatives, adopting dyadic performance indicators: technological competitiveness and business performance. Analyzing 218 Korean ventures, our study shows that firms valuing OL, characterized by acquisitive and experimental learning, exhibit high EO, facilitating productive use of knowledge-based resources and enhancing performance. Importantly, EO fully mediates the performance implications of OL. Our findings suggest that a comprehensive learning approach for knowledge acquisition and experimentation provides ventures, often facing smallness and newness liabilities, with a fertile entrepreneurial ground for increased innovation returns.

Key words: Organizational learning, Acquisitive learning, Experimental learning, Innovation performance, Entrepreneurial orientation

1) First Author, ribinseo@postech.ac.kr

2) Corresponding Author, jihoonpark@hanyang.ac.kr

1. Introduction

In today's knowledge-driven economy, organizational learning (OL) is a critical discipline for ventures, particularly small, technology-intensive firms, as it enables them to acquire and generate knowledge-based resources for sustained competitive advantage (Alegre & Chiva, 2013). Learning organizations possess the capability to integrate existing resources and capabilities, transforming them into distinctive competencies (Real et al., 2014). From the resource-based view and its extension, the knowledge-based view, OL emerges as a foundational factor for innovation. Consequently, existing research posits that enhancing an organization's learning practices promotes the exploitation of established knowledge and the exploration of new knowledge, fostering internal innovation processes (Baker & Sinkula, 2009; Jiménez-Jiménez & Sanz-Valle, 2011; Kreiser, 2011). In the context of ventures, the role of OL becomes particularly critical as these firms often confront turbulent business environments and numerous unexpected challenges while addressing crisis-induced adversities (Antonacopoulou & Sheaffer, 2014). By harnessing the implications of OL for crisis management, ventures can develop resilience and adaptability, enabling them to navigate uncertainties and capitalize on emerging opportunities (Smith & Elliott, 2007).

Despite the widespread recognition of OL's impact on innovation, the process by which learning practices translate into performance in the context of ventures—infant business entities seeking to capitalize on emerging opportunities in technological domains—remains underexplored. Researchers in the field have cautioned that the performance-by-learning mechanism is not self-evident, as the value capture of OL

can be significantly influenced by contextual conditions in which learning takes place (Zhao et al., 2011). This notion suggests that even when firms possess similar learning abilities, their distinct approaches to knowledge utilization and combination, governed by managerial conditions, can yield different performance outcomes. Seo (2019) argued that ventures often face competitive disadvantages, such as resource constraints, unstructured innovation approaches, deficient multidisciplinary competencies, and social legitimacy disarrangements, leading to diminished innovation returns. Consequently, their inherent liabilities of smallness and newness make it challenging to reap substantial benefits from learning efforts. It is unreasonable to simply assume that ventures adopting OL will produce expected outcomes. A more realistic expectation relies on investigating factors that contribute to the performance-by-learning mechanism.

One internal issue in materializing the value of learning is on the firms' strategic posture toward the productive exploitation of knowledge-based resources for value creation, which is conceptualized by entrepreneurial orientation (EO) (Bouncken et al., 2014; Wang, 2008; Zhao et al., 2011). EO encompasses the managerial practices, approaches, and decision-making styles that embody a firm's strategic stance, aimed at leveraging innovative ideas and experimentation; anticipating and responding to future environmental shifts; and engaging in investments with uncertain outcomes (Covin & Lumpkin, 2011). While there has been an ontological debate regarding whether EO represents attitudinal, behavioral, dispositional characteristic among strategic decision makers (Covin & Lumpkin, 2011), research in the literature of strategic management posit that EO is involved in the managerial process of firms to utilize resources productively in exploiting new opportunities for value creation (Rauch

et al., 2009). From this perspective, entrepreneurial firms—in Miller's (1983) explication, those being innovative, proactive, and risk-taking simultaneously—show a strong tendency to leverage the value of internal knowledge bases in pursuing entrepreneurial opportunities (Brouthers et al., 2015; Sciascia et al., 2014; Wiklund & Shepherd, 2003) as high-EO contributes to creating a nucleus of resources for generating new profit streams (Covin & Wales, 2019). A dominant focus of research has been on investigating the catalytic role of EO in the learning process for resource utilization and integration (e.g., Altinay et al., 2016; Alegre & Chiva, 2013; Kreiser, 2011; Real et al., 2014; Wang, 2008; Zhao et al., 2011).

We presume that EO may facilitate firms' strategic efforts to convert knowledge-based resources embedded within organizations into innovation performance. These knowledge-based resources, derived from learning, represent non-exclusive and non-exhaustible strategic assets (Kreiser, 2011). This is particularly important for ventures seeking entrepreneurial opportunities, as they rely more heavily on their ability to fully utilize resources compared to other types of firms (Wiklund & Shepherd, 2003; Zahra et al., 2009). OL influences a firm's capacity to broaden and deepen its internal knowledge base, providing a fertile foundation for implementing entrepreneurial initiatives aimed at innovation strategies for performance enhancement. In this process, EO may serve as an explanatory factor underlying the transformation of knowledge-based resources into commercial profits, contributing to the performance-by-learning mechanism. Although this proposition can offer theoretical insights into the mechanism, little is currently known about the entrepreneurial process by which learning practices can be translated into innovation performance.

Addressing the knowledge gap, we constructed a theoretical framework to explore the following research questions: (Q1) How do ventures derive benefits from OL for innovation performance, and (Q2) To what degree does their EO influence the OL–innovation performance relationship? To address these questions, we examined a sample of 218 Korean technology-intensive ventures primarily focused on innovation in technological domains. This sample selection is justified by the fact that continuous learning is a vital tool for firms seeking new applications of technological knowledge to capitalize on emerging opportunities (Seo, 2019), and their performance generation process relies on entrepreneurial initiatives to introduce competitive offerings with market appeal (Bouncken et al., 2016). To maintain comparability with existing studies, we conceptualize the OL dimensionality as acquisitive learning and experimental learning, which occur when firms uniquely synthesize knowledge-based resources (Kreiser, 2011; Li et al., 2010; Zahra et al., 1999). EO is conceptualized as the extent to which a firm demonstrates a consistent pattern of entrepreneurial postures in business operations (Covin & Wales, 2019; Rauch et al., 2009).

Our study's distinctive feature is the dyadic innovation performance indicators for ventures: technological competitiveness and business performance. Although innovation performance can be measured in diverse ways (Rosenbusch et al., 2011), using one-dimensional performance indicators may result in misinterpreting their performance generation process (Seo, 2019). The findings from this study contribute to the literature by substantiating the theoretical argument that small firms aiming to exploit entrepreneurial opportunities necessitate adequate resource and competence bases, which can be fostered by intensifying

learning efforts (Anderson et al., 2009; Real et al., 2006).

To achieve the research objective, the structure of this study is as follows. First, we discuss the theoretical framework leading to a series of hypotheses. Next, we present our research method about the sample selection and data-collecting procedures, as well as the introduction of research constructs. Then, we report our findings and discuss their implications based on an analysis of the data collected. Finally, we state the conclusions of this study with its limitation and guidelines for future search.

2. Theories and Hypotheses

2.1. Organizational learning

As an avenue for sustaining innovativeness and competitiveness, OL becomes one of the key mechanisms to refine existing knowledge and generate new knowledge, expressing the purpose of innovation (Crossan et al., 1999). March (1991) defines OL as the managerial discipline of firms toward the active acquisition, assimilation, mobilization, and generation of knowledge-based resources to cope with changing environments and to achieve competitive advantage. Through the dynamic process where the knowledge-relevant activities occur simultaneously, firms can seek a balance between developing, sharing, and accessing the value of current and/or new knowledge that expands resource/competence bases (Real et al., 2006). As the learning outcomes should either be enhanced capabilities for adapting environmental changes or strategic decisions for radical and/or incremental changes in an existing knowledge base for competitive advantage (Kreiser, 2011),

learning organizations can achieve flexibility in the innovation process and refine their strategy by utilizing external knowledge acquired (Cohen & Levinthal, 1990).

Implementing OL can bolster a venture's crisis response capability by fostering adaptability, innovation, and strategic decision-making processes. Unforeseen events, such as the COVID-19 pandemic, triggered widespread economic upheaval, profoundly impacting various industry players, particularly ventures, which are subject to the liabilities of smallness and newness (Seo & Lee, 2021). These inherent disadvantages in ventures hinder the attainment of necessary returns during crises, exacerbating their survival challenges. Nevertheless, OL empowers ventures to cultivate adaptive capacity, a vital component of crisis response (Antonacopoulou & Sheaffer, 2014). Adaptive capacity pertains to an organization's ability to modify its behavior, structures, and systems to navigate turbulent circumstances that may generate exogenous shocks (Williams et al., 2017). By continuously learning from external sources, ventures can develop organizational resilience and enhance crisis response by leveraging their expanded knowledge bases.

Furthermore, OL implementation can refine firms' crisis management strategies by fostering knowledge management, which facilitates the identification, acquisition, and sharing of knowledge and expertise within an organization (Smith & Elliott, 2007). This process bolsters their ability to create repositories of best practices, lessons learned, and pertinent market information, enabling them to make informed decisions during crises. Knowledge sharing and effective decision-making allow firms to exploit and explore the unique value of knowledge-based resources to develop optimal crisis response solutions (Seo & Lee, 2021). In essence, OL practices stimulate innovation, which is crucial for identifying

and seizing new opportunities to ensure survival during challenging times. By persistently pursuing novel ideas, processes, and technologies, ventures can devise innovative solutions to address crises and adapt to fluctuating market conditions.

While there is a consensus in the literature on the innovation implication of OL, previous conceptualizations of OL have drawn upon a wide variety of theoretical lenses when assessing the presence and/or consequences of the learning process. Research on exploitative and exploratory learning (March, 1991) focuses primarily on whether existing knowledge (exploitation) or new knowledge (exploration) is enhanced as a straight result of learning. Research on absorptive capacity (Cohen & Levinthal, 1990) concentrates mainly on whether an organization can effectively acquire and assimilate external knowledge (potential absorptive capacity) or transform and exploit this knowledge internally (realized absorptive capacity). research on adaptive and generative learning (Slater & Narver, 1995) considers whether OL results in incremental change (adaptive learning) or radical change (generative learning) to the firm's current knowledge bases.

The different approaches lead to no unified dimensionality of OL in the literature, but scholars conceive two distinctive learning functions: knowledge acquisition and experiment (Kreiser, 2011; Yang et al., 2009; Zahra et al., 1999; Zhao et al., 2011). According to Bruneel et al. (2010), learning within an organization occurs when a firm not only acquires external knowledge (i.e., knowledge acquisition) but synthesizes new knowledge in experimental ways (i.e., knowledge experiment). Knowledge acquisition involves a learning process to acquire and assimilate external knowledge. An inflow of external knowledge enhances a

firm's managerial competence through access to its operational status (Real et al., 2014). However, knowledge acquisition cannot produce firm-specific resources in isolation, knowledge experiment to explore and create new knowledge that is distinct to a particular organization is necessary (Zahra et al., 1999). This entails the integration and/or generation of new knowledge-based resources that enable ongoing innovation for radical changes in internal knowledge bases (Hughes et al., 2007). Knowledge acquisition and experiment are mutually complementary rather than exclusive. Once firms acquire or exchange knowledge-based resources from external sources, these resources, previously unconnected with firm-internal contexts, should be reprocessed and incorporated into their existing knowledge base for appropriate utilization (Kreiser, 2011).

Against this backdrop, we adopt two distinct learning practices: *acquisitive learning*, which centers on exploiting existing knowledge, and *experimental learning*, which emphasizes generating new knowledge through experimentation. Acquisitive learning involves an organization's capacity to acquire, assimilate, and apply existing knowledge to achieve efficiency (Kreiser, 2011). This process includes refining, extending, and leveraging the organization's knowledge base to support work processes and routines. Within the OL framework, acquisitive learning consists of (a) internal knowledge sharing, which fosters collaboration among members and facilitates knowledge flow, (b) external knowledge acquisition, which gathers insights from external sources to inform decision-making, (c) knowledge assimilation, which integrates acquired knowledge into existing organizational systems to ensure accessibility and usability, and (d) knowledge exploitation, which applies acquired and assimilated knowledge to improve current

operations (Zhao et al., 2011; Gupta et al., 2020).

While acquisitive learning is essential for achieving incremental improvements and efficiency gains, experimental learning focuses on generating new knowledge and often leads to radical innovations that capture new opportunities (Kreiser, 2011). This approach enables adaptation to changing environments by (a) encouraging members to propose innovative ideas that challenge the status quo, (b) testing new ideas through trial-and-error processes to validate their feasibility and effectiveness, (c) learning from failures as opportunities for adaptation and improvement rather than setbacks, and (d) identifying and pursuing emerging market or technology trends with the potential to drive future growth. Ultimately, both acquisitive and experimental learning are crucial for firms to maintain competitiveness and adapt to evolving environments (Dess et al., 2011).

According to Zahra et al. (1999), research can benefit from distinguishing between acquisitive and experiment learning practices because acquisitive learning supports a firm's activities to obtain and assimilate knowledge-based resources that exist outside the firm's boundaries. As knowledge acquisition often precedes knowledge exploitation in a learning process, acquisitive learning is important for expanding a firm's knowledge base (Zahra et al., 1999). While this learning practice typically promotes incremental changes in managerial routines or innovation strategies, experimental learning produces radical changes in the existing knowledge base (Kreiser, 2011). Firms can promote an internal process of integrating and exploiting knowledge-based resources through experimental learning, leading to the creation of firm-specific knowledge.

2.2. Learning for being entrepreneurial

While numerous studies have explored the performance implications of OL for innovation from various theoretical perspectives, the OL-innovation performance relationship has not been consistently supported by empirical evidence, suggesting that this connection is not self-evident (Real et al., 2014). Argote (2011) posited that learning is a research area that particularly benefits from the development of theoretical frameworks that account for performance-by-learning mechanisms. In this context, one specific area of investigation pertains to firms' strategic posture towards the effective utilization of resources for value creation, which is encapsulated by the EO concept.

As an essential driver of innovation and performance, EO reflects a firm's strategic stance towards pursuing new opportunities and revitalizing existing operations by embracing risks and fostering openness to new ideas and experimental processes (Covin & Lumpkin, 2011). EO has been linked to a managerial discipline that embraces a strategic stance, enabling firms to take preemptive actions and seize new opportunities in unfamiliar domains, while providing flexibility to experiment with promising ideas in innovative ways and committing additional resources to innovation (Covin & Wales, 2019). Consequently, EO is characterized by three organizational traits: *innovativeness*, which signifies the inclination to support novel ideas and experiments that deviate from existing operational approaches and foster new market offerings; *proactiveness*, denoting the propensity to address future market needs and establish first-mover preferences ahead of rivals; and *risk-taking*, referring to the willingness to allocate a relatively large portion of resources to opportunities that may result in

potentially costly failures (Covin & Lumpkin, 2011).

As the combination of these dimensions, EO is considered a vital driver of innovation and performance from various perspectives. Firstly, a compelling explanation from the resource-based view posits that EO addresses the firms' managerial processes of productive resource mobilization and utilization for competitive advantage (Wiklund & Shepherd, 2003). In this context, EO contributes to innovation growth, particularly during resource scarcity, by facilitating the efficient redeployment of critical resources (Zhang & White, 2016). Secondly, the knowledge-based view suggests that EO can amplify a firm's learning orientation and related activities, enabling them to better adapt to changing environments and compete against rivals (Wang, 2008). This perspective acknowledges that firms with high EO can derive greater benefits from learning, facilitating knowledge acquisition and generation to expand their knowledge base (Jiang et al., 2016). Lastly, studies from the resource dependency-based view argue that EO encompasses a firm's intention to establish strategic networks as a pathway to acquire complementary resources (Li et al., 2017). Consequently, EO assists in capturing the benefits of newly acquired and generated knowledge, leveraging opportunities for performance improvement.

To elucidate the EO-performance relationship, researchers have identified numerous contextual factors, including industry type, market conditions, competitive intensity, economic conditions, and environmental turbulence (e.g., Morgan & Anokhin, 2020). Some studies have emphasized the importance of internal resource and competence bases, which enable firms to capitalize on entrepreneurial opportunities through innovation processes (e.g., Alegre & Chiva, 2013; Anderson et al., 2009; Cope, 2005; Hughes et al., 2007;

Kreiser, 2011; Real et al., 2014; Wang, 2008; Zahra et al., 1999; Zhao et al., 2011). Rosenbusch et al.'s (2011) meta-analysis found no significant performance effects of innovation-focused initiatives; however, it revealed considerable disadvantages for small firms that face the liabilities of smallness and newness. This outcome is at least partially attributable to the resource-intensive nature of entrepreneurial innovation as a strategic initiative (Wiklund & Shepherd, 2005), suggesting that firms employing EO may be unable to exploit entrepreneurial opportunities for innovation without adequate knowledge-based resources.

In this regard, OL which contributes to expanding firms' knowledge bases is crucial for entrepreneurial firms. Wang (2008) posits that learning serves as an effective means to revitalize and enhance the internal resource and competence bases required for innovation; consequently, small knowledge-intensive firms tend to place significant value on learning to address their resource constraints. Learning organizations with a high entrepreneurial orientation (EO) can foster an environment conducive to innovation, as their learning outcomes provide them with greater confidence in resource superiority, enabling them to be more entrepreneurial and increasing their potential to achieve higher innovation returns (Baker & Sinkula, 2009). Baker and Sinkula (2009) argue that a firm can more rapidly develop superior resource and competence bases through knowledge, leading to the creation of competitive offerings with market appeal. This reasoning suggests that learning for knowledge acquisition and experimentation provides a generative knowledge base to implement entrepreneurial initiatives for innovation, an area that has received limited attention in the literature. Consequently, we examine the sequential relationships between OL, EO, and innovation performance within the

context of ventures.

2.3. Hypotheses

Innovation requires the acquisition and integration of specialized knowledge inputs from different areas. Intensified learning practices facilitate an innovation process to seek out new applications and combinations of knowledge-based resources (Bruneel et al., 2010). In the process, firms that highly value learning are likely to reconfigure and renovate the constructs of their experience, expertise, and capabilities and to produce new insights into business strategy (Cohen & Levinthal, 1990). In this respect, scholars have shed light on the importance of acquiring external knowledge from outside organizational boundaries as well as generating new knowledge-based resources (Kresiser, 2011; Zhao et al., 2011). As such, the combination of acquisitive and experimental learning enables a firm to benefit from its complementarities for innovation success.

Firstly, acquisitive learning pertains to accessing and internalizing preexisting knowledge from external environmental sources, such as suppliers, customers, universities, and even competitors (Li et al., 2010). The acquisition of external knowledge facilitates the identification of emerging opportunities and proactive actions to address environmental changes through innovation (Baker & Sinkula, 2009). As a result, knowledge gained through acquisitive learning can expand a firm's perspective and enhance its capacity to recognize and capitalize on significant market opportunities. By acquiring competitors' or partners' know-how and best practices, firms can refine their operational routines and develop well-tailored competencies more efficiently (Ireland et al., 2003). Li et al. (2010) suggest that effective acquisitive

learning can bolster a firm's knowledge base by augmenting the breadth and depth of relation-specific knowledge at its disposal. Through continuous knowledge acquisition, the firm can attain a more profound understanding of external knowledge and effectively apply such knowledge.

Second, firms also need to use experimental learning to construct the required adaptability of acquired knowledge. Sustainable competitive advantage is achieved when a firm explores and creates inimitable firm-specific knowledge related to promoting experimentation within the firm and generating first-hand knowledge from direct experiences (Li et al., 2010). For this, experimental learning produces competitive knowledge-based resources and then transforms them into a unique format that is difficult to emulate (Zhao et al., 2011). The integration and exploration of new knowledge are important in determining the quality of experimental learning (Kreiser, 2011). The integration and exploitation of new knowledge sources are important in determining the quality of experimental learning. Li et al. (2010) argue that experimental learning helps a firm to gain a much deeper understanding of the existing knowledge and to accumulate tacit knowledge. Through the experimental learning-by-doing approach a firm may derive new and distinctive knowledge as well as creative thinking useful for innovation. Taken together, adopting OL represented by acquisitive and experimental learning contributes positively to the innovation performance of ventures. Therefore, we suggest the following hypothesis.

H1. Organizational learning is positively associated with the innovation performance of ventures.

Entrepreneurial firms can exploit the value of OL to obtain and create competitive knowledge-based resources

that are conducive to innovation projects implemented to proactively realize emerging opportunities ahead of competitors (Wiklund & Shepherd, 2003; Zahra et al., 1999). An intensive learning practice for knowledge acquisition and exploitation (a) supports novel ideas, experimentation, and creative processes that lead to new product/process innovation, (b) provides valuable market knowledge and information for analyzing market changes and competitors' actions, and (c) generates knowledge-based resources to commit to opportunities (Cope, 2005; Li et al., 2010). This implies that learning for knowledge acquisition and exploitation produces an ideal setting to configure an entrepreneurial strategy for better performance (Hughes et al., 2007). This leads us to an assumption that intensifying learning activities to expand internal knowledge bases may provide ventures with a fertile resource ground to take the entrepreneurial posture to be more innovative, proactive, and risk-taking to capitalize on innovation opportunities for value creation.

Adopting an entrepreneurial mode of learning becomes an enabler to exercise constructive operational routines for productive knowledge utilization (Aljanabi, 2017). This can turn into a facilitator of knowledge interpretation which is of the essence to transform private knowledge of individuals to organization-specific one (Hughes et al., 2007). Ireland et al. (2003) explain that acquiring external knowledge and generating new knowledge promote, respectively, the opportunity- and advantage-seeking behaviors of entrepreneurial firms. Li et al. (2010) argue that acquisitive learning can help a firm to identify more opportunities, generate new ideas, and succeed in innovative initiatives. As a result of learning, firms can apply the entrepreneurial mode of strategic actions necessary to compete with and outperform rivals (Aljanabi, 2017; Green et al., 2008). The scale and

scope of existing knowledge-based resources form the cornerstone of entrepreneurial firms' strategic processes (Covin et al., 2006). Knowledge is an outcome of the learning process; learning contributes to the incremental expansion of knowledge scale and scope. Therefore, OL shapes a fertile ground for the manifestation and implementation of EO. We propose the following hypothesis regarding OL's role on EO.

H2. Organizational learning is positively associated with the entrepreneurial orientation of ventures.

For entrepreneurial firms, an extensive knowledge base, cultivated through a dynamic learning process that integrates the intelligence and expertise of individuals within the organization, can function as a valuable strategic asset for performance enhancement (Crossan et al., 1999). Learning effectiveness depends on organizational characteristics that shape a firm's strategic posture toward efficient resource utilization for performance improvement, with EO being a prominent characteristic of entrepreneurial firms seeking value creation (Wang, 2008). This notion suggests that EO can elucidate how learning organizations can capitalize on the value of newly acquired and generated knowledge-based resources to achieve increased innovation returns. Examining the primary effect of EO allows us to advance this proposition.

The mechanisms underlying the EO-performance relationship can be categorized into five primary research streams. First, early studies in the mainstream suggest that EO aids in identifying and translating new opportunities into firms' growth trajectories (Covin & Slevin, 1991; Morgan & Anokhin, 2020; Wiklund, 1999). Second, subsequent research explores EO's role in realigning and adjusting business strategies to align with environmental changes (Covin et al., 2006;

Green et al., 2009; Wiklund & Shepherd, 2005). Third, studies employing the resource-based view explain that EO encompasses how firms utilize resources to enhance performance (Hitt et al., 2001; Lee et al., 2001; Wiklund & Shepherd, 2003). Forth, research adopting the network-based view highlights EO's function as a catalyst in firms' social interactions with others, leveraging profit streams (Stam & Elfring, 2008; Wales et al., 2013). Lastly, in the stream where the present study is situated, researchers regard EO as a learning construct that fosters firms' knowledge-based resources, which are utilized as strategic assets for performance improvement (Kreiser, 2011; Real et al., 2014; Wang, 2008; Zhao et al., 2011). These findings lead us to infer that high EO enables firms to outperform competitors and attain a performance advantage.

EO can play a mediating role in the performance implications of OL by transforming the learning mechanism into the process of crafting and executing innovative solutions. Employing the OL practices produce valuable insights and knowledge on technology, which can be used to make intelligent decisions about potential risks of innovative initiatives. Embracing the calculated risks enables firms to exploit new entrepreneurial opportunities and materialize innovative ideas from their learning processes, enhancing innovation performance. OL also expands the firms' knowledge on business environment, allowing them to identify emerging market trends and respond to technological changes. Proactive firms with the high willingness to anticipate and act on market conditions can apply the knowledge gained by learning to introduce offerings with market appeals ahead of competitors, thus improving innovation returns. Moreover, the OL employment equips firms with stronger experience necessary to foster innovative initiatives toward long-term

business continuity. By nurturing such innovation orientation, entrepreneurial firms can materialize values of the learning-by-experiment into original offerings with high customer values, leading to their potential for performance improvement.

Integrating these perspectives, we propose a chain of effects within the performance-by-learning mechanism. From the resource orchestration viewpoint, achieving a balance between exploitation (i.e., utilizing existing resources and capabilities) and exploration (i.e., seeking new opportunities and resources) is essential for maximizing performance through learning. In the journey towards resource orchestration, EO guides firms to effectively exploit existing knowledge-based resources and explore new ones, attaining an optimized balance. Consequently, learning organizations can foster entrepreneurial initiatives that integrate and disseminate knowledge acquired through learning, promoting the sharing of ideas, best practices, and lessons learned, which, in turn, result in improved innovation performance. Thus, entrepreneurial approaches to create and capture the value of knowledge bases advanced by OL can enhance firms' intelligent decision-making processes to outperform competitors (Morgan & Anokhin, 2020). Based on the hitherto arguments, we propose a mediating role for EO in translating the performance implications of OL.

H3. Entrepreneurial orientation of ventures mediates the relationship between organizational learning and innovation performance.

3. Research Method

3.1. Samples

We evaluate our hypotheses using data from innovation

projects conducted by Korean ventures. According to the Act of Special Measures for Promotion of Venture Business, the Korean government identifies small, technology-intensive firms with high growth potential as strategic business groups by issuing Venture Business Certificates. The Ministry of SMEs and Startups conducts annual surveys to examine their business operations and supports ventures' technological innovation to facilitate the successful commercialization of their innovation-driven market offerings. This study offers a partial perspective on the situation, given the limited research on technological innovation among Korean ventures.

To identify a suitable research population, we utilized a dataset from the 2015 Korean Venture Business Investigation Survey conducted by the ministry. This survey targeted a randomly selected population of ventures and gathered information on 2,072 individual firms. After excluding respondents who had closed their businesses or provided invalid contact information, we filtered the available contact details of 813 firms from the data. In August 2016, we emailed invitations to the chief executive/technology officers (or their equivalents who could assess the activities and outcomes of technological innovation, as well as the general

business status and firm performance) of these firms to participate in our online survey system.

We received a total of 222 questionnaires from individual firms. After excluding four invalid and incomplete responses, the final sample consisted of 218 usable responses for analysis, yielding a 26.8 percent effective response rate. To test for nonresponse bias, we analyzed potential differences between early and late responses, as late respondents are more likely to resemble nonrespondents than early respondents (Armstrong & Overton, 1977). Insignificant differences in firm age and size were found between responding and non-responding firms ($F_{age} = 0.60$, $F_{size} = 0.46$, *n.s.*), indicating that nonresponse bias was not a major concern.

<Table 1> presents the general profiles of respondents. The industries with the most firms are machine and material products (25.2 percent), electricity and electronics (21.1 percent), and information communication (11.0 percent). Of the firms, 78 percent have less than 50 (average 40.1) employees, while 53.7 percent have operated for less than 10 (average 11.7 years) business years. Most respondents answered that their target market was in the growth (52.8%) or maturity (39.8%) phase rather than in the introduction

<Table 1> Descriptive statistics

Item	Frequency (%)	Item	Frequency (%)	Item	Frequency (%)
<i>Industrial classification</i>		<i>Market lifecycle</i>		<i>Business year</i>	
Machine/Materials	55 (25.2)	Introduction	13 (6.0)	Less than 5	34 (15.6)
Electricity/Electronics	46 (21.1)	Growth	115 (52.8)	6-10	83 (38.1)
Information Communication	24 (11.0)	Maturity	87 (39.8)	11-15	67 (30.7)
Knowledge Service	19 (8.7)	Decline	3 (1.4)	16-20	22 (10.1)
Chemical	18 (8.3)	Full-time employees		20+	12 (5.5)
Bio and Medical	15 (6.9)	Less than 10	16 (7.3)		
Energy and Resource	11 (5.0)	11-50	154 (70.7)	<i>Average employees</i>	40.1
Others	30 (13.8)	51-100	32 (14.7)	<i>Average business year</i>	7.7
		101-300	16 (7.3)	(<i>n</i> = 218)	

(6.0%) or decline (1.4%) phase. These statistics reflect a good degree of heterogeneity in the general attributes of the sample firms. We now turn to the explanation of the construct measures

3.2. Measurements

Since the measures were drawn from existing scales to ensure the construct validity, appropriate adjustments were made to the setting and language. Since all items on the questionnaire are delivered to informants in Korean ventures, we apply a double translation method to retain the items' conceptual equivalence. One of the authors translated the English items into Korean, while another translated them back to English. Two other academics then compared the original items and the back-translated ones to check and ensure translation consistency as well as no loss of meanings between the original and translated measures. All are shown in <Table 2> and are scored on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

While knowledge accumulation on the OL construct has been substantial, we used the OL scales developed by Zhao et al. (2011) for acquisitive learning (OLA) and experimental learning (OLE). As mentioned, we expect that their OL components help capture the salient facets of learning for knowledge acquisition and exploitation within an organization. Based on the OL scale proposed by Zhao et al. (2011), we selected 10 measures and allocated five for each component. Considering the characteristics of ventures, we modified the measurement statement without changing essential meanings.

Based on Covin and Wales' (2019) definition, EO was conceptualized as a firm's attributive degree to which it supports and exhibits a sustained pattern of entrepreneurial mode of strategic actions. While Miller (1983) originally conceptualized EO as a multidimensional construct, we operationalized it as a one-composite second-order construct reflecting innovativeness, proactiveness, and risk-taking. To retain this study's consistency and comparability with extant research, we operationalize EO as a composite second-order

<Table 2> Measurement properties

Construct	Loading	t-value
Organizational learning		
Acquisitive learning (AVE = 0,673, CR = 0,911, α = 0,893) <i>In general, my firm...</i>		
1. actively seeks to acquire knowledge from external sources (e.g., competitors, customers, or industry reports).	0,819	12,04
2. regularly shares and exchanges knowledge among employees within the organization.	0,751	10,88
3. effectively assimilates new knowledge into existing systems, processes, and routines.	0,849	12,81
4. consistently applies acquired knowledge to improve our current operations, products, or services.	0,735	13,96
5. encourages employees to refine and extend their knowledge and skills in their areas of expertise. ^b	0,762	–
Experimental learning (AVE = 0,692, CR = 0,918, α = 0,894) <i>In general, our firm...</i>		
1. fosters a culture of experimentation and creative problem-solving.	0,763	12,08
2. actively supports the generation and testing of innovative ideas, products, processes, or business models.	0,807	12,96
3. views failures as learning opportunities rather than setbacks.	0,790	12,63
4. continuously explore new knowledge to drive future growth and competitive advantage.	0,818	13,19
5. encourages employees to challenge the status quo and propose innovative solutions. ^b	0,789	–

Construct	Loading	t-value
Entrepreneurial orientation (AVE = 0,660, CR = 0,946, α = 0,874)		
(Innovativeness) <i>In general, my firm...</i>		
1. favors a strong emphasis on R&D, technological leadership, and innovation	0,736	12,32
2. has been characterized by dramatic changes in new lines of product/services	0,713	11,79
3. values new, creative solutions more than conventional solutions for problem-solving	0,666	10,79
(Proactiveness) <i>In general, my firm...</i>		
4. is typically the first to initiate actions against competitors rather than respond	0,794	13,73
5. is very often the first to introduce new products/services and technology	0,777	13,30
6. is typically unhesitating in competing with rivals to realize opportunities	0,765	13,01
(Risk-taking) <i>In general, my firm's top managers...</i>		
7. encourage commitment to innovative strategies, some of which will fail	0,744	12,51
8. have a strong preference for high-risk projects with chances of high return	0,783	13,44
9. believe that bold and wide-ranging actions are necessary for the achievement of business objectives ^b	0,826	–
Innovation performance		
Technological competitiveness (AVE = 0,542, CR = 0,855, α = 0,842) <i>The technological outputs...</i> ^a		
1. has leading-edge features compared to competing technologies	0,679	9,27
2. can be applied to the development of further technologies	0,750	10,18
3. is technically superior to the existing technology	0,705	6,61
4. is complex and too difficult to be copied and reproduced by others	0,680	11,87
5. has a well-defined target market ^b	0,720	–
Business performance (AVE = 0,632, CR = 0,895, α = 0,846)		
1. Sales growth	0,704	9,40
2. Revenue growth	0,745	9,89
3. Organizational growth (growth in the numbers of employees)	0,815	10,68
4. Product/service variety	0,684	9,15
5. Customer satisfaction <i>achieved for the last three years</i> ^b	0,702	–

*** $p < 0,001$ ($n = 218$)

^a The technology outputs indicate innovation-based market offerings developed internally within the preceding three years.

^b Initial loading was fixed to 1 to set the scale of the construct.

construct reflecting innovativeness, proactiveness, and risk-taking. In this study, we measure the construct by nine items of the Miller/Covin and Slevin scale, regarded as a methodologically defensible approach (Covin & Lumpkin, 2011; Covin & Wales, 2012).

To reflect the nature of ventures pursuing innovation outputs and outcomes, we adopted dyadic indicators of their innovation performance: technological competitiveness *and*

business performance. The reasons for this approach are that the innovation performance of ventures can be defined in various ways and that they typically pursue developing innovation-based outputs for competitive advantage as well as achieving market-based outcomes for business growth simultaneously.

Technological competitiveness refers to the extent to which a firm's competitive advantage in a technological domain

is derived from internally developed, innovation-based outputs. Drawing upon the Korea Technology Finance Corporation's Technology Rating System, we devised a unique measurement scale to assess the degree of technological competitiveness among ventures. This system relies on expert subjective evaluations of a firm's intellectual property, considering its technological superiority, marketability, and business feasibility. In accordance with Nunnally and Bernstein's (1994) procedures, we initially converted the scoreboard into a quantifiable scale within the R&D alliance context, resulting in an initial scale comprising eight items. The final stage involved establishing the construct's validity and reliability through an exploratory factor analysis of data collected from 118 managers attending executive courses, yielding a refined scale consisting of five items.

We concur with the perspective that comparing a firm's business performance to that of its competitors yields valuable insights. To assess competitor-based business performance following the completion of their most recent R&D alliances, respondents were asked to evaluate their performance using Wiklund and Shepherd's (2003) scale: sales growth, revenue growth, organizational growth (measured by employee number growth), product/service variety, and customer satisfaction. These were rated on a Likert scale, ranging from 1 (= much lower than competitors) to 5 (= much higher than competitors).

For model specification, we considered firm size (natural logarithm of the total number of full-time employees) and firm age (natural logarithm of the number of years for which a firm had been in business in 2015) as control variables, expected to covary with the research variables. Some previous studies on both OL and EO also controlled for the variables (Altinay et al., 2016; Covin et al., 2006; Lee et al., 2001;

Stam & Elfring, 2008; Wiklund & Shepherd, 2005).

4. Results

4.1. Diagnostic test

As shown in <Table 2>, the exploratory factor analysis to discriminate the measures of each construct provides sufficient factor loadings (> 0.60) and Cronbach's alphas (> 0.80) for all measures, indicating acceptable levels of internal consistency (Anderson & Gerbing, 1988). The confirmatory factor analysis to test convergence validity and composite reliability shows that the fit indices are acceptable ($\chi^2 = 597.3$, $df = 376$, CFI = 0.854, CFI = 0.946, TLI = 0.937, SRMR = 0.050) with significant loadings (> 0.60). The estimated average variance extracted (AVE > 0.5) and composite reliability (CR > 0.7) of each variable are greater than the cut-off points, indicating adequate convergent validity (Anderson & Gerbing, 1988). <Table 3> shows that the square root of the AVE estimate (diagonal elements) is greater than each of the correlation coefficients in the corresponding rows and columns (off-diagonal elements), supporting the constructs' discriminant validity (Fornell & Larcker, 1981).

<Table 3> also presents the means, standard deviations, and correlations, indicating the following: no variable is highly skewed, all variables are close to a normal distribution to justify normality assumptions and the variance inflation factors suggest no multicollinearity concerns. Overall, these results indicate the measures' validity and reliability for further analysis. The correlation coefficients (r) between the composite variables vary from 0.409 to 0.589. The

〈Table 3〉 Correlations

Construct	Mean	S.D.	1	2	3	4	5	6
1. Acquisitive learning	3.81	0.74	<i>0.820^b</i>					
2. Experimental learning	3.51	0.73	0.620**	0.832 ^b				
3. Entrepreneurial orientation	3.72	0.63	0.631**	0.647**	<i>0.812^b</i>			
4. Technological competitiveness	4.04	0.71	0.486**	0.483**	0.689**	<i>0.736^b</i>		
5. Business performance	3.73	0.64	0.409**	0.425**	0.569**	0.631**	<i>0.795^b</i>	
6. Firm age ^a	2.21	0.63	-0.076	-0.020	-0.118	-0.068	-0.055	
7. Firm size ^a	2.00	0.89	0.096	0.087	0.091	-0.034	0.017	0.179**

** $p < 0.01$ (two-tailed significance, $n = 218$)

^a Natural logarithm values of firm age and size were presented.

^b The values in italics on the diagonal line represent the square roots of the average variance extracted estimates.

coefficients between the OL components ($r = 0.620$) and the innovation performance indicators are significant and relatively high ($r = 0.631$). These imply that the higher-order concepts of OL and innovation performance are represented by and reflected in their corresponding dimensions appropriately. EO is associated more positively with technological competitiveness and business performance than two OL dimensions are with the innovation performance indicators. Given the relatively high correlation between the independent variables ($r_{OLA-OLE} = 0.620$, $r_{OLA-EO} = 0.631$, $r_{OLE-EO} = 0.647$), we consider the variance inflation factor (VIF) to diagnose the multicollinearity issue. The diagnosis confirms that a critical level of multicollinearity is not identified across the measures ($VIF_{OLA} = 1.8$, $VIF_{OLE} = 1.9$, $VIF_{EO} = 2.1$).

Since we collected self-reported data from a single source, the data may be subject to the common method variance (CMV) issue. To alleviate such concern, we ensured the respondents' anonymity and mixed the measures to reduce the social desirability and consistency motif in their evaluation. Next, we used the unmeasured latent method factor (ULMF) in a single confirmatory factor analysis to

rule out any CMV possibility (Podsakoff et al., 2003). We first specified a baseline model, adding the first-order variables with all the measures, and then an alternative model in which all the measures were loaded on the ULMF. The baseline model ($\chi^2 = 597.3$, $df = 376$, GFI = 0.85, CFI = 0.95, TLI = 0.94, SRMR = 0.050) and the alternative model ($\chi^2 = 595.3$, $df = 375$, GFI = 0.85, CFI = 0.95, TLI = 0.94, SRMR = 0.050) showed similar levels of fit indices. The change in χ^2 was marginally significant ($\Delta\chi^2 = 2.0$, $\Delta df = 1$, $p = 0.16$), while the average variance attributed to ULMF was 6.5 percent, corresponding to the amount of CMV. These results indicated that CMV was not a major concern.

4.2. Hypothesis test

The data analysis instrument employed for the hypothesis test is the partial least squares structural equation modeling (PLS-SEM). This is an effective technique for constructing and testing original models (Hair et al., 2011). As covariance-based SEM requires a sound theoretical foundation and a valid measurement model, it is inappropriate

here. Furthermore, PLS-SEM offers a strong tool, the bootstrapping process, for investigating mediating effects and their significance. Bootstrapping is a non-parametric resampling procedure without the assumption of normality of the sample distribution (Hair et al., 2013). MacKinnon et al. (2004) confirm, via simulation, that this procedure, which closely considers the direct and indirect effects of a mediator. We used. The analysis was conducted by bootstrapping with 5,000 resamples and a 95-percent confidence interval (CI). For the structural model assessment, we estimated the path coefficient (β), its significance (t -value), standard error (SE), and CI, as well as the R2 and Q2 values of the endogenous variables (Hair et al., 2011).

The analysis to test the hypotheses was conducted through two models: one for Hypothesis 1 and another for Hypotheses 2 and 3. We controlled for firm age and size in the models, confirming that the control variables had non-significant effects (*n.s.*) on the endogenous variables. Results of testing the OL-innovation performance relationship are presented in <Table 4>. We ruled out EO from the model since it was not specified in the hypotheses. The results reveal a positive effect of the OL components (OLA and OLE) on the innovation performance indicators (TC and BP). Specifically, the coefficients for the paths from OLA and

OLE to TC and BP are significantly positive ($\beta_{OLA-TC} = 0.32, t = 4.47$; $\beta_{OLA-BP} = 0.23, t = 2.90$; $\beta_{OLE-TC} = 0.30, t = 4.09$; $\beta_{OLE-BP} = 0.29, t = 3.43$). Their CIs do not contain zero, indicating that the effects are significantly different from zero, at a 95 percent confidence level. TC and BP are sufficiently explained (R^2) and predictable (Q^2) by the exogenous variables (Hair et al., 2011), which implies that the higher the OL for knowledge acquisition and exploitation, the higher the innovation performance achieved in both the technological and business domains of ventures. Thus, the results support Hypothesis 1.

Hypotheses 2 and 3 testing involves the procedure for analyzing the mediation effect of EO (Hair et al., 2013). <Table 5> illustrates the total effects of the OL components on the innovation performance indicators (*a*). These total effects can be expressed as the sum of the direct (*b*) and indirect effects (*c*) of the OL components on the innovation performance indicators ($a = b + c$). The indirect effects (*c*) are the product of the direct effect of the OL components on EO (*c'*) and the direct effects of EO on the innovation performance indicators (*c''*), that is, $c = c' * c''$. Thus, $a = b + c' * c''$. This approach isolates the OL components' direct effects on EO (*c'*) and their indirect effects on the innovation performance indicators ($c' * c''$), as described in Hypotheses 2 and 3, respectively.

<Table 4> Hypothesis test results (direct effects)

Path	Innovation performance									
	Technological competitiveness ($R^2 = 0.301, Q^2 = 0.217$)					Business performance ($R^2 = 0.212, Q^2 = 0.123$)				
	β	t	SE	CIL	CIU	β	t	SE	CIL	CIU
Controls	-0.055	0.826	0.067	-0.173	0.045	-0.038	0.441	0.085	-0.176	0.101
Acquisitive learning	0.317	4.467***	0.071	0.201	0.434	0.234	2.902**	0.081	0.100	0.369
Experimental learning	0.296	4.084***	0.072	0.179	0.417	0.285	3.433***	0.083	0.151	0.422

*** $p < 0.001$, ** $p < 0.01$ ($n = 218$)

〈Table 5〉 Hypothesis test results (indirect effects)

Path	Mediator					Innovation performance indicators									
	Entrepreneurial orientation (R ² = 0.577, Q ² = 0.273)					Technological competitiveness (R ² = 0.523, Q ² = 0.380)					Business performance (R ² = 0.311, Q ² = 0.196)				
	β	t	SE	CIL	CIU	β	t	SE	CIL	CIU	β	t	SE	CIL	CIU
Controls	-0.098	1.135	0.086	-0.157	0.110	0.065	0.771	0.084	-0.146	0.122	0.030	0.372	0.081	-0.132	0.136
Total effect															
Acquisitive learning						0.317	4.408***	0.072	0.197	0.432	0.235	2.912**	0.081	0.108	0.370
Experimental learning						0.291	4.096***	0.071	0.176	0.409	0.279	3.351***	0.083	0.138	0.413
Direct effect															
Acquisitive learning	0.289	5.175***	0.056	0.200	0.381	0.102	1.346	0.076	-0.025	0.230	0.076	0.887	0.086	-0.064	0.218
Experimental learning	0.533	10.035***	0.053	0.443	0.616	-0.105	1.497	0.070	-0.213	0.016	-0.013	0.164	0.082	-0.150	0.118
Entrepreneurial orientation						0.742	10.148***	0.073	0.392	0.703	0.549	5.804***	0.095	0.612	0.854
Indirect effect (through EO)															
Acquisitive learning						0.214	4.391***	0.049	0.137	0.298	0.159	3.749***	0.042	0.095	0.233
Experimental learning						0.396	7.465***	0.053	0.307	0.480	0.293	5.039***	0.058	0.199	0.389

*** $p < 0.001$, ** $p < 0.01$ ($n = 218$)

As shown in the table, the coefficients for the paths from OLA and OLE, representing the OL components, to EO are significantly positive ($\beta_{OLA-EO} = 0.29$, $t = 5.18$; $\beta_{OLE-EO} = 0.53$, $t = 10.04$), while the intervals do not contain zero. These results indicate that OL contributes affirmatively to EO and support Hypothesis 2. When EO is introduced into the model as a mediator, OLA and OLE no longer have significant direct effects on TC and BP ($\beta_{OLA-TC} = 0.10$; $\beta_{OLA-BP} = 0.08$; $\beta_{OLE-TC} = -0.11$; $\beta_{OLE-BP} = -0.01$, *n.s.*). Their indirect effects via EO, however, are significant and positive ($\beta_{OLA-TC} = 0.21$, $t = 4.39$; $\beta_{OLA-BP} = 0.16$, $t = 3.75$; $\beta_{OLE-TC} = 0.40$, $t = 7.47$; $\beta_{OLE-BP} = 0.29$, $t = 5.04$), with no zero-containing intervals. These results suggest a full mediation effect of EO in the relationship between OL and innovation performance, supporting Hypothesis 3.

5. Conclusion

5.1. Discussion and contributions

Our findings contribute significantly to the literature on OL and EO. Drawing on the EO theory, this study investigated the sequential process of influence from OL to EO and innovation performance in ventures. Although several studies posit that EO is an antecedent of OL (Kreiser, 2011; Zhao et al., 2011; Wang, 2008; Real et al., 2014), we propose that EO is involved in addressing OL's performance implication. The findings support the proposition, suggesting that intensive learning activities reinforce the entrepreneurial behaviors to be innovative, proactive, and risk-taking at the firm level, which, in turn, produces fruitful outcomes.

First, and most importantly, we found that OL was conducive to EO. The learning process to acquire and exploit

knowledge-based resources expands firms' knowledge/competence bases (Real et al., 2006). Consequently, firms gain confidence in their resource bases, which, in turn, leads to an elevated willingness to utilize such resources to strategically capture new opportunities and achieve wealth creation. This strategic posture of firms is the locus of EO (Wiklund & Shepherd, 2003). We thus suggest that firms that highly value OL are likely to create a favorable atmosphere for entrepreneurial behaviors. This is consistent with Wang's (2008) explanation that a learning organization provides an ideal setting to implement an entrepreneurial strategy to exploit wealth-creating opportunities. Our argument is corroborated by Anderson et al. (2009) and suggests that enhancing resource bases fundamentally shapes and directs firms' entrepreneurial behaviors.

The EO implication for acquisitive and experimental learning forces firms to focus on their different but complementary roles in the entrepreneurial process. Acquisitive learning leads to an inflow of external knowledge from the market/industry. Such knowledge and information about markets, customers, competitors, and partners help firms rejuvenate market offerings and/or renew managerial processes (innovativeness) and adopt forward-looking perspectives to explore and act on future market needs ahead of their competitors (proactiveness). By learning and utilizing the technological knowledge and expertise that exist outside organizational boundaries, technology-intensive firms can generate new and creative solutions to technical problems. Their risk management skills, derived from technological innovation, can be enhanced through knowledge of competitors' risk management practices (risk-taking).

Meanwhile, the knowledge-based resources derived by one economic actor from external sources may be

non-exclusive and accessible to others (Kreiser, 2011). For performance advantage, experimental learning produces firm-specific knowledge that is typically inimitable by competitors. The learning process, per se, is an innovation process that combines internal and external knowledge (innovativeness). New knowledge offers valuable clues to how to proactively compete against existing and potential rivals and attain market leadership (proactiveness). The more a firm's knowledge base expands, the more its resources are committed to innovation projects (risk-taking). For EO, experimental learning is more important than acquisitive learning. A possible explanation for this is that experimental learning, which creates more firm-specific knowledge, helps firms recognize entrepreneurial opportunities that are highly exploitable for enhanced performance.

Second, this study confirms the contribution of OL to ventures' innovation performance. This implies that ventures that engage in intensive learning for knowledge acquisition and exploitation achieve a higher competitive advantage in both the technological and business domains than those that do not. This is consistent with the solid argument in OL research that learning is an effective instrument for firm performance and growth (Alegre & Chiva, 2013; Altinay et al., 2016; Real et al., 2014). Our finding on the positive relationship between OL and innovation performance is not necessarily surprising. However, the straightforward relationship becomes insignificant when EO is considered. An interesting finding is the full mediation role of EO in the OL-performance relationship: Technically, OL indirectly (not directly) affects innovation performance through EO. This finding implies that, for ventures, evolving as a learning organization encourages entrepreneurial behaviors throughout the organization, which, in turn, leads to improved innovation

performance. This is because the EO-performance relationship that emanates from OL is much more significant than the direct OL-performance relationship. Based on the empirical evidence, we conclude that the trajectory from learning to performance is predicated on firms' entrepreneurial behaviors to be innovative, proactive, and risk-taking, which involves how firms utilize resources productively and strategically.

Consequently, this study contributes to addressing the important questions of how and why OL impacts performance, which has not been sufficiently explored to date. Jiménez-Jiménez and Sanz-Valle (2011) suggest that the OL-performance relationship, as the primary focus in the literature, could be elaborated more by investigating the meaningful conditions and factors that facilitated it. Scholars have endeavored to do this in various spectrums: network participation (Kreiser, 2011), organizational and environmental characteristics (Jiménez-Jiménez & Sanz-Valle, 2011), and market orientation (Real et al., 2014). Along with these, we suggest that EO is one of the critical conditional factors for firms employing OL to achieve higher innovation performance. Our findings on the sequential OL-EO-performance relationship contradict the argument in previous studies that EO facilitates a firm's learning process (Hughes et al., 2007; Kreiser, 2011; Real et al., 2014; Zhao et al., 2011). Is this true? We also advocate the notion that entrepreneurial firms are the most likely to derive benefits from learning for the expansion of knowledge bases (Wang, 2008), which is a logical basis for their argument. Meanwhile, we suggest that the relationship between OL and EO is not unilateral, but reciprocal and supplementary. Firms necessarily encourage interactions with external parties to facilitate the learning process (Bruneel et al., 2010).

The social networks that entail knowledge transfer among parties promote the recognition of new and valuable opportunities to be exploited; the learning activities encourage entrepreneurial firms to be more innovative, proactive, and risk-taking when facing such opportunities.

5.2. Practical implications

We suggest two recommendations for practitioners. First, learning for knowledge acquisition and exploitation is crucial for ventures, especially small firms suffering resource constraints. Such firms can benefit from OL, not only in updating and upgrading their knowledge-based resources but also in discovering new opportunities to create differentiated profit streams. These can be achieved by cultivating a learning environment within an organization and reinforcing the relevant capability to acquire and assimilate external knowledge, as well as by integrating and generating new knowledge. The developed resources and competencies become firm-specific assets and a source of sustainable performance advantage. Second, It is advantageous for managers to consider the complementarity between OL and EO. With OL configured as a key strategic discipline, firms need to consider EO's role in creating innovation performance and facilitating OL's performance implication. EO is a strategic attitude that must be supported by certain organizational conditions. This study's findings suggest that such conditions prevail in a learning organization. Practitioners should develop new practices to foster an entrepreneurial innovative, proactive, and risk-taking environment within an organization, such as individual and collective learning, learning by action, and learning by trial

and error.

We recommend that managers consider the OL-EO-performance relationship as an *entrepreneurial learning process*. Entrepreneurial learning is a strategic learning process, from the discovery of an opportunity, through the productive acquisition and exploitation of knowledge-based resources, to wealth creation by means of innovativeness, proactivity, and risk-taking. Thus, firms can energetically translate their OL into innovation-based outputs and market-based outcomes.

5.3. Limitations and future research

This study has some limitations. These, however, pave the way for new lines of future research. First, since OL occurs dynamically over time, studying it may require longitudinal data while we relied on cross-sectional data. Despite the theoretical agreement on the OL-performance relationship, the reverse causal relationship, that better performance may promote OL, is possible. We suggest that future research could consider this causality using a longitudinal study. Second, although we used previously verified subjective performance measurements, quantitative/objective measures on innovation performance, can be more accurate and objective in estimating innovation performance. Private firms were generally reluctant to divulge their financial data to external parties, while ventures' performance varies widely. Further research can develop and employ more accurate measurement sets. Third, given that this study uses a sample of Korean technology-intensive ventures, we recommend that researchers consider the unique geographical setting inherent in the data. Despite the argument that EO, which refers to firms' strategic attitudes in management,

is a universal concept (Seo, 2019), individuals' perceptions of EO may vary across countries with different cultural backgrounds. A future line of research might be an empirical study to test our theoretical model or EO's performance implication in multinational samples. Lastly, we suggest that OL and EO researchers consider firms' social networks with external parties. Networks are an important means for firms to exchange complementary knowledge and expertise and facilitate their innovation process. The entrepreneurial learning process can occur at both intra-firm and inter-firm levels. We believe that the theory of social capital, which refers to the sum of assets embedded in networks, is key to our understanding. This suggests a future line of research that would examine social capital's role in the relationships among research constructs.

〈References〉

[국외 문헌]

1. Alegre, J., & Chiva, R. (2013). Linking entrepreneurial orientation and firm performance: The role of organizational learning capability and innovation performance. *Journal of Small Business Management*, *51*(4), 491–507.
2. Aljanabi, A. (2017). The mediating role of absorptive capacity on the relationship between entrepreneurial orientation and technological innovation capabilities. *International Journal of Entrepreneurial Behavior & Research*, *24*(4), 818–841.
3. Altinay, L., Madanoglu, M., De Vita, G., Arasli, H., & Ekinci, Y. (2016). The interface between organizational learning capability, entrepreneurial orientation, and SME growth. *Journal of Small Business Management*, *54*(3), 871–891.
4. Anderson, B. S., Covin, J. G., & Slevin, D. P. (2009). Understanding the relationship between entrepreneurial orientation and strategic learning capability: An empirical investigation. *Strategic Entrepreneurship Journal*, *3*(3), 218–240.
5. 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.
6. Antonacopoulou, E. P., & Sheaffer, Z. (2014). Learning in crisis: Rethinking the relationship between organizational learning and crisis management. *Journal of Management Inquiry*, *23*(1), 5–21.
7. Argote, L. (2011). Organizational learning research: Past, present and future. *Management Learning*, *42*(4), 439–446.
8. Baker, W. E., & Sinkula, J. M. (2009). The complementary effects of market orientation and entrepreneurial orientation on profitability in small business. *Journal of Small Business Management*, *47*(4), 443–464.
9. Bouncken, R. B., Pl schke, B. D., Pesch, R., & Kraus, S. (2014). Entrepreneurial orientation in vertical alliances: Joint product innovation and learning from allies. *Review of Managerial Science*, *10*(2), 381–409.
10. Brouthers, K. D., Nakos, G., & Dimitratos, P. (2015). SME entrepreneurial orientation, international performance, and the moderating role of strategic alliances. *Entrepreneurship Theory and Practice*, *39*(5), 1161–1187.
11. Bruneel, J., Yli-Renko, H., & Clarysse, B. (2010). Learning from experience and learning from others: How congenital and interorganizational learning substitute for experiential learning in young firm internationalization. *Strategic Entrepreneurship Journal*, *4*(2), 164–182.
12. Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152.
13. Cope, J. (2005). Toward a dynamic learning perspective of entrepreneurship. *Entrepreneurship Theory and Practice*, *29*(4), 373–397.
14. Covin, J. G., & Lumpkin, G. T. (2011). Entrepreneurial orientation theory and research: Reflections on a needed construct. *Entrepreneurship Theory and Practice*, *35*(5), 855–872.
15. Covin, J. G., & Slevin, D. P. (1991). A conceptual model of entrepreneurship as firm behavior. *Entrepreneurship Theory and Practice*, *16*(1), 7–25.
16. Covin, J. G., & Wales, J. (2012). The measurement of entrepreneurial orientation. *Entrepreneurship Theory and Practice*, *36*(4), 677–702.
17. Covin, J. G., & Wales, J. (2019). Crafting high-impact entrepreneurial orientation research: Some suggested guidelines. *Entrepreneurship Theory and Practice*, *43*(1), 3–18.
18. Covin, J. G., Green, K. M., & Slevin, D. P. (2006). Strategic process effects on the entrepreneurial orientation–sales growth rate relationship. *Entrepreneurship Theory and Practice*, *30*(1), 57–81.
19. Crossan, M. M., Lane, H. W., & White, R. E. (1999). An organizational learning framework: From intuition to institution. *Academy of Management Review*, *24*(3), 522–537.
20. Dess, G. G., Pinkham, B. C., & Yang, H. (2011). Entrepreneurial orientation: Assessing the construct's validity and addressing some of its implications for research in the areas of family business and organizational learning. *Entrepreneurship Theory and Practice*, *35*(5), 1077–1090.

21. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.
22. Green, K. M., Covin, J. G., & Slevin, D. P. (2008). Exploring the relationship between strategic reactiveness and entrepreneurial orientation: The role of structure–style fit. *Journal of Business Venturing*, *23*(2), 356–383.
23. Gupta, V. K., Niranjana, S., & Markin, E. (2020). Entrepreneurial orientation and firm performance: The mediating role of generative and acquisitive learning through customer relationships. *Review of Managerial Science*, *14*, 1123–1147.
24. Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS–SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152.
25. Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Editorial–partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long Range Planning*, *46*(1–2), 1–12.
26. Hitt, M. A., Ireland, R. D., Camp, S. M., & Sexton, D. L. (2001). Strategic entrepreneurship: Entrepreneurial strategies for wealth creation. *Strategic Management Journal*, *22*(6–7), 479–491.
27. Hughes, M., Hughes, P., & Morgan, R. E. (2007). Exploitative learning and entrepreneurial orientation alignment in emerging young firms: Implications for market and response performance. *British Journal of Management*, *18*(4), 359–375.
28. Ireland, R. D., Hitt, M. A., & Sirmon, D. G. (2003). A model of strategic entrepreneurship: The construct and its dimensions. *Journal of Management*, *29*(6), 963–989.
29. Jiang, X., Yang, Y., Pei, L., & Wang, G. (2016). Entrepreneurial orientation, strategic alliances, and firm performance: Inside the black box. *Long Range Planning*, *49*(1), 103–116.
30. Jim nez–Jim nez, D., & Sanz–Valle, R. (2011). Innovation, organizational learning, and performance. *Journal of Business Research*, *64*(4), 408–417.
31. Kreiser, P. M. (2011). Entrepreneurial orientation and organizational learning: The impact of network range and network closure. *Entrepreneurship Theory and Practice*, *35*(5), 1025–1050.
32. Lee, C., Lee, K., & Pennings, J. M. (2001). Internal capabilities, external networks, and performance: A study on technology–based ventures. *Strategic Management Journal*, *22*(6–7), 615–640.
33. Li, L., Jiang, F., Pei, Y., & Jiang, N. (2017). Entrepreneurial orientation and strategic alliance success: The contingency role of relational factors. *Journal of Business Research*, *72*, 46–56.
34. Li, Y., Zhang, C., Liu, Y., & Li, M. (2010). Organizational learning, internal control mechanisms, and indigenous innovation: The evidence from China. *IEEE Transactions on Engineering Management*, *57*(1), 63–77.
35. MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate Behavioral Research*, *39*, 99–128.
36. March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, *2*(1), 71–87.
37. Miller, D. (1983). The correlates of entrepreneurship in three types of firms. *Management Science*, *29*, 770–791.
38. Morgan, T., & Anokhin, S. A. (2020). The joint impact of entrepreneurial orientation and market orientation in new product development: Studying firm and environmental contingencies. *Journal of Business Research*, *113*, 129–138.
39. Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory*. New York: McGraw–Hill.
40. Rauch, A., Wiklund, J., Lumpkin, G. T., & Frese, M. (2009). Entrepreneurial orientation and business performance: An assessment of past research and suggestions for the future. *Entrepreneurship Theory and Practice*, *33*(3), 761–787.
41. Real, J. C., Leal, A., & Roldán, J. L. (2006). Information technology as a determinant of organizational learning and technological distinctive competencies. *Industrial Marketing Management*, *35*(4), 505–521.
42. Real, J. C., Roldán, J. L., & Leal, A. (2014). From entrepreneurial orientation and learning orientation to business performance: Analysing the mediating role of organizational learning and the moderating effects

- of organizational size. *British Journal of Management*, *25*(2), 186–208.
43. Rosenbusch, N., Brinckmann, J., & Bausch, A. (2011). Is innovation always beneficial? A meta-analysis of the relationship between innovation and performance in SMEs. *Journal of Business Venturing*, *26*(4), 441–457.
 44. Sciascia, S., D’Oria, L., Bruni, M., & Larra eta, B. (2014). Entrepreneurial orientation in low- and medium-tech industries: The need for absorptive capacity to increase performance. *European Management Journal*, *32*(5), 761–769.
 45. Seo, R. (2019). Entrepreneurial orientation and innovation performance: Insights from Korean ventures. *European Journal of Innovation Management*, *23*(4), 675–695.
 46. Seo, R., & Lee, Y. W. (2021). Crisis management strategies of startups in the COVID-19 pandemic. *Journal of APEC Studies*, *13*(1), 1–22.
 47. Slater, S., & Narver, J. (1995). Market orientation and the learning orientation. *Journal of Marketing*, *59*(3), 63–74.
 48. Smith, D., & Elliott, D. (2007). Exploring the barriers to learning from crisis: Organizational learning and crisis. *Management Learning*, *38*(5), 519–538.
 49. Stam, W., & Elfring, T. (2008). Entrepreneurial orientation and new venture performance: The moderating role of intra- and extraindustry social capital. *Academy of Management Journal*, *51*(1), 97–111.
 50. Wales, W. J., Parida, V., & Patel, P. C. (2013). Too much of a good thing? Absorptive capacity, firm performance, and the moderating role of entrepreneurial orientation. *Strategic Management Journal*, *34*(5), 622–633.
 51. Wang, C. L. (2008). Entrepreneurial orientation, learning orientation, and firm performance. *Entrepreneurship Theory and Practice*, *32*(4), 635–657.
 52. Wiklund, J. (1999). The sustainability of the entrepreneurial orientation–performance relationship. *Entrepreneurship Theory and Practice*, *24*(1), 37–48.
 53. Wiklund, J., & Shepherd, D. (2003). Knowledge-based resources, entrepreneurial orientation, and the performance of small and medium-sized businesses. *Strategic Management Journal*, *24*(13), 1307–1314.
 54. Wiklund, J., & Shepherd, D. (2005). Entrepreneurial orientation and small business performance: A configurational approach. *Journal of Business Venturing*, *20*(1), 71–91.
 55. Williams, T., Gruber, D., Sutcliffe, K., Shepherd, D., & Zhao, E. (2017). Organizational response to adversity: Fusing crisis management and resilience research streams. *Academy of Management Annals*, *11*(2), 733–769.
 56. Yang, Y., Narayanan, V., & Zahra, S. (2009). Developing the selection and valuation capabilities through learning: The case of corporate venture capital. *Journal of Business Venturing*, *24*(3), 261–273.
 57. Zahra, S. A., Kuratko, D. F., & Jennings, D. F. (1999). Guest editorial: Entrepreneurship and the acquisition of dynamic organizational capabilities. *Entrepreneurship Theory and Practice*, *24*(1), 5–10.
 58. Zhang, W., & White, S. (2016). Overcoming the liability of newness: Entrepreneurial action and the emergence of China’s private solar photovoltaic firms. *Research Policy*, *45*(3), 604–617.
 59. Zhao, Y., Li, Y., Lee, S. H., & Chen, L. B. (2011). Entrepreneurial orientation, organizational learning, and performance: Evidence from China. *Entrepreneurship Theory and Practice*, *35*(2), 293–317.

● 저 자 소 개 ●



서 리 빈 (Ribin Seo)

포항공과대학교 산업경영학과 대우부교수 및 기업가정신 융합부전공 주무교수로 재직 중이다. University of Manchester에서 경영학 박사 학위를 취득하였고, Manchester Institute of Innovation Research 연구원을 역임했다. Technovation, Journal of Knowledge Management, R&D Management, International Journal of Entrepreneurial Behavior & Research, European Journal of Innovation Management, 지식경영연구, 중소기업연구, 전략경영연구, 기술혁신연구, 벤처창업연구 등의 국내외 학술지에 논문을 발표했다.



박 지 훈 (Ji-Hoon Park)

현재 한양대학교 경영대학 경영학부 조교수로 재직 중이다. 한국과학기술원(KAIST)에서 경영공학 박사학위를 취득하였다. 주요 관심분야는 개방형 혁신, 사회적 기업가정신 등이다. 지금까지 Research Policy, Technovation, Asian Business & Management, Technology Analysis & Strategic Management, Asian Journal of Technology Innovation, 지식경영연구, 중소기업연구, 기술혁신연구, 사회적가치와 기업연구 등 주요 국내외 학술지에 논문을 발표하였다.

〈 국문초록 〉

벤처기업의 조직학습과 혁신성과: 기업가적 지향성의 매개역할

서리빈*, 박지훈**

조직 학습은 벤처기업이 성공적인 혁신 창출에 필요한 지식 기반을 구축하는데 필수적이다. 하지만 이러한 벤처기업의 조직 학습이 성과 향상에 어떤 기제로 영향을 미치는지에 관해서는 더 많은 연구가 필요한 상황이다. 이에 본 연구는 벤처기업의 학습-성과 기제에 기업가적 지향성이 어떻게 작용하는지 살펴보았으며, 본 연구가 벤처기업 맥락의 연구라는 점을 고려해 두 유형의 혁신 성과 지표를 활용하였다: 기술경쟁력, 사업 성과. 본 연구는 총 218개 국내 벤처기업을 대상으로 수집한 자료를 분석하였으며, 그 결과 획득적 학습과 실험적 학습의 조직 학습을 강조하는 기업일수록 높은 수준의 기업가적 지향성을 나타냄을 확인하였다. 이는 벤처기업이 조직 학습을 많이 수행할수록 지식 기반 자산을 보다 생산적으로 활용하는 기업가적 지향성이 높다는 것을 의미한다. 또한 본 연구는 기업가적 지향성이 벤처기업의 조직 학습과 혁신 성과를 완전 매개함을 확인하였다. 본 연구는 상대적으로 작은 규모와 짧은 업력으로 인해 한계에 직면하는 벤처기업이 지식을 습득하고 활용하기 위한 조직 학습을 통해 혁신 성과를 향상시킬 수 있음을 보였다는 점에서 기존 연구 및 실무에 기여한다.

주제어: 조직학습, 획득적 학습, 실험적 학습, 혁신성과, 기업가적 지향성

* 포항공과대학교

** 한양대학교