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Lean Startup: Operationalizing Lean Startup Capability and testing its performance implications

Rainer Harms [a,b] and Mario Schwery [a]

[a]BMS/NIKOS, University Twente, The Netherlands; [b]National Research University Higher School of Economics, Moskva, Russia

ABSTRACT

Many startups use Lean Startup (LS). But is it effective? While there are emerging qualitative findings, quantitative evidence does not yet exist. To address this gap, we developed an operationalization of the degree to which startups use LS (Lean Startup Capability, LSC). We then analyzed the LSC-performance relationship. We found a strong and robust relationship. A discussion contextualizes our findings. The LSC operationalization is relevant for research as future efforts can build on and extend it. The contribution to entrepreneurial practice is that we carved out the element of LSC, and showed that LS is indeed linked to performance.

KEYWORDS

Experimental entrepreneurship; Lean Startup; opportunity exploration

Introduction

Lean Startup (LS) is a toolset for opportunity exploration (Bakker & Shepherd, 2017) that emphasizes iterative experimentation and early customer insight. Entrepreneurs make their implicit assumptions about their venture explicit. Then, they submit their assumptions to empirical tests. Their results deliver new insights that either supports their assumptions or inspire the entrepreneur to change. Entrepreneurs that use LS avoid costly mistakes early on and increase the likelihood of success. LS proposes tools such as variants of the business model canvas, qualitative and quantitative market research, and prototyping to support the exploration of opportunities toward an economically sustainable venture (Maurya, 2012; Ries, 2011). Hence, LS is a toolset for *experimental entrepreneurship*, which is defined as approaches to the entrepreneurial process that emphasize experimentation rather than (formal) planning, improvisational learning, or trial and error (Block & MacMillan, 1985; Lynn, Morone, & Paulson, 1996; Miner, Bassoff, & Moorman, 2001; Sull, 2004).

LS is very popular. Hundreds of universities worldwide teach LS (LeanstartupCo, 2018), several large companies such as Intuit and Dropbox

CONTACT Rainer Harms r.harms@utwente.nl University Twente, BMS/NIKOS, Postbus 217, Enschede 7500 AE, The Netherlands

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endorse it, and it is the foundation of a National Science Foundation program to turn scientists into entrepreneurs (Blank, 2012). LS meetups exist globally. LS conferences draw thousands of visitors. However, despite its popularity, quantitative research on whether LS is effective is scarce.

Previous LS research has done a masterful job in rooting LS in literature streams such as design thinking (Mueller & Thoring, 2012), bricolage and effectuation (Frederiksen & Brem, 2017), organizational learning, real options, and new product development (Contigiani & Levinthal, 2018). However, most empirical research on LS is qualitative (Bjoerk, Ljungblad, & Bosch, 2013; Lindgren & Münch, 2016; Mansoori, 2017). While these studies provide valuable insights into LS, quantitative approaches are needed to move LS research from a nascent to an intermediate phase (Edmondson & McManus, 2007).

Quantitative LS studies focus on experimentation. For example, Camuffo, Cordova, and Gambardella (2017) compare performance between incubees from two incubators. Both incubators' programs were based on LS, but one placed a heavy emphasis on a scientific approach to experimentation. Ladd (2016a) used the number of experiments that startups executed to indicate LS. The focus on experimentation is a good starting point. Yet LS is more than experimentation. For example, it also contains activities such as generating early customer insights, learning, and iteration.

Hence, LS is a bundle of activities. This bundle of activities is conceptualized under the capability-based perspective as the Lean Startup Capability (LSC). We define *Lean Startup Capability* as the LS-based cross-functional capability bundle (Grant, 1996) that the venture performs when it engages in opportunity incubation (Vogel, 2016). From the perspective of capability bundles, research that focuses on one of part of the LSC bundle, and does not capture other constituent elements of LSC, fails to test LSC performance. In terms of measurement theory, research needs to safeguard construct validity.

We developed an operationalization that considers the full spectrum of LSC. Researchers can use our operationalization to analyze the antecedents, processes, and outcomes of LS. Entrepreneurs, incubator managers, and educators benefit as they obtain evidence on which to decide whether they want to use or promote LS. To realize the contributions, we ask two research questions. First, how can we measure LSC? Second, is the degree to which ventures use LSC positively related to performance?

Background

Entrepreneurs use LS to develop their initial idea toward a validated and scalable business. Hence, LS is a method of opportunity exploration. LS may be preceded by and interwoven with design thinking that emphasizes that entrepreneurs gain a deep understanding of customer/user needs (Mueller & Thoring, 2012). It may be followed by and interwoven with processes of iterative product development such as agile development (Ghezzi, 2019) and processes aimed to scale the business (Blank, 2013, 2006).

LSs' approach to opportunity exploration emphasizes experimentation (experimental entrepreneurship). Experimental entrepreneurship's roots in the management literature may be traced back to Mintzberg, Raisinghani, and Théoret (1976), who illustrate that active search and iterative design of solutions are hallmarks of unstructured, strategic decision–making. In innovation management, Lynn et al. (1996) illustrate that companies such as Corning, GE, Motorola, and Searle used a "probe and learn" process in new product development and marketing. They found that "these companies … ran a series of market experiments – introducing prototypes into a variety of market segments" (p. 15). In entrepreneurship, Block and MacMillan (1985, p. 184) argue that "starting a new business is essentially an experiment. Implicit in the experiment are several hypotheses (commonly called assumptions) that can be tested only by experience." Chandler, DeTienne, McKelvie, and Mumford (2011) suggest that experimentation is a key dimension of the effectual approach to new venture development. With "disciplined entrepreneurship," Sull (2004) argues for a process where entrepreneurs test hypotheses empirically. The theory-based view of the firm (Felin & Zenger, 2017) argues that entrepreneurs are theorists (Felin & Zenger, 2009) that combine imagined possibilities into models and hypotheses and submit them to logical reasoning, social experimentation (Gemmell, Boland, & Kolb, 2012), and rigorous empirical tests.

Theorizing, experimenting, using data from experiments for behavioral or cognitive change, and repeating the cycle until the entrepreneur reaches a validated and scalable business model is an iterative process. When we conceptualize LS as an iterative process, two questions follow.

The first question is about the elements of this process that we need to use to operationalize LSC. In other words, what are the activities that ventures perform when they use LS to explore opportunities? Second, once we know what these activities are, we can analyze if the bundle of these actives is related to performance in ventures. As a bundle of activities, LS can be conceptualized as a capability (Bingham, Eisenhardt, & Furr, 2007). This capability bundle can help entrepreneurs to develop better theories about what is an attractive business opportunity (Felin & Zenger, 2017). This capability bundle also allows entrepreneurs to be quicker in developing these theories by helping entrepreneurs to build experience, develop standard operating procedures, and gain confidence (Bakker & Shepherd, 2017). We begin to answer these questions by first describing the sample we used for operationalization and analysis. We then develop and discuss the operationalization, and analyze and discuss its performance implications. We close with implications.

Measurement of LSC and an analysis of its performance implications

Sample

The population is the software ventures subset of about 2,100 active technology-based startups in Berlin (Startup Genome, 2017). LS is particularly useful for software ventures: Software allows for fast product iterations, Business-to-Consumer (B2C) and some Business-to-Business (B2B) software ventures have a large user base for experimentation (Harms, Marinakis, & Walsh, 2015), and software developers are usually familiar with experimentation in product development (Paternoster, Giardino, Unterkalmsteiner, Gorschek, & Abrahamsson, 2014). We included young (younger than six years, Zahra, Ireland, & Hitt, 2000) software ventures that have recently finished the development of a digital product or service.

We chose Berlin as a geographical context because the Berlin ecosystem is a rather mature one, with a high share in in- and outbound international entrepreneurs (Startup Genome, 2017). This connectedness and international mobility lead to an exchange of ideas on management practices such as Lean Startup. The Lean Startup scene is also connected globally, with the global and continental Lean Startup Summits as hubs of idea exchange. These arguments support the assumption that there is no Berlin-specific Lean Startup implementation or Berlin-specifics in the LSC-performance relationship. Also, founders of technology-based ventures are less likely to be impacted by national culture than those of non-technology-based ventures (Harms & Groen, 2017). Hence, we argue that our findings can be generalized beyond the particular location.

We used a multipronged approach to collect data, as we were aware of low response rates from online or mailed surveys. First, we used social media sites of community platforms such as the German Startup Association, Silicon Allee, and START Berlin. Second, we used personal contacts with ventures in co-working spaces and accelerators such as Axel Springer plug&play, Innogy, Betahaus, we work, ahoy, and rainmaking loft. Finally, we used referrals via snowball sampling that originated from the personal contacts of one of the authors. We contacted a total of 450 entrepreneurs and reached 100 valid responses. The final response rate was about 22 percent, which compares well among quantitative studies on startups (Chandler et al., 2011).

Nonresponse bias was assessed by comparing responses between early and late respondents (Rogelberg & Stanton, 2007). We correlated the number of days of response (after the first response) with other constructs. Only one of fourteen correlations was significant, which indicates the absence of nonresponse bias. The potential for common method bias (CMB) was limited ex ante through procedural remedies of the survey (Podsakoff, MacKenzie, Podsakoff, & Lee, 2003). Ex post, a partial correlation approach test (Podsakoff et al., 2003) revealed that the correlation between LSC and performance remained strong and significant after the first general factor had been partialed out. Hence, CMB is likely to not affect the results of this study (Doty & Glick, 1998).

Measuring LSC

LSC as a multidimensional construct

We began to operationalize LSC with the assumption that LSC is composed of several activities that together define LSC. For example, Ries (2011) conceptualized LS as activities around the build/measure/learn loop. We conceptualize LSC as a formative model (Jarvis, MacKenzie, & Podsakoff, 2003) because performing these activities is a matter of choice. Hence, LSC is composed of these activities, and not caused by them. Also, activities of LSC are not required to be performed together, thus, they do not have to covary. We then developed this formative construct with the design guidelines for formative indicators (Diamantopoulos & Winklhofer, 2001): content specification, indicator specification, and assessment of indicator collinearity.

To specify the first-order indicators, we started with a critical observation of the practical phenomenon. Here, we synthesized practitioners' first-person, holistic experience of how they use LS (Thompson, Locander, & Pollio, 1989). Phenomenological interviews (Cope, 2005a; Thompson et al., 1989) with three LS experts (Alexander Osterwalder, Eric Ries, and Ash Maurya) and six entrepreneurs (Patz, 2013) provided insights in how they use LS. The interviews were coded (open and axial coding). Open coding resulted in 146 individual codes, which were aggregated to ten higher-level concepts. Six of these higher-level concepts refer to the activities that entrepreneurs perform (Patz, 2013, p. 28), and hence to LSC. These concepts were iteration, experimentation, characteristics (customer orientation), validation, learning, and prototyping. Because the team context often appeared as a topic in the phenomenological study, and because other prior LS research has emphasized knowledge sharing in teams (Harms, 2015), we also included knowledge sharing. Additionally, because the topic of hypotheses (for example, "hypothesis-driven entrepreneurship," Eisenmann, Ries, & Dillard, 2011) appeared prominently in the Lean Startup literature, we included hypothesis testing.

We modeled each first-order indicator as a reflective second-order construct. These indicators share common themes and are expected to covary (Jarvis et al., 2003). To specify the indicators for the second-order construct, we reviewed the literature to find established scales that matched the content of the first-order indicator as good as possible. We drew on the Cui and Wu (2017) scale for "experimental NPD" for "experimentation," and on the Calantone, Cavusgil, and Zhao (2002) scale on "commitment to learning" for "learning." Established scales that fit the content domain of the LS for the first-order indicators "iteration," "customer orientation," "validation," "prototyping," and "hypothesis testing" could not be identified. For those constructs, we developed our own items. In the item development process, we were inspired by the LS item list proposed by Rübling (2016), our literature review, and discussion with entrepreneurs. We followed item formulation guidelines (clarity, length, directionality, lack of ambiguity, and avoidance of jargon, Diamantopoulos & Winklhofer, 2001).

We used a 5-point Likert-type scale, with several items reverse coded. The original item pool was pretested on a sample of eight entrepreneurs, which led us to slightly reformulate a few items. The LSC-indicators referred to LSC as activities performed in a particular project, which allowed the respondents to link their responses to real experience, and to avoid recall bias.

In exploratory factor analysis (EFA with Promax to allow for correlations between factors), the scree-plot based on the full item set suggested a five-factor solution. Items about experimentation and iteration loaded on one factor (iterative experimentation). Items about customer insight, validation, learning, and hypothesis testing loaded on the respective factor. Items for knowledge transfer and prototyping did not emerge as empirically distinct dimensions as they were found loading with almost all other LSC elements and were considered as omnipresent and conceptually covered in the other constructs. These two were excluded from further operationalization.

Indicator collinearity was addressed with confirmatory factor analysis (CFA). The average variance extracted (AVE) for four constructs is above .4, which is acceptable (Huang, Wang, Wu, & Wang, 2013). For one construct, AVE is just below threshold. The AVE of each of the latent constructs is higher than the highest squared correlation with any other latent variable (Fornell & Larcker, 1981). Composite reliability is above the threshold for all of the five constructs (Bagozzi & Yi, 1988). See Table 1 for the operationalization and Table 2 for the correlations.

An internal replication of the EFA and the CFA (Osborne, 2014) indicated that the results (factor structure, Cronbach's alpha, AVE, composite reliability (CR) could be replicated to a great extent. Differences may be a result of the lower-than-necessary sample size after the sample split (Anderson & Gerbing, 1984; Gorsuch, 1983). Finally, for each factor, we calculated the factor score (with a mean of 0 and a standard deviation (STDV) of 1) and added those factor scores to form a reflective first-order – formative second-order construct (Jarvis et al., 2003).

Table 1. LSC operationalization – full versus sample split.

	Mean	SD	Cr. α	AVE	CR	Item-to-total	Factor Loading (EFA)	Factor Loading (CFA)
Iterative experimentation								
We viewed new product/service development as cycles of experiments, learning, and additional experiments.	4.25	0.94	.842	.450	.837	.589	.541	.676
We did not try many different product/service solutions before we found the right one.®	3.34	1.34				.524	.734	.557
We engaged in many trial and error processes in product/service development before we had a complete understanding of the market and technology.	3.55	1.28				.708	.758	.767
We repeated the process of testing until all key business model assumptions have been validated.	3.38	1.24				.611	.610	.675
We took an experimental approach that relied on frequent trial and error to find the right product/service solution.	3.55	1.31				.644	.682	.718
We frequently design and run experiments on elements of our business model.	3.53	1.01				.641	.607	.724
Customer insight								
It is important to gain deep market insight (= talking directly to customers) to better understand our customer's problem.	4.79	0.56	.747	.490	.788	.660	.852	.872
When we developed the solution, we never had the customer in mind.®	4.69	0.80				.501	.352	.515
We invested significant effort into understanding the problem and learning about the user and its social context.	4.13	1.03				.561	.415	.552
It is important to gain deep market insight into how our solution solves the customer problem.	4.63	0.68				.564	.832	.803
Validation								
We used metrics to measure the impact of product/service improvements on customer behavior.	3.57	1.26	.772	.481	.732	.389	.631	.617
We did not use data-driven tests to improve our human judgment in the decision making the process.®	3.42	1.22				.466	.591	.632
We have metrics available to test the product/service acceptance by customers and sales performance.	3.82	1.07				.405	.695	.814
Learning								
The organization's ability to learn is not considered as key to our competitive advantage.®	4.18	1.04	.727	.395	.721	.545	.696	.565
The basic values of our organization include learning as a key to improvement.	4.37	0.84				.520	.688	.591
Venture learning is an investment, not an expense.	4.44	0.74				.479	.403	.643
Learning in our organization is a key commodity necessary to guarantee organizational survival.	4.40	0.91				.526	.453	.706
Hypotheses testing								
We formulated a series of assumptions about the market needs and how best to deliver it.	4.24	0.911	.597	.541	.702	.425	.621	.723
We translated the vision about our product/service and its value proposition into falsifiable assumptions.	3.65	1.100				.425	.588	.749

The CFA for hypotheses testing is based on a separate CFA, because the full analysis did not converge with the HT items.

Table 2. Correlations of the LSM dimensions.

	1	2	3	4
1. Iterative experimentation				
2. Customer insight	.363**			
3. Validation	.433**	.297**		
4. Learning	.348**	.458**	.135	
5. Hypothesis testing	.229**	.183#	.195#	.233*

#*p* < .1, **p* < .05, ***p* < .01.

Describing the dimensions of LSC

Customer insight is the capability to understand customers and users deeply. It is built on a market-oriented philosophy (Slater & Narver, 1998) that puts potential customers' latent needs central in solution development. With an in-depth understanding of customer/user needs, entrepreneurs avoid costly mistakes in solution development. Activities include market research that focuses on latent rather than expressed needs (Slater & Narver, 1998) and conscious use of identified needs in opportunity exploration.

Hypotheses testing is the capability to formulate and test explicit hypotheses about the venture and its environment. Implicit assumptions are made explicit and put to empirical tests. The test results help the entrepreneur to explore, refine, and develop their opportunity toward exploitation (Felin & Zenger, 2017). Activities include the explication of implicit hypotheses that feed into iterative experimentation to generate cognitive and behavioral learning.

Iterative experimentation is the capability to run several experiments on all elements of a business. Iterative experimentation addresses the continuous, rather than sporadic, nature of experimentation (Block & MacMillan, 1985; Lynn et al., 1996; Sull, 2004).

Validation refers to the use of data to monitor the impact of decisions based on the results of iterative experiments. Data helps entrepreneurs to cancel out human decision-making biases (Eisenmann et al., 2011; York & Danes, 2014). Hence, validation helps entrepreneurs to get a more objective view of the venture. These arguments are line with the literature on evidence-based management (Pfeffer & Sutton, 2006; Rousseau, 2006). Activities include, for example, the use of McClure (2007) pirate metrics.

Learning is the capability to use new information to update beliefs and actions. Learning aims to understand better (cognitive learning) the value-generating potential of the opportunity (Felin & Zenger, 2017). It is also aimed to inform action ("pivot or persevere"; behavioral learning). The literature proposes a positive relationship between learning and performance (Baker & Sinkula, 1999; Calantone et al., 2002; Real, Roldán, & Leal, 2014; Wang, 2008). Activities include, for example, the accumulation of experiences, the articulation, and codification of knowledge (Zollo & Winter, 2002).

Discussing the operationalization

Our first research question was on how to operationalize LSC. Based on the suggestion of the phenomenological interviews (Patz, 2013), we identified a five-factor solution that consists of customer orientation, hypothesis testing, iterative experimentation, validation, and learning. The psychometric properties are good, except for hypothesis testing. Issues with discriminant validity remain, but we expected that subdimensions correlate. Instrument validity needs to be ascertained with a larger pretest (Perneger, Courvoisier, Hudelson, & Gayet-Ageron, 2014). Prototyping and knowledge sharing were thought of as separate dimensions of LSC. In our operationalization, these topics did not emerge as empirically distinct dimensions. Cross-loadings indicate that other constructs may have already covered items' meanings.

The operationalization adds to the literature because it provides a multidimensional, multi-item measure of experimental entrepreneurship. A multidimensional operationalization is superior because LSC covers more activities than only experimentation. A multi-item operationalization is superior because it allows alleviating measurement error (Diamantopoulos, Sarsted, Fuchs, Wilcynski, & Kaiser, 2012).

Future research should address the limitations and refine our operationalization, as original operationalizations of complex constructs are rarely perfect (Chandler et al., 2011). We now discuss refinements on the subconstruct level and the level of the higher-order construct.

At the level of the subconstructs, the operationalization of hypothesis testing needs to be improved; for example, by adding further items to increase reliability (Diamantopoulos et al., 2012). The AVE for learning is slightly below the threshold, which also suggests that further improvement is necessary. For iterative experimentation, two items referred to trial and error, which may blur the line between experimental and trial-and-error learning (Miner et al., 2001).

At the level of the higher-order construct (LSC), we needed to check discriminant validity (differentiation between LSC and other related constructs). First, LSC taps into conceptually different dimensions than, for example, effectuation (Chandler et al., 2011), bricolage (Senyard, Baker, & Davidsson, 2009), learning orientation (Wang, 2008), and market orientation (Jaworski & Kohli, 1993). At the same time, there may be an overlap in the content domain between LSC and related constructs. For example, LSC shares the element of experimentation with the effectuation scale (Chandler et al., 2011), yet LSC emphasizes methodical rather than ad hoc experimentation. Second, we expected that the dimensions covary as a result of the phenomenological study from Patz (2013). Covariation leads to sideloadings and a relatively low degree of discriminant validity. Should discriminant validity be a concern from the measurement side, second-order constructs that better discriminate need to be developed.

Finally, our operationalization of LSC is based on the firms' actions at the project level. This operationalization is in line with an activities-based conceptualization of capabilities (Laaksonen & Peltoniemi, 2018). This action-based conceptualization is based on the assumption that "in order to do something, the firm has to have a capability for doing it" (Laaksonen & Peltoniemi, 2018, p. 191). The operationalization may diverge from an experience-based conceptualization of capabilities, which takes into account that it takes experience to build capabilities (Laaksonen & Peltoniemi, 2018). Future research can use experience and action-based indicators for capabilities, and link them to performance in mediation-type analyses. Such a research design clearly distinguishes between these types, and can answer the additional question about the conditions under which experience-based capabilities translate into action or not.

We need to acknowledge these shortcomings. However, we believe that the operationalization developed here is a good starting point for further empirical inquiry into the measurement and analysis of LSC.

The performance implications of LSC

LSC-performance relationship: Development of hypotheses

LSC as a capability bundle. We conceptualize LSC as the realized capability to perform activities related to LS. Hence, LSC is a capability in the sense of the capabilities-based view (Bingham et al., 2007). The CBV argues that firms' heterogeneity in their ability to perform specific actions can explain performance differences. Each of the LSC dimensions is such a capability, which is rooted in particular literatures with specific theoretical backgrounds (Contigiani & Levinthal, 2018).

Adding to the capability view is the notion that LSC is a capability bundle (Lichtenstein & Brush, 2001), which implies that it is not a single capability, but the integrated bundle of LSC dimensions that are related to performance. The argument for capability bundles is supported by the theory-based view (TBV, Felin & Zenger, 2017), by experiential learning theory (ELT, Corbett, 2005; Kolb, 1984), by a narrative of how the LSC dimensions are interlinked (see below), and by the correlations between LSC dimensions (see Table 2).

The TBV proposes that successful strategies originate from theories. Theories are a coherent, abstract, causal representation of the world (Felin & Zenger, 2017). In entrepreneurship practice, theories concern questions about which activities entrepreneurs should engage in, which assets they might buy, and how entrepreneurs will create value. Theories are developed by experimenting on initial conjectures: Felin and Zenger (2017, p. 262) point out that "as with scientific theories, an economic theory commonly originates with a question or problem … . Such problems or questions may prompt a novel hypothesis or conjecture about paths to a solution and lead to experimentation. Through further refinements …, the problem becomes more fully framed, and a more well-formulated theory may emerge."

The LSC bundle is also linked to ELT (Corbett, 2005). ELT suggests that entrepreneurs use experience, reflection, abstract conceptualization, and active experimentation (Corbett, 2005; Kolb, 1984). These learning types are reflected in the LS process of customer-oriented experimental learning (Figure 1): Direct experience and reflection create a subjective stock of knowledge (Minniti & Bygrave, 2001). Abstract conceptualization transforms the subjective stock of knowledge (assumptions) into specific hypotheses. Hypotheses guide active experimentation, which gives rise to new experiences. Corbett argues that entrepreneurs learn best when they cycle through all four forms of learning. This argument supports the notion of the integrated nature of the LS process and supports the idea of LSC as a capability bundle.

The LS process of customer-oriented experimental learning. We now argue how the integrated bundle of LSC dimensions allows entrepreneurs to develop better theories on customer value. The premise is that the more accurate the entrepreneurs' theories fit the real world, the better decisions they can make. The premise also suggests that if one of the capability dimension were missing, entrepreneurs might find it challenging to develop a theory that reflects market reality (see Figure 1).

First, through customer orientation, the entrepreneurs' attention is focused on an area of crucial importance to startups (Maurya, 2012). From a TBV perspective, theories guide observation and perception (Felin & Zenger, 2017). Entrepreneurs need to decide which questions will drive their experiments. Questions on marketing (Gruber, 2007) and other critical business areas (Ladd, 2016a) have been shown to have significantly positive performance implications. The entrepreneurial process literature suggests that entrepreneurs should gather low-cost, high-impact information (Bennett & Chatterji, 2016) such as through social experimentation (Gemmell et al., 2012).

Second, once core areas of inquiry are selected, entrepreneurs need to formulate conjectures about state variables and cause-effect relationships. These conjectures or hypotheses, are the starting point for experimental learning. The deliberate variation of inputs characterizes experimental learning. Experimental learning allows entrepreneurs to reflect and to develop generalizable knowledge (Miner et al., 2001).

Third, experimentation based on the previously generated hypotheses allows entrepreneurs to detect false positives (opportunities that seemed profitable, but turn out not to be) and false negatives (opportunities that did not seem to be profitable, but would have been, Camuffo et al., 2017). Experiments deliver signals that represent the distribution of potential returns to an opportunity.

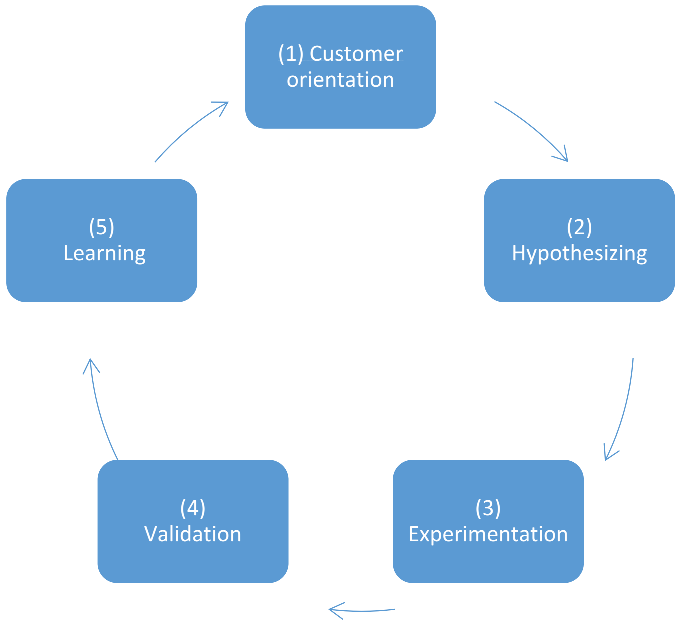

Figure 1. The LS process of customer-oriented experimental learning.

Entrepreneurs that experiment more stringently can obtain better information about the actual distribution of potential returns, and can then make a better decision of whether to abandon, change, or further invest in the opportunity (Camuffo et al., 2017). This line of argument is based on the assumption that opportunities exist that can be discovered through experimentation, and on real-options logic (Camuffo et al., 2017).

Experimentation also allows entrepreneurs to create opportunities through early stakeholder involvement. For example, when entrepreneurs – who know about what is technologically feasible – interact in social experiments with customers (Gemmell et al., 2012), customers become aware of new opportunities. Entrepreneurs that – consciously or not – shape the emerging opportunity to fit their passion and technological capability can increase the chance of success.

Fourth, experiments generate data that entrepreneurs use to monitor the impact of their decisions. The validation dimension reflects the data-driven nature of decision-making. The use of data helps to ameliorate human biases in decision-making (Eisenmann et al., 2011; York & Danes, 2014). Hence, validation helps entrepreneurs to get an objective view of the venture.

Fifth, LSC suggests that entrepreneurs use validated evidence to learn. LS supports two main types of learning: experimental learning (Miner et al., 2001) and error-based learning (Petkova, 2009). Experimental learning is based on deliberately created experiences (experiments). These experiments concern information about states (for example, customer needs) and relationships (for example, problem-solution fit). Entrepreneurs can analyze and reflect on the results of their experiments. Miner et al. (2001) compare experimental learning with improvisational and trial-and-error learning. Trial-and-error learning is one where experiences are not generated deliberately and is used more in an ad hoc way. Trial-and-error learning may lead to low to moderate amounts of reflection and more local rather than generalizable results.

Error-based learning works best under the conditions of "(1) a well-defined task, (2) clear standards for determining how appropriate the answers/outcomes are, and (3) immediate, specific feedback" (Petkova, 2009, p. 347). The hypotheses-based nature of iterative experimentation creates these conditions. In particular, entrepreneurial learning is triggered by learning events (Cope, 2005b; Minniti & Bygrave, 2001). LS creates these learning events before they can get critical for the venture (small, intelligent failures, Sitkin, 1992).

To sum up, LSC contributes positively to performance. Entrepreneurs can meet time and budget requirements because they can avoid costly failures through early intervention (Hayes, Wheelwright, & Clark, 1988). Early customer engagement and the use of explicit hypotheses facilitate these interventions. Experimentation creates data that can be used to counteract decision-making biases (Eisenmann et al., 2011; York & Danes, 2014). These data enable experimental learning that entrepreneurs use to update their theory of how to create value.

Hypothesis 1: The higher the degree of LSC, the higher the performance.

Key contingencies. The net benefits of LS are a function of its costs and benefits or unit cost of information obtained by LS. Costs are the time and effort that is required to obtain the information that leads to learning and reduction of uncertainty. For example, this includes costs for finding and engaging respondents, and for adapting the solution. We argue that the unit cost of information obtained by LS is context specific. We explored external uncertainty, innovativeness, and the customer type (B2B or B2C) as drivers of the unit cost of information.

The higher the market and technological uncertainty, the stronger the LSC-performance relationship. First, consider uncertainty because of missing information. Under high uncertainty, an additional unit of effort spent on learning will increase knowledge significantly. However, the more entrepreneurs already know, the less additional knowledge they will gain per unit of additional learning effort. In a world without uncertainty, entrepreneurs do not gain information by spending resources on LS (Eisenmann et al., 2011). These decreasing returns on information are known from qualitative market research, where the rate of additional customer problems discovered decreases with an increase in the number of customers interviewed (Griffin & Hauser, 1993). Second, consider true uncertainty (Knight, 1921). Here, LS helps entrepreneurs to remain flexible by enabling detection of early market signals (Camuffo et al., 2017) and enabling flexible product development process (Thomke & Reinertsen, 1998). However, there are also decreasing returns to flexibility (Stennek, 1994).

Hypothesis 2: The LSC-performance link is moderated by market and technological uncertainty: The higher the market and technological uncertainty, the stronger the LCS-performance relationship.

The degree of innovativeness that a venture pursues also affects the LSC-performance relationship. The degree of innovativeness influences the unit costs of information. Information obtained on incremental innovation may be more reliable than information on radical innovation. For radical innovation, past experiences (Enkel, Kausch, & Gassmann, 2005) and local search biasses (Keinz & Prügl, 2010) constraint the respondents. The build-measure-learn model is considered "a vehicle for incremental innovation" (Fagerholm, Münch, & Mäenpää, 2017, p. 298).

Hypothesis 3: The LSC-performance link is moderated by the degree of innovativeness: The more radical innovation is, the weaker is the LSC-performance relationship.

Whether the entrepreneur addresses a B2B or a B2C market is also related to the costs of information, and thus to the effectiveness of LSC. In B2C markets, entrepreneurs have a large number of customers. Thus, they can frequently iterate without compromising brand equity (White & White, 2017) and endangering the venture's reputation as a technology leader (Vendelo, 1998). In B2B markets, the number of potential customers is lower. This lower number makes it riskier to use iterative experimentation.

Hypothesis 4: The type of business moderates the LSC-performance link: It is stronger for B2C than for combined B2B and B2C business, which is again stronger than for B2B businesses.

Testing the LSC-performance relationship. The dependent variable was *project performance*, defined as the on-time and on-budget creation of a high-quality solution (Atkinson, 1999). We addressed the project level rather than the whole venture level, as startups may have several projects. Hence, entrepreneurs may use LS for new projects, but not for established ones. Then,

Table 3. Correlations of key constructs.

	1	2	3	4	5	6
1. Year						
2. Stage	−.573**					
3. Performance	.165	.202*				
4. LSC	.069	.143	.507**			
5. Market uncertainty	−.019	.272*	.397**	.432**		
6. Technology uncertainty	−.296**	.419**	.337**	.355*	.431**	
7. Innovation	.035	−.050	.271*	.230*	.049	.268**

*$p < .05$, **$p < .01$.

LSC influences new project performance, but not venture performance in general. A formative construct of the "iron triangle" from the project management literature (Atkinson, 1999) was used. It contains items for cost (Atkinson, 1999; Mishra & Shah, 2009; Naumann & Jenkins, 1982), time (Lynn, Reilly, & Akgün, 2000; Tanev, Rasmussen, Zijdemans, Lemminger, & Limkilde, 2015), and quality (Atuahene-Gima, Li, & De Luca, 2006) of the LS project. These items were measured on a 5-point scales.

Market uncertainty was based on items from the Jaworski and Kohli (1993) market turbulence scale (three items, Cronbach's alpha of .635) and reflects the perceived market uncertainty at the start of the project. Technology uncertainty was based on items from the Jaworski and Kohli (1993) technological turbulence scale (three items, Cronbach's alpha of .715). It reflects the perceived technological uncertainty at the start of the project. Items for innovation type were based on Gatignon, Tushman, Smith, and Anderson (2002). Higher values indicate a higher degree of radicalism (four items, Cronbach's alpha of .673). Entrepreneurs self-assessed the type of business. We used dummy coding with B2B as a reference category; the first dummy indicating mixes, and the second dummy indicating B2C. Controls were the founding year, and venture stage (ordinal; idea development, startup, early growth, rapid growth, maturity).

The method of analysis is the moderated regression analysis. See Table 3 for correlations. We ascertained normality. We find an equal distribution of residuals in the P-P plot, which indicates homoscedasticity. The low Variance Inflation Factor (VIF) indicates the absence of multicollinearity.

Results. We found a moderately strong (Cohen, 1988), robust, and highly significant relationship between LSC and performance. This effect was stronger than usual in entrepreneurship research (Connelly, Ireland, Reutzel, & Coombs, 2010). More mature ventures performed better. The performance was not related to the degree of uncertainty or business type. Of the moderators, the business type had an impact on the LSC-performance relationship, with the mixed category showing a significantly stronger relation between LSC and performance. See Table 4 for the regression results.

Table 4. Regression on project performance.

	(0)	(1)	(2)	(3)	(4)
Founding year	.275**	.227*	.279**	.251*	.232*
Venture stage	.271**	.227**	.274**	.249*	.272**
LSC	.444***	.451***	.436***	.425***	.257*
Market uncertainty	.102	.102	.115	.121	.120
Technology uncertainty	−.134	−.155	−.133	−.134	−.097
Inno	.228*	.209*	.233*	.235*	.238*
Business Dummy 1	−.044	−.043	−.051	−.051	−.013
Business Dummy 2	−.007	−.014	−.099	−.010	−.011
LSC * Market uncertainty		.123			
LSC * Technology uncertainty			−.052		
LSC * Innovation				−.085	
LSC * Business Dummy 1					.344**
LSC * Business Dummy 2					.023
F (full model)	7.473***	6.925***	6.631**	6.730**	8.116**
R^2 (full model)	.397	.409	.399	.402	.477

Dependent variable: project performance; standardized coefficients; *$p < .05$, **$p < .01$, ***$p < .001$.

Discussing the LSC-performance relationship

Discussing the direct LSC-performance relationship. Our second research question was if and under what conditions LSC contributes to performance. We found a moderately strong, positive, and significant relationship between LSC and performance. Our quantitative support for the LSC-performance relationship adds to the literature on LS. While prior work tends to be conceptual or qualitative, we offer a quantitative approach that can move LS research from a nascent to an intermediate phase (Edmondson & McManus, 2007). We go beyond previous qualitative approaches that used the single facet of "experimentation" (Camuffo et al., 2017; Honig & Hopp, 2016), and show that LSC is a bundle of several capabilities.

As a caveat to the LSC-performance relationship, the literature discusses decreasing returns to experimentation, even though our data do not suggest them. One reason for decreasing returns is experiment creep that "occurs when an experiment drags on too long, costs too much or lacks clarity about which sources of uncertainty are being tested" (Sull, 2004, p. 76). Another reason is the erosion of confidence, where too much customer feedback may deteriorate entrepreneurs' confidence (Ladd, Lyytinen, & Gemmell, 2015). Finally, the concept of theoretical saturation from qualitative research informs us that additional respondents lead to decreasing marginal insights (Griffin & Hauser, 1993).

Decreasing returns to new information beget the question of when entrepreneurs should transition from exploration to exploitation. The literature on opportunity evaluation and decision speed addresses this transition (Bakker & Shepherd, 2017). A low degree of novelty and a high degree of competition may prompt entrepreneurs to make faster decisions on whether and how they should continue their entrepreneurial process (Choi, Lévesque, & Shepherd, 2008). This is because novelty and competition influence the tension between the desire to capitalize quickly on an opportunity and to obtain more information about the value of the opportunity (Bakker & Shepherd, 2017). Also, entrepreneurs who have developed experience, procedures, and confidence (Bakker & Shepherd, 2017) are likely to make faster decisions. Research on stopping rules in the LS context is expected (Ladd, 2016b).

Discussing critical contingencies of the LSC-performance relationship. We argued that the unit cost of information affects the net benefits to customer-oriented experimental learning. These unit costs of information are contingent on context. We found that market uncertainty, technological uncertainty, and the degree of innovativeness do not influence the LSC-performance relationship. We speculate that this is because our research context did not capture rather low (for example, retail) or extremely high (for example, nanotechnology) degrees of uncertainty or degrees of innovativeness. We found that the B2B or the B2C context affects the LSC-performance relationship. It is strongest in the mixed category, with no apparent differences between B2B and B2C. We speculated that B2C startups might find a higher number of respondents that can be partners in iterative experimentation. Our data seem to suggest that it may not be quantity, but could be the heterogeneity of experience that stimulates performance of LSC (Beckman & Haunschild, 2002).

There are findings in emerging LS research that seem to contradict ours. For example, Ladd et al. (2015) found no linear relation between experimentation and performance while we found a positive relationship between LSC and performance. At the root, it may be differences in context, which lead to differences in costs of experimentation: The context of Ladd et al. (2015) is one where experimentation is costly (hardware, remote areas). Such a context may lead to a zero net benefit of experimentation. In a context of high cultural distance ("customers of remote areas of developing nations", Ladd et al., 2015), experimentation together with active customer engagement may lead to results that are difficult to interpret, may overwhelm the entrepreneurs, and deteriorate the link between customer insight and performance. Our research context is one where prototyping is relatively cheap (software), and the customers are culturally and geographically close (Berlin area). To conclude, the costs of prototyping in particular (Ladd et al., 2015) and experimentation in general (Gemmell et al., 2012) can impact on the effectiveness of LSC.

Many developments lower the cost of experimentation, and may thus make LSC more effective. Some of these developments are computer simulation, rapid prototyping, cloud computing, open source, and 3D printing (Contigiani & Levinthal, 2018). Other factors, such as the regulatory context, and reputation costs of failed experiments (Contigiani & Levinthal, 2018) may lead to higher costs of experimentation. We would expect LSC to be less effective in these contexts.

Further research, limitations, and implications

Several topics are relevant for future research. First, while our contextualization toward software startups controls for unobserved variance, it also limits the generalizability of the results. For example, managers of corporate innovation centers (Furr, Dyer, & Christensen, 2014) may focus on additional performance metrics such as strategic fit. Also, an extension to materials-based ventures (Harms et al., 2015), the education context (Harms, 2015), or international entrepreneurship (Neubert, 2018) will provide further insight to practitioners. In a similar vein, even though we argued that the results could be extended to other locations, limited geographical generalizability may still be an issue that should be scrutinized empirically. Second, while we treated LSC holistically, research may focus on which factors or combinations of factors are particularly strongly related to performance. Approaches from the qualitative comparative analysis (QCA) family of analysis methods are suitable for such an approach (Ragin, 2008). Third, a longitudinal study would move our research from correlation closer to causality. Most importantly, our study did not test the iterative and circular nature of customer-oriented experimental learning and the mechanisms that underlie its operations directly. While we infer the circular process from ELT (Kolb, 1984), the phenomenological interviews from Patz (2013), and other qualitative research on LS practice (Mansoori, 2017), focused analyses are required. Finally, research into the performance implications of combining LS with other methods for software venture and product development such as design thinking and agile development (Ghezzi & Cavallo, 2018) is promising, as these approaches may be used together (Pantiuchina, Mondini, Khanna, Wang, & Abrahamson, 2017). Also, research can compare LS and other approaches to new venture development such as effectuation or bricolage (Ghezzi, 2019).

Implications for practice are that with some confidence, entrepreneurs, educators, and accelerator managers may use and advocate LS, particularly for software ventures. It is not yet possible to infer further detailed advice on how to specify each of the steps, and the connection between the steps. A faulty application in each step could deteriorate the performance implications of LSC. For example, entrepreneurs may survey a biased set of customers, may not design specific hypotheses, do not apply appropriate empirical methods, and do not learn from the results. For example, Ladd et al. (2015) and York and Danes (2014) warn that the decision-making biases that LS is supposed to reduce can still influence its effectiveness.

To conclude, we believe that research that reflects on the performance implications of popular management tools is particularly relevant for practice. Our results show that LS is a useful toolbox for software startups. Our results move beyond qualitative evidence and toward quantitative validation. At the same time, we support the literature on experimental entrepreneurship. The research and practitioner community will welcome future efforts to broaden and deepen the scope of this effort.

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ORCID

Rainer Harms http://orcid.org/0000-0002-3835-5582

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