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Entrepreneurial Learning and Indian Tech Startup Survival: An Empirical Investigation

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Abstract This paper investigates the linkage between the mode of transformation of entrepreneurial learning into outcomes and the subsequent impact of these learning outcomes in enhancing the survival of high-tech startups in India. The study uses data from 45 high-tech startups headquartered across different locations in India for the purpose of analysis. Survival Analysis of the data is conducted to determine which mode of learning transformation and what type of en trepreneurial decision making preference have a significant influence on the survival of Indian high-tech startups and to what extent do they impact their survival. The results indicate that entrepreneur's prior startup experience, explorative mode of learning transformation, causal decision making of the entrepreneur and availability of funding for the startup as the key factors that reduce the time to survival of Indian high-tech startups. They also provide key insights on how these factors impact the startup survival in this region.

Keywords Entrepreneurial learning, high-tech startup survival, effectuation, India

I. Introduction

In recent times, high-tech startups have gained increased attention across the world from multiple stakeholders in our society. Policy makers and governments view these high-tech startups as a new way to realize the goals of job creation, innovation and economic development (Kirchoff and Spencer, 2008). Young skilled individuals joining the workforce view startups as a preferred occupational choice. High-tech startups have been extensively studied in the entrepreneurship literature from multiple discipline-based perspectives, the prominent ones being economic, strategic management, evolutionary and behavioral sciences.

While high technology startup firms have been credited with contributing to economic growth by way of job creation and innovation (Kirchhoff, 1994; 2008), a review of the characteristics of these startups reveal that they have a

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high failure rate (Stinchcombe, 1965). Given these seemingly contradicting observations, one can infer that the contribution to economic development is through those startup firms that have been able to overcome the difficulties during the early stages of the firm lifecycle and emerged successfully. Hence, high-tech startup survival has been one of the most probed phenomena from different perspectives.

A couple of decades ago, entrepreneurship researchers focused on explaining the phenomenon of startup lifecycle events such as survival and success from a static perspective. However, of late, there has been broad consensus in the community that entrepreneurship is a complex and dynamic process (Wiklund et al., 2009; Kim and Shin 2017; Song et al., 2017). More specifically, researchers have moved away from trying to identify traits of successful entrepreneurs or from examining the characteristics of successful firms to a more process-based mode of examining entrepreneurship. Recent studies have attempted to understand entrepreneurship as "a continuous learning process" (Politis, 2008). Researchers have applied the core concepts of learning theory to different entrepreneurial contexts. Politis and Gabrielsson (2005) observed, "Entrepreneurship occurs at the intersection of the individual's perception of an entrepreneurial opportunity and his or her ability to pursue that opportunity". Shane and Venkataraman (2000) further explained that entrepreneurs develop different skills and capabilities and therefore keep piling up their stocks of information as part of their careers. Furthermore, these stocks of information gathered by the entrepreneurs influence their ability to recognize entrepreneurial opportunities, act on them and exploit the situation to their economic benefit.

Research from the past decade has delved deeper into the above facets, trying to unravel how entrepreneurs learn from experiences, and how the experiences further help the entrepreneur in enhancing the performance of the venture or in reducing the time to survival of the startup. The role of prior startup experience in entrepreneurial learning (Politis and Gabrielsson, 2005), the distinction between entrepreneurial learning and entrepreneurial knowledge (Reuber et al., 1990), the exploration of the intermediate process of entrepreneurial learning where "experience is transformed into knowledge" (Minniti and Bygrave, 2001; Politis and Gabrielsson, 2005) are some of the notable contributions that have expanded our understanding in this domain. Barring the above contributions, there are very limited studies that try to integrate the above concepts and understand the variance in entrepreneur learning, as well as the variance in learning outcomes that may impact the survival of startups. This study is an initial attempt to understand the end-to-end perspective of the causes of variance in entrepreneurial learning and learning outcomes, and to study the impact of these variations on the survival of the entrepreneur's venture.

Based on the aspects mentioned in the above discussion, the primary goal of this study is to examine the linkage between entrepreneurial learning, its modes of transformation to learning outcomes, and subsequently, the impact of such learning outcomes on high-tech startup survival. To achieve this aim, we first study different theoretical contexts that have enhanced our understanding of entrepreneurial learning (Kolb, 1984; March, 1991). We then explore the literature that describes the modes by which the entrepreneurial learning is transformed into entrepreneurial knowledge (Politis and Gabrielsson, 2005; Politis, 2008). Second, we identify one such learning outcome candidate - the decision-making preference of the entrepreneur to examine if the mode of learning transformation has an impact on learning outcomes, and whether this in turn would impact the time to survival of high-tech startups (Sarasvathy, 2001; 2008). At the outset, we are interested to find out which is the dominant learning transformation mode of entrepreneurs. And then, we seek to understand if any particular preference for a decision-making style helps the entrepreneurs to reduce the time to survival.

The reminder of the study is organized as follows. The next section presents a review of literature, wherein a synthesis of past literature pertaining to survival of startups and entrepreneurial learning processes is presented. The literature review is then followed by a section that outline the conceptual framework linking the process of entrepreneurial learning to its outcomes, and subsequently the impact of learning outcomes to startup survival. Next is a section that describes the research methodology, wherein the sample frame and measures and variables used in the study, and the empirical methods of analysis adopted. We then present the detailed analysis of the results obtained. The study concludes with a discussion of the findings, as well as a summary of the contributions made together with its limitations.

II. Literature Review

We present here the review of literature on entrepreneurial learning and modes of transformation of learning into learning outcome. We then focus on examining the existing literature that deals with entrepreneurial decision-making as one such learning outcome. Finally, we explore the literature linking such learning outcomes to high-tech startup survival.

1. Entrepreneurial Learning

In recent years, researchers have applied the concepts and ideas of experiential learning theory to the field of entrepreneurship in an attempt to extend existing knowledge on entrepreneurial learning. These contributions observed that entrepreneurs learn through a hands-on and practical process where entrepreneurs develop and accumulate knowledge by applying their existing skills and knowledge in new ventures, thereby developing new knowledge in the process (Sullivan, 2000; Rae and Carswell, 2001; Politis and Gabrielsson, 2005; Middleton and Donnellon, 2014).

Since there are many different contexts in which entrepreneurial learning can be studied, it is natural to expect multiple definitions of the same. In their meta-analysis review, Wang and Chugh (2014) summarized a few well-accepted definitions of entrepreneurial learning. Entrepreneurial learning has been defined as "learning in the entrepreneurial process" (Politis, 2005). Rae (2005) defined entrepreneurial learning as, "learning to recognize and act on opportunities, and interacting socially to initiate, organize and manage ventures". Young and Sexton (2003) defined entrepreneurial learning as "the variety of experiential and cognitive processes used to acquire, retain and use entrepreneurial knowledge".

Two theories of entrepreneurial learning, namely, experiential learning (Cope, 2003; Minniti and Bygrave, 2001) and organizational learning (Covin et al., 2016; Covin et al., 2006; Wang, 2008), dominate the literature related to entrepreneurial learning. The experiential learning contributions can primarily be traced back to the work of Kolb (1984). Subsequently, many variants and related theories have emerged inspired by Kolb's contributions. Key among them are "learning-by-doing" (Balasubramanian, 2011; Cope, 2003), "learning from past business experience" (Lamont, 1972), "learning from positive and negative experiences" (Minniti and Bygrave, 2001), "learning from past experience" (Sardana and Scott-Kemmis, 2010), and "learning from participation and from the experience of others who are involved in startup related activities" (Lévesque et al., 2009).

There have also been significant contributions emanating from the theories of organizational learning, the origins of which could be traced to March (1991). Some of the key contributions that have originated from this strand of theory are "single- and double-loop learning" (Argyris and Schön, 1978), "organizational learning" (Huber, 1991), "and absorptive capacity and external learning" (Cohen and Levinthal, 1990). The theory of organizational learning has been applied to entrepreneurial learning studies in multiple contexts by different scholars. For example, Chaston et al. (2001) examined whether entrepreneurial firms used higher-order learning. Lant and Mezias (1990) studied on aspects of organizational learning theory that helped to conceptualize entrepreneurship.

2. Modes of Entrepreneurial Learning Transformation

With the above background and overview of entrepreneurial learning, we now shift our focus to understand how this learning gets transformed into knowledge, which the entrepreneur uses as part of his daily activities to perform his duties. Prior studies that examined entrepreneurial learning as an experiential learning process have stressed that the experience of the entrepreneur (prior skills and knowledge) and the new knowledge acquired by the entrepreneur need to be examined separately (Reuber and Fischer, 1994; Politis 2005; Mian et al., 2016).

In an attempt to provide linkage between the experiences of entrepreneurs and the knowledge acquired by entrepreneurs, a few studies have explored the transformation process between the above two aspects (Reuber and Fischer, 1999). Politis and Gabrielsson (2005) identified two distinctive courses of transformation of entrepreneur's experiences into knowledge, one through exploitation and the other through exploration. They further explained, "in the process of exploitation, entrepreneurs choose actions that replicate or are closely related to the ones they have previously taken, thereby exploiting their pre-existing knowledge". In the latter case, that of exploration, "the entrepreneurs choose entirely new actions that are distinct from the ones that they have already taken, thereby exploring new domains where they have no previous experience".

Thus, the exploratory transformation process can be viewed as "variance-seeking learning" that increases "performance variance", whereas the exploitative transformation process as "mean-seeking learning" that improves "mean performance and decreases variance" (McGrath, 2001). Middleton and Donnellon (2014) studied the entrepreneurs in accelerators and incubators and noted that entrepreneurs learnt the what, why and how of the execution of entrepreneurial actions at these entities. However, it has to be noted that these modes of transformation are not mutually exclusive. Levinthal and March (1993) posited that a proper balance between exploration and exploitation is crucial for ensuring survival and success of ventures. Mintzberg and Waters (1982) had drawn attention to the need of this balance by stating that "exploitation of successful new ideas provides resources to support new exploration". These studies indicate that entrepreneurs need to tread the fine line of balancing between risk and returns for every action they undertake.

3. Decision Making as a Learning Outcome

The discussion thus far has elaborated on the importance of entrepreneurial learning, as well as the need to appreciate the transformation of experiences into knowledge. Continuing with the same perspective, we now seek to understand how entrepreneurs used this knowledge to carry out various actions and activities. This examination will provide a measure of the learning and utilization of knowledge that they have developed. Politis (2008) identified three learning outcomes that entrepreneurs can be measured against as they embarked on the activities of managing a new venture.

Decision-making is one such critical learning outcome that can be used to measure the effectiveness of the entrepreneurial journey. Gabrielsson and Politis (2011) noted that entrepreneurs, specifically during the initial phases of the startup lifecycle, have to take many decisions on a daily basis, such as fine-tuning their business idea, identifying or carving out a niche market for their offerings, addressing technical problems, obtaining the required resources, hiring key personnel, etc. They observed that all these decisions have a long-term impact (Boeker, 1988) and crucial and important decisions taken at the early lifecycle stages may have long-lasting impact on the future success and growth of the new venture (Vohora et al., 2004). Therefore, studying entrepreneurial decision-making as a learning outcome is useful in aiding a better appreciation of the process whereby entrepreneurs create economic value by way of exploitation of the entrepreneurial opportunity.

Sarasvathy (2001) identified two modes of reasoning that were used by entrepreneurs when they made decisions on their business or new ventures: causation and effectuation. Causation is described as “a problem-solving decision-model that rests on the logic of prediction” (Sarasvathy, 2001; Sarasvathy and Dew 2005). In this model, the entrepreneur makes a decision based on a choice among the available means to achieve a given result. The choice of means in this case is motivated by the entrepreneur’s knowledge along with the final result that the entrepreneur wants to create (Gabrielsson and Politis, 2011). The core driving logic of this decision-making model is that “the entrepreneur can control the future, to the extent that he can predict the future”. This logic is accomplished by continuous planning, collection of information to understand and analyze the progress of the activities against the plan, and identifying the root cause of deviations discovered for those activities that had different outcomes against the plan (Gabrielsson and Politis, 2011).

Effectuation is based on a different problem-solving decision model that relies on the logic of “control”, where the entrepreneur pursues entrepreneurial activities based on what can be done, given the means that are currently available (Sarasvathy, 2001; Sarasvathy and Dew 2005). In this model, the entrepreneur makes a choice of the end result that can be created, with the given means. The choice of the final result achieved is dependent on the entrepreneur. The choice of this end result is driven by the entrepreneur’s ability to discover and use contingencies. The core logic driving the effectual model is that, to the extent that an entrepreneur can control the future, he does not need to predict it (Sarasvathy, 2001). While effectuation considers the external environment to be endogenous to the entrepreneur's decisions and actions, causation views the external environment as an exogenous factor influencing the entrepreneurial decision-making (Gabrielsson and Politis, 2011).

Although causation and effectuation seem to be describing two complementary approaches to entrepreneurial decision-making, Sarasvathy (2001) underlined that "both decision-making logics are integral parts of human reasoning and can occur simultaneously, overlapping and intertwining over different contexts of decisions and actions". Gabrielsson and Politis (2011) noted that entrepreneurs prefer and use either effectual or causal reasoning or both at different times, depending on their individual circumstances and preferences. Although the decision-making preference of entrepreneurs would be heavily influenced by the unique situational context (Douglas, 2005), in this study the primary focus is on examining whether there is entrepreneurial preference for one type of decision-making logic over the other. Further, if there is such preference, is this a result of a predominant style of learning transformation, and finally, if this preference has any impact on the firm survival. This approach is similar to studies conducted by Wiltbank et al. (2009) and Brettel et al. (2012), where the former contrasted effectuation against causation to examine angel investing outcomes; and the latter contrasted effectuation against causation to examine decision making in the corporate environment.

4. Survival of High-Tech Startups

From the lens of experiential learning, a couple of key abilities of entrepreneurs are recognized as important factors in enabling entrepreneurs to solve the challenges during the startups' emergence and survival. These are "abilities to recognize and act on entrepreneurial activities" (Shane and Venkataraman, 2000) and "coping with liabilities of newness" (Stinchcombe, 1965; Shepherd et al., 2000). Gabrielsson and Politis (2011) indicated that the capability to identify and work on entrepreneurial opportunities is usually a mark of the successful entrepreneur.

Prior literature stresses that entrepreneurs need to have the right skills or past experience to deal with the challenges of liability of newness that a new venture presents. Politis (2008) observed that these liabilities are routine and conventional problems related to the people and task management in the new venture, the uncertainty that exists in the discovery of the value of new product/service in the marketplace, problems with obtaining long-term external finance, and challenges in hiring skilled and resourceful personnel to the new organization. Prior studies have indicated that experienced entrepreneurs would have acquired intangible knowledge about all the key stakeholders that they need to deal with, as they start a new venture. They would have established good relationships with reliable suppliers, have a deep insight on the viable markets, availability of product and resources, which increases their ability to identify and act on entrepreneurial opportunities (Covin et al., 2016; Ronstadt, 1988; Shepherd et al., 2000). This body of literature therefore suggests that habitual entrepreneurs, by virtue of their prior startup experience, possess a greater ability to tolerate and withstand unfavorable shocks and to take corrective actions as required in their new venture.

From a learning perspective, irrespective of whether the entrepreneur is experienced or novice, it is pertinent to note that, as the entrepreneur immerses himself in the process of setting up a new venture, he would need to continually upgrade and enhance the critical resources and capabilities (Brush et al., 2001). The outcome of this endeavor is largely determined by the convergence of the entrepreneur's skills, preferences and attitudes in response to the various challenges they face (Markman and Baron, 2003). Rerup (2005) observed that these experientially acquired capabilities would significantly improve venture performance, when these activities take place in a favorable external environment.

III. Conceptual Framework and Research Objectives

While the previous section dealt with the key theoretical issues concerning entrepreneurial learning, its mode of transformation into knowledge, and its role in impacting survival of high-tech startups, in this section, we seek to provide the linkage to these identified tenets by way of developing a conceptual framework. We detail the findings in subsequent sections.

From the above discussions, it is clear that entrepreneurs gain new experiences and therefore develop new knowledge as an ongoing process (Politis and Gabrielsson, 2005). Subsequent discussions have revealed that exploration and exploitation are two dominant modes of transformation of these new experiences to knowledge (Minniti and Bygrave, 2001). There have also been studies that have identified key learning outcomes, which are a demonstration of application of the acquired entrepreneurial knowledge (Politis, 2008). One such important learning outcome is decision-making of the entrepreneur that has been observed to make an impact on the survival or success of the startup. Causation and effectuation have been discussed as two such dominant decision-making styles that entrepreneurs employ for decision-making (Sarasvathy, 2001).

Building on these attempts, a conceptual framework is developed, which is depicted in Figure 1, to answer the variance in entrepreneurs' knowledge acquisition and to link this variance to startup survival.

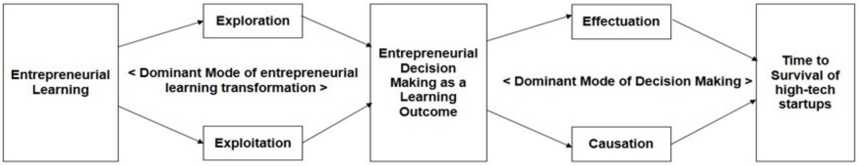

Figure 1 Conceptual framework of the study

This framework seeks to understand on how learning of entrepreneurs varies in the process of learning transformation either through exploration or exploitation. Second, it further tries to link the effect of variance of entrepreneurial learning outcome to survival of startups. Based on the above framework, the research objectives of this study are as follows:

- What is the dominant mode of learning transformation exhibited by the early stage high-tech startup entrepreneurs?
- What is the dominant mode of decision-making preference exhibited by early stage high-tech startup entrepreneurs?
- How does the dominant mode of learning and decision making preference affect the time to survival of high-tech startups?

The next section describes the data collected to validate the above framework, the characteristics of the sample, the variables and measures used in the study, the method of statistical analysis to validate the data.

IV. Scope, Data Description and Research Methods

1. Scope

The above objectives are studied with respect to high-tech startups headquartered and operating across different cities in India. The scope of this study was restricted to IT high-tech startups that have their registered headquarters in India. Since there is no single credible database of startups operating out of India, the database of high-tech startups was procured from Industry associations such as National Association for Software and Services Companies (NASSCOM) and Indian Software Product Industry Round Table (iSPIRT), and Incubation Centers such as Microsoft Accelerator, T-Labs, N S Raghavan Center for Entrepreneurial Learning at IIM Bangalore. This enabled us to develop a consolidated database of high-tech startups. This consolidated database contains data of 1567 startups.

To ensure that the consolidated database is representative of the overall population, we obtained the demographic distribution of startups data from the consolidated database, and compared it with well-accepted Industry Reports such as the iSPIRT Product Industry Monitor Report 2014. We find that the consolidated database is representative on all dimensions that we could assess: industry demographics such as location, age of the startup, market sector, founder profiles such as education, experience and external funding status.

The founders of 200 startups from this consolidated database were picked and contacted with a request to participate in the study. These 200 startups were chosen using a stratified sampling technique to ensure that they were representative of the population. Among them, 72 founders responded to the request, of which 27 founders did not want to participate in the study. The research instrument was then sent to the remaining 45 founders who agreed to participate in the study, indicating a 22.5% response rate. A semi-structured interview schedule was personally administered by the researcher or administered over telephone to all the founders who agreed to participate in the study during the month of February 2014. The methodology followed for the interview is described in the following sections.

2. Sample Characteristics

The duration of operation of the startups in the sample ranges from 6 months to 120 months. About 73% of the startups in the sample had found their product market fit (milestone for survival), while the remainder 27% were new firms created, but yet to claim survival. About 91% of the founders in the sample had a minimum of one-year industry experience. About 49% founders of the sample had prior startup experience. About 94% of the founders possessed either startup experience or industry experience at the time of creation of their startup. The founders' age at the time of starting up in the sample ranged between 22 years to 49 years. In terms of founders' education, about 9% of the founders had a non-engineering graduate education (science, commerce, arts degree), 44% of them had an engineering bachelor's degree and 47% had masters' engineering degree or higher educational qualification when they started their venture.

3. Variables and Measures

A semi-structured interview schedule was developed to collect the primary data to analyze the objectives of this study. The schedule was designed to collect basic profile information related to the founder and the startup, as well as to collect information related to modes of learning transformation, preference of decision-making styles and the time taken by the startup to reach the survival milestone. Standard scales of measurement from prior literature were adopted to collect information on learning transformation modes and preference of decision-making styles. Industry experts and startup entrepreneurs validated the schedule. The various dependent and independent variables used in the study are as follows:

Dependent Variable The dependent variable used in this study is time to survival of the startup in months. The time in months of operation of the startup since formal incorporation (labelled as 'stime' for the analysis) and whether the startup has achieved survival or not (labelled as 'survst' for the analysis) taken together form the dependent variable. The respondents to our questionnaire reported the month and year that they formally created the startup. The startup that had achieved product-market fit at the time of conducting the survey is considered to have survived. Startups that had not yet achieved this milestone are considered not having survived at the time of observation.

The event of product-market fit is used as a proxy to measure startup survival. This milestone indicates that the startup has been able to achieve repeatable sales with a standardized offering, and that it has now a formidable set of initial customers that have validated the offering and are paying for the offering.

Independent Variables: Mode of Learning Transformation The preference between the two modes of learning transformation (exploratory, exploitative) form one set of independent variables. This multi-item construct is adopted from Politis and Gabrielsson (2005). This ten-item question provides the respondents with a choice between exploration and exploitation using a Likert scale consisting of five items each. The raw scores collected from the interview schedule are converted to binary scale using weighted average method and used for the survival analysis. This variable is labelled as 'Ol' for the analysis.

Preference for Decision-Making The preference between two dominant modes of decision-making (effectuation and causation) form the other set of independent variables. This multi-item measure is borrowed from Brettel et al. (2012). This scale contrasts effectuation items with causation items using a six-point Likert scale to measure whether there is preference for an effectual or causal approach of decision-making. This scale has a total of 23 items covering four dimensions, namely, means versus goals (7 items), affordable loss versus expected returns (5 items), partnerships versus competitive market analysis (4 items) and acknowledge the unexpected versus overcome the unexpected (6 items). The raw scores collected from the interview schedule are converted to binary scale using weighted average method. This variable is labelled as 'dlogic' for the analysis.

Control Variables This study uses entrepreneur-specific and startup-specific factors as control variables. Relevant industry and startup experience, age and education of the entrepreneur represent the entrepreneur-specific factors that are used as controls. The sales turnover in Indian currency, the research and development capability and funding status of the startup form the startup-specific factors that are controlled for.

Relevant Industry Experience A discrete dichotomous variable that indicates whether or not the founder has previous industry experience has been used for analysis. This variable takes the value of 1 for every startup founder who has industry experience, prior to founding the current startup considered for the study. A value of 0 for this variable indicates that the founder of the startup does not possess any previous industry working experience. This variable is labelled as 'fiexp' for the analysis.

Prior Startup Experience A discrete dichotomous variable that indicates whether or not the founder has prior startup experience has been used for analysis. This variable takes the value of 1 for every startup founder who has experience working in a startup either as an employee or as a founder, prior to founding the current startup considered for the study. A value of 0 for this variable indicates that the founder of the startup does not possess any previous startup experience. This variable is labelled as 'fsexp' for the analysis.

Age of the Entrepreneur The age of the entrepreneur in years, at the time of founding the current startup has been used for analysis. This variable is labelled as 'fage' for the analysis.

Education of the Entrepreneur The education of the entrepreneur is categorized using two dummy variables. The base reference variable indicates graduate education without an engineering degree (degree in Science, Arts and Others); the first dummy variable indicates graduate education with a technical (engineering) degree, and the second dummy variable indicating education with a technical master's degree or above. This variable is labelled as 'fedn' for the analysis. The base reference variable takes the value of 1 for every founder of the startup whose education credentials is a non-engineering degree. A value of 0 for the base reference variable indicates the absence of a non-engineering degree of the founder. The first dummy variable 'fedn(1)' takes the value of 1 for every startup founder who has a technical (engineering) degree as his/her education credentials. A value of 0 for this variable indicates the absence of a technical (engineering) degree of the founder. The second dummy variable 'fedn(2)' takes the value of 1 for every startup founder who has education credentials of a master's technical (engineering) degree or above. A value of 0 for this variable indicates the absence of a master's technical degree or a higher technical qualification (for example, PhD) of the founder.

Sales Capability of the Startup The sales capability of the startup is measured as the number of customers/products offered at the time of primary data collection (Ensley et al., 2003).

R&D Capability of the Startup The R&D capability of the startup is measured as the average work experience of the R&D team measured in number of years at the time of the data collection (Thornhill, 2006).

Financial Capability of the Startup Measured by a discrete dichotomous variable that indicates whether or not the startup obtained funding external to its founder's and his family's funds. This variable is labelled as 'fin' for the analysis. A value of 1 for this variable indicates that the startup was funded from external sources, and conversely, a value of 0 for this variable indicates that the startup under consideration is not funded from external sources.

The external environment factors such as Industry sector, region/geography, and policy are ensured to be controlled by the research design by limiting the scope of study to one industry based out of one country that has the same policies at macroeconomic levels.

4. Method of Analysis

In this study, we use Survival analysis as the method of analysis to examine the stated objectives. Survival analysis deals with analyzing the time to the incidence of an event. The survival model works on a set of assumptions, primary ones being that when the observation of the data ends and the analysis begins, the observed data set would typically have a combination of units in such a fashion that the event in question has actually occurred for some units, whereas the event may not have occurred for others (Aalen et al., 2008). The key advantage of this model is that it helps the data analysts to deal with missing information, often referred to as censored information. In the study, if the startup has not yet achieved the product-market fit at the end of the data collection phase, then this startup would be censored "on the right", that is, we know that this particular startup's survival time is known to exceed the time duration between its formal creation and the closure of observation. Since product-market fit is taken as proxy to measure startup survival, the above scenario indicates that the startup has not yet achieved the survival milestone.

In survival analysis, the times at which certain events occur are assumed to be realizations of some random process (Allison, 1995). So T, the time for an event to occur for a particular observation, is a random variable having a certain probability distribution. Different methods are used to model survival data depending on the kind of distributions that the survival time T follows. The survival function, which represents the unconditional probability of surviving longer than "t" time units, has the following general form: $S(t) = \text{Probability } (T>t) = 1–F(t)$ where $F(t)$ is the cumulative distribution function of the random variable T, denoting time to failure (Chatterjee, 2010). The focus of survival analysis would be to model the hazard rate $h(t)$ which is defined as $h(t) = f(t)/S(t)$.

There are semi-parametric and parametric models to use with survival data. The Cox Proportional Hazards Model (Cox, 1972) is the most widely used. The Cox Proportional Hazards Model is popular because it does not require one to make an assumption about the exact parametric form of the underlying distribution of survival time. Also, in this model, hazards for two individuals are proportional, with a proportionality constant that is independent of time. However, in our study, since the independent variables change over time, and that this change between the variables cannot be assumed as proportionally constant, we use a parametric method of Accelerated Failure Time (AFT) models for our analysis. These models are fitted based on the assumption that survival times captured in the data follow certain well-known distributions (Klein and Moeschberger, 1997).

V. Results and Discussion of Findings

The descriptive statistics for the variables that were used in the analyses are presented in Table 1.

Table 1 Descriptive statistics of the variables used for analysis

	Min	Max	median	mean	Sd
stime	6	120	42	42.38	25.47
survst	1	2	2	1.73	0.45
fiexp	0	1	1	0.91	0.29
fsexp	0	1	0	0.49	0.51
fage	22	49	32	34.20	7.83
fedn	1	3	2	2.38	0.65
sales	1	1500	60	124.57	238.80
dev	0.5	7	2.5	2.89	1.81
Fin	0	1	0	0.33	0.48
Ol	0	1	1	0.67	0.48
dlogic	0	1	0	0.40	0.50

A standard estimator of the survival function in the presence of censoring is the Kaplan-Meier Product Limit Estimator. This is a non-parametric method of estimation. Plots of the Kaplan-Meier estimates of the survival function against time provide a visual understanding of the survival function (Chatterjee, 2010).

For a visual inspection of the distribution of the survival time, the plot of the survival function $\hat{S}(t)$ as estimated by the Kaplan-Meier estimator against time is provided in Figure 2.

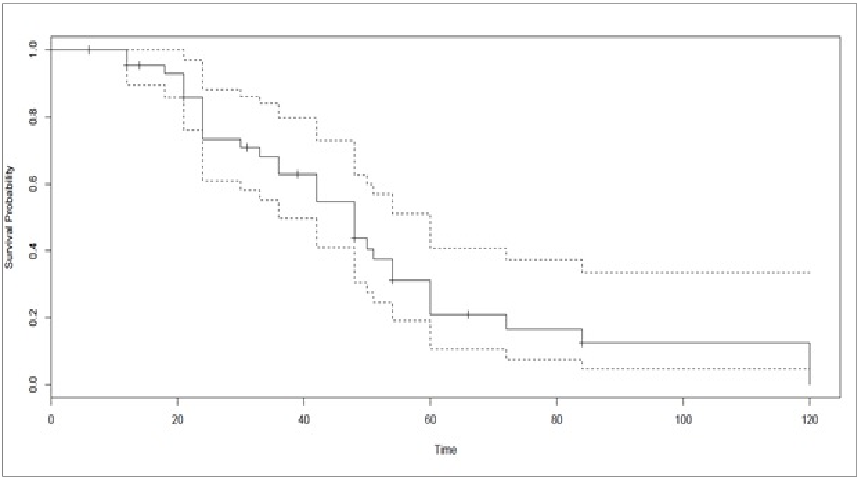

Figure 2 KM plot of survival probability against time in months

The full model containing all the independent variables and control variables represented in R - an open source statistical software package is provided below:

```
> model1=surv_data~fiexp+fsexp+fedn+fage+sales+dev+fin+ol+dlogic
> model1.step=stepAIC(survreg(model1))
```

For arriving at the most parsimonious model from the above full model, Akaike's Information Criterion (AIC) (Akaike, 1974) was used. AIC is a numerical measure that weighs the likelihood of a model against its complexity. The AIC of the AFT model is defined as: AIC = -2LL + 2 (c + a) where LL is the logarithm of the model likelihood (log-likelihood), c is the number of covariates and a is the number of ancillary parameters (Weibull distribution has two parameters, λ and α, while exponential has only one parameter, λ). A lower value of the AIC suggests a better model.

The appropriate distribution of survival times to be used for analysis is determined by building AFT models for the above data using each of the following distributions: Exponential, Weibull, Log-logistic and Log-normal. The resulting AIC computed for each of the distributions used, which provides the most optimal model containing the independent variables is presented in Table 2.

Table 2 AIC computation for AFT models with different assumed distributions

Distribution	Least AIC Value	Optimium Model corresponding to least AIC Value
Exponential	343.24	surv_data ~ fsexp + fage + sales + fin + ol + dlogic
Weibull	310.03	surv_data~fsexp + fin + ol + dlogic
Log-Logistic	313.96	surv_data ~ fsexp + fin + ol + dlogic
Log-normal	318.58	surv_data ~ fiexp + fsexp + fage + dev + fin + ol + dlogic

Since the Weibull model is found to have the lowest AIC for most of the models we choose to use this as the standard distribution that we subsequently discuss in this study. The output of the computation using the Weibull distribution is provided in Table 3.

Table 3 Results of the AFT optimum model execution

> optimum_model=surv_data~fsexp+fin+ol+dlogic > summary(survreg(optimum_model, dist="weibull") Call: survreg(formula=optimum_model, dist="weibull")				
	Value	Std. Error	Z	P
(Intercept)	4.573	0.178	25.761	2.42E-146
fsexp1	-0.216	0.142	-1.521	1.28E-01
fin1	-0.481	0.149	-3.219	1.29E-03
ol1	-0.41	0.171	-2.4	1.64E-02
dlogic1	-0.12	0.157	-0.765	4.44E-01
Log(scale)	-0.943	0.137	-6.902	5.14E-12
Scale=0.389 Weibull distribution Loglik(model)=-149 Loglik(intercept only)=-157.5 Chisq=17.04 on 4 degrees of freedom, p=0.0019 Number of Newton-Raphson Iterations: 6 n=45				

All the variables present in the most efficient model are highly significant with very small p values, significant at 0.001 levels.

The results indicate that entrepreneur's prior startup experience, explorative mode of learning transformation, causal decision-making of the entrepreneur and availability of funding for the startup are the key factors that reduce the time to survival of Indian high-tech startups. This study validates a portion of the prior work related to the mode of learning transformation, impact of learning outcomes and availability of funding on startups in the context of emerging economies (Politis and Gabrielsson, 2005; Politis, 2008; Audretsch and Lehmann, 2004; Suh et al., 2012; Kim and Ko, 2014). The empirical results of this study pertaining to entrepreneurial decision-making preference extend the knowledge in this field.

In this study, prior industry experience and prior startup experience were introduced as two independent control variables. The results indicate that prior startup experience will impact the survival time of a startup rather than prior industry experience. The results indicate that prior startup experience will accelerate the time to achieve survival by a factor of exp(-0.216)=0.8 times (i.e. 80% shorter survival time in comparison to the baseline). This is explainable, specifically in the context of emerging economies, since the entrepreneur would need to deal with an increased degree of liabilities of newness, given the under developed infrastructure and environment support system that exists in the region of operation. Having prior experience of starting up, dealing with uncertainty, adds to the bundle of knowledge and therefore when the entrepreneur embarks on the second venture, he would be much more prepared to overcome the liabilities of newness in comparison to another individual, who may have mere industry and domain knowledge, but ventures to start up for the first time. These results also validate some of the earlier empirical findings (Westhead et al., 2005; Politis, 2008).

Explorative mode of learning transformation relies on variance-seeking learning. This mode of learning transformation has been shown to contribute to huge success as well as failure (Politis and Gabrielsson, 2005). The results indicate that explorative mode of learning will accelerate the time to achieve survival by a factor of exp(-0.41)=0.66 times (i.e. 66% shorter survival time in comparison to the baseline). This study revalidates the findings obtained in prior literature this studied exploratory learning under different contexts. Ucbasaran and Westhead (2002) stated that opportunity-seeking entrepreneurs, who continuously scan the environment for new entrepreneurial opportunities often strive for variation with the goal to learn something new. Politis and Gabrielsson (2005) observe that entrepreneurs who are highly explorative are alert and would become more effective in identifying and acting on entrepreneurial opportunities.

Causal decision-making helps in reducing the liability of newness as it focuses on converging entrepreneurial actions towards mean performance and repeatability. The decision-making based on past data and experience tries to bring structure and direction to the overall activities of the startup, which usually operates in a volatile environment. Hence, causal decision-making by the entrepreneurs reduces the risks that arise out of dealing with liability of newness and therefore help in reducing time to survival of the startup. The results indicate that causal-decision making will accelerate the time to achieve survival by a factor of exp(-0.12)=0.89 times (i.e. 89% shorter survival time in comparison to the baseline).

Funding has long been researched and established as a key factor that contributes to the survival of a startup. The results indicate that funding will accelerate the time to achieve survival by a factor of exp(-0.481)=0.62 times (i.e. 62% shorter survival time in comparison to the baseline). Audretsch and Lehmann (2004) established funding as being a key factor in influencing the survival of high-tech startups. Funding of the startup helps the entrepreneur in multiple ways. It frees the entrepreneur to focus his energies and abilities to exploit the entrepreneurial opportunity, and also provides additional cushion to react and deal with uncertain circumstances that a startup might face in its early stages.

VI. Summary and Inferences

This study contributes to the existing body of knowledge on entrepreneurial learning and high-tech startup survival. At the outset, by taking an end-to-end examination approach, this study investigated the linkage between the mode of transformation of entrepreneurial learning into outcomes and the subsequent impact of these learning outcomes in enhancing the survival of high-tech startups in India. Two modes of transformation of entrepreneurial learning - explorative and exploitative - and two preferences of entrepreneurial decision-making (learning outcome) - effectual and causal - were examined for their impact and influence on startup survival. This initial attempt to understand the entire process is a contribution to the literature and research on entrepreneurial learning and entrepreneurial decision-making domains.

The study uses data collected from 45 high-tech startups operating across different cities in India. Survival Analysis of the data using Accelerated Failure Time models is conducted to determine which mode of learning transformation and what type of entrepreneurial decision making preference have a major influence on Indian high-tech startups survival. The results indicate that entrepreneur's prior startup experience, explorative mode of learning transformation, causal decision-making of the entrepreneur and availability of funding for the startup are the key factors that reduce the time to survival of Indian high-tech startups. The results of this study provide insights on how the entrepreneur, through exploratory learning transformation, will increase his skills in recognizing opportunity (Shane and Venkataraman, 2000) and, by leveraging causal decision-making preference, would be able to cope with the liabilities of newness (Stinchcombe, 1965). The findings provide a better understanding of the mode of learning transformation and dominant decision-making preferences of startup entrepreneurs operating in emerging economies such as India. They also provide key insights on how these factors impact the startup survival in this region.

This paper validates a portion of prior work related to the mode of learning transformation and availability of funding for startups in the context of emerging economies. The empirical results of this study pertaining to entrepreneurial decision-making preference expand the knowledge in this field. For high-tech startup entrepreneurs in emerging economies, it provides insights on the factors they need to focus on enhancing their chances of survival. For the policy-makers, investors and practitioners and other stakeholders who are focused on emerging economies, the outcomes of this study provides insights on the type of factors that need to be kept in mind to create a vibrant startup ecosystem in the region. Next, the study explains how the variance in learning outcomes, in this case by conscious choice of a preferred decision-making, will help reduce or advance the time to survival of the entrepreneur's startup.

Finally, for entrepreneurs contemplating on setting up high-tech startups in emerging economies, it provides insights on the factors they need to focus on enhancing their chances of survival and success. For policy-makers, investors and practitioners focusing on emerging economies, it reveals the type and kind of micro factors that should be examined to enable a vibrant startup ecosystem in the region.

However, this study has certain limitations for generalization. There is scope for further insights and investigation into the micro aspects of additional factors impacting the learning transformation of entrepreneurs, as well as on factors that influence the preference of decision-making of entrepreneurs. For example, one could further examine if there is any preference of learning transformation of experience into knowledge between novice and experienced entrepreneurs. Next, this study examines only the dominant mode of learning transformation and preference to decision-making among entrepreneurs. In reality, entrepreneurs, based on the context, use both modes of learning transformation and decision-making. Further, most variables considered in this study are binary in nature, thereby limiting the ability to study the correlations, and also the ability to study other dimensions of decision making such as trade-off between effectiveness and risk.

Lastly, Survival analysis as a method needs to evolve substantially to ensure higher reliability of the results. Since the initiation and termination of research observations are essentially artificial, there is always an instance in which it is impossible to confirm whether or not survival is possible. Survival analysis is very complicated due to the complexity of the outcome variables and incomplete censoring, and there are many problems that have not yet been solved statistically.

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References

Aalen, O.O., Borgan, Ø. and Gjessing, H.K. (2008) Survival and Event History Analysis: A Process Point of View, New York: Springer-Verlag, .
Akaike, H. (1974) A new look at the statistical model identification, IEEE Transaction on Automatic Control AC-19, 716-723.
Allison, P.D. (1995) Survival Analysis Using SAS®: A Practical Guide, Cary, NC: SAS Institute Inc.
Argyris, C. and Schön, D.A. (1978) Organizational Learning: A Theory of Action Perspective, Reading, MA: Addison-Wesley.
Audretsch, D.B. and Lehmann, E.E. (2004) Financing high-tech growth: the role of banks and venture capitalists, Schmalenbach Business Review, 56, 340-357.
Balasubramanian, N. (2011) New plant venture performance differences among incumbent, diversifying, and entrepreneurial firms: the impact of industry learning intensity, Management Science, 57, 549-565.
Boeker, W. (1988) Strategic change: the effects of founding and history, Academy of Management Journal, 32(3), 489-515.
Brettel, M., Mauer, R., Engelen, A. and Kupper, D. (2012) Corporate effectuation: entrepreneurial action and its impact on R&D project performance, Journal of Business Venturing, 27, 167-184.
Brush, C.G., Green, P.G. and Hart, M.M. (2001) From initial idea to unique advantage: the entrepreneurial challenge of constructing a resource base, Academy of Management Executive, 15, 64-78.
Chaston, I., Badger, B. and Sadler-Smith, E. (2001) Organizational learning: an empirical assessment of process in small U.K. manufacturing firms, Journal of Small Business Management, 39, 139-151.
Chatterjee, D. (2010) Studies on some aspects of liquidity of stocks: limit order executions in the Indian stock market, Ph.D thesis, Department of Management Studies, Indian Institute of Science.
Cohen, W.M., Levinthal, D.A. (1990) Absorptive capacity: a new perspective on learning and innovation, Administrative Science Quarterly, 35, 128-152.
Cope, J. (2003) Entrepreneurial learning and critical reflection: discontinuous events as triggers for higher-level learning, Management Learning, 34, 429-450.
Covin, J.G., Green, K.M. and Slevin, D.P. (2006) Strategic process effects on the entrepreneurial orientation-sales growth rate relationship, Entrepreneurship Theory and Practice, 30, 57-81.
Covin, J.G., Garrett, R.P., Gupta, J.P., Kuratko, D.F. and Shepherd, D.A. (2016) The Interdependence of Planning and Learning Among Internal Corporate Ventures, Entrepreneurship Theory and Practice.
Cox, D.R. (1972) Regression models and life-tables with discussion, Journal of the Royal Statistical Society: Series B, 34, 187-220
Douglas, D. (2005) The human complexities of entrepreneurial decision making: a grounded case considered, International Journal of Entrepreneurial Behaviour and Research, 11(6), 422-435.

Ensley, M.D., Pearson, A. and Pearce, C.L. (2003) Top management team process, shared leadership and new venture performance: a theoretical model and research agenda, Human Resource Management Review, 13, 329-346.
Furdas, M. and Kohn, K. (2011) Why is startup survival lower among necessity entrepreneurs? a decomposition approach, Preliminary Version, April 2011.
Gabrielsson, J. and Politis, D. (2011) Career motives and entrepreneurial decision-making: examining preferences for causal and effectual logics in the early stage of new ventures, Small Business Economics, 36, 281-298.
Haber, S. and Reichel, A. (2007) The cumulative nature of the entrepreneurial process: the contribution of human capital, planning and environment resources to small venture performance, Journal of Business Venturing 22(1), 119-145.
Huber, G.P. (1991) Organizational learning: the contributing processes and the literatures, Organization Science, 2, 88-115.
Kim, C.H. and Ko, C.R. (2014) Success and failure factors of technology commercialization: a Korean case, Asian Journal of Innovation and Policy, 3(1), 25-49.
Kim, Y.J. and Shin, S.J. (2017) What causes technology commercialization to succeed or fail after transfer from public research organizations, Asian Journal of Innovation and Policy, 6(1), 23-44.
Kirchhoff, B.A. (1994) Entrepreneurship and Dynamic Capitalism: The Economics of Business Firm Formation and Growth, Westport, Conn: Praeger.
Kirchhoff, B.A. and Spencer, A. (2008) New high tech firm contributions to economic growth, Proceedings of International Council for Small Business World Conference, Halifax, Canada: Nova Scotia.
Klein, J.P. and Moeschberger, M.L. (1997) Survival Analysis, Techniques for Censored and Truncated Data, New York: Springer-Verlag, 502.
Kolb, D.A. (1984) Experiential Learning: Experience as the Source of Learning and Development, Englewood Cliffs, NJ: Prentice Hall.
Lant, T.K. and Mezias, S.J. (1990) Managing discontinuous change: a simulation study of organizational learning and entrepreneurship, Strategic Management Journal, 11, 147-179.
Lamont, L.M. (1972) What entrepreneurs learn from experience, Journal of Small Business Management, 10, 36-41.
Lévesque, M., Minniti, M. and Shepherd, D. (2009) Entrepreneurs' decisions on timing of entry: learning from participation and from the experiences of others, Entrepreneurship Theory and Practice, 33, 547-570.
Levinthal, D.A. and March, J. (1993) The myopia of learning, Strategic Management Journal, 14, 95-112.
March, J.G. (1991) Exploration and exploitation in organizational learning, Organization Science, 2(1), 71-87.
Markman, G.D. and Baron, R.A. (2003) Person-entrepreneurship fit: why some people are more successful as entrepreneurs than others, Human Resource Management Review, 13, 281-301.
McGrath, R.G. (2001) Exploratory learning, innovative capacity, and managerial oversight, Academy of Management Journal, 44, 118-131.
Mian, S., Lamine, W. and Fayolle, A. (2016) Technology business incubation: an overview of the state of knowledge, Technovation, 50, 1-12.

Minniti, M. and Bygrave, W. (2001) A dynamic model of entrepreneurial learning, Entrepreneurship Theory and Practice, 25(3), 5-16.
Mintzberg, H., Waters, J.A. (1982) Tracking strategy in an entrepreneurial firm. Academy of Management Journal, 25(3), 465-499.
Politis, D. (2008) Does prior start-up experience matter for entrepreneurs' learning?, Journal of Small Business and Enterprise Development, 15, 472-489.
Politis, D. and Gabrielsson, J. (2005) Exploring the role of experience in the process of entrepreneurial learning, Working Paper Series, Lund Institute of Economic Research, 2005/1.
Rae, D. and Carswell, M. (2001) Towards a conceptual understanding of entre-preneurial learning, Journal of Small Business and Enterprise Development, 8, 150-158.
Rae, D. (2005) Entrepreneurial learning: a narrative-based conceptual model, Journal of Small Business and Enterprise Development, 12, 323-335.
Rerup, C. (2005) Learning from past experience: footnotes on mindfulness and habitual entrepreneurship, Scandinavian Journal of Management, 21, 451-72.
Reuber, R.A., Dyke, L.S. and Fischer, E.M. (1990) Experiential acquired knowledge and entrepreneurial venture success, Academy of Management Best Paper Proceedings, 69-73.
Reuber, R.A. and Fischer, E.M. (1994) Entrepreneurs' experience, expertise, and the performance of technology-based firms, IEEE Transactions on Engineering Management, 41(4), 365-374.
Reuber, R.A. and Fischer, E.M. (1999) Understanding the consequences of founders' experience, Journal of Small Business Management, 37(2), 30-45.
Ronstadt, R. (1988) The corridor principle, Journal of Business Venturing, 3, 31-40.
Sarasvathy, S.D. (2001) Causation and effectuation: toward a theoretical shift from economic inevitability to entrepreneurial contingency, Academy of Management Review, 26(2), 243-263.
Sarasvathy, S.D. and Dew, N. (2005) New market creation through transformation, Journal of Evolutionary Economics, 15(5), 533-565.
Sarasvathy, S.D. (2008) Effectuation: Elements of Entrepreneurial Expertise, Northhampton, MA and Cheltenham: Edward Elgar.
Sardana, D. and Scott-Kemmis, D. (2010) Who learns what? a study based on entrepreneurs from biotechnology new ventures, Journal of Small Business Management, 48, 441-468.
Shane, S. and Venkataraman, S. (2000) The promise of entrepreneurship as a field of research, Academy of Management Review, 25, 217-226.
Shepherd, D.A., Douglas, E.J. and Shanley, M. (2000) New venture survival: ignorance, external shocks, and risk reduction strategies, Journal of Business Venturing, 15, 393-410.
Stinchcombe, A.L. (1965) Social Structure and Organizations, In: James, G. (ed.), Handbook of Organizations, Chicago: Rand McNally, 142-193.
Suh, M.K., Park, J.O. and Park, B.S. (2017) Determinants of R&D commercialization by SMEs after technology transfer, Asian Journal of Innovationand Policy, 6(1), 45-57.

Suh, S.H., Ko, J.O. and Lee, S.Y. (2012) An empirical study on the success factors of inter-firm alliances for new product development: with a focus on the SMEs in Korea, Asian Journal of Innovation and Policy, 1(1), 71-91.

Sullivan, R. (2000) Entrepreneurial learning and mentoring, International Journal of Entrepreneurial Behaviour and Research, 6, 160-175.

Thornhill, S. (2006) Knowledge, innovation and firm performance in high and low technology regimes, Journal of Business Venturing, 21(5), 687-703.

Ucbasaran, D. and Westhead, P. (2002) Does entrepreneurial experience influence opportunity identification?, In: Bygrave, W.D. et al., (eds.), Frontiers of Entrepreneurship Research, Wellesley, MA: Babson College.

Vohora, A., Wright, M. and Lockett, A. (2004) Critical junctures in the development of university high-tech spin-out companies, Research Policy, 33(1), 147-175.

Wang, C.L. (2008) Entrepreneurial orientation, learning orientation, and firm performance, Entrepreneurship Theory and Practice, 32, 635-656.

Wang, C.L. and Chugh, H. (2014) Entrepreneurial learning: past research and future challenges, International Journal of Management Reviews, 16, 24-61.

Watson, W., Steward, W. and BarNir, A. (2003) The effects of human capital, organizational demography, and interpersonal processes on venture partner perceptions of firm profit and growth, Journal of Business Venturing 18(2), 145-164.

Westhead, P., Ucbasaran, D. and Wright, M. (2005) Decisions, actions, and performance: do novice, serial, portfolio entrepreneurs differ?, Journal of Small Business Management, 43, 393-417.

Wiklund, J., Patzelt, H. and Shepherd, D.A. (2009) Building an integrative model of small business growth, Small Business Economics, 32, 351-374.

Williams, M.K. and Donnellon, A. (2014) Personalizing entrepreneurial learning: a pedagogy for facilitating the know why, Entrepreneurship Research Journal, 4(2), 167-204.

Wiltbank, R., Read, S., Dew, N. and Sarasvathy, S. (2006) What to do next? the case for non-predictive strategy, Strategic Management Journal, 27, 981-998.

Young, J.E., Sexton, D.L. (2003) What makes entrepreneurs learn and how do they do it?, Journal of Entrepreneurship, 12, 155-182.