ENTREPRENEURIAL INNOVATION AS A LEARNING SYSTEM

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ABSTRACT

We surveyed 172 technology entrepreneurs to explore links between learning style and learning flexibility and decision making behaviors hypothesized to produce entrepreneurial innovation and success. Our findings reveal a system of entrepreneurial learning and innovation with subtle and surprising interactions between learning processes and behavioral mediators.

Keywords: Entrepreneurship; innovation; learning; experimentation; decision making; creativity.

TABLE OF CONTENTS

INTRODUCTION

Entrepreneurs rely upon innovation to create new markets and to differentiate themselves in highly competitive markets (Schumpeter 1947; Amabile 1997; Shane 2003). Innovation is the cornerstone of successful entrepreneurship within dynamic emerging markets and requires both expert level domain knowledge and the ability to acquire and apply new knowledge to solve problems (Shane 2000). Learning is the cognitive and social process of knowledge acquisition and has recently emerged as a robust theoretical platform for studying how entrepreneurs generate innovative ideas (Corbett 2007; Dimov 2007; Armstrong and Mahmud 2008; Chandler and Lyon 2009; Baum and Bird 2010; Baum, Bird et al. 2011; Gemmell, Boland et al. 2011).

Researchers have used experiential learning theory as a framework to theorize about the processes of research innovation, entrepreneurial opportunity recognition, ideation and knowledge acquisition (Carlsson, Keane et al. 1976; Kolb 1984; Corbett 2005; Corbett 2007; Armstrong and Mahmud 2008; Gemmell, Boland et al. 2011). The Kolb Learning Style Inventory (LSI) is the most established instrument for assessing the preferred experiential learning mode for individuals (Kolb 1984) and now includes a Learning Flexibility Index (LFI) to measure the participant's ability to flexibly adopt different learning modes on a situational basis (Sharma and Kolb 2009). Cognitive flexibility is key to innovation and there is evidence that technology domain experts are prone to entrenchment that inhibits their ability to innovate (Pinard and Allio 2005; Kolb and Kolb 2005a; Dane 2010). Despite the conceptual and descriptive utility of experiential learning theory, there remain significant gaps in the application of Kolb's learning style and, in particular, learning flexibility as antecedents to entrepreneurial behaviors and performance.

Individual learning traits are most likely to influence firm performance through indirect or mediating processes such as strategic actions, behaviors or competencies (Rauch & Frese, 2000). Strategic decision speed and the use of "multiple iterative methods" have been shown to mediate the effects of individual cognitive traits on new venture growth within dynamic industries (Baum and Bird 2010). Our study envisions innovation as a non-linear, recursive cyclical learning system featuring rapid cycles of iterative decision making and experimentation, we therefore adopted decision speed and experimentation as our behavior/practice mediators.

We surveyed 172 technology entrepreneurs, all either CEOs and/or founders of their current firms, to explore the relationships between individual learning style traits and entrepreneurial innovation and firm performance via behavioral mediators. Our data provides new insight into how domain experts use complex cycles of learning and experimental problem solving to innovate and succeed as entrepreneurs. These findings yield surprising conclusions regarding the interaction of learning modes, learning flexibility, experimental practices and decision cycles within our system of entrepreneurial innovation.

LITERATURE REVIEW AND HYPOTHESES

Experiential Learning and Entrepreneurship

Learning facilitates the development and enactment of entrepreneurial behaviors and provides perhaps the "only sustainable source of competitive advantage" (Senge 1993 p. 3) for organizations (Rae and Carswell 2000). Cognitive scientists define learning as a means of acquiring information that can be reduced, elaborated, interpreted, stored and retrieved (Huber 1991), however, most management researchers prefer to view entrepreneurial learning as an ongoing social, behavioral and experiential cycle rather than as an outcome or goal.

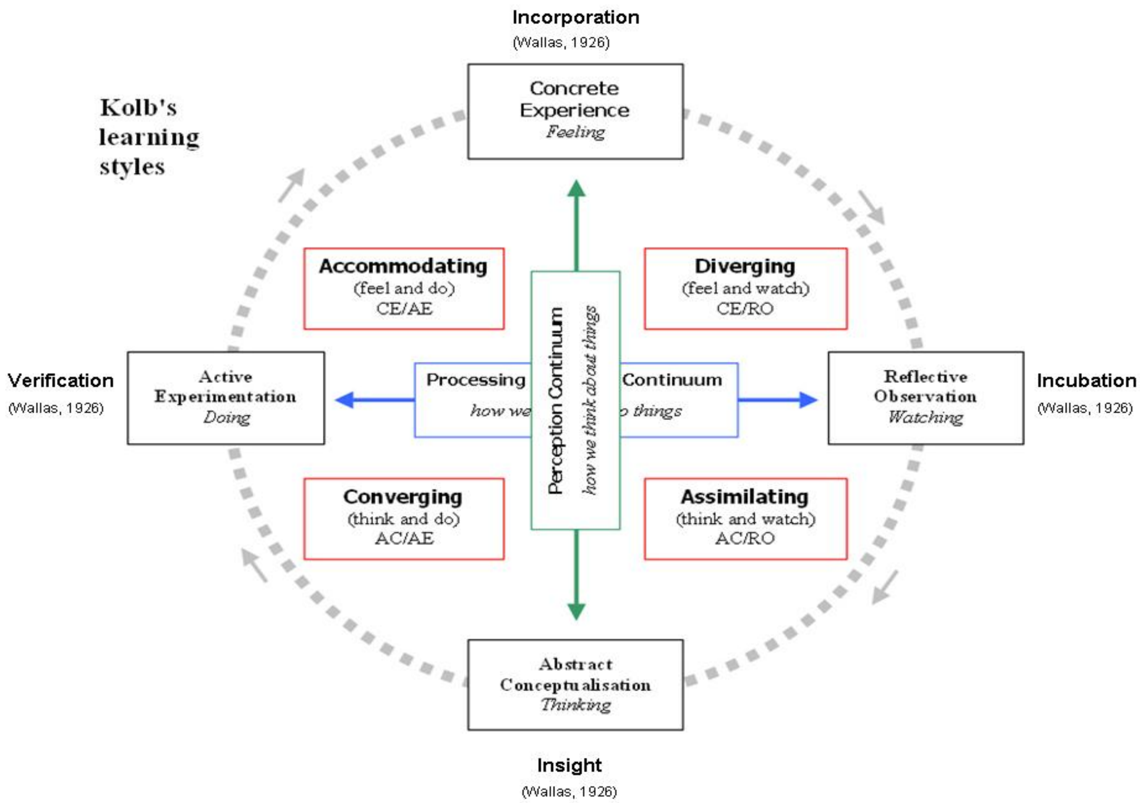
According to Minniti and Bygrave (2001) successful entrepreneurs learn two types of knowledge: (1) domain knowledge regarding their technology and/or market and (2) a more generalized tacit knowledge of "how to be an entrepreneur". Entrepreneurs gain tacit knowledge experientially by monitoring and filtering outcomes of experiments that test competing hypotheses. Positive experiential outcomes are often subject to representativeness heuristic bias, i.e. the tendency to overestimate the frequency, relevance and predictive reliability of previous experiences as they relate to solving new problems (Tversky 1974; Busenitz and Barney 1997; Minniti and Bygrave 2001). There is recent evidence that domain knowledge and entrepreneurship knowledge are interwoven to create strong domain specificity of entrepreneurial practice. Technology entrepreneurs with expert level technology product and market domain knowledge develop practical and innovative new business ideas in a wide variety of domains but they almost exclusively limit their practice to a single domain (Gemmell, Boland et al. 2011).

Politis (2005) extended Minniti's model by explaining how entrepreneurs learn experientially through two different transformational modes, either exploitation of existing knowledge by testing actions similar to earlier experiences or exploration of entirely new actions. Holcomb et al. (Holcomb, Ireland et al. 2009) demonstrated that entrepreneurs gain tacit knowledge for opportunity recognition both directly (through experience) and vicariously (through indirect observation of the actions and results achieved by others). According to Holcomb, entrepreneurs are heavily influenced by the representative heuristic bias along with two other heuristic mechanisms: the "availability heuristic," the tendency to use information that most easily comes to mind (usually based upon the timing or emotionality of the information) and the “anchoring heuristic,” the tendency to move slowly and incrementally from an initial estimated solution (Tversky 1974).

Entrepreneurship and Kolb’s Theory of Experiential Learning

David Kolb describes learning as “the process whereby knowledge is created through the transformation of experience” (Kolb 1984 p. 38). According to Kolb, experiential learning is a recursive cycle of grasping and transforming experience through the resolution of “dialectic tension” or opposing means of experience acquisition and transformation. Kolb’s theory of experiential learning builds upon John Dewey’s description of learning as the “continuing reconstruction of experience” (Dewey 1897 p. 79) through four learning modes: Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC) and Active Experimentation (AE). Effective learning requires “touching all four bases”; however, most individuals have a preference for certain modes which constitutes their “learning style.” Our 2011 grounded theory study mapped the classical Wallas stages of creativity into the Kolb learning space extended to encompass multi-level social interactions (Wallas 1926; Csikszentmihalyi 1996; Gemmell, Boland et al. 2011) (see Figure 1 below).

FIGURE 1
Cycle of Learning and Creativity (Gemmell, Boland et al. 2011)



A researcher who administered a 24 item normative version of the Kolb LSI found that technology entrepreneurs who favor Kolb's Active Experimentation and Abstract Conceptualization learning modes discovered more opportunities, suggesting that learning asymmetries contribute to knowledge asymmetries that impact opportunity recognition (Corbett 2007). Armstrong and Mahmud (2008) also used the normative form of the Kolb LSI and found that managers who favor Kolb's Active Experimentation learning mode have higher tacit knowledge acquisition.

Experimentation as an Entrepreneurial Practice

Entrepreneurship researchers have defined experimentation as a conscious goaldriven search for improvement through iterative revision while monitoring for results (Thomke 2003; Baum and Bird 2010). New business formation and entrepreneurial strategic development benefit from ongoing iterative adjustments through trial and error experimentation (Nicholls-Nixon, Cooper et al. ; Gemmell, Boland et al. 2011). Entrepreneurs routinely experiment by demonstrating partially developed prototypes to assess market reaction, validate new product designs and identify new customers (Thomke 2003). Baum and Bird (2010) demonstrated how Swift Action and Multiple Iterative Actions mediate the effect of Sternberg's Successful Intelligence (Sternberg 1999) on new venture growth. Experimentation is a predominantly beneficial entrepreneurial practice; however, it can also lead to faulty decision making through biased overestimation of the prevalence of an event based upon only a few data points (Miner 2001; Hmieleski and Corbett 2006).

Flexibility and Expertise

Domain expertise is a key factor in both innovation and entrepreneurial performance (Amabile 1997; Shane 2000). However, expertise is a double-edged sword that can induce loss of flexibility and creativity in problem solving (Dane 2010). Experts change their mental representations of tasks less often than novices (Anzai and Yokoyama 1984) and consequently struggle to adapt problem solving methods to new environments (CaÑAs, Quesada et al. 2003). Domain expertise is generally the product of well established, complex and relatively fixed schemas that are prone to becoming "brittle" and ineffective by changes in circumstance (Lewandowsky and Thomas 2009 p. 13).

Experience and expertise benefits the entrepreneur's sensitivity and awareness of patterns (Dimov 2007) but it also leads to heavily biased and heuristic based decision making (Tversky 1974; Holcomb, Ireland et al. 2009). The entrepreneur might, under the pressure of time and circumstance, tend to overestimate the similarities between a current problem and one solved in the past and to use the same solution rather than engaging the new problem as a learning experience. Prior related knowledge can interact with biased risk/return perceptions to influence the allocation of limited entrepreneurial resources (Garnsey 1998; Ravasi and Turati 2005). Managers facing a forced choice decision between two projects might either "starve" or inappropriately escalate resources to one project based upon recent related experience and biased interpretations of perceived risk (Barry M 1976; Staw and Fox 1977).

Parker's (2006) study found that entrepreneurs adjust expectations based on experiential feedback only 16% of the time suggesting that entrepreneurs place much greater weight on previous information and experience than on learning opportunities from new information. The accumulation of experience can also impact cognitive entrenchment. Parker found older and more experienced entrepreneurs only adjusted beliefs 14% of the time while younger and less experienced entrepreneurs exhibited much greater sensitivity to new information by responding at the rate of 21%.

Learning style has been demonstrated to influence career interests and areas of domain expertise development (Kolb and Kolb 2005a). For example, the study of engineering relies upon "formism" as an underlying philosophy of knowledge that is most likely to attract someone with a converging learning style whereas the study of marketing and sales would be more likely based upon contextualism or pragmatism which would likely attract an accommodating style (Willcoxson and Prosser 1996).

Learning style is intrinsically context sensitive and learning mode preferences can vary on a situational basis (Sadler-Smith 2001; Mainemelis, Boyatzis et al. 2002). Sadler-Smith compared and contrasted personality, cognitive style (defined as preferred ways of organizing and processing information) and learning style as key traits for management studies. Curry (1983) visualized human traits as analogous to layers of an onion with personality at the core wrapped by the cognitive style layer followed by an outer learning style layer. The personality core represents a relatively fixed and non-varying trait while each subsequent layer becomes increasingly more context sensitive. Systematic variability of cognitive traits on a conscious level is indicative of higher order integrative development and metacognitive processes and decision rules (Akrivou 2008; Kolb and Kolb 2009). Such metacognitive traits are conducive to the learning of entrepreneurial expertise (Robert Mitchell, Shepherd et al. 2011) suggesting that any study of entrepreneurial learning style traits should also examine learning flexibility in order to factor in the wide variety of learning contexts encountered by entrepreneurs.

Entrepreneurs and Strategic Decision Speed

Eisenhardt (1989) found that executive teams composed of fast decision makers in the microcomputer industry exhibited superior performance while using more information to develop more alternative trial ideas than did slow decision makers. A study by Judge and Miller (1991) of companies from three industries: biotech, textiles and hospitals, showed that biotech industry executives who considered more decision alternatives, made decisions faster with a positive impact on financial performance. This result was unique to the biotech industry alone, demonstrating the influence of industry dynamics on decision speed and suggesting that such studies should be done on an industry specific basis. Kessler and Chakrabarti (1996) demonstrated the negative effect of domain expertise on the decision speed of new technology product developers. Functional experts were found to inhibit decision making processes due to their lack of diverse frames of reference and inability to contribute to diverse functional aspects of product development (Purser, 1994).

Subsequent studies of strategic decision speed and firm results have yielded mixed results. Extrinsic pressures to make rapid decisions have been shown in several studies to have a negative effect on Innovation (Amabile 1983; Amabile 1993; Baer and Oldham 2006). Another study of small/medium sized companies demonstrated how rapid decision making improved firm revenue growth but not profits among companies in dynamic industries (Baum and Wally 2003). Older and more experienced internet entrepreneurs made faster decisions than their younger and less experienced peers but were also more likely to ultimately suffer firm closure within four years (Forbes 2005). Another study found that the pressure of funding and acquisition transactions often leads technology entrepreneurs to fail by abandoning their learning process in favor of rapid, reactive decision making (Perlow, Okhuysen et al. 2002).

Hypotheses

This study focuses on two dimensions of learning style preference as antecedents of behavior and performance: (1) the individual ability to flexibly engage different learning modes based upon the learning situation and (2) the preference for using the Active Experimentation learning mode rather than the Reflective Observation mode (as measured by the AE-RO score from the Kolb Learning Style Inventory).

The effects of individual traits upon firm performance are most commonly mediated by processes involving strategic actions, behaviors or competencies (Baum, 1995; Epstein and O'Brien 1985). Even core cognitive traits such as intelligence typically account for only perhaps 20% of performance (Sternberg and Hedlund 2002). The direct influence of traits on firm performance is likely even weaker in complex technology industries with less process orientation and higher trait variability than in task/process-oriented industries (i.e., assembly lines) with lower trait variability (Mischel 1968).

We therefore conceptualized a high level model shown below in Figure 2 and sought behavioral mediators that (1) reflect the findings of our grounded theory study of entrepreneurial ideation and (2) have demonstrated efficacy in predicting entrepreneurial company performance. Based on these two criteria, we selected two behavioral mediators: “Swift Action,” the speed of strategic decision making, and “Experimentation.” Our study targeted technology firms in highly dynamic industries where rapid development of creative and innovative solutions is most crucial.

FIGURE 2
High Level Conceptual Model

Building on the preceding literature, we hypothesize that individual entrepreneurs with a preference for Active Experimentation over Reflective Observation will more likely engage in experimental practices and thereby attain greater firm level innovation.

Hypothesis 1. The Active Experimentation learning mode (AE-RO) has a positive indirect effect on Innovation via Experimentation when controlling for firm revenue.

We focus a great deal on the act of experimentation because of its unique and powerful role within entrepreneurial practice; however, the other stages of learning are equally important to the overall process of innovation and new business formation. Furthermore, we posit that flexible learners are less likely to suffer decision biases and entrenchment (particularly during the Assimilating phase of the learning cycle) consequently allowing them to more easily innovate.

We therefore hypothesize that entrepreneurs with greater learning flexibility will, in the process of using all learning modes, move more efficiently and quickly through the experiential learning process, resulting in more innovative ideas and higher levels of performance.

Hypothesis 2. Learning Flexibility has a positive indirect effect on Innovation via Swift Action when controlling for firm revenue.

Experimentation appears to be a predominantly entrepreneurial practice - the scale of investment in a typical corporate product launch and the public relations costs of a highly visible failed experiment discourage large corporations from engaging in experimentation (Sull 2004; Gemmell, Boland et al. 2011). We therefore hypothesize that the practice of experimentation positively impacts entrepreneurial performance both directly and indirectly through the mediator Swift Action. We have hypothesized partial mediation because the literature has produced mixed/uncertain results regarding the effects of Swift Action on performance; hence, we expect the Swift Action influence to be less impactful on Innovation than the direct effects of Experimentation.

Hypothesis 3. Swift Action positively and partially mediates the direct positive effects of Experimentation on Innovation when controlling for revenue.

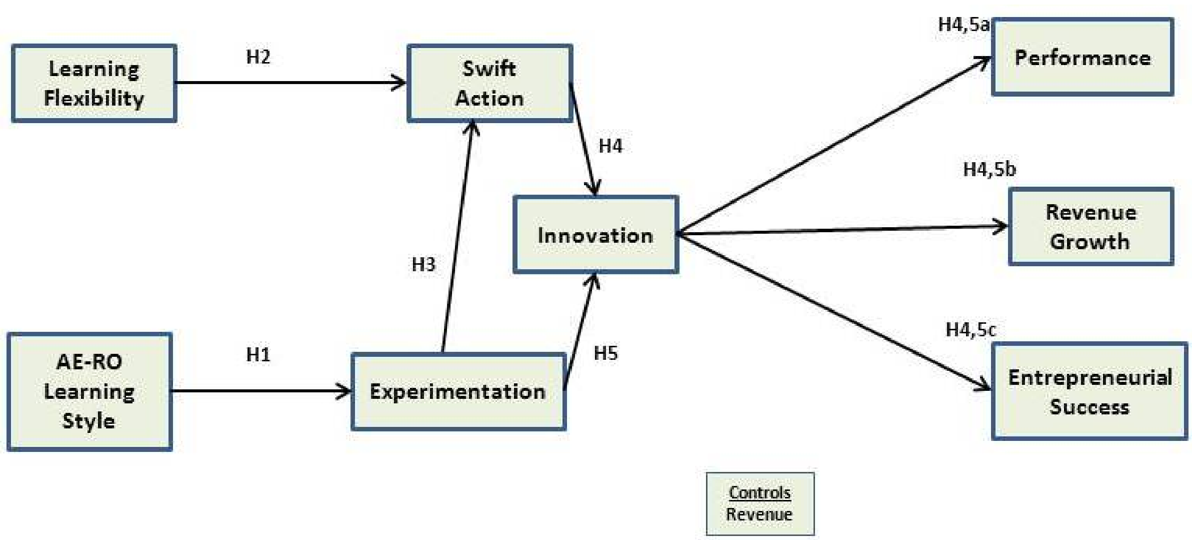
Innovation as a mediator of swift action and experimentation. Numerous studies have linked product and process innovation to entrepreneurial firm performance (Schumpeter 1947; Shan, Walker et al. 1994; Hitt, Hoskisson et al. 1997; Garcia and Calantone 2002); we therefore expect innovation to mediate the effects of entrepreneurial behaviors and practices on firm performance and individual entrepreneurial success. Given the mixed outcomes of decision speed and firm performance studies, our hypotheses H4a, b, c only foresee indirect effects between Swift Action and our three performance direct variables. On the other hand, we anticipate strong positive effects between experimentation and firm performance and success, hence our partial mediation hypotheses H5a, b and c. These are summarized as follows:

Hypothesis 4a, b, c. Swift Action has positive indirect effects on a) firm Performance, b) Revenue Growth and c) Entrepreneurial Success via Innovation when controlling for revenue.

Hypothesis 5a, b, c. Innovation positively and partially mediates the direct positive effects of Experimentation on a) firm Performance, b) Revenue Growth and c) Entrepreneurial Success when controlling for revenue.

Building on our qualitative grounded theory study and the current base of literature and theory, we developed a model to guide our quantitative study (see Figure 3).

FIGURE 3
Conceptual Model of Learning, Innovation and Entrepreneurial Performance



RESEARCH DESIGN AND METHODS

Sample

We conducted this study by surveying 202 technology entrepreneurs located throughout the United States. A special effort was made to gain geographically diverse participation from all regions of the U.S. (see Table 1). We contacted active technology entrepreneurs from our personal network who are either founders and/or CEO of their current company. Responses from entrepreneurs outside our network were carefully reviewed to ensure valid responses solely from technology entrepreneurs based upon responses to questions about the participant's history as an entrepreneur, their current title and at what stage they joined their current company.

TABLE 1
Demographic Summary

N= 172	No. Responses	%
Region		
Northeast U.S.	12	7
Southeast U.S.	44	26
Midwest U.S.	21	12
Southwest U.S.	9	5
Western U.S.	21	12
Not reported	65	38
Industry		
Hardware/software systems	41	24
Software	34	20
Internet/e-commerce	53	31
Electronics	12	7
Biotechnology	4	2
Clean Energy	4	2
Telecom	3	2
Medical Devices	5	3
Other Technology	16	9
Joined Current Firm As		
Founder	132	77
Principal/Officer and early employee (first 25)	23	13
Early employee (first 2(5)	17	10
Position in Current Firm		
CEO	106	62
CFO/CTO/CIO	12	7
VP/SVP/EVP/Director	54	31
Education		
High School	11	6
Some College	46	27
College Degree	58	34
Masters Degree	39	23
Doctoral Degree/Professional Degree (JD, MD)	13	8
Not reported	5	3

Data Collection

Data was collected over a three month period from May to July, 2011 via an online survey using Qualtrics. The initial data collection effort focused on the researcher's personal network of technology entrepreneurs, which resulted in 66 complete surveys (38% of the total). The balance of responses came from a carefully screened professional research panel.

The survey instrument totaled 46 items (including demographic data items) and was organized in sections by factor (not randomized), starting with a mix of both exogenous and endogenous factors and ending with the 20 items for the Kolb Learning Style Inventory.

Wherever possible, items were carefully adopted from extant literature, based upon their theoretical relevance and demonstrated causal predictive efficacy, with minimal or no changes. However, one construct – Swift Action - had to be composed and tailored specifically for the technology industry. We also created an "Entrepreneurial Success" construct from four items: current firm revenue growth, current firm position (with CEO as the highest score), status upon joining the current firm (founder as the highest score), number of start-ups (serial entrepreneurialism), number of strategic exits and size of largest strategic exit.

Measures

AE-RO. The Kolb Learning Style Inventory (LSI) v.3.1 is composed of twenty forced choice questions asking the participant to rank four choices of their preferred learning method (4=most like me, 1=least like me). Each choice represents one of four learning modes and the ranked score for each mode over the first twelve questions is summed to create four raw Learning Style scores. AE-RO is the Active Experimentation raw score minus the Reflective Observation raw score.

Some researchers contend the four learning modes should be measured using normative rather than ipsative (forced choice) scales (Geiger, Boyle et al. 1993) and question Kolb's basic premise of dialectic tension between opposing learning modes. Learning involves not only thoughts but also higher level integration of the five senses, behaviors, emotions, experiences and social interactions through a dialectical process of acquisition and transformation (Kolb 1984; Akrivou 2008). The dialectic nature of Kolb's experiential learning requires forced choice questions to resolve the tension and preference for polar opposite modes. It should be further noted that while the four learning mode scales are ipsative, the AE-RO combination score is not ipsative (Kolb and Kolb 2005b).

While there has been considerable debate about the ipsative versus normative analysis of learning orientation, our position is that this research project is best served by utilizing the forced ranking nature of the traditional test to gain sharper resolution of the entrepreneur's preference for Active Experimentation. Furthermore, the ipsative test provides necessary contrast to measure the situational variances that are foundational to the LFI measure. Learning flexibility has not been validated as a normative construct and would likely result in an impractically long survey.

Learning Flexibility Index (LFI). The final eight items in the Kolb LSI v3.1 query learning preferences in different settings. Learning flexibility is defined as LFI = 1 –W where W is the Kendall's Coefficient of Concordance (Legendre 2005). W is calculated as follows:

$$W = (12s - 3p^2n(n + 1)^2)/p^2 (n^3 - n)$$

$$\text{Where, } s = \sum\nolimits^{n}_{i=1} R_i^2$$

$$p = \text{Number of learning contexts} = 8$$

n = Number of learning modes = 4

R = Row sum of ranks

The row sum of ranks is the sum of the ranking scores (from 1 to 4) for each of the four learning modes across the eight learning contexts.

Swift action. Swift action is an industry specific construct that has been shown in prior entrepreneurship and strategy literature to mediate the effect of individual traits on firm performance (Baum and Wally 2003; Baum and Bird 2010). We developed our own version of Swift Action by creating three strategic innovation decision-making scenarios relevant to any technology company and asking respondents to estimate their decision making time-frame for each scenario.

The first scenario was a "New Product Development Decision" worded as follows: "You are excited about an idea for a new product or service that could double next year's growth rate. Your development personnel are tied up on other projects so pursuing your idea will require a reassessment of your current product roadmap. Indicate the approximate number of days it would take you to decide whether to pursue the new product."

The second scenario was a "Strategic Partnering/Technology Licensing Decision" worded as follows: "You have identified a partner with a key technology that could unlock new markets and opportunities for your firm. You lack appropriate resources to develop the technology in-house. Additionally, resources to manage the partnership and absorb the technology are limited. Indicated the approximate number of days it would take you to decide whether to pursue the partnership."

The third scenario was a "Target Market Decision" worded as follows: "You have identified two markets for your technology that appear to offer similar high growth opportunities; however, you cannot pursue both market opportunities with existing resources. You have been evaluating both markets but know you need to focus on just one of them. Indicate the approximate number of days it would take you to decide which market to pursue."

Participants responded to the "number of days to make your decision" by moving sliders across a scale from 0 days to 100 days. The responses were inverted (divided into 100) and scaled logarithmically.

Experimentation. Experimentation was measured using five items based upon "Multiple Iterative Items" from Baum and Bird (2010). Typical statements were "We frequently experiment with product and process improvements" and "We regularly try to figure out how to make products better". Each item was measured using a five point Likert scale (1=Strongly disagree, 5=Strongly agree).

Innovation. Innovation was measured using three items based upon the "Performance" construct from Song, Dyer, and Thieme (2006). Questions included "Our new product development program has resulted in innovative new products", "From an overall revenue growth standpoint our new product development program has been successful" and "Compared to our major competitors, our overall new product development program is far more successful at producing innovative products." Each item was measured using a five point Likert scale (1=Strongly disagree, 5=Strongly agree).

Performance. We chose a single broad firm performance construct from Reinartz, Krafft, and Hoyer (2004) with four items that asked participants to self-rate overall financial performance and success attaining market share, growth and profitability. Each item used a five point Likert scale (1=Poor, 5=Excellent).

Entrepreneurial success. Entrepreneurial success is a new construct developed to measure the track record and career success of an individual entrepreneur calculated through a weighted sum of five factors: Position in current company, status upon joining the company (i.e., founder, early employee, officer), number of strategic exits/liquidity events, largest strategic exit/liquidity event, serial entrepreneurialism (number of start-ups). The resulting scale yielded a measure of career success that ranged for this sample from 2 to 27.

Revenue growth. Revenue growth was measured with a single item per Low & Macmillan (1988), "Approximately what percentage annualized revenue growth has your company experienced over the last year?" The item was measured over a six point scale (1 = Revenue declined, 6 = 50+%).

Appendix A includes a table summarizing the definitions, items and sources of the constructs used in this study.

DATA ANALYSIS

Data Screening

The research model was tested using AMOS and SPSS for Windows (PASW Statistics Gradpack 18.0, 2010). Our initial data set of 202 survey responses was first screened for missing data and checked for modeling assumptions of normality, skewness, kurtosis, homoscedasticity, multi-collinearity and linearity. Independent variables LFI and AE-RO did not display multi-collinear with VIF scores of 1.000. All items yielded skewness and kurtosis scores below +/-1.00 except for Swift Action which displayed marginal kurtosis (1.09) but was deemed acceptable without transformation.

Four respondents were discarded due to incomplete Kolb LSI/LFI data. We rejected another 26 respondents who were judged to be non-technology entrepreneurs based upon responses to questions about participants' current employment, their industry and entrepreneurial experience. The remaining 172 responses had a total of five missing data points (<3%) and mean imputation (Hair, Black et al. 2010) was used to calculate these missing values. Data imputation is an acceptable technique in cases where <5% of data is missing (Tabachnick and Fidell 2000).

Swift Action data was transformed per ex ante literature (Baum and Wally 2003) as follows:

$$SA = \text{Imputed Factor Scores per AMOS CFA analysis}$$

$$\text{Swift Action} = \log_{10} 100/SA$$

Learning Style Constructs

The Kolb Learning Style Inventory is a long-standing and well-established psychometric test with high construct validity based upon numerous studies of factor analysis (Katz 1986; Willcoxson and Prosser 1996). A study of science students, who should possess traits similar to the technology experts in our study, found both high internal consistency (coefficient Alpha ranged from .81 to .87 – see Appendix B) and confirmation of the two bipolar learning dimensions per Kolb's theory. We therefore used the test unmodified and chose to not refactor the 20 items in the Kolb LSI.

Factor Analysis

We performed Exploratory Factor Analysis (EFA) using SPSS to evaluate and reduce the 15 items associated with Innovation, Performance, Experimentation and Swift Action to a smaller number of latent variables that, if possible, coherently reflect the four distinct a-prior theoretical constructs consistent with our research expectations. Because our goal was to identify latent constructs expected to produce scores on underlying measured variables

(Tabachnick and Fidell 2000) in the presence of non-normality (Fabrigar, Wegener et al. 1999) and given our exclusive interest in shared variance (Costello 2005) and because communalities of most variables exceed .5 (Hair, Black et al. 2010) we also performed common factor analysis (CFA).

Our EFA was performed with Principle Axis Factoring (PAF) and Promax rotation based upon our assessment that the items are non-orthogonal and our ultimate goal of structural equation modeling. We evaluated the latent root criterion in which possible factors with an eigenvalue less than 1.0 are excluded as well as scree plot analysis to determine how many factors should be included. The initial 15 items yielded a four factor solution with eigenvalues>1.0 and exhibited acceptable loadings exceeding .5 and minimal cross-loadings (<.2).

TABLE 2
Four Factor Pattern Matrix (Principal Axis Factoring, Promax Rotation)

	Innovation	Performance	Experimentation	Swift Action
i1	.844			
i2	.572			
i3	.622			
p1		.876		
p2		.874		
p3		.860		
p4		.878		
exp1			.714	
exp2			.819	
exp4			.551	
sa1				.861
sa2				.861
sa3				.863

TABLE 3
KMO and Barlett's Test Results

KMO, Barlett's Test and Total Variance Explained	
KMO Measure of Sampling Adequacy	.811
Barlett's Test of Sphericity	
o Approximate Chi –Square	1099.438
o Df	78
o Significance	.000
Total Variance Explained	66.8%

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) builds on shortcomings of EFA including: (1) inability to constrain some factor loadings to zero, (2) inability to correlate measurement errors, and (3) inability to specify which factors are associated (Bollen 1989). We performed this CFA analysis using structural equation modeling (AMOS) and began by reviewing the factors and their items and established face validity. We specified the measurement model in AMOS with the four factors derived from EFA, each identified or over-identified. Each factor was hypothesized to be reflective (caused by the latent construct) and for the items to therefore move together. The latent constructs were allowed to correlate with other constructs given no evidence to the contrary. Error terms within constructs could be correlated, however, error terms across different constructs were not allowed to be correlated. Our sample size of 172 was deemed sufficient based upon Hoelter's Critical N values that indicate the model is acceptable at the .05 significance level with N=131 and at the .01 significance level with N=148.

CFA confirmed factor validity (convergent and discriminant) of the four constructs (see Tables 4 and 5). Discriminant validity was examined further by comparing the square root of AVE to the construct correlations (see Table 5) per the recommendation that the square root of AVE should exceed the correlations of that construct and all others (Liang, Saraf et al. 2007). The measurement model obtained using AMOS exhibited satisfactory fit statistics (Chi-squared = 85.1, df = 48, CMIN/df = 1.774, SRMR = .0565, CFI = .962, AGFI = .887, TLI = .947, RMSEA = .067 and PCLOSE = .111). While an ideal RMSEA score is .05 or less, a value of about .08 or below indicates a reasonable error of approximation and is therefore satisfactory (Bollen and Long 1993). Furthermore, RMSEA is within the 10/90 percentile range and the PCLOSE of .111>alpha = .05 and indicates acceptable fit.

TABLE 4
Factor Validity Test Results

Factor	CR	AVE	MSV	ASV	Convergent Validity CR>AVE AVE>.5	Discriminant Validity MSV<AVE ASV<AVE
Innovation	**0.75**	**0.51**	**0.38**	**0.23**	Yes	Yes
Performance	**0.90**	**0.76**	**0.31**	**0.14**	Yes	Yes
Experimentation	**0.79**	**0.56**	**0.38**	**0.17**	Yes	Yes
Swift Action	**0.89**	**0.74**	**0.01**	**0.00**	Yes	Yes

TABLE 5
Discriminant Validity

Factor	Innovation	Performance	Experimentation	Swift Action
Innovation	**.714**			
Performance	.558***	**.872**		
Experimentation	.616***	.343***	**.748**	
Swift Action	.085	.027	-.046	**.860**

Square root of AVE in bold on diagonals

Common Methods Bias (CMB) Testing

An un-rotated principal component analysis with single factor extraction (Harman's single-factor test) was also done to explore the presence of common method bias in our study, resulting in 31.1% of variance explained with all items loading into a single factor.

However, Podsakoff, MacKenzie, Lee, and Podsakoff (2003) characterize the Harman single-factor test as a diagnostic technique that “actually does nothing to statistically control for (or partial out) method effects” (p. 889) and therefore does not adequately confirm the absence of CMB. We therefore also employed the marker variable technique (Lindell and Whitney 2001) which attempts to control for CMB by including “a measure of the assumed source of method variance as a covariate in the statistical analysis” (Podsakoff, MacKenzie et al. 2003 p. 889). Application of the marker variable technique requires the inclusion in the study of a variable that is theoretically unrelated to at least one of the focal variables. The correlation observed between the marker variable and the theoretically unrelated variable is interpreted as an estimate of CMB (Lindell and Whitney 2001). Our marker variable analysis yielded a common factor loading of 4% and therefore provided satisfactory evidence of the absence of common method bias.

Controls

All sample companies were small entrepreneurial firms, however, some factors could be influenced by the size and stage of the company (Perlow, Okhuysen et al. 2002), therefore we used revenue as a control to account for variance based on company size (see Appendix E for control effects).

Mediation Analysis and Path Modeling

We performed mediation analysis using causal and intervening variable methodology (Baron and Kenny 1986; MacKinnon, Lockwood et al. 2002) and techniques described by Mathieu and Taylor (2006). Mediated paths connecting independent variables to dependent variables through a mediating variable were analyzed to examine the direct, indirect, and total effects. For each of the mediation hypotheses being tested, a model was first run without the mediation paths (only direct effects). Then, the analysis was performed again using the AMOS bootstrapping option to analyze direct and indirect effects with mediation. After testing for mediation effects, we restored the full model and trimmed the insignificant paths to achieve a final path model.

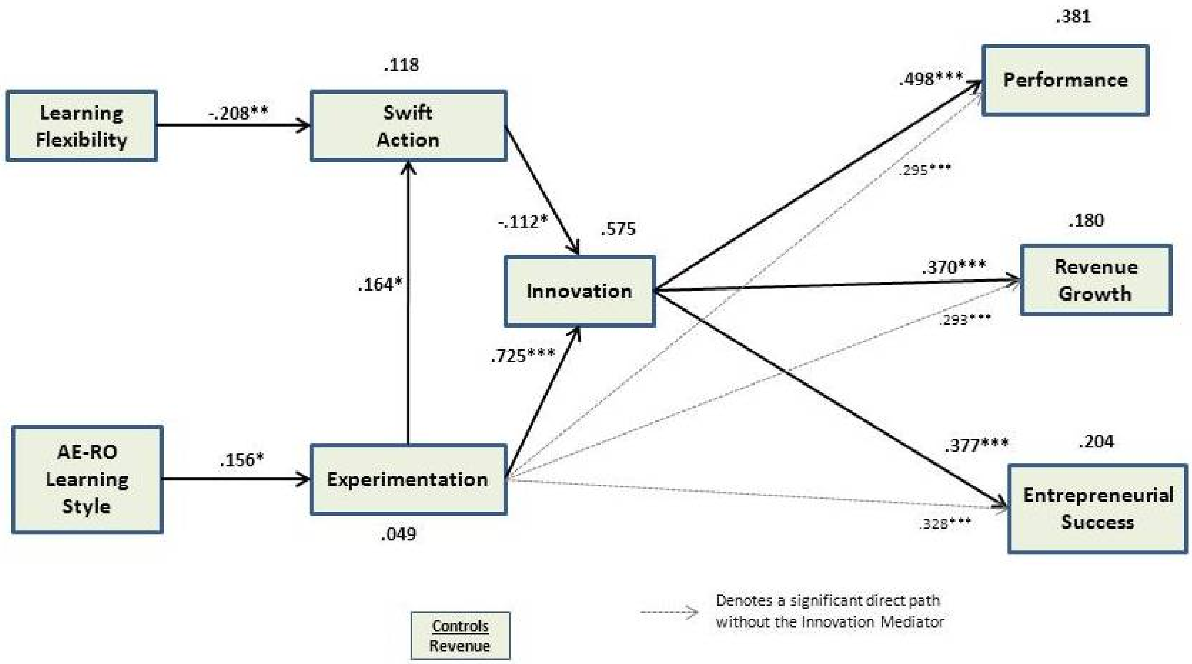
Model Fit

Table 6 summarizes the key model fit parameters for both the category and experience multi-group models. Our goodness of fit (GOF) analysis focused primarily on the following parameters: CMIN/df (Tabachnick and Fidell 2000), SRMR, CFI (Hu and Bentler 1999) and PCLOSE (Joreskog & Sorbom, 1997).

TABLE 6
Model Fit Summary for Path Model

Trimmed Category Model		
Key GOF Parameters	**Criteria**	**Value**
CMIN/df	<2	1.068
Probability	Higher	.378
SRMR	<.05	.042
AGFI	>.90	.936
CFI	>.95	.997
RMSEA	<.05	.020
PCLOSE	>.50	.776

FIGURE 4
Final Trimmed Path Model
(significant paths without the Innovation mediator shown in dashed light gray)



RESULTS

Table 7 provides the means, standard deviations and bivariate correlations for the study constructs. The results of mediation testing for each of the nine hypotheses are summarized in Table 8.

Hypothesis 1 proposed that preference for the Active Experimentation learning style over Reflective Observation (AE-RO) would have an indirect positive effect on innovation via experimental practices. In accordance with previous studies of trait effects on performance we anticipated no direct effects between learning traits and firm performance; however, we did expect learning style to predict certain entrepreneurial behaviors such as propensity to solve problems through experimental methods versus protracted reflection and analysis. We also expected the effects of learning traits effects to propagate through mediators to indirectly influence firm performance. This was indeed the case as AE-RO showed no direct through effects on innovation, either with or without experimentation as a mediator. However, the model indicated moderate and significant indirect effects (beta = .120, $p<.05$) thus confirming our indirect effects hypothesis.

Similarly, hypothesis 2 posited an indirect positive relationship between learning flexibility and innovation via strategic decision speed. Mediation tests resulted in a very weak but significant indirect relationship (beta = .025, $p<.05$), thereby providing marginal support for Hypothesis 2.

Hypothesis 3 stated that decision speed would positively mediate the direct positive relationship between experimentation and innovation. Entrepreneurs who experiment are more likely to quickly choose a course of action and, in the process, achieve greater innovation. We expected a strong positive relationship between experimentation and innovation both with and without decision speed as a mediator, hence our anticipation of partial mediation. As expected, the model displayed a very strong positive relationship between experimentation and innovation both with the mediator (beta =.725, $p<.001$) and without the mediator (beta = .708, $p<.001$). Surprisingly, the indirect effects via swift action were negative (beta = -.018, $p<.05$). Our hypothesis 3 of partial mediation is supported, although the mediating process is different than we expected (more details about this are in discussion).

Hypothesis 4a, b and c anticipated that strategic decision speed would indirectly positively influence our three performance outcomes: overall firm performance, revenue growth and individual success as an entrepreneur. Mediation testing confirmed weak but significant effects (H4a: beta = -.068, $p<.01$; H4b: beta = -.037, $p<.01$ and H4c: beta = - .032, p<.01). Once again, the hypotheses are confirmed although the effects were surprisingly reversed from what was expected (negative rather than positive).

Hypotheses 5a, b and c stated that experimentation would have strong positive effects on firm performance, revenue growth and entrepreneurial success, positively mediated by innovation. Strong positive effects in the absence of the innovation mediator were indeed observed (H5a: beta = .295, p<.001; H5b: beta = .293, p<.001; H5c: beta = .328, p<.001), however, in the presence of innovation, all direct effects became insignificant. Indirect effects were strong (as expected) and significant (5a: beta = .443, p<.01; 5b: beta = .249, p<.01; 5c: beta = .214, p<.01). Thus, mediation hypotheses were confirmed although in the form of full mediation rather than partial.

TABLE 7
Inter-factor Correlations, Cronbach Alpha, Means and Standard Deviations

N=172	Innovation	Performance	Experi-mentation	Swift Action	Learning Flexibility	AE-RO	Entrep. Success	Rev Growth
Mean	3.119	3.055	2.411	.820	.704	6.081	12.971	3.05
SD	.589	.935	.430	.473	.187	11.988	3.945	1.657
Innovation	**.754**							
Performance	..492***	**.900**						
Experimentation	.657***	.301**	**.784**					
Swift Action	.042	.025	-.143	**.895**				

Cronbach Alpha in bold on diagonals.
*p<.05, **p<.01, ***p<.001

TABLE 8
Mediation Testing Summary and Hypotheses Results

Hypothesis	Direct beta No mediator	Direct Beta With mediator	Indirect beta With mediator	Mediation	Support
H1: AE-RO->Experimentation->Innovation	.058 ns	-.032 ns	.120*	Indirect Effects	Yes
H2: LFI->SwiftAction->Innovation	.052 ns	-.022 ns	.025*	Indirect Effects	Yes
H3: Experimentation->SwiftAction->Innovation	.708***	.725**	-.018*	Partial Mediation	Yes
H4a: SwiftAction->Innovation>Performance	.026 ns	.094 ns	-.068**	Indirect Effects	Yes
H4b: SwiftAction->Innovation->RevGrowth	.065 ns	.102 ns	-.037**	Indirect Effects	Yes
H4c: SwiftAction->Innovation->EntrepSuccess	.028 ns	.060 ns	-.032**	Indirect Effects	Yes
H5a: Experimentation->Innovation->Performance	.295***	-.144 ns	.443**	Full Mediation	Yes[1]
H5b: Experimentation->Innovation->RevGrowth	.293***	.054 ns	.249**	Full Mediation	Yes [1]
H5c: Exper->Innovation->EntSuccess	.328***	.119 ns	.214**	Full Mediation	Yes[1]

Note[1]: Mediation supported as hypothesized, although full versus partial mediation.

DISCUSSION

The results of this study provide support for individual learning style traits as predictive measures of entrepreneurial behaviors and practices. Learning flexibility and the learning style preference for active experimentation have modest but significant effects on the behaviors of technology entrepreneurs who develop innovative products and processes.

Our study confirms the profound role of experimental practices within our learning system of innovation. Our model suggests that an overwhelmingly large portion of the innovation performance achieved by our entrepreneurs (52%) can be explained by their hands-on, iterative approach to learning and problem solving.

The positive indirect influence of learning flexibility and innovation was confirmed as expected; however, it was unexpectedly achieved via a chain of two consecutive negative effects. Entrepreneurs with high learning flexibility were more likely to take longer to make key strategic decisions; however, in the process of doing so, they were more innovative. Our result adds to the literature of mixed results regarding the relationship between decision speed and firm results and suggests that technology entrepreneurs are slightly more innovative when taking time to more carefully consider the options for and consequences of key decisions.

Extrinsic pressure has been long understood as having a detrimental influence on creative potential (Amabile 1983). However, some pressure can be viewed as synergistic and beneficial to the creative product, especially when it is applied during relatively convergent processes such as documentation of a creative work (Amabile 1993). Technology entrepreneurs are usually under enormous pressure from investors, particularly in the very early stages, to quickly produce a product and generate cash-flow. Such pressure on entrepreneurs has been shown to detrimentally influence decision cycles, especially major strategic decisions related to or influenced by investment or M&A transactions (Perlow, Okhuysen et al. 2002).

In retrospect, the negative relationship between learning flexibility and decision speed is perhaps not so surprising. Entrepreneurs in our 2011 grounded theory qualitative study exhibited what we viewed as "learning agility," or the ability to efficiently converge to a desired solution or decision (Gemmell, Boland et al. 2011). Agility and efficiency are not to be confused with speed: a flexible learner may take longer to traverse each learning cycle but in the process of taking the time to utilize and benefit from each phase of learning, they spiral and converge more directly toward the desired outcome. Technology entrepreneurs who are flexible learners - in spite of the enormous environmental pressures - appear to achieve greater innovation by taking slightly longer to consider more alternatives, to reflect upon those alternatives and to ultimately converge to a solution and take action.

Our study also revealed a fascinating interaction between experimentation and decision-making. Experimentation delivers two counteracting effects on innovation – a strong direct positive relationship and a weaker indirect negative relationship via decision speed as a mediator. Entrepreneurs with a proclivity to experiment appear more comfortable pushing ahead quickly with a trial solution despite the moderately detrimental effect of rapid decision speed on Innovation. However, the act of experimentation very strongly leads to new innovations and more than compensates for the loss of innovation via hasty decision making. The net effect of experimentation on innovation is strongly positive but less so that it would be without the counteracting negative influence of decision speed.

As expected, innovation mediates the effects of both decision speed and experimentation on firm level results and entrepreneurial performance. However, we again see the two counteracting forces: experimentation as a strongly positive effect and decision speed as the mildly negative influence via innovation. Experimentation had strong positive effects on all of our DVs even without innovation as a mediator, further reinforcing the extraordinary role of conscious iterative decision practices.

CONCLUSIONS AND IMPLICATIONS TO PRACTICE

Our study reveals the interesting balance between the overwhelming benefits of experimentation - both as a preferred learning mode trait and a developed practice - and the risks of circumventing an effective learning process by rushing to experiment. Literature has demonstrated that entrepreneurial domain experts, given the pressures faced by the typical technology start-up, might be inclined to quickly adopt a heuristic solution and "give it a try." Entrepreneurs tend to draw upon their most recent or impactful experiences (availability heuristic bias) and to be over-confident in their belief that a previous solution is applicable to a current problem (representative heuristic bias), even in the face of unsound data or statistically flawed methods such as small data samples (Tversky 1974; Busenitz and Barney 1997). Entrepreneurs make these errors in spite of evidence that the predicted and desired outcome is actually quite improbable based on historical data. Heuristic decision making helps entrepreneurs deal with day-to-day issues but it is a dangerous and flawed approach to important strategic decisions.

Experimentation can either facilitate learning or undermine it. Entrepreneurs are most innovative when they utilize experimentation as a key practice without ignoring the other learning processes. Entrepreneurs will be more successful and innovative when they take some time to reflect upon multiple alternatives and to test trial ideas socially before making important decisions.

Our study shows that the practice of experimentation develops more easily among entrepreneurs with a learning preference for active experimentation; however, it is also a key entrepreneurial skill that can be developed through education, coaching and practice. Entrepreneurship education can continue to adopt experiential teaching methods to better simulate the entrepreneurial environment and to encourage and develop the skills to experiment with an idea, both socially and physically.

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Our study is limited to entrepreneurs within the technology industry and the results should not be generalized to apply to other businesses that are less dynamic and less reliant on innovation. Access to technology entrepreneurs for data collection is extraordinarily challenging and our study is hampered by the relatively low number of respondents in our sample.

Our findings provide interesting new insight into the role of strategic decision making within entrepreneurial innovation; however, our survey did not specifically query the entrepreneurs' decision methodology. A follow-up study could focus specifically on their decision processes to add depth and certainty to our interpretation of this study's results. Qualitative research, perhaps even an ethnographic or case study methodology, could more deeply delve into the entrepreneurial behaviors or organizational dynamics behind this phenomenon.

APPENDIX A
Construct Definitions, Items and Sources

Construct	Definition	Items	Source
Active Experimentation Learning Mode (AE-RO)	Individual preference for the Active Experimentation learning mode over the Reflective Observation mode.	Twelve forced answer rankings.	(Kolb 1984)
Learning Flexibility	Individual adoption of different learning styles based on the situation.	Eight forced answer rankings.	(Sharma and Kolb 2009)
Swift Action	Strategic decision-making speed.	Three strategic scenarios: 1. New Product Development Decision 2. Strategic Partnering/Technology Licensing Decision 3. Target Market Allocation of Resource Decision.	(Baum and Wally 2003) modified and adapted for technology industry.
Experimentation	Practice of experimentation as an iterative approach to problem solving.	1 We frequently experiment with product and process improvements. 2. Continuous improvement in our products and processes is a priority. 3. After we decide and act, we are good at monitoring the unfolding results. 4. We regularly try to figure out how to make products work better. 5. We make repeated trials until we find a solution.	(Baum and Bird 2010)
Innovation	Firm level product innovation.	1. Our new product development program has resulted in innovative new products. 2. From an overall revenue growth standpoint our new product development program has been successful. 3. Compared to our major competitors, our overall new product development program is far more successful at producing innovative products.	(Song, Dyer et al. 2006)
Performance	Firm competitive performance.	Relative to your competitors, how does your firm perform concerning the following statements: 1. Achieving overall performance. 2. Attaining market share. 3. Attaining growth. 4. Current profitability.	(Reinartz, Krafft et al. 2004)
Entrepreneurial Success	Composite index of individual success as an entrepreneur	Weighted sum of factors: 1. Position in current company. 2. Status upon joining the company (i.e. founder, early employee, officer) 3. Number of strategic exits/liquidity events. 4. Largest strategic exit/liquidity event. 5. Serial entrepreneurialism – number of start-ups.	New Item
Revenue Growth	Current firm trailing one year revenue growth.	Approximately what percentage annualized revenue growth has your company experienced over the last year?	(Low and MacMillan 1988)
Revenue (control)	Current Revenue	What was your company's revenue last year?	(Low and MacMillan 1988)

APPENDIX B
Kolb Learning Style Inventory (LSI) Scale Reliability and Intercorrelation Matrix (Willcoxson & Prosser, 1996)

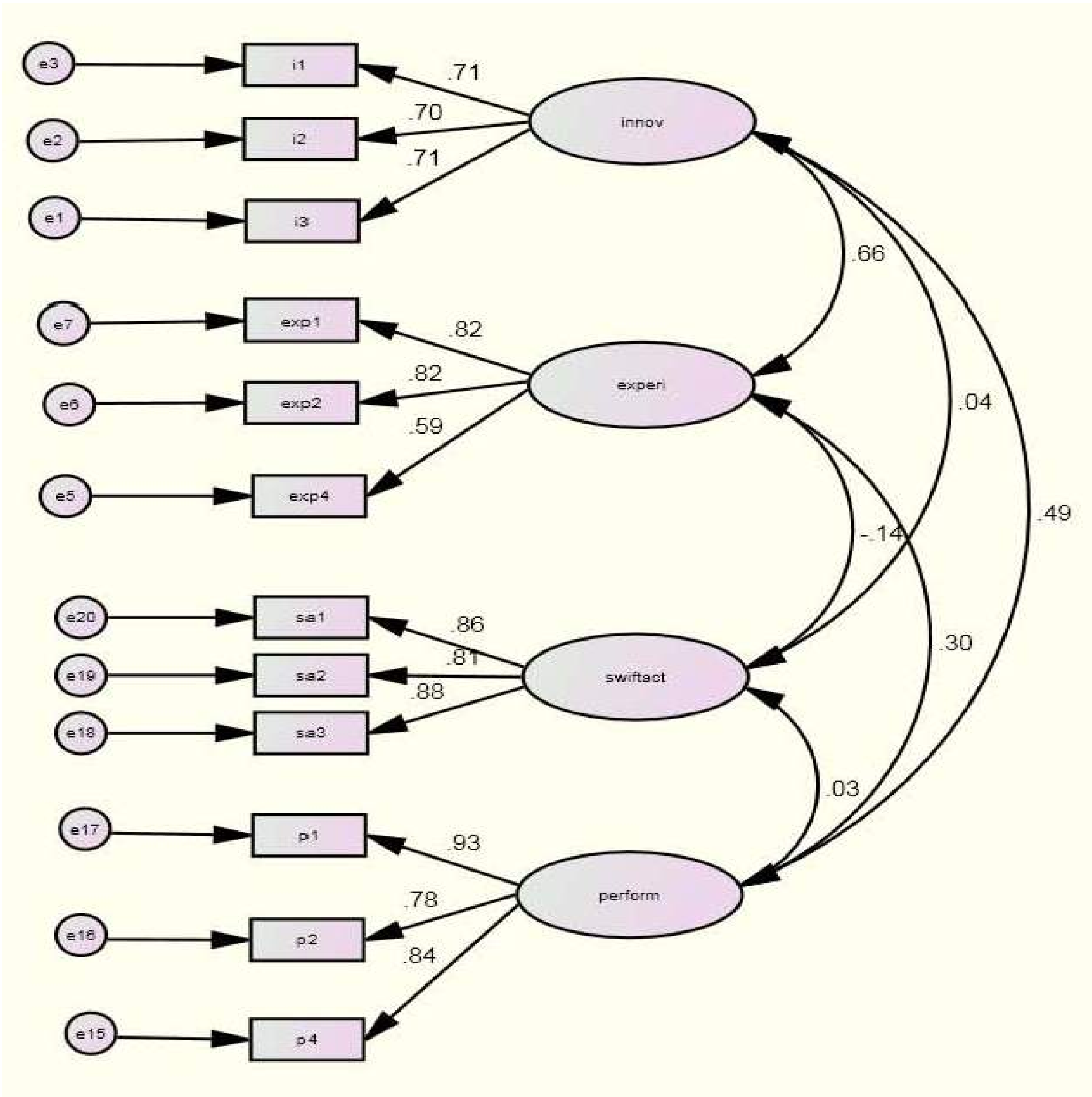
Scale	CE	RO	AC	AE	AC-CE	AE-RO
CE	**.82**	-.24**	-.42**	-.34***	-.85***	-.08
RO		**.81**	-.17*	-.47***	.04	-.84***
AC			**.83**	-.32***	.83***	-.10
AE				**.87**	.03	.88
AC-CE						-.01

Cronbach Alpha in bold on diagonals
*p<.05, **p<.01, ***p<.001

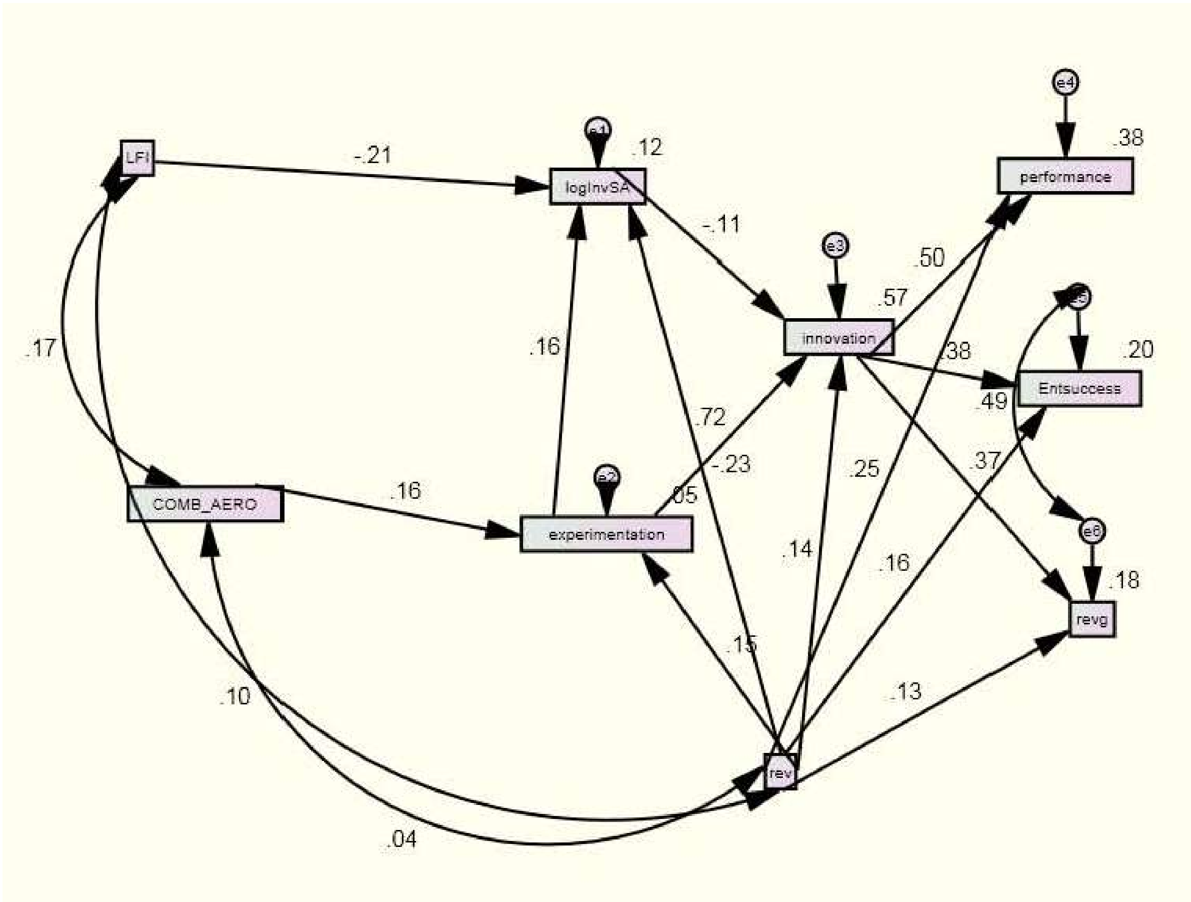
Kolb Learning Style Inventory (LSI) Factor Loadings Demonstrating AC-CE and AE-RO Bipolar Dimensions (Willcoxson & Prosser, 1996)

Science Student Sample N=94	Factor 1	Factor 2
Scale		
CE		-.92
AC		.79
RO	.81	
AE	-.92	

APPENDIX C
Final CFA Path Loadings



APPENDIX D
Final SEM Path Diagram from AMOS



APPENDIX E
Effects of Revenue as a Control

	Experimentation	Swift Action	Innovation	Performance	Rev Growth	Entrepreneurial Success
Revenue	.151*	-.230**	.136**	.252***	.128 ns	.164*

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