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Innovation talent as a predictor of business growth

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Abstract

Purpose – The purpose of this paper is to explore whether innovation talent is predictive of business results. This question is important because companies exist to generate business results such as profitability and market expansion. To study this question, the authors conducted four phases of international research. They found that innovation talent is statistically predictive of business results. The Innovation Profiler ("the instrument") is a web-based assessment tool based on the research. It was designed to detect the full array of specific innovation skills in individuals, skills that correlate with real-world business results.

Design/methodology/approach – The research presented in this paper follows four phases: a qualitative phase followed by two correlational studies; and finally, a validation research phase. The researchers wanted to answer the questions: "Is innovation talent predictive of business results?" "Which dimensions of innovation talent are most predictive of business results?" The research compares the attitudes, value and beliefs of innovators (both entrepreneurs and intrapreneurs) to the business results they achieved and compares innovators to the general population.

Findings – The research findings are that: innovation talent is highly correlated with positive business results. Innovators have significantly higher Innovation Profiler scores than the general population. Within the population of innovators, top scorers are associated with a larger number of positive business results than bottom scorers. Intrapreneurs, while sharing many characteristics with entrepreneurs, tend to score higher on innovation skills. The Innovation Profiler does not produce adverse selection bias with respect to gender or ethnicity.

Research limitations/implications – Most psychographic instruments are normative, including the Innovation Profiler; they rely on scaled responses that measure the extent to which individuals consider statements to apply to them personally. Normative instruments are faked more easily than *ipsative* (forced choice) measures, which ask people to choose from two to four answer options that are usually perceived as equally desirable. However, it has also been argued that the relative standing of respondents (i.e. their relative scores) in the samples is relatively unaffected by normative instruments.

Practical implications – This study provides significant statistical support for the validity of the Innovation Profiler as a predictor of innovation talent and of business results from innovation. The authors hope that by identifying the innovation characteristics that correlate with business outcomes, the authors have contributed to the field. Companies can use this knowledge to accelerate their organizational transformation.

Social implications – This research, and the Innovation Profiler based on it, enable companies to see and measure innovation talent for the first time. This talent is not held by the few and the privileged. In fact, women score as high as men and non-whites score slightly higher than whites. Innovation talent, as measured by the Innovation Profiler, can be an equalizer in the workforce. Finally, we hope that this paper helps companies attract more innovators into their workforce and to recognize and use more of their valuable skills.

Originality/value – To the authors' knowledge, this is the first study to ask. "Can we predict the business results from innovation based on who is involved?" After extensive review of the literature, the authors have not found any other study asking this question. This study is also novel for: including intrapreneurs and entrepreneurs; and for including samples across the Americas, Europe, Asia and Africa. The study

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demonstrates a strong relationship between innovation talent and positive business results, with effect sizes that appear to exceed personality and other factors.

Keywords Benchmarking, Measurement, Organizational assessment, Innovation leadership, Innovation types

Paper type Research paper

1. Introduction and background

In this section, we will provide the context for this research, which includes the business need for innovation, relevant prior research on innovators and the limitations of current approaches to corporate innovation from a talent perspective.

Let us begin by asking why organizations increasingly need innovation. Today large organizations are being disrupted by the pace of change. According to the World Economic Forum (WEF), since the year 2000, over 50 per cent of the Fortune 500 has fallen off the Fortune 500 list (Nanterme, 2016). Innovation has become an imperative for their survival. While large companies have traditionally been managed to deliver predictable, incremental growth, today large organizations are seeking to transform themselves. They seek to deliver higher growth and longevity through innovation, also known as "corporate entrepreneurship". Corporate entrepreneurship, defined as a sum of organizational innovation, renewal, and venturing efforts (Sebora and Theerapatvong, 2010 cited in Anderson *et al.*, 2014), is positively associated with financial performance (Zahra, 1993).

In fact, a study by Deloitte found that 94 per cent of large companies believe they need to become more agile, adaptable and learn faster (Bersin *et al.*, 2017). To this end, half of them are undergoing organizational transformation. A recent report on *The State of Innovation* found that 83 per cent of large companies feel they are moderately or very at risk of disruption (Anonymous, 2018, p. 10). The WEF found that we are entering the Fourth Industrial Revolution. The WEF says that the pace of change is not expected to be linear. It will be exponential (Schwab, 2016). We are living in an era that has been called "the Innovation Age".

How are companies staffing for the Innovation Age? Surprisingly, the way companies hire workers has not changed much since the First Industrial Revolution. In the early days of mass production, companies sought workers, who followed established procedures, could tolerate a lot of repetition, strict oversight of their work and were respectful of authority (Hill, 1996) This approach made sense at the time when the goal was to evolve from hand-made goods to consistent, mass-manufactured products. However, today, companies need to hire for very different skills. Today companies need workers, who can thrive in uncertainty and who can learn continuously. They need employees with a growth mindset, who possess persistence and grit. They need workers with the ability to synthesize from disparate information sources, and to constantly create the new.

If the reader has any doubt about these changing requirements, consider that until the year 1900, human knowledge used to double every century. Soon, according to IBM, the "Internet of Things" (IOT) will lead to the doubling of knowledge every 11 hours (IBM Global Technology Services, 2006) We take the position that, with knowledge changing this fast, organizations cannot just hire workers for their subject matter knowledge. They need to hire workers, who can create, share and leverage new knowledge at high speed. The authors believe that in the future, teams will not be measured by their production efficiency, but by their innovation output.

The predominant approach to hiring today remains focused on "extrinsic factors" such as job functions and tasks. This approach is the legacy of Frederick W. Taylor, an

Industrial Engineer at Bethlehem Steel, at the beginning of the twentieth century (Smither, 2004). According to *Leadership IQ*, today, 46 per cent of new hires fail in the first 18 months and 89 per cent of the failure is due to intrinsic characteristics[1], not functional skills (Murphy, 2015). Once a short list of candidates is formed with the requisite "extrinsic" qualifications, employers hire for "fit[2]". Lauren A. Rivera of Northwestern University found that hiring for fit often means hiring people like ourselves (Rivera, 2012). Businesses need to drill into the core attitudes and motivations of candidates as they pertain to likely business outcomes, beyond the apparent comfort of "team fit" and "hiring people like us".

So far, we have discussed the accelerating pace of change that is disrupting large companies. We have described that business leaders want their organizations to become more innovative and agile, and that their approach to staffing has not evolved with the pace of external change. This is so, despite the increasing interest in entrepreneurship.

A lot of research has been conducted on the characteristics of entrepreneurs (Stuart and Abetti, 1987, pp. 215-230) (Lee-Ross, 2015, pp. 1094-1112) (Thompson, 2004, pp. 243-248) and on the effect of entrepreneurial styles on venture outcomes (Howell and Avolio, 1993, pp. 891-902) (Stauffer, 2016, pp. 4-26). However, with the exception of some single or small country studies (Lukeš *et al.*, 2017), little research has attempted to identify the characteristics most predictive of business success of intrapreneurs (Vargas-Halabi *et al.*, 2017), employees who innovate within an established organization. Companies typically both invest corporate venture capital in external ventures (founded by entrepreneurs); and develop new products and services within their existing organizations (led by intrapreneurs). So, it is important to study both entrepreneurs and intrapreneurs. Finally, we decided to study both because the similarities and differences between entrepreneurs and intrapreneurs is an important, unanswered research question.

MIT Sloan found that, alongside Corporate Venture and M&A, companies are increasingly realizing that they must transform their internal capabilities for continuous reinvention. Thus, alongside entrepreneurship, intrapreneurial talent is becoming a hot topic (Somers, 2018). There is a large and growing body of innovation management content pertaining to intrapreneurial programs, but research on the subject tends to focus on the firm or country level (Antoncic and Hisrich, 2003), rather than on the individual level. Business publications on intrapreneurship tend to be qualitative, and lack scientific rigor (Govindarajan and Desai, 2013).

Finally, much of the research on innovation talent focuses on creativity (Basadur and Finkbeiner, 1985). The researchers suspected that creativity is but one dimension of innovation talent. Additionally, much of the creativity research (and available tools) focuses on individual "preference" for a process or part of the process, not their ability. Such tools may focus on the individual's preference for one process over another (such as the innovation cycle vs the status quo Cycle) (Stauffer, 2015, pp. 233-248). Otherwise, they may focus on one phase of the innovation process over another phase (such as the "Front End" opportunity, discovery and ideation phase versus the "Back End" implementation and scale phase) (Basadur, 2004, pp. 103-121). Anderson *et al.* concluded that, the major omission of (existing) frameworks is that each one of them mainly centers either on the first step (i.e. idea generation) or on the second step of the innovation process (i.e. idea implementation) Anderson *et al.* (2014). As the most successful innovation teams are responsible for the entire innovation cycle through to scale (Comella-Dorda *et al.*, 2016), this process-based construct appears to the authors to have limited utility.

2. Research methodology – overview

The research presented in this paper follows four phases: a qualitative phase followed by two correlational studies; and finally, a validation research phase. The researchers wanted to answer the questions: "Is innovation talent predictive of business results?" "Which dimensions of innovation talent are most predictive of business results?" And "How are entrepreneurs and intrapreneurs different?" The research compares the attitudes, value and beliefs of innovators[3] to the business results they achieved, and compares innovators to the general population[4].

The qualitative phase was conducted in Silicon Valley, CA, among 50 US- and foreign-born innovators from a broad range of business sectors. Participants in the qualitative phase had achieved at least three significant business successes. Participant successes in all phases of the research were defined by the following business results. The venture:

- achieved profitability;
- achieved sustained growth (20 per cent or more) for five or more years;
- achieved hyper-growth (growing 100 per cent or more for three or more years);
- was profiled by analysts as a leader in its sector;
- continued to operate after the founder's departure;
- achieved consistently high customer satisfaction and repeat sales;
- expanded internationally or globally;
- was acquired; or
- was listed on the public stock market (IPO).

The two cross-sectional (correlational) studies were conducted internationally with innovator and general population samples in the Americas, Europe, Asia and Africa. The final validation study was conducted in the USA.

3. Hypotheses

The research was designed to test the following hypotheses:

H1. Innovators have significantly higher innovation scores than the general population.

H2. Within the population of Innovators, top scorers are associated with a larger number of positive business results than bottom scorers.

H3. Entrepreneurs are similar to intrapreneurs in their innovation profiles.

H4. Innovation scores are not associated with "adverse selection" (characteristics of protected demographic groups, e.g. women, non-whites or adults age 40+).

4. State of the art: measuring innovation skill

The topic of this paper is part of a larger field of inquiry on internal innovation. Internal innovation pertains to firms achieving innovation results with existing employees and resources, in contrast to firms obtaining innovation results through external means such as mergers and acquisitions. The current state of the art in driving internal innovation tends to focus mainly on introducing new innovation processes, such as design thinking and lean start-up or on changing the work environment in an effort to induce more creativity and collaboration.

In both of these worthy approaches, the assumption is that, with an improved process or environment, employees can become more innovative.

Today, the innovation community lacks a precise understanding of the role of innovation skill in driving internal innovation. Consequently, innovation teams are often formed based on members' functional expertise (e.g. education attainment and years of relevant work experience), personality assessments, subjective judgments or apparent creativity.

However, our research shows that: individuals fall on a spectrum of overall innovation skill, they possess a wide array of discrete innovation skills and creativity is only one of the many skills required in innovation. The Innovation Profiler ("the instrument") is a web-based assessment tool designed to detect the full array of specific innovation skills in individuals, skills that are proven to correlate with real-world business results.

The screening and profiling of individuals for hiring and placement purposes has a long history in occupational psychology. While resumes and interviews tend to provide HR decision-makers primarily with information about candidates' functional expertise, there are three other domains that are often used for screening purposes: cognitive ability, personality and situational judgment (Ployhart, 2006).

Cognitive ability: refers to general intelligence. While this type of profiling has its uses, hiring decisions based on cognitive ability fails to capture domain-specific knowledge, creativity, interpersonal skills and other kinds of know-how that may be either implicit or explicit.

Personality: profiling tends to involve Myers–Briggs, Strengthsfinder or Big 5 Personality traits, broadly defined dispositions, such as neuroticism or openness to experience that are known to vary in the population. However, general personality assessments provide limited insight into the innovation skills of individuals, which depend on a wide array of specific and inter-dependent skills.

More recently, the assessment of job candidates by means of situational judgment tests (SJTs) has become more prevalent. SJTs present individuals with realistic work scenarios and ask candidates to choose most/least effective behavioral options for addressing the situation. However, SJTs tend to be related to cognitive ability more than other factors and the technique makes it difficult to separate different constructs assessed in the test (McDaniel *et al.*, 2001).

Finally, with the increasing interest in innovation around the world, there has been a greater focus on creativity in the workplace (Chen and Kaufmann, 2008). While there have been some attempts to define idea generation skills for consumer research and co-creation panels (Rossi, 2011), the topic of creativity remains surprisingly undefined for innovation purposes. Our research found that:

- there are different kinds of creativity (such as artistic skill or creative writing);
- not all aspects of creativity correlate with improved business outcomes from innovation; and
- there are many additional skills beyond creativity that are needed to realize innovations in the real world.

For example, successful innovation also requires skill at idea selection, planning in uncertainty, team formation, pattern recognition, persuasion, the ability to overcome resistance to change, adaptability to changing circumstances, resourcefulness and a host of other skills. These skills, moreover, are specific to implementing innovations, as opposed to implementing established procedures. Consequently, the traditional focus on expertise, personality and a narrow definition of creativity is rife with shortcomings as a means of selecting individuals for innovation and forming innovation teams.

There have also been some attempts to define the phase of the creative process and individuals' preferences for one over another phase. For example, one tool on the market detects "whether a person is drawn to a certain mental activity rather than whether he or she is good at engaging in that activity". As is common in the innovation field, the research behind this tool was validated based on concurrence with previous frameworks (called "concurrent validity"), namely; Myers–Briggs, Kirton and Basadur. This tool has not been validated based on its ability to predict outcomes (called "predictive validity").

With this understanding of the state of the art, the researchers developed a psychographic assessment, the Innovation Profiler, to markedly improve the business outcomes of innovation.

5. Research methodology – detailed discussion

The research presented in this paper follows four phases, a qualitative phase followed by two cross-sectional studies and finally, a validation research phase. The following is a detailed discussion of these phases. The non-technical reader may wish to skip to research findings.

5.1 Phase 1: qualitative research

The initial phase of the instrument's development was exploratory. The main objectives were to gain an understanding of the psychological and behavioral profile of serial, successful entrepreneurs and intrapreneurs, including their motivations, characteristics and competencies, so as to form hypotheses that could be tested in the subsequent research phases (Baum and Locke, 2004, pp. 587-589). Semi-structured interviews were conducted with 50 US- and foreign-born respondents, in fields ranging from technology to consumer goods to financial services and healthcare. The sample was balanced between entrepreneurs and intrapreneurs, in addition to their investors and advisors. A descriptive analysis of the data allowed us to identify patterns that formed the basis for developing a quantitative research instrument (Clark and Watson, 1995, pp. 209-319).

5.2 Phase 2: item development and pilot

The instrument's initial item pool consisted of a combination of existing questions, based on a literature review and new questions that captured the dimensions that emerged from the qualitative research phase. The questionnaire review was done in collaboration between a subject matter expert and quantitative research specialist to assess face validity through a content adequacy assessment[5]. We administered a pilot survey with a first draft of 134 questions to respondents (n = 1,281). The sample was drawn from the Americas, Europe, Asia and Africa. The sample was recruited from a large online panel provider. This pilot laid the groundwork for Phase 3, re-testing the emerging "skill clusters," and testing additional items to ensure the robustness of each skill cluster.

5.3 Phase 3: item refinement and scoring

Our third research phase administered a survey of about 200 questions (including filler[6] items) to an international sample of respondents (n = 845) from the Americas, Europe, Asia and Africa. The sample was recruited from a large online panel provider. It represented the general population of adults with some college education and a quota of entrepreneurs and intrapreneurs, who were screened on the basis of their professional status and activities. In addition, the research instrument contained several self-reported questions on the business results (patents, profitability, sustained growth, hyper-growth, etc.) achieved by the individuals.

The psychographic items (developed with the help of the pilot and collaboration between subject matter and methodological experts) were five-point Likert-type scale questions, asking individuals about the extent to which given statements apply to them personally. The international sample allowed us to retain questions (in English) that were generalizable across cultures.

The questionnaire also included an instrument that assessed individuals' propensity for socially desirable responding (Crowne–Marlowe scale (Ballard, 1992), allowing us to identify and potentially eliminate items that most strongly correlated with social desirability. Correlations with social desirability were very low for all items (Pearson correlation < 0.2).

We analyzed psychographic items in the instrument by means of exploratory factor analysis to determine underlying dimensions and eliminate or re-assign items that loaded only poorly (<0.60) on a given factor. This was further aided by an analysis of different dimensions' internal consistency (reliability).

We used objective variables to identify questions that were most strongly associated with professional roles and achievements. This process involved, firstly, a comparison of the general population with intrapreneurs and entrepreneurs on individual item scores. Secondly, we calculated a business results score and correlated this score with the psychographic items in our research instrument.

This process resulted in a selection of items that could be used for the calculation of innovation role scores (Entrepreneur, Intrapreneur, etc.) and an overall innovator score. The internal consistency (reliability) of individual skill clusters is very high (Cronbach's alpha between 0.85 and 0.95; Table I).

5.4 Phase 4: validation

Our fourth phase entailed a validation and replication of the instrument. It was conducted on an American online sample from the same panel provider ($n = 335$). The data obtained in this phase enabled us to finalize the instrument from the previous phase. As a final validation of our instrument, we tested two main hypotheses that emerged from the previous round of research:

- Entrepreneurs and intrapreneurs have significantly higher innovation scores than the general population.
- Within the population of entrepreneurs and intrapreneurs, top scorers are associated with larger number of business results than bottom scorers.

Our data provide good support for our hypotheses (Tables II and III), based on regression analyses performed on our original (instrument development) and validation samples and controlling for demographic variables available for each sample. Results show that being an Entrepreneur or Intrapreneur has a statistically significant effect on the Innovation score (a normed score on a 100-point scale). Being in this group is associated with Innovation scores that are about 18 and 16 points, respectively, higher than the rest of the sample.

Within the population of enterpreneurs and intrapreneurs, Innovation scores also have a statistically significant association with Business Results (measured on an 11-point scale). For example, moving 80 points from the bottom (10) to the top (90) on the Innovation score is associated with about 2.5 additional business results in the development sample and about 1.5 business results in our validation sample.

Innovation skill cluster	Cronbach's alpha	Sub-cluster	No. of items
Drive	0.904	Ambition	3
		Intensity	2
		Initiative	2
		Persistence	1
Disrupt	0.886	Boundary-breaking	3
		Thriving in uncertainty	3
		Confidence	4
Create	0.945	Growth mindset	6
		Novelty-seeking	4
		Problem-solving	2
		Uncommon connections	3
Connect	0.952	Relating	6
		Persuasion	5
		Social intelligence	3
		Team-building	4
Control	0.864	360° involvement	2
		Financial orientation	5
		Competitiveness	1
Think	0.845	Information capacity	3
		Pattern-recognition	1
		Reflection	2
Deliver	0.888	Adaptability	2
		Resourcefulness	3
		Contextual goal-orientation	2
Give	0.845	Benefitting others	2
		Making the world better	2

Table I. Cronbach's alpha for the eight innovation skill clusters

Independent variable	Model 1: development sample Coefficient	t	Model 2: validation sample Coefficient	t
Constant	53.987***	17.459	47.989**	8.403
Country: Brazil (0 = USA)	−1.434	−0.483		
Country: Singapore (0 = USA)	2.314	0.767		
Country: South Africa (0 = USA)	9.769**	3.274		
Country: UK (0 = USA)	−4.335	−1.757		
Education (0 = no college degree; and 1 = college degree)	4.683*	2.319	−0.560	−0.179
Age[b]	−1.678***	−4.820	−1.319*	−2.326
Gender (0 = male; and 1 = female)	−8.404***	−4.568	2.939	0.826
Ethnicity (0 = white; and 1 = non-white)			9.992*	2.470
Entre-/Intrapreneur (0 = no; and 1 = yes)	17.738***	8.443	16.142***	4.933

Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; $F(8, 836) = 24.66$; $R^2 = 0.19$ (Model 1); $F(5, 252) = 7.270$; $R^2 = 0.13$ (Model 2); [a]100-point score (1-100 range); [b]Ordinal variable (5-year bands)

Table II. Unstandardized coefficients for regression of entrepreneur and intrapreneur status on innovation score[a], controlling for demographic variables

5.5 The final instrument

The final Innovation Profiler tool gathers basic information about the respondent's demographics, along with a core of 108 psychographic questions. It includes items designed to reduce the possibility of faking.

Table III. Unstandardized coefficients for regression of innovation score on business results[a], controlling for demographic variables

Independent variable	Model 1: development sample Coefficient	t	Model 2: validation sample Coefficient	t
Constant	0.806	1.348	1.162*	2.303
Country: Brazil (0 = USA)	−0.406	−1.015		
Country: Singapore (0 = USA)	0.888	1.936		
Country: South Africa (0 = USA)	0.031	0.077		
Country: UK (0 = USA)	0.308	0.707		
Education (0 = no college degree; and 1 = college degree)	0.384	1.189	0.363	0.883
Age[b]	−0.061	−1.245	0.090	1.135
Gender (0 = male; and 1 = female)	−0.339	−1.335	−0.317	−0.703
Ethnicity (0 = white; and 1 = non-white)			0.903	1.513
Innovation score[c]	0.032***	6.115	0.020*	2.463

Notes: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$; $F(8, 252) = 7.286$; $R^2 = 0.19$ (Model 1); $F(5, 84) = 2.470$; $R^2 = 0.13$ (Model 2); [a]11-point score (0-10 range); [b]Ordinal variable (5-year bands); [c]100-point score (1-100 range)

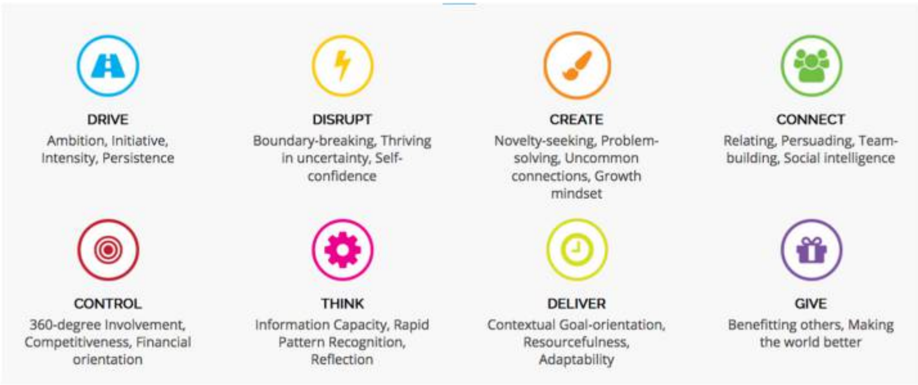
5.5.1 Items for internal survey validation. As with any self-administered assessment, "faking" is always a concern. The Profiler includes 32 filler items. In total, 16 of these items are used for the calculation of an acquiescence adjustment score (AAS). The AAS measures an individual's degree of acquiescence ("yea-saying" or the tendency to agree with statements, regardless of their content), a type of response bias that may occur in surveys (Welkenhuysen-Gybels *et al.*, 2003). The technique adjusts individual innovation scores based on responses to several pairs of decoy questions where agreement with both items can be considered contradictory (e.g. "I like to surround myself with people from diverse backgrounds" vs "I prefer to associate with people who are similar to me [. . .]"), taking into account the known proportion of variance in the overall score that can be explained by the AAS.

5.5.2 Skill clusters. The Innovation Profiler consists of 76 psychographic questions that make up eight skills clusters defined in the two correlation studies: Drive, Disrupt, Create, Connect, Control, Think, Deliver and Give. The clusters are further subdivided into 26 sub-clusters as shown in Figure 1.

5.5.3 Benchmarks. There are two benchmarks against which individuals' and teams' scores can be compared: individuals see their results compared to the general population sample of adults age 21+ with some college ("GenPop"). Using the dashboard, employers can view all individual results compared to GenPop and the Innovator Benchmark. The latter represents the 80th percentile score of entrepreneurs and intrapreneurs, who have achieved at least three significant business results (representing the average number of business results of the top 20 per cent of entrepreneurs and intrapreneurs).

6. Differences between entrepreneurs and intrapreneurs

Our in-going hypotheses was that entrepreneurs and intrapreneurs share similar innovation profiles. If any difference was expected, our assumption was that entrepreneurs faced greater barriers to success and that successful entrepreneurs would require higher levels of innovation skill and would score higher, than intrapreneurs.



Source: Authors

Figure 1.
The eight innovation skill clusters in final instrument

Comparing entrepreneurs and intrapreneurs to the general population, they are certainly more alike than different. However, our findings do not suggest that entrepreneurs possess greater innovation skill than intrapreneurs. In fact, we found that intrapreneurs have higher mean scores on all of the Innovation Skill Clusters, particularly, Connect, Disrupt and Think (Table IV).

7. Adverse selection

Employers are understandably concerned about any instrument that could result in "adverse selection". Adverse selection refers to a bias (whether intentional or unintentional) against hiring protected demographic groups such as minorities, women or workers age 40+. We analyzed the research data from the US respondents by age, gender and ethnic group to investigate this question (Table II, Model 2).

Table IV.
Innovation and cluster scores[a] by entre-/intrapreneurship status[b]

Entre/intrapreneur	Innovation score	Connect	Control	Create	Deli-ver	Dis-rupt	Drive	Give	Think
Entrepreneur[c]									
Mean	66.9	69.6	69.7	72.2	72.1	67.6	72.0	71.3	67.1
SD	11.9	17.0	16.4	16.3	16.2	16.1	16.1	18.8	16.5
N	328	328	328	328	328	328	328	327	328
Intrapreneur[c]									
Mean	68.5	72.4	70.5	73.1	73.7	70.4	73.3	72.3	70.6
Std. Deviation	11.1	15.3	15.6	16.2	15.2	14.5	16.1	17.8	14.4
N	96	96	96	96	96	96	96	96	96
Entrepreneur OR Intrapreneur[c]									
Mean	66.6	69.5	69.0	71.7	71.7	67.0	71.6	71.1	66.8
SD	11.7	16.7	16.2	16.2	16.1	16.0	16.2	18.5	16.2
N	362	362	362	362	362	362	362	361	362

Notes: [a]Scores are normed, where maximum possible score = 100; [b]sample: combined data from development and validation research; [c]groups are not independent: n = 62 are categorized as both entrepreneurs and intrapreneurs

We found that, while there are minor differences in some skill cluster scores by gender, age and ethnicity, there are no statistically significant differences in the overall Innovation score by gender (Table V); there are some differences based on ethnicity, but in favor of non-whites (Table VI); and there are some differences by age, where respondents of 18-34 and 35-54 years of age tend to have slightly higher overall Innovation scores than those age 55+ (Table VII). However, the difference is less than five percentage points. Longitudinal research would be needed to determine whether this is due to an age or cohort effect.

Gender	Innovation score	Connect	Control	Create	Deliver*	Disrupt	Drive	Give
Male								
Mean	55.1	56.7	55.6	58.0	58.6	54.9	58.6	59.7
SD	16.1	18.53	17.2	18.2	18.2	17.5	18.1	19.7
N	166	166	166	166	166	166	166	166
Female								
Mean	54.2	58.3	54.3	58.4	61.7	52.5	58.9	60.4
SD	13.7	15.93	15.7	16.7	15.8	15.5	17.0	17.7
N	346	346	346	346	346	346	346	345
Total								
Mean	54.5	57.8	54.7	58.2	60.7	53.3	58.8	60.2
SD	14.5	16.81	16.2	17.2	16.7	16.2	17.3	18.4
N	512	512	512	512	512	512	512	511

Notes: [a]Scores are normed, where maximum possible score = 100; [b]Sample includes US respondents only; statistical significance is based on ANOVA tests of between-groups differences: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Table V. Innovation and cluster scores[a] by gender[b]

Ethnicity	Innovation score**	Connect*	Control***	Create*	Deliver	Disrupt***	Drive	Give	Think
White									
Mean	53.3	56.6	53.4	57.2	60.0	51.8	58.0	59.8	53.4
SD	14.5	16.64	16.1	17.6	16.9	16.0	17.4	18.4	16.8
N	370	370	370	370	370	370	370	369	370
Non-white									
Mean	58.1	60.9	59.4	61.2	62.7	57.7	61.3	61.8	56.6
SD	14.7	17.24	16.1	15.7	16.2	16.8	17.4	18.6	15.3
N	123	123	123	123	123	123	123	123	123
Total									
Mean	54.5	57.7	54.9	58.2	60.7	53.3	58.8	60.3	54.2
SD	14.7	16.88	16.3	17.2	16.7	16.4	17.4	18.5	16.5
N	493	493	493	493	493	493	493	492	493

Notes: [a]Scores are normed, where maximum possible score = 100; [b]Sample includes US respondents only; statistical significance is based on ANOVA tests of between-groups differences: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Table VI. Innovation and cluster scores[a] by ethnicity[b]

Age	Innovation core*	Connect	Control*	Create	Deliver	Disrupt	Drive*	Give	Think*
18-34									
Mean	56.8	58.9	57.2	60.4	60.9	54.8	60.5	60.8	57.0
SD	14.3	16.3	15.8	17.2	17.2	15.9	17.4	17.9	15.4
N	147	147	147	147	147	147	147	146	147
35-54									
Mean	55.1	59.2	55.7	58.3	61.2	53.0	60.7	59.4	54.6
SD	14.7	17.19	16.0	17.2	15.6	15.2	17.5	18.2	16.9
N	133	133	133	133	133	133	133	133	133
55+									
Mean	52.6	56.3	52.6	56.8	60.2	52.5	56.6	60.2	52.2
SD	14.4	16.89	16.4	17.0	17.1	16.9	17.0	18.8	16.4
N	232	232	232	232	232	232	232	232	232
Total									
Mean	54.5	57.8	54.7	58.2	60.7	53.3	58.8	60.2	54.2
SD	14.5	16.81	16.2	17.2	16.7	16.2	17.3	18.4	16.3
N	512	512	512	512	512	512	512	511	512

Notes: [a]Scores are normed, where maximum possible score = 100; [b]sample includes US respondents only; statistical significance is based on ANOVA tests of between-groups differences: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Table VII.
Innovation and cluster scores[a] by age[b]

8. Research findings

The research findings are that:

- Innovation talent, as measured by the Innovation Profiler, is highly correlated with positive business results.
- Innovators have significantly higher Innovation Profiler scores than the general population.
- Within the population of innovators, top scorers are associated with a larger number of positive business results than bottom scorers.
- Intrapreneurs, while sharing many characteristics with Entrepreneurs, tend to score higher on Innovation Skills.
- There are no statistically significant differences in overall innovation scores by gender. There are some differences based on ethnicity, but in favor of non-whites. There are some differences by age, where the youngest respondents tend to have slightly higher overall innovation scores than the oldest respondents.

9. Research limitations

There has been a long debate in the scientific literature about the faking of responses in job candidate screening, such as personality measures. Research has produced mixed findings in terms of the extent to which different types of validity for those measures is compromised by such distortions (Donovan *et al.*, 2003, pp. 81-206). Most psychographic instruments, (including the Innovation Profiler based on this research), are normative; they provide an inter-individual assessment in which scores are standardized against a population norm, often relying on scaled responses that measure the extent to which individuals consider statements to apply to them personally. Normative instruments may be more susceptible to response bias than *ipsative* (forced choice) measures. These instruments usually ask people to choose two out of four answer options, such as the options that are "most true" and "least true" of them (Bowen *et al.*, 2002, pp. 240-259, cited in Tristan, 2009).

However, it has also been argued that the relative standing of respondents (i.e. their relative scores) in the samples is relatively unaffected by normative instruments (Bowen *et al.*, 2002, pp. 247-256). Moreover, individuals' desire to give the "right answers" should be far greater in staff selection than employee screening. To address bias, we screened out questions that were associated with socially desirable responding when the questionnaire was developed. In addition, the instrument includes a technique (described previously) that allows us to adjust for acquiescence bias. Future versions of the instrument may adopt an *ipsative* methodology to maximize the validity of the instrument, which would be particularly relevant if it is employed in candidate selection/screening rather than employee profiling contexts.

The research was conducted on individuals. Further research is needed on innovation teams and on entire organizations, to determine whether innovation scores are also predictive of team and organizational business results. Furthermore, research is needed on the innovation capabilities of towns, cities and regions to measure whether their ability to thrive in rapid change reflects their populations of innovation talent.

10. Discussion

This study provided significant statistical support for the validity of the Innovation Profiler as a predictor of innovation talent, and of business results from innovation.

The major theoretical implication of this research is that to date, innovation research has tended to focus either on front-end (creativity) skills or the back-end (delivery) skills. The research presented in this paper identified a common set of eight skills that are strongly associated with success in the overall innovation process.

There are several managerial implications of the research, as follows:

- To date, organizations have predominantly hired employees based on their functional abilities and perceived "cultural fit". Companies for which innovation is a corporate priority should also consider the innate innovation talent of candidates in their hiring process.
- In the past, organizations have formed teams primarily based on functional diversity. However, the innovation talent of team-members should also be considered to achieve coverage of the eight innovation skills and an average score in line with the team's innovation objectives.
- In the business sector, there is a tendency to use the terms "innovation" and "creativity" inter-changeably. The research in this paper makes clear that creativity, while essential, is just one component of innovation skill. The seven other skills include, for example, a set of inter-personal behaviors represented in the Connect skill cluster, as well as financial orientation, part of Control.
- Organizations today are keen to drive a "culture of innovation," yet, the exact components of such a culture remains vague. The research in this paper provides terminology (the eight skill clusters) that organizations can use to clarify the behaviors they wish to support in their workforce to drive a culture of innovation.

Questions for further research include:

(1) Innovation teams
- How do teams formed with Innovation Profiler data perform compared to teams formed without such innovation talent data?
  - What is the ideal composition of innovation teams with respect to the innovation scores of the members?
  - What is the role of the team leader's innovation profile versus profiles of the rest of the team?
  - How much weight should the leader be given in calculating team scores?

(2) Innovation training
- To what extent can innovation skills, behaviors or characteristics be developed, and through what kinds of experiences or training?
  - Are some people more trainable than others?
  - Can innovation scores explain a person's trainability?

(3) Innovation culture
- To what extent can the 8 Innovation Profiler skills be used to design an effective culture of innovation?
  - What is the relative impact of innovation culture or process vs employee innovation skill?

(4) Innovation talent and the growth of firms
- Is innovation talent more associated with certain business results than with other results?
- Are innovation scores associated with success at certain kinds of innovation, e.g. disruptive innovation vs incremental innovation?
- What is the ideal ratio of innovation talent in an organization to maximize growth (e.g. How many innovators do you need, and of what types)?
  - Are organizations with more innovation talent more successful at innovation?
  - Are organizations with more innovation talent faster-growing?

This study provided significant statistical support for the validity of the Innovation Profiler as a predictor of innovation talent and of business results from innovation. The authors hope that, by identifying the innovation characteristics that correlate with business outcomes, they have contributed to the field. Companies can use this knowledge to accelerate their organizational transformation.

Notes

1. "Intrinsic characteristics" refers to attitudes and values.
2. Hiring for "fit" refers to the practice of hiring people who share similar backgrounds and characteristics of the existing workforce and leadership.
3. Throughout this paper, the term "innovators" refers to our samples of entrepreneurs and intrapreneurs.
4. In the research, the "general population" was defined as adults age 21 and older with some college.

5. According to Duy Tan University, "Several content assessment methods have been described in the research methods literature (Nunnally, 1978). One common method requires respondents to categorize or sort items based on their similarity to construct definitions. This can be conducted using experts in a content domain".
6. The term "Filler items" refers to items that are not scored, but are used to obscure the purpose of the research instrument.

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