Using Bayesian Analysis to Refine the Measurement of the Innovative Capacities of Engineers

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***Abstract*— In this research-to-practice paper we provide the context for our research and review our process for conducting our engineering innovativeness factor analysis using Bayesian statistical approaches rather than using the traditional principal components analysis (PCA). Our purpose in discussing this analysis approach is to demonstrate that we found the Bayesian analysis approach to be a superior way to refine factors and reduce survey items when developing our instrument for assessment of engineering innovativeness characteristics.**

Keywords— innovation, engineering, innovativeness

I. Introduction

Developing science and engineering skills are regarded as a critical economic strategy across the world [1]. Over the last 30 years global competition and innovation in products and services has selected new winners and losers [2] and the leading role that the U.S. has had in technological innovation is disappearing [3, 4]. Training engineers to become more innovative is a national priority, says C.D. Mote, President of the National Academy of Engineering. He adds that "Innovation capability should be a new indicator of US workforce readiness to compete successfully in the global economy".

Every engineer needs to understand their innovative capacities, to assess their need to exercise those capacities and to grow their innovative capacities over time relative to the needs of the communities they serve [5-7]. Based on our prior seven years of work: our research question was:[8].

"*What is the best method for defining the critical engineering innovativeness factors in our engineering innovativeness measurement instrument?"*

II. Foundation Studies

While there is prior research on innovativeness characteristics, almost none of the research focused on engineers [9-11]. Instead, research on innovativeness for engineers tends to focus on whether engineers are creative [12, 13], good problem solvers [10], and/or whether they possess design skills [11] and entrepreneurial skills [14-17]. Both the engineering research community and global societies link innovativeness with creativity and entrepreneurial behavior but do not use a clear definition of innovative engineering behavior [16, 18].

Our innovativeness research started with interviews with over 50 peer-identified master/expert engineering innovators. We analyzed their views about innovative behaviors using a grounded theory approach [19, 20]. Results of that initial qualitative work were combined with results from a focus group of engineering experts and results from a three-phase Delphi study on engineering innovativeness involving 150 engineers nominated for their innovation achievements [21].

Fig. 1 displays the 20 engineering innovativeness characteristics derived from our grounded theory, focus group and Delphi studies [21, 22].

Engineering Innovativeness Characteristics
Alternatives Seeker, Analytical, Associative Thinker, Challenger, Collaborator, Communicator, Creative, Curious, Developer Experimenter, Implementer, Knowledgeable, Leader, Market/Business Savvy, Passionate, Persistent, Risk Taker, Self-Reliant, User Empathetic

Fig. 1: Combined Grounded Theory and Delphi Studies: Characteristics [22]

III. RESEARCH METHODS

A. Instrument Development

Using our 20 item set of three-ways-verified engineering innovativeness characteristics, we found 27 validated instruments that had constructs that measured one of more of our characteristics in three major categories: entrepreneurship,

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information processing, and motivation/self-efficacy. In total, 84 constructs from these 27 instruments were selected as related to one or more of the 20 characteristics.

Next, we submitted a 200 item draft instrument to a Face Validity test using 25 experienced engineers and ranked each of the 10 items per characteristic as to whether the item was consistent with a characteristic definition. As a result, we ended up with an instrument with 105 items for the 20 characteristics. Item analysis was our next validation step. and 200+ students from 7 engineering schools and 200+ professional engineers from 7 companies completed a draft survey. Using Chronbach Alpha scores of the 20 characteristic item groups we eliminated 8 items in the draft measurement survey leaving 97 items [23].

B. Factor Analysis Data Collection

A Qualtrics web-based survey was next used to collect factor data anonymously. Innovation or innovativeness was not mentioned in the instrument or during its administration. The survey was entitled, ABAKAS self-assessment, (ABAKAS = Assessment of Behaviors, Attitudes, Knowledge, Attributes, and Skills***).*** A red herring question item was randomly presented in the survey and eliminated about 3% of professional respondents and 5% of student respondents. All partial surveys were discarded. Any respondent with a standard response deviation less than 0.15 was removed as were all survey responses which were done in less than one minute. Average survey completion time was 17 minutes.

Survey data for our factor analysis work was collected from professional engineers in two waves and from student engineers in a single wave. The initial cleaned corporate sample from 8 companies was 1086 professional engineer participants. A second corporate sample was 1,000+ engineers from a single company which employs over 8,000 professional engineers. Cleaned student data from engineering students was collected from 943 students from 6 schools.

C. Bayesian Factor Analysis Approach

We conducted Bayesian factor analysis using BayesiaLab, a software environment for Bayesian belief network (BBN) modeling from Bayesia [24]. BayesiaLab implements BBN-based factor analysis, called Probabilistic Latent Factor Induction (PLFI). PLFI is a machine-learning-derived method defined by a proprietary algorithm from Bayesia [24] rather than by an explicit mathematical model. It is contrasted with traditional PCA methods by Conrady & Jouffe [25]. Although proven to work well in practice, it should not be confused with Bayesian variants of traditional multivariate statistical factor analysis [26].

The BayesiaLab PLFI method is based in Information Theory, more strongly than in Multivariate Statistical Analysis. As such, its underpinnings are derived in the Information Theory and Machine Learning (Computational Learning Theory) literature. The pathway through that literature to BayesiaLab merges ideas from Statistics for categorical data analysis [27] with those from Information Theory [28-30] and Computer Science and Machine Learning [31-34].

The advantages of the PLFI approach over PCA stem from the fact that PLFI addresses categorical variables directly rather than by transforming them into continuous variables. Also, PLFI is based upon the mathematical modeling relationships of the variables that may either be data-derived, theory-derived or any combination of data and theory. This gives it greater flexibility and broader applicability than PCA. A final distinction is that the resulting factors from PLFI are not uncorrelated (orthogonal) as are those from PCA and therefore lend themselves to further association modeling.

IV. FINDINGS

We then conducted PCA factor analysis and Bayesian factor analysis on our professional engineer data. We discovered that Bayesian factoring explained over 70% of the variability in our data with 24 factors. However, PCA analysis with 20 factors and an Eigen value of 0.94 could explain only 60% of the variability in the factor data.

During our factor analysis work we found that using the professional factors with the student data gave us a better solution than using student data derived factors. Therefore, we decided a separate student measurement instrument was not needed. We also found that the Bayesian approach provided better predictive results because of non-liner relationships between some of our variables. We tested this hypothesis and discovered several non-liner item variable relationships as shown in an example in Figure 3.

Another significant result of our factoring was the regrouping of items in our instrument against factors with different item groupings than our survey construction work. In table 2 a sample of the item acronyms (DEV-3, DEV-1) in each factor description map back to our constructed 20 characteristics grouping of items. As shown in Table 2 Items in our ‘new’ Bayesian derived factors are grouped differently than in our initial survey instrument item mapping.

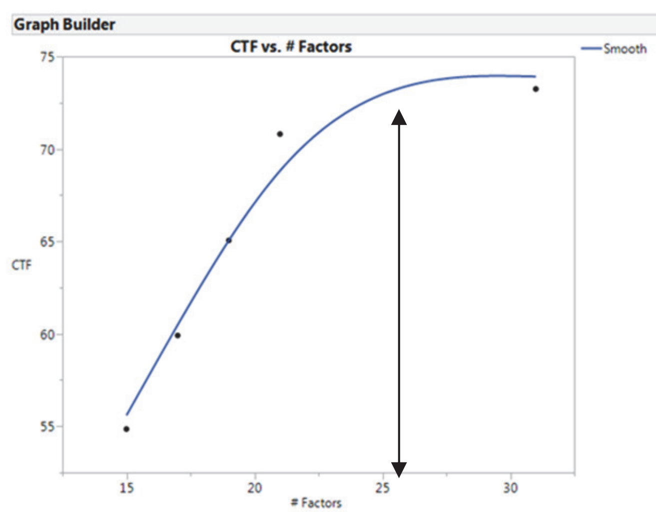

Fig. 2: Bayesian Contingency Table Fit vs. # Factors

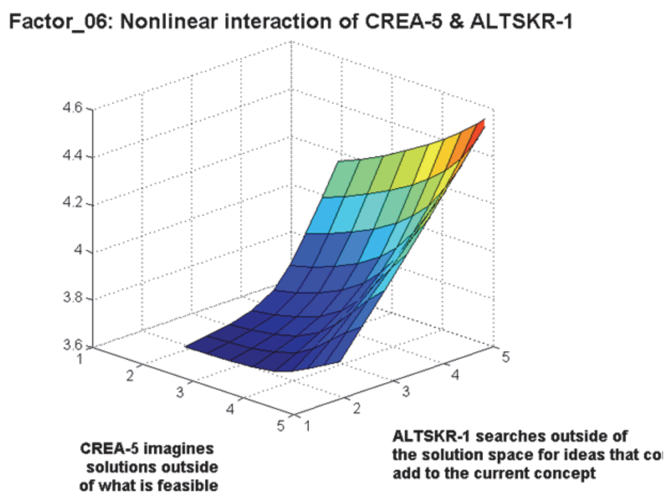

Fig. 3: Non-linear item relationship example.

To finalize item reduction, we conducted a Markov Blanket Analysis. Markov Blanket analysis is used as an effective means of performing variable selection when predicting a "target" variable [33]. In our case, the target was a factor, and the candidate predictors are the items. The Markov blanket of a target variable is the minimal set of variables that renders the target independent of all other variables outside that minimal set. The minimal set is called "the Markov blanket of the target".

Setting each factor as a target and the items as the other variables, we applied Markov blanket analysis separately for each factor to find the smallest set of items that sufficiently explains the information in the factor. The implication is that once we know a respondent's answers for the items comprising a factor's Markov blanket, none of the respondent's other answers for any item outside of this blanket adds any new information to our knowledge of the factor. So, we can eliminate these outside items as either being redundant with respect to those already in the Markov blanket.

Of the items remaining in the Markov blanket of a factor, some contribute strongly in capturing the information of the factor and others, possibly, much less so. Using mutual information, you can quantify the strength of this contribution and drop items with weaker contributions. Mutual information is an information theoretic metric that measures how much information is shared between two variables [31-34]. Mathematically, it has connections to traditional statistical tests based upon likelihood ratios for testing independence amongst categorical variables. As shown in Table 1, BayesiaLab reports the mutual information metric for each factor and each item contributing to the factor definition.

As a result of the factor analysis and a Markov Blanket analysis of the items we were able to reduce the draft instrument's 97 total items to 81 items for 24 factors. Self-Reliant, was eliminated as a factor. The five new factors were titled: Overcomes, Empathizes. Empowers, Plans and Solves-Problems. All new factors are listed in Table 2.

TABLE I. SAMPLE RESULTS OF BAYESIAN FACTORING

Factor	CTF	Survey Item	Mutual Infor mation
[Factor_ 2] Devel ops	69.4%	DEV-3 -turns ideas into something tangible	0.6108
		DEV-1 -brings ideas to life by demonstrating them	0.5445
		EXPR-5 -prefers to take action by testing things out	0.4223
		DEV-5 -turns abstract ideas into concrete products	0.4125
		COMM-4 -expresses a clear sense of a designs purpose	0.2685
[Factor_ 5] Know ledge able	73.9%	KNOW-1 -has both a breadth and depth of knowledge about the problem and solution	0.5877
		KNOW 2-is technically excellent in his/her field	0.5411
		KNOW-3 -is very knowledgeable about the product	0.4479
		SELFR- -trusts his/her own ability to size up a problem correctly	0.4091
		SELFR-4 -trusts his/her intuition when solving problems	0.3463

TABLE II. NEW ENGINEERING INNOVATIVENESS FACTORS

Factor	Factor Definition
Overcomes:	Prevails despite opposition.
Collaborates:	Incorporates ideas and strategies of others.
velops:	Creates something tangible.
Empowers:	Builds an environment that enables others.
Experiments:	Learns through testing and observation.
Knowledgeable:	Possesses relevant expertise, skills, and/or abilities.
Imagines:	Considers unfamiliar or untested ideas.
Associates:	Connects ideas from different domains.
Identifies Opportunities:	Recognizes unmet needs.
Visionary	Creates a compelling future vision.
Challenges	Contests the current way of doing things.
Analyzes:	Breaks down complex things into simpler parts.
Explores:	Gathers information strategically.
Questions:	Reluctant to accept conventional thinking.
Takes Risk:	Accepts and learns from failure.
Plans Ahead:	Prepares for the future.
Communicates	Shares information clearly.
Curious:	Is eager to learn.
Market Savvy	Understands business value.
Seeks Alternatives:	Looks for a variety of options.
Empathizes:	Understands what is important to others.
Persists	Keeps going when others might give up.
Passionate:	Shows enthusiasm for their work.
Implements	Moves projects forward to completion.

V. CONCLUSIONS

We concluded that the Bayesian approach provided us with better factor solutions and keener insights into the construction of our instrument not so readily available from our PCA analyses.

VI. FURTHER RESEARCH

We are researching pre/post or comparison applications of the new factors for interventions, experience, or demographics.

VII. Limitations

Our benchmark factor samples are skewed towards schools/companies located the Midwest and manufacturing companies.

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References

[1] T. Kelley and J. Littman, *The Art of Innovation*. New York: Doubleday, 2001.

[2] T. L. Friedman, *The World is Flat: A Brief History of the Twenty-First Century*. New York: Farrar, Straus & Giroux, 2005.

[3] K. Jablokow, S. Purzer, D. Ferguson, and M. Ohland, "Collaborative Research: Identifying and Assessing Key Factors of Engineering Innovativeness," 2012.

[4] G. Locke. (2010). *Remarks at Kauffman Foundation States of Entrepreneurism Address*. Available: http://www.commerce.gov/NewsRoom/SecretarySpeeches/PROD01_008812

[5] National Academy of Engineering, *Educating the engineer of 2020: adapting engineering education to the new century*. Washington, DC: National Academies Press, 2005.

[6] National Academy of Sciences, National Academy of Engineering, and Institute of Medicine, *Rising Above The Gathering Storm: Energizing and Employing America for A Brighter Economic Future*. Washington, D.C.: National Academy of Sciences, 2007.

[7] Ferguson Daniel *et al.*, "Do Engineering Creativity/innovation Courses Impact Engineering Innovativeness?," in *Frontiers in Education*, Indianapolis, IN, 2017: IEEE.

[8] D. Ferguson, J. Cawthorne, B. Ahn, and M. Ohland, "Engineering Innovativeness," *Journal of Engineering Entrepreneurship,* vol. 4, no. 1, pp. 1-16, 2013.

[9] Ragusa G., "Engineering creativity and propensity for innovative thinking in undergraduate and graduate students," in *American Society for Engineering Education*, Vancover B.C., Canada, 2011: American Society for Engineering Education.

[10] J. Welch, "Problem-solving skills utilized by graduating engineers from a baccalaureate program to solve problems," Ed.D., Pepperdine University, United States -- California, 2009.

[11] C. Bollfrass, "Designing innovative engineers," *Hart's E&P* vol. 81, no. 10, p. 94, 2008.

[12] T. Amabile, "Creativity and Innovation in Organizations," Harvard Business School, Boston, MA1996.

[13] N. Genco, "An Experimental Investigation of the Innovation Capabilities of Engineering Students," in *American Society of Engineering Education*, Austin, TX, 2010.

[14] M. Ames and M. A. Runco, "Predicting Entrepreneurship From Ideation and Divergent Thinking," *Creativity & Innovation Management,* Article vol. 14, pp. 311-315, 2005.

[15] T. J. Kriewall and K. Mekemson, "Instilling the Entrerpreneurial Mindset into Engineering Undergraduates," *The Journal of Engineering Entrepreneurship,* vol. 1, no. 1, pp. 5-19, 2010.

[16] A. Bement, D. D. Dutta, and L. Patil, "Educate to Innovate: Factors That Influence Innovation: Based on Input from Innovators and Stakeholders," National Academy of Engineering and the University of Illinois at Urbana-Champaign, Washington, D.C.2015.

[17] C. Fry, "Bringing innovation and the entrepreneurial mindset (Back) into engineering: The KEEN Innovators Program," *ASEE Annual Conference and Exposition, Conference Proceedings,* vol. ISSU, no. PAGE, 2010.

[18] Ferguson Daniel M. and Ohland Matthew W., "What is Engineering Innovativeness?," *International Journal of Engineering Education,* vol. 28, no. 2, 2011.

[19] J. S. Brown, A. Collins, and S. Newman, "Cognitive apprenticeship: Teaching the crafts of reading, writing, and mathematics," Hillsdale, NJ: : Lawrence Erlbaum Associates., 1989, pp. 453-494.

[20] J. S. Brown, A. Collins, and P. Duguid, "Situated cognition and the culture of learning," *Educational researcher,* vol. 18, no. 1, pp. 32-42, 1989.

[21] Ferguson D, Purzer S, Ohland M, Jablokow K, and Menold J, "Using a Delphi Study to Confirm the Characteristics of an Engineering Innovator," presented at the Annual Conference 2015: American Society of Engineering Education, Seattle, WA 2015.

[22] D. Ferguson, "How Engineering Innovators Characterize Engineering Innovativeness: A Qualitative Study," PhD., Engineering Education, Purdue, West Lafayette. IN, UMI 3613121, 2013.

[23] Menold Jessica, Jablokow Kathryn, Ferguson Daniel M , Ohland Matthew W, and S. Purzer, "The Characteristics of Engineering Innovativeness: A Cognitive Mapping and Review of Instruments," *International Journal of Engineering Education,* vol. 32, no. 1, pp. 64-83, 2016.

[24] Bayesia. (2018). *Bayesia S.A.S. Corporate Homepage*. Available: www.bayesia.com

[25] S. Conrady and L. Jouffe, "Probabilistic Latent Factor Induction with BayesiaLab: A side-by-side comparison with traditional factor analysis," B. L. whitepaper, Ed., ed, 2014.

[26] E. C. Merkle and Wang Ting, "Bayesian latent variable models for the analysis of experimental psychology data " *Psychon Bull Rev,* vol. 25, pp. 256-270, 2018.

[27] A. Agresti, *Categorical Data Analysis*. Wiley, 2012.

[28] C. Shannon, "A Mathematical Theory of Communication," *The Bell System Technical Journal,* vol. 27, no. 3,4, pp. 379-423,623-656,, 1948.

[29] S. Kullback, *Information Theory and Statistics*. Dover, 1959.

[30] T. M. Cover and Thomas.J. A, "Entropy, relative entropy and mutual information," *Elements of Information Theory,* pp. 12-49, 1991.

[31] J. Pearl, "Fusion, Propagation, and Structuring in Belief Networks," *Artificial Intelligence,* 1985.

[32] J. Pearl, *Probabilistic reasoning in intelligent systems: networks of plausible inference*. Morgan Kaufmann, 1988.

[33] J. Suzuki, "Learning Bayesian belief networks based on the minimum description length principle: basic properties," *IEICE transactions on Fundamentals,* vol. E82-A, no. 9, 1999.

[34] D. Koller and N. Friedman, *Probabilistic Graphical Models: Principles and Applications*. MIT Press, 2009.