Inventive behaviour of farm scientists: a structural equation model

Balusu Gopichand[1,*], V. L. Madhuprasad[2] and G. Chaitra[3]

[1]National Institute of Agricultural Extension Management, Rajendranagar, Hyderabad 500 030, India
[2]Farmers' Training Institute, University of Agricultural Sciences, Bengaluru 560 065, India
[3]Agricultural Extension, Diploma Agriculture College, Kathalagere 577 219, India

The farm scientists working in State Agricultural Universities (SAUs), strive to solve the problems of farmers from different agro-climatic zones of the country. Inventions of them are crucial for change. Therefore, the present study explores different dimensions that can be included to measure the inventive behaviour of farm scientists, especially in SAUs, as reflected in the model developed. Moreover, this study illustrates how the dimensions identified have implications for the inventive behaviour of farm scientists that helps to overcome the lacuna in this competitive, innovative research environment.

Keywords: Agricultural universities, farm scientists, factor analysis, inventive behaviour, scientific temper.

THE history of Indian agricultural scientists' inventions has helped to resolve significant scientific research questions. Even though India has increased its investment in agricultural research and extension from 0.4% of agricultural GDP in 1981 to 0.96% in 2011, the research quality has been consistently poor. This is mainly due to the inadequate institutional capacity of agricultural higher education to adapt and remain relevant[1].

The contributions of agricultural scientists to research differ with their degree of involvement in research, academics, administration and extension, the four major activities especially in SAUs. To establish empirical evidences, many behavioural concepts of agricultural scientists have been studied in social sciences in general or agricultural extension in particular. In the present study, the inventive behaviour of farm scientists was analysed in terms of the actions of individual scientists during the creative thinking process. It falls in the recognition and research stages of the innovation development process. Generally, this is considered as a dormant stage to the outside world, but many changes occur in his/her behaviour. Inventive behaviour is when a farm scientist aims to introduce or apply his/her novel ideas in research to solve problems identified in the farming system. It strives to improve the efficiency of the public agricultural research system.

The inventions and innovations are used alternatively in many forums, even they differ conceptually. However, the major mandate of scientists is to invent rather than innovate. The major characteristics of any invention is its novelty and being revolutionary. It is the process by which new ideas or practices are created or developed. Thus, invention is the materialization of ideas generated by creativity. The innovation development process accommodates invention in the first two stages, i.e. research and development (R&D).

The study by Erickson[2] on inventive behaviour was restricted to patent protection. It highlighted the importance of venture capital and financial aspects, the governmental R&D policy, defence spending, antitrust regulation, entrepreneurial culture, etc. that will encourage inventors to behave differently. In addition to the above studied dimensions, the scientists should understand the existing situations and visualize or conceptualize the novel solutions that generates inventions. This is more emphasized with the organizations targeting maximum successful outcomes with the rapid globalization.

Inventive behaviour as a formative construct

The present study conceptualized the inventive behaviour as a formative second-order construct. This shows that dimensions will lead to inventive behaviour construct but not vice-versa. Further, small fluctuations in the dimensions directly affected inventive behaviour. However, the convergence cannot be ascertained. Thus, less or no consideration of any dimensions could affect the inventive behaviour construct. It was also assumed that variates do not exist between dimensions, i.e. a decrease in the creative potential might not simultaneously decrease the risk-bearing ability. However, nomenclature of the dimensions of inventive behaviour should have potential difference. Therefore, inventive behaviour is operationally defined as an individual farm scientist's behaviour that aims to introduce or apply novel ideas in research to solve problems identified in the farming system. In this study, a scale was developed to measure the inventive behaviour of farm scientists in SAUs.

Selection of dimensions

The inventive behaviour concept was found to be reasonably apt as a multi-dimensional scale rather than a uni-dimensional

*For correspondence. (e-mail: gopichandbalusu@gmail.com)

scale, as many factors were involved in such behaviour patterns. A review of the literature was done on the different activities of scientists performed or involved in invention process. The dimensions mental alertness, creativity, conceptual skills, financial management, resource utilization, decision-making, achievement motivation, organizational climate, information utilization and leadership were identified as measurable and valid for the construct. Further, publications ranging from invention to innovation, scientists' tastes, inventive thinking skills, inventive problem solving, thinking outside the box, understanding scientists, etc. were examined for dimension selection and their underlying items. After carefully consulting with experts and reviewing relevant literature, six dimensions were selected for consideration. These dimensions include creative potential, inventive-proneness, technical competency, risk-bearing, planning and decision-making ability. The dimensions were further operationalized to establish clear measurement benchmarks to frame the corresponding statements or items.

Research design and instrumentation

An ex-post facto research design was employed to conduct this study. Robinson[3] defined ex-post facto research design as any systematic enquiry into which the variables have not been directly manipulated because they have already occurred, or are inherently not manipulated. Keeping this in view, the adaptability of the proposed design to the type of study, variables under consideration and size of the sample were evaluated. After an extensive review of the literature and discussions with experts from related areas, 115 statements in 6 dimensions were selected. These were formulated to measure inventive behaviour according to 14 criteria summarized by Edwards[4]. Further, to test the validity and reliability of scale relevancy, a pre-test conducted by following the summated rating scale method suggested by Likert[5] and Edwards[4].

Subjects

Data were collected in four phases. In the first phase, experts from the Extension Education, Agricultural Extension and Social Sciences of Indian Council of Agricultural Research (ICAR) institutions, SAUs and other relevant institutions were included to determine content validity and relevancy of inventive behaviour statements. A total of 115 statements/ items to determine were sent to 140 experts on a five-point continuum, viz. most relevant (MR) to not relevant (NR), with a score of 5 to 1. A total of 60 experts returned duly filled questionnaires.

The second phase intended to test the reliability and statistical validity of the items for Likert-scale developed in the five-point continuum and the sample selected were the farm scientists from the Bidhan Chandra Krishi Viswavidyalaya (BCKV), West Bengal. BCKV was selected due to an average ranking (33.40) of five years (2016–20), close to the national average of ICAR rankings (34.34). The questionnaire was sent to 100 scientists handling research projects through e-mail. The respondents were requested to indicate their degree of agreement or disagreement against each statement on a five-point continuum. Out of 100 respondents, 36 responded.

In the third phase, a pretested questionnaire was sent to all farm scientists of SAUs in India, excluding Karnataka and BCKV, to identify factors through exploratory factor analysis (EFA). The questionnaire was administered to 1247 farm scientists for EFA. However, 497 had responded. The sample size satisfied the item-to-sample ratio (1 : 5) for 48 items. For confirmatory factor analysis (CFA) and structural equation model (SEM), all scientists working in the Directorates of Research with a minimum of five years of experience in SAUs of Karnataka were considered as respondents. One hundred and ninety-nine scientists responded to the pretested questionnaire.

Statistical analysis

Relevancy percentage, weightage for relevancy of items and mean relevancy score, split-half reliability and statistical validity were the methods used in statistical analysis for relevancy, reliability and validity. Furthermore, EFA (principal axis factoring with varimax rotation), CFA and SEM were employed for validity and reliability.

Reliability

(i) Half test reliability formula:

$$r_{1/2} = \frac{(N(\sum XY) - (\sum X)(\sum Y))}{\sqrt{(N\sum X^2 - (\sum[\![X)]\!]^2) - (N\sum Y^2 - (\sum[\![Y)]\!]^2)}},$$

where $\sum X$ is the sum of scores of the odd number items, $\sum Y$ the sum of scores of even number items, $\sum X^2$ the sum of squares of odd number items and $\sum Y^2$ is the sum of squares of even number items.

(ii) Whole test reliability formula:

$$r_{11} = \frac{2r_{1/2}}{1 + r_{1/2}},$$

where $r_{1/2}$ is the half test reliability.

Statistical validity

Statistical/intrinsic validity $V = (\sqrt{r_{11}}/2)$.

Through the implementation of EFA, a structure was developed based on the underlying construct being analysed.

It is a technique applicable for variable reduction which identifies the number of latent constructs and underlying factor structure from a set of variables[6]. This is followed by CFA, a multivariate statistical procedure used to test the representation of variables to the number of constructs. It confirms the measurement model. SEM is a set of techniques to measure and analyse the relationships between observed and latent variables. It is more powerful than regression analysis. It examines linear causal relationships among variables, while accounting for measurement errors. It also provides a flexible framework for developing and analysing the complex relationships among multiple variables. This allows researchers to test the validity of a theory using empirical models.

Results

The results of the present study include the relevancy test, item analysis, reliability, validity and factor analysis (EFA, CFA and SEM). Fifty-seven statements were retained after applying a relevancy percentage (RP) of 80% and above, and a mean relevancy score (MRS) of 3.75 and above[7]. The retained items were subjected to a *t*-test. Forty-eight items were selected considering *t* values equal to or greater than 1.75 (ref. 4). Further, the *r*-value of Pearson's correlation coefficient or half test reliability was 0.79. Consequently, the reliability coefficient of the entire test was 0.88 (the Spearman–Brown prophecy), resulted in higher reliability of the scale. The statistical validity was found to be 0.93 at a 1% level of probability. The expert's judgement at the relevancy test satisfied the content or construct validity of the scale. Thus, the developed scale was suitable for analysing the inventive behaviour of farm scientists. Therefore, the final scale consists of 48 statements for measuring the inventive behaviour of farm scientists.

Factor analysis to develop inventive behaviour model for farm scientists

There were no missing data as they were collected using Google Forms. The existence of outliers is a common phenomenon. The resulting sample contained 482 out of 497 responses after removing multivariate outliers identified using the Mahalanobis test ($P < 0.002$).

Cronbach's alpha was used to measure the correlation between items within a dimension. The Cronbach's alpha values for creative potential, inventive proneness, risk-bearing ability, technical competency, risk-bearing ability, planning ability and decision-making were 0.75, 0.051, 0.768, 0.544, 0.768, 0.482 and 0.777 respectively. With the removal of one item in technical competency, a significant Cronbach's alpha value (>0.70) was obtained. However, the inventive proneness and planning ability were not considered for further analysis due to their low Cronbach's alpha values. Further, the sample underwent the Mahalanobis test, and 473 responses were retained. The skewness and kurtosis values showed no significant distraction to the normality of the data and confirmed multivariate normality. The initial reliability and validity tested data were subjected to EFA to identify the latent factor structure using principal component analysis and varimax rotation.

In the process of extracting factors, the first factor tries to place maximum possible common variance. Subsequent factors are in turn intended to account for the maximum amount of the remaining common variance until no common variance remains. The EFA-estimated Kaiser–Meyer–Olkin (KMO) value of 0.743 was above the minimum level of 0.5, and a significant Bartlett's chi-square ($\chi^2 = 845.546$; $P < 0.001$) indicated that the sample size chosen for this study was adequate[6]. The inter-item correlation was also fit for the test. The items with commonalities (>0.50), total variance (>0.60 for social science) and rotated pattern matrix structure were according to construct. The selected items were repeatedly tested and the final suitable results were presented (Table 1).

The model fit summary included different parameters, and all the regression weights of maximum likelihood estimates of CFA were significant; therefore, the items were retained. The estimates showed that all the variables affected the items positively. The standardized regression weights were λ values used to calculate average variance extracted (AVE) and composite reliability (CR).

The covariance between the errors or extraneous variables was established by considering the modification indices in the CFA model. A relationship was established with the error variables within the dimension based on the modification indices obtained, and the CFA test was run for the standard regression weights (λ) again.

$$\mathrm{CR} = \frac{\sum \lambda^2}{(\sum \lambda)^2 + (\sum \delta)},$$

where λ represents the standardized factor loadings and δ represents the error variance $\delta = 1 - \lambda$.

$$\mathrm{AVE} = \sum \lambda.$$

The standardized regression weights λ depict the effect of dimension on its items. In case of AVE, as observed in Table 2, λ is less than 0.5. The significant value of λ confirms the convergent validity of the construct, even though CR is greater than 0.6 (ref. 8).

The sample for SEM analysis consists of 194 farm scientists after excluding outliers from 199 respondents. The skewness values greater than 2.5 and less than 0.40 are problematic; such values were not found in this study. Further, the CR value of multivariate kurtosis was similar to CFA (3.43), showing acceptable normality of the sample.

The model chi-square value/degrees of freedom (CMIN/Df) of 1.75 indicated that the data did not deviate from

Table 1. Factor rotation and variance of exploratory factor analysis

							Total variance explained								
			Rotated component matrix[b]				Initial eigenvalues			Extraction sums of squared loadings[c]			Rotation sums of squared loadings		
Latent factor	Items	Communality[a]	1	2	3	4	T	POV	CP	T	POV	CP	T	POV	CP
Creative potential	CP_2	0.49				0.66	4.01	28.62	28.62	04.01	28.62	28.62	02.29	16.39	16.39
	CP_3	0.68				0.77	1.38	09.88	38.50						
	CP_4	0.52				0.71	1.36	09.72	48.22						
Technical competency	TC_3	0.57	0.61				1.22	08.72	56.94	01.38	09.88	38.50	02.06	14.72	31.11
	TC_4	0.51	0.68				0.86	06.11	63.06						
	TC_5	0.58	0.69				0.78	05.57	68.63						
	TC_6	0.53	0.61				0.70	05.04	73.67						
	TC_7	0.59	0.65				0.66	04.69	78.36						
Risk-bearing	RB_4	0.64		0.75			0.62	04.42	82.77	01.36	09.72	48.22	01.81	12.94	44.05
	RB_5	0.62		0.72			0.60	04.28	87.05						
	RB_6	0.59		0.73			0.55	03.90	90.96						
Decision-making	DM_5	0.56			0.71		0.48	03.43	94.39	01.22	08.72	56.94	01.81	12.90	58.01
	DM_6	0.64			0.79		0.42	03.02	97.42						
	DM_7	0.48			0.51		0.36	02.58	100						

[a]Initial communality = 1.

[b]Rotation method: Varimax with Kaiser normalization.

[c]Extraction method: Principal component analysis.

Note: T, Total; POV, Percentage of variance; CP, Cumulative percentage.

Table 2. Normality and variance of confirmatory factor analysis (CFA) and structural equation model (SEM)

		CFA						SEM			
OEV[a] (label)		Residual covariance						Residual covariance			
EFA	CFA	Maximum	Minimum	UEV[b]	λ[c]	AVE[d]	CR[e]	Maximum	Minimum	SMC[f]	UEV[b]
CP_2	CP_1	0.040	0.003	e1	0.43	0.37	0.70	0.012	0.002	0.125	e7
CP_3	CP_2	0.050	0.001	e2	0.87			0.030	0.001	0.345	e8
CP_4	CP_3	0.030	0.002	e3	0.42			0.038	0.001	0.089	e9
TC_3	TC_1	0.050	0.009	e4	0.57			0.051	0.006	0.269	e10
TC_4	TC_2	0.020	0.006	e5	0.51			0.037	0.001	0.201	e11
TC_5	TC_3	0.060	0.004	e6	0.73	0.63	0.82	0.079	0.004	0.173	e12
TC_6	TC_4	0.090	0.002	e7	0.58			0.057	0.001	0.331	e13
TC_7	TC_5	0.060	0.001	e8	0.65			0.038	0.005	0.243	e14
RB_4	RB_1	0.060	0.001	e9	0.55			0.028	0.004	0.519	e1
RB_5	RB_2	0.030	0.001	e10	0.71	0.40	0.76	0.042	0.001	0.224	e2
RB_6	RB_3	0.040	0.003	e11	0.62			0.041	0.001	0.366	e3
DM_5	DM_1	0.050	0.001	e12	0.34			0.039	0.004	0.080	e4
DM_6	DM_2	0.690	0.008	e13	0.40	0.28	0.60	0.057	0.004	0.089	e5
DM_7	DM_3	0.030	0.002	e14	0.76			0.020	0.005	0.336	e6

[a]OEV, Observed endogenous variables; [b]UEV, Unobserved endogenous variables; [c]Standardized regression weights; [d]AVE, Average variance extracted; [e]CR, Composite reliability; [f]SMC, Squared multiple correlation (estimation).

normality. Further, the results in root mean square residual, goodness of fit index and the adjusted goodness of fit index values were 0.22, 0.92 and 0.88, showing the fitness of the model[9]. With respect to baseline comparisons, the normed fit index, Tucker–Lewis index and comparative fit index values were 0.84, 0.89 and 0.92 respectively, and almost significant. Further, the root mean square error of approximation (RMSEA) value was 0.06 and showed ideal[10]. Therefore, it was appropriate to consider the resulting SEM model. The items CP_1 and DM_2 were significant at 5% level, whereas the others were at 1%. The estimates revealed that all the variables affected the items positively (Figure 1).

The structural model analysis showed that technical competency significantly affected creative potential, and the null hypothesis (H_1) was rejected. Similarly, the null hypothesis (H_2) was rejected as the creative potential of farm scientists did not affect the risk-bearing ability in the resulted model. In the case of the null hypothesis (H_4), the risk-bearing ability had no direct and significant effect on decision-making, and therefore it was rejected. Further, H_3 was accepted because of no significant effect shown by technical competency on risk-bearing ability. Consequently, technical competency had no significant relation with decision-making, so the null hypothesis (H_5) was accepted. Creative potential was also observed to have no direct and positive effect on decision-making ability, leading to the acceptance of the null hypothesis (H_6) (Figures 2 and 3).

Discussion

In this study, the dimensions that contribute to the inventive behaviour of farm scientists were identified. Also, a scale was developed to measure the dimensions of the inventive behaviour of farm scientists in SAUs. Among them, inventive proneness and planning ability had less scope to be individual dimensions as they had more similarities with the other dimensions, such as creative potential, risk-bearing ability and decision-making ability. Further, the results of SEM showed that technical competency directly contributes to creative potential as it alters a scientist's thinking process while acquiring expertise in an activity. It also brings confidence to think out of the box or lateral thinking. In other words, if one is technically competent and desires to invent something new, there would be little chance of duplication of efforts of already developed inventions. This is supported by the findings of Choi *et al.*[11], that when individuals are less technically competent, they fear using less familiar technology, which is the root cause of creative inhibition.

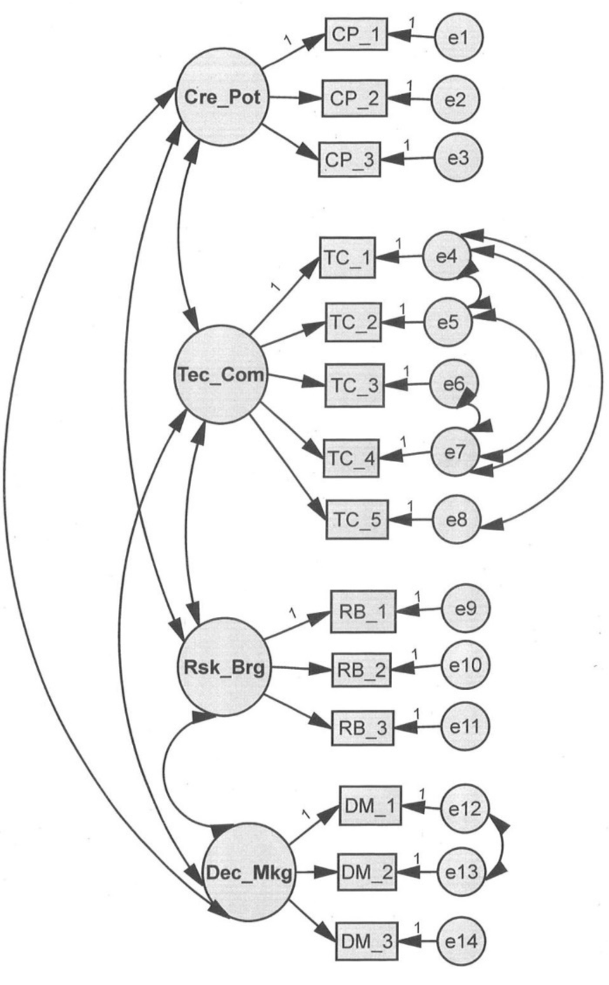

Figure 1. Confirmatory factor analysis of the inventive behaviour of farm scientists.

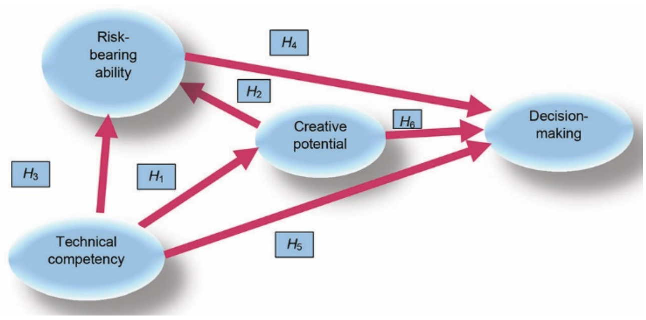

Figure 2. Conceptual model of the inventive behaviour of farm scientists. H_1: Technical competency of farm scientists has no significant relation with creative potential. H_2: Creative potential of farm scientists does not affect the risk-bearing ability. H_3: Technical competency has no significant effect on risk-bearing ability. H_4: Risk-bearing ability has no direct and significant effect on decision-making. H_5: Technical competency has no significant relation with decision-making. H_6: Creative potential does not affect directly and positively the decision-making ability.

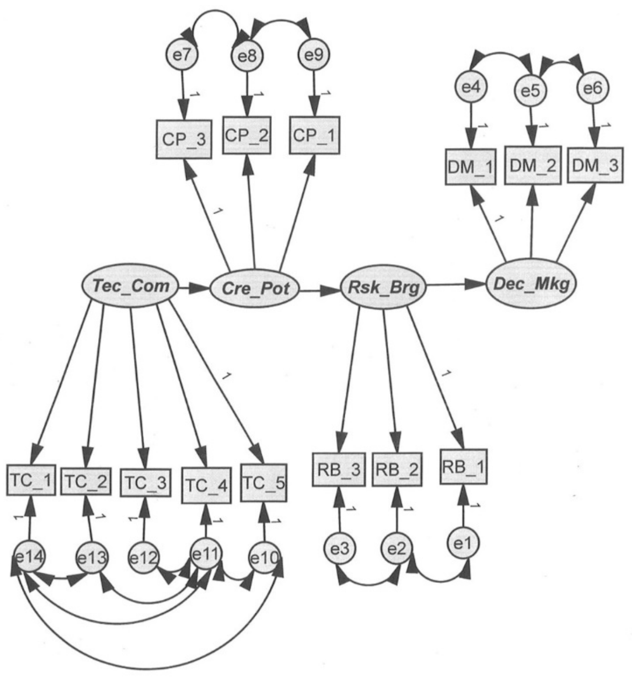

Figure 3. Structural equational model of the inventive behaviour of farm scientists.

The more interesting observation was that creative potential leads to risk-bearing ability, unlike technical competency, which might be due to the creative thoughts that propel the individual to take the risk, as farm scientists believe it will ensure some findings for empirical evidence to solve the problems existing. Support may be taken from the findings of different behavioural patterns observed in the creative decision-making process that the virtual world offers[12]. Further, the risk-bearing ability leads to decision-making, as individual scientists will be experienced in making decisions once they take risks. The experience gained would form the overall view on sequence of events that happens in research projects or procedures. Thus, one can plan research with calculated risk anticipating the probable problems in future.

In the present study, an extensive review of the literature was made and dimensions were selected by grouping many relevant concepts. Future research can take note of the inclusion of any possible dimensions that can be included in inventive behaviour model. Each dimension of the inventive behaviour components could be studied in-depth to advocate policy recommendations to create/improve the inventive behaviour environment in agricultural research. Testing the proposed model in diverse geographic locations and universities is also essential since inventive behaviour patterns may vary by discipline. Intensive research should focus on technical competency and other dimensions to standardize inventive behaviour measurement by discipline. Additionally, further emphasis and measurement techniques are necessary to encourage lateral thinking.

Conclusion

The multi-dimensional construct appropriately aggregates several dimensions and forms a inventive behaviour model. The utilization of a robust and relevant scale to evaluate inventive behaviour would help to frame strategies that are essential to facilitate inventions. ICAR, which is involved in policy decisions of agricultural research, could include the significantly contributing dimensions like creative potential, risk-bearing ability, technical competency and decision-making ability for recognition of farm scientists in addition to highly-rated publications to encourage them to invent. Further, inventive behaviour programmes are needed to enhance the scientists voluntarily starting the novel ways of visualization and research.

Conflict of interest: The authors declare that there is no conflict of interest.

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