7-15-2012

Exploring Characteristics Of Expertise In Information Systems

Sharmistha Dey
Queensland University of Technology, Australia, s.dey@qut.edu.au

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Sharmistha Dey, Queensland University of Technology, Australia, s.dey@qut.edu.au

Abstract

Experts' views and commentary have been highly respected in every discipline. However, unlike traditional disciplines like medicine, mathematics and engineering, Information System (IS) expertise is difficult to define. This paper attempts to understand the characteristics of IS-expert through a comprehensive literature review of analogous disciplines and then derives a formative research model with three main constructs. Further, this research validates the formative model to identify the characteristics of expertise using data gathered from 220 respondents using a contemporary Information System. Finally this research demonstrates how individuals with different levels of expertise differ in their views in relation to system evaluations.

Keywords: Expert, Novice, Intermediate, System evaluation, Knowledge, Experience

1   INTRODUCTION

Prior research suggests that expertise (as a positive indication of degree of proficiency) is not a simple reflection of one's innate abilities and capabilities, but rather a combination of acquired complex *skills, experience and knowledge capabilities* (Ericsson and Smith 1991; Hunt 2006; Norman, Eva et al. 2006; Yates and Tschirhart 2006). Social science researchers have demonstrated the positive impact of extended deliberate practice and deliberate learning of skills on individual performance (Eriksson, Krampe et al. 1993). Furthermore, heuristics are established on the approximate number of years of deliberate practice is required to attain a high level of expertise. For example, Simon and Chase (1973) have demonstrated that it takes 10-years of intensive deliberate practice to attain high degree of proficiency in maths, swimming, tennis and chess. However, they agree that such heuristics are 'stable' only for some disciplines, where the expertise is not influenced by situational factors (Chase and Simon 1973; de Groot 1978).

In practice, expert's views are regularly sought, particularly in system evaluations. Moreover, fundamental definitions of Information Systems recognize that the quality of an Information System relies heavily on the 'quality' of the users. Despite wealth of past research on expertise on concepts of years of experience and deliberate practice, past research cannot be easily transferred to understand the 'quality' or 'expertise' of the users the dynamic discipline of Information Systems. Thus, to-date, none of the past Information System (IS) studies attempt to understand the characteristics of the degree of proficiency of an IS user.

Employing the aforementioned prepositions, this research attempts to define the salient characteristics of expertise in the discipline of Information Systems. In doing so, we derive insights from the Generalized Expertise Measurement (GEM) of Germain (2009), Knowledge types of Davenport (1998), years of experience research by Simon and Chase (Simon and Chase 1973) and conceptual work on the degree of proficiency by Ericsson et al. (1991). The formative model of expertise will then be derived using the salient constructs that would purportedly measure expertise of an individual in Information Systems. Since each of the constructs makes a unique contribution to expertise, the research model conceives the phases as dimensions 'forming' expertise. The expertise model is thus conceived and operationalised as a hierarchical, multidimensional, formative index (arrows pointing in). The derivation of the model would facilitate the identification of three levels of expertise based on their degree of proficiency: novice, intermediates and experts; where an 'expert' holds the highest degree of proficiency, followed by intermediate and novice. The main research question of the study is,*" What are the salient characteristics of an Expert in the Information Systems discipline?"*

Once the characteristics of expertise are identified, we classify them into three groups (novice, intermediate and expert) using two methods (to triangulate), and then demonstrate how these three groups have different views in system evaluations. In addition to the results of construct validation, to the extent that these three groups differ on system evaluations on the 'state-of-the-system' further evidences the strength of the constructs measuring expertise of IS.

The paper proceeds in the following manner. The paper begins with a critique of related literature to derive the salient characteristics of an expert. Next, the paper discusses the research model followed by an explanation of the data collection method. The paper then reports details of all statistical analyses that were conducted. Lastly, the three groups (based on levels of expertise) are applied to the IS Impact model to show the differences in their views regarding system evaluation.

2 CHARACTERISTICS OF AN EXPERT

The salient characteristics of an expert are derived through the key concepts of the aforementioned definitions. The levels of expertise, also known as the 'degree of proficiency', is generally associated with skills, expertise and knowledge, which extends over a continuum, from *novice → intermediate → expert*, where an 'expert' holds the highest degree of proficiency (Eriksson and Charness 1994). Expertise, in general, is defined as superior performance in terms of success, swiftness, and/or accuracy. In between two extremes of experts and novices are the intermediates. The following review of literature describes aspects that have been discussed in social science discipline describing expertise (degree of proficiency). It first introduces 'Years of experience' and 'Deliberate practice' as two of the most commonly used constructs in determining 'expertise'. The review then introduces 'Knowledge' as an important construct for Information System expertise. Thirdly, the review introduces 'Socio-behavioural factors' that contributes to an individual's expertise.

2.1 Years of Experience

'Years of experience' is one of the most common researched constructs in association with the level of expertise. Social Science research on expert performance and expertise (Chi, Glaser et al. 1988; Ericsson and Smith 1991) has shown that important characteristics of experts' superior performance are acquired through experience arguing that exceptional performance is an outcome of the environmental circumstances, such as the duration and structure of activities. Eriksson et al. (1993) hypothesized that the individuals' performances are a monotonic function of the deliberate practice. They argued that the accumulated amount of deliberate practice and the level of performance an individual achieves at a given age is a function of the starting age for practice and the weekly amount of practice.

The view that merely engaging in a sufficient amount of practice, regardless of the structure of that practice, leads to maximal performance has a long and contested history and is demonstrated in a series of classic studies of Morse code operators. Bryan et al. (1897) and Bryan et al. (1899) identified plateaus in skill acquisition, when for long periods subjects seemed unable to attain further improvements. However, they observed, with extended efforts, operators could restructure their skill to overcome plateaus. Keller (1958) later showed that these plateaus in Morse code reception were not an inevitable characteristic of skill acquisition, but could be avoided by different and better training methods.

Though it is tautological that 'years of experience' is related to and at times influences the degree of proficiency, such a proficiency-classification that is purely based on the years of experience, for contemporary IS may lead to inconsistent interpretations. Such a simple classification based solely on the number of years would be unreasonable, especially given that a contemporary IS includes many user cohorts ranging from senior managers to data-entry operators - each cohort with a diverse set of skills and capabilities. In parallel disciplines, it has been established that it takes ten-years to become an expert from the time at which practice was initiated (Simon and Chase 1973). Simon and Chase's (1973) "10-year rule" is supported by data from a wide range of domains: music (Sosniak 1985), mathematics (Gustin 1985), tennis (Monsaas 1985), and swimming (Kalinowski 1985). Given that Simon and Chase's 10-year rule has been generalized in a range of disciplines, it is intriguing to evaluate whether the same findings are generalized in Information System discipline as well.

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[1] Research demonstrates that some minimal biological attributes may also lead to the acquisition of expertise. This is considered beyond the scope of the study.

2.2   Knowledge contributes to expertise

Germain (Germain and Ruiz 2009) describes knowledge as an integral aspect of ones' expertise. In the knowledge management stream of literature in IS discipline too there is strong recommendations for end-user knowledge for system success (Davenport 1996; Davenport 1998; Davenport 1998; Gable, Scott et al. 1998; Bingi, Sharma et al. 1999; Sumner 1999). Research suggest that managing a contemporary Information System as a high knowledge intensive task that necessarily draws upon the experience of a wide range of people with diverse skills and knowledge capabilities (Gable and Klaus 2000; Soh, Sia et al. 2000). Davenport (1998b) identifies three types of knowledge that are necessary for managing contemporary Information System lifecycle: (1) software-specific knowledge, (2) business process knowledge and (3) organization-specific knowledge. The three types of knowledge project the complete breadth of knowledge capabilities required for an end-user in an IS and provide the foundation for defining the characteristics of an expert in IS.

Software specific knowledge refers to the knowledge, skills and expertise that those employees' possess in relation to the operation of the system features and functions. Business process knowledge refers to the in-depth understanding of business possesses that the employee engages with. Davenport (1998) asserts that business process knowledge of an employee should reflect not just the functional area that s/he is involved in, but the entire business process that one is engaged in. Moreover, similar to prepositions by Kaplan and Norton (1996), and in light of Davenport's (1988) arguments on types of knowledge, employees' organizational knowledge too is vital in defining ones' expertise. Organizations of the 'knowledge-era' focus on increasing effectiveness through establishing strong foundations in knowledge, which includes not only software knowledge but employees' knowledge of business processes and work practices. Akin to Xu et al., (2003), we argue that most (if not all) business processes are situational in nature, where the software is adapted to meet needs of specific business circumstances. In light of the aforementioned, it is argued that the two knowledge types of an IS employee are largely responsible for the degree of proficiency.

Moreover, in general (and regardless of the study context), 'training' has been identified as a critical aspect that contributes to employees' knowledge. Such formal training programs ensure wider distribution of highly context-specific knowledge that can be particularly useful throughout the phases of an IS lifecycle (Pan and Chen 2005). In the interest of understanding the contribution of formal training on software and business knowledge, this study includes 'formal training' as an antecedent of overall knowledge.

2.3   Socio-behavioural Factors

Recent research by Germain (Germain and Ruiz 2009), who developed a psychometric measure of perception of employee expertise termed 'Generalized Expertise Measure (GEM)'explores the socio-behavioural traits associated with expertise. This is one of the very few studies undertaken to understand expertise from a perceptual viewpoint. GEM defines an "expert" as someone who manifests the following qualities with respect to their work role: (i) specific education, training and knowledge, (ii) ability to assess importance in work-related situations, (iii) capacity to improve themselves, (iv) intuition and (v) self-assurance and (vi) confidence in their knowledge. These factors contribute to an individual's level of expertise (example: proactive self learning). This research argues that Experience, Knowledge and socio-behavioural factors contribute to an individual's level of expertise.

Herein we adapt guidelines of GEM to Information Systems. In the survey instrument (Appendix A) the sections 'Proactive self-learning' and 'Willingness to adapt' relates to the 'Socio-behavioural' construct of the research model (figure 1).

2.4 THE MODEL

As per the Petter et al. (2007) guidelines for identifying formative variables, measures of expertise; (i) need not co-vary, (ii) are not interchangeable, (iii) cause the core-construct as opposed to being caused by it, and (iv) may have different antecedents and consequences in potentially quite different nomological nets. Expertise herein is conceived of as a construct that encompasses the *three* constructs identified above (knowledge possessed by the respondent, years of experience, and socio-behavioural attributes of the respondent). Appendix A shows all items measured in this study.
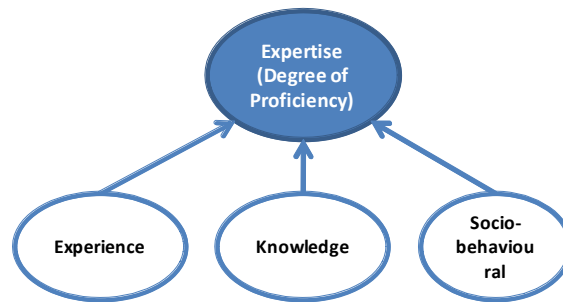

Figure 1: Research model

Once the characteristics of an IS expert are identified and validated, we seek to explore how they evaluate a system; specifically observing whether there are differences in a system evaluations.

In IS evaluations (commonly known as IS success), respondent's characteristics has been recognized as an important consideration. The respondents' perspective is the first question of the seven questions by Cameron and Whetten (1983). However, most system evaluation studies do not pay a close attention to the characteristics of the respondent. It is our belief that an expert is able to provide a better and more insightful evaluation of a system. Thus we argue herein that organizations will benefit by paying close attention to system evaluations of 'experts'.

We selected the IS-Impact measurement model of Gable, Sedera and Chan (Gable, Sedera et al. 2008) that employs 28 measures arranged under 4 dimensions to assess the level of success of a contemporary IS for this purpose. It is our expectation that the three groups will demonstrate statistically significant differences which then argues for the existence of the three levels of expertise: novice, intermediates and expert.

3 THE SAMPLE AND DATA COLLECTION

We developed a survey instrument that included 23 questions pertaining to expertise. Section one of the survey instrument gathered demographic data (respondent's name, employment title, employment description, and the number of years with the organization). The 23 questions in section two included questions to determine the level of expertise of a respondent using; 4 questions of proactive self-learning, and 5 questions on willingness to adapt, 7 questions on knowledge competencies, 4 questions on knowledge sharing and 3 questions on training. The complete survey instrument is available in Appendix A. Section three included the validated 28 questions of the IS-impact measurement model of Gable et al. (Gable, Sedera et al. 2008). The survey instrument was circulated to all 350 direct operational and management users at three medium sized organizations using SAP Enterprise System in India between July – September 2009. The survey received 220 valid responses (with a response rate of 63%). All questionnaire items were measured using seven-point Likert scales with the end values (1) "Strongly Disagree" and (7) "Strongly Agree", and the middle value (4) "Neutral". The draft survey instrument was pilot tested with a selected sample of staff of a single organization with 10 users (3 managers and 7 operational staff).

4   CONSTRUCT VALIDATION

For all constructs, factor scores for all measures were generated in SPSS by performing factor analyses with principal components and Varimax rotations. To test construct validity, factor analyses were conducted using the Principal Component Analysis extraction method with Varimax rotation. Reliability was calculated for each construct using Cronbach's alpha coefficient. This analysis can assess the convergent and discriminant validity (Gudi 2009). All the measurement items with the same construct should have high loadings on their component (convergent validity) and low loadings on other factors (discriminant validity). This supports the measures' validity as measurement items should be more highly correlated with their own scales than with other scales.

	Measures	PSL	WTA	KMC	KSH	TRN
PSL1	I regularly refer to corporate database (e.g. intranet) for additional information, before processing my tasks.	0.861				
PSL2	I regularly learn about company policies and guidelines through information repositories (e.g. intranet/internet) relevant to my tasks.	0.918				
PSL3	I regularly visit SAP web forums seeking better ways of completing my tasks.	0.934				
PSL4	I regularly learn new things relevant to my tasks.	0.929				
WTA1	I refer to best practices and apply them to my tasks.		0.819			
WTA2	I use the Internet to obtain new knowledge and apply then to my tasks.		0.862			
WTA3	I apply useful suggestions for my tasks gained from brainstorming meetings with my colleagues.		0.852			
WTA4	I search information for my tasks from various knowledge sources administered by the organization.		0.871			
WTA5	I am ready to accept new knowledge and apply it to my tasks when necessary.		0.874			
KMC1	I fully understand the core knowledge necessary for my tasks.			0.764		
KMC2	My knowledge of SAP is more than enough to perform my day-to-day tasks.			0.737		
KMC3	I have colleagues and workmates helping me with SAP related problems and issues (inversely worded).			0.783		
KMC4	I rarely contact SAP helpdesk for software related problems.			0.701		
KMC5	I rarely make mistakes when completing my tasks in SAP.			0.819		
KMC6	I have an in-depth knowledge of the tasks that I must do on a day-to-day basis.			0.683		
KMC7	**I have a good knowledge of the organizational goals, procedures and guidelines.**			**0.585**		
KSH1	I regularly share my knowledge of tasks with my colleagues.				0.745	
KSH2	I suggest work improvements to my managers/colleagues often.				0.729	
KSH3	My colleagues come to me for assistance when they are faced with a work related issue.				0.77	
KSH4	I regularly contribute to knowledge sharing forums within my organization.				0.894	
TRN1	I have received appropriate formal training on the business processes in my department.					0.94
TRN2	I have received adequate SAP training on my tasks and processes.					0.923
TRN3	I have received formal introduction on the organization, its goals and objectives.					0.743

Table 1: Factor Analysis

In the table above, no cross-loadings have been reported since they were not above 0.3. This analysis supports scale validity because each item loaded on its construct significantly (p<0.01) and more highly than 0.7 (Hair 1998). However KMC7 scored less. KMC7 was not removed since in the reliability test the Cronbach's Alpha score was high. To validate the reliability of the measures indicated for the constructs, Cronbach's alpha technique was used. The purpose of performing the analysis for reliability is to examine whether the measures consistently represent the construct that is being measured (Green and Salkind 2005). Reliability was calculated for each group of items of reflective constructs, representing 0.931 for Proactive Self-Learning, 0.917 for Willingness to Adopt, 0.835 for Knowledge Competency, 0.772 for Knowledge Sharing and 0.845 for Training. All values are above .60 and considered acceptable (Nunnally 1967). Therefore the results suggest that the validity and reliability of the data are adequate for testing the research model.

Furthermore, we conducted inter-construct correlations. We observe that WTA4 has a higher correlation with PSL2, PSL3 and PSL4. WTA5 has a high correlation with PSL2, PSL3 and PSL4. However, WTA4 and WTA5 was retained since there were no cross loadings in the factor analysis and the Cronbach's alpha score was high. It provides support for construct validity because the square root of the average variance shared between each construct and its indicators is higher than 0.50 and in majority of the cases is higher than the variance it shares with other constructs (Fornell and Larcker 1981).

5   STRUCTURAL EQUATION MODELLING

The individual path coefficients of the PLS structural model (figure 2) can be interpreted as standardised beta coefficients of ordinary least square regressions.
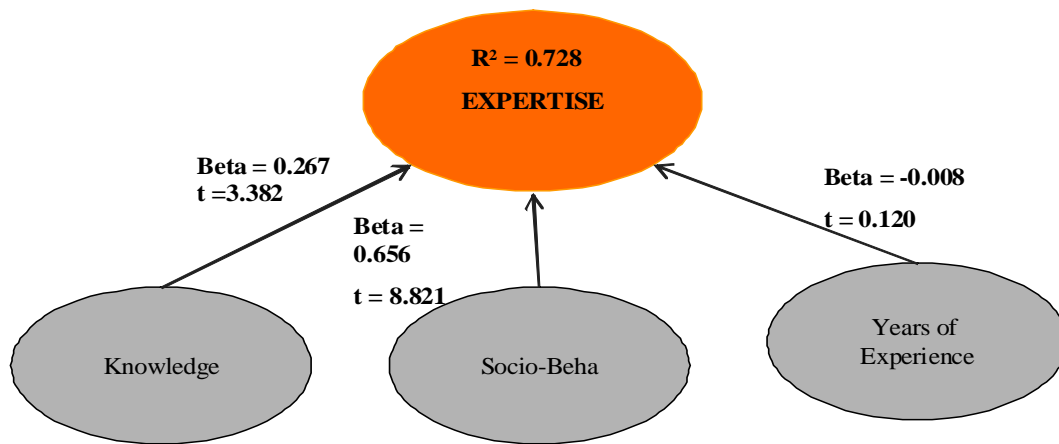

Figure 2: Results of the PLS analysis of the Formative Expertise Model

The socio behavioural construct has the highest beta. Therefore it is the strongest contributor to expertise. The path coefficient is good, strong and significant.

The significance level is determined by the 't' score. The 't' score for Knowledge->Expertise is: 3.382, Socio->Expertise: 8.821 and Experience->Expertise: 0.120. These 't' scores indicate that knowledge and socio-behavioural factors have a strong significance to expertise. Information Systems being a dynamic discipline, where technology evolves rapidly, ones' experience (number of years) may not be as relevant as it is in other static fields like, music, tennis and chess.

6   GROUPING OF RESPONDENTS

Having validated the expertise model, we now develop methods to derive meaningful groups to categorize respondents based on their expertise. Herein, we employ 2 methods: (1) based on standard deviations following guidelines of Ericsson and Charness (Eriksson and Charness 1994) and (2) exploratory cluster analysis.

6.1   Method 1: Using mean, standard deviation

This method has been employed in social science research. The analysis looks at how respondents could be classified using the averages, mean and standard deviation. Records (respondents) recording mean values for a construct above the summation of standard deviation and mean are considered as an expert. Respondents with mean values less than the deduction of standard deviation from the overall mean are considered novice; and the remainder are considered as intermediates.

6.2   Procedure

We calculated the average per construct (i.e. knowledge competency and socio-behaviour) for each respondent. Next, we calculated the total mean and standard deviation for the construct. The classification in table 2 is derived using the following equations: Novice= Individual mean < (Total mean - Total Std. Dev) and Expert=Individual mean > (Total mean + Total Std. Dev). The test results use those values in the calculations below (table 2).

		#	Socio-Behaviour	#	Knowledge	#	Experience
1	Novice	33	15%	8	4%	21	10%
2	Intermediate	175	80%	209	95%	165	75%
3	Expert	12	5%	3	1%	34	15%

Table 2: Results of Method 1

Results suggest that most (at least 75% of the respondents) can be classified as intermediates in all three constructs. The dominant construct in determining Expertise Construct in the PLS analysis was Socio Behavioural factors. That classification suggests reasonable percentages for the three groups. Also, though both Knowledge and Socio make statistically significant contributions to the overall expertise, we note that an "expert" in one construct does not become an expert in the second construct. This, we believe is commonsense, but requires logical triangulated evidence.

6.3   Method 2 – Cluster Analysis using SPSS

The analysis below demonstrates the results and interpretation of cluster analysis. Cluster analysis seeks natural groupings of items (based on prior logic). Literature suggests the use of step-wise clustering in similar instances (against other methods like K-means, Hierarchical clustering). Step-wise is an exploratory procedure. We first attempted using the step-wise cluster analysis using the averages that we have calculated in Method 1. For this analysis SPSS "cluster quality" indicators were poor for all three constructs. Similarly, the results did not propose meaningful clusters.

We then used the "dominant cluster indicator" in SPSS to determine whether there is/are any variable/s that are deemed suitable for 2-step cluster analysis. This is a new indicator that has been introduced in SPSS. The dominant cluster indictors suggested the use of Criterion Item 1 (note that this was the only indicator to have come out of this analysis). The criterion item 1 is "In my organization, my colleagues recognize me as someone with high expertise". This relates to a quasi "third-party" evaluation of one's expertise, even though the assessment is made by the respondent. Third party evaluations are highly encouraged, yet deemed difficult to implement, in expertise studies.

Using the criterion item 1, we received 3 cluster groups using the step-wise clustering method. The goodness of the cluster analysis that was measured through 'cluster quality' in SPSS was recorded as "Good". The distribution of the sample is depicted in table below. The table was derived by counting the indicator variable (marked as 1, 2, and 3) that was automatically inserted in the SPSS file as a new variable.

		#	Cluster Groups
1	Novice	25	11%
2	Intermediate	182	83%
3	Expert	13	6%

Table 3: Distribution of the Sample

Next, we sought a relationship between what was discovered through previous analysis and (using standard deviation and mean) the results of the cluster analysis. In this we wanted to see to what extent the cluster analysis results match with the results obtained using the standard deviation analyses.

6.4   Results and Analysis

The cluster sample (record-by-record) was then compared to the results of method 1. Comparing results showed that the cluster groupings have close association with the sample groupings based on the Socio Behavioural cluster. The results match is depicted below. The table below demonstrates how many records of the groupings based on Socio-Behavioural cluster match with the three cluster groupings. The table shows that there is a good match between cluster analysis groupings and groups derived through standard deviation / mean of socio-behavioural factors.

Cluster Group	Non-Matching	% of sample	Match (%)
1	3	1.36%	99%
2	16	7.27%	93%
3	7	3.18%	97%

Table 4: Match between Cluster Analysis groupings and Groups

6.5   Observations and Interpretations

Given that our PLS analysis demonstrated that socio-behavioural factors is the most dominant construct in determining 'Expertise', the results of the cluster analysis does not look arbitrary. With a high percentage of individual records of the cluster analysis mapping to an item that supposedly measures "What others think about my abilities" triangulate the mappings of expertise through socio-behavioural factors (or vice-versa).

7   APPLYING THE GROUPS TO IS IMPACT MODEL

Having derived three groups based on expertise, we now see whether the three cohorts have different views of system success (IS Impacts); measured using the 28 items. The independent sample t-tests at the item level are applied herein to investigate the differences between pairs of expertise for each item of IS impact model. Moreover, I conducted the independent sample t-tests at the aggregated construct level (average of all measures under a construct).

7.1 Results and Analysis

Table 5 demonstrates results of the independent sample t-tests using the items of the IS impact model, where the significant differences are observed and marked with 'X'.

Items	Ex vs. Nov	Ex vs. Int	Int vs. Nov	Items	Ex vs. Nov	Ex vs. Int	Int vs. Nov
II1	X			SQ3	X		
II2	X	X	X	SQ4			
II3	X	X	X	SQ5			
II4	X	X	X	SQ6	X	X	
OI1				SQ7	X		
OI2				SQ8	X		
OI3				SQ9	X		
OI4	X	X		IQ1			
OI5	X	X	X	IQ2			
OI6	X	X		IQ3			
OI7	X	X	X	IQ4	X		
OI8	X	X		IQ5	X	X	X
SQ1	X	X		IQ6	X		
SQ2	X	X		IQ7	X		
X = Significant differences at 0.05							

Table 5: Results of the independent sample t-tests

Table 6 shows results of the independent sample t-tests for the aggregated IS impact measures. For example, here the II items are aggregated to a single measure (averaged).

	QUALITY		IMPACTS	
	INFORMATION	SYSTEM	INDIVIDUAL	ORGANIASATION
	Sig / t-value*	Sig / t-value*	Sig / t-value*	Sig / t-value*
Expert / Novice	0.02 / -2.41	0.01 / -2.86	0.00 / -3.35	0.03 / -1.89
Expert / Intermediate	0.56 / -.36	0.87 / 0.24	0.00 / -4.41	0.03 / -2.65
Intermediate / Novice	0.67 / -.19	0.10 / -.58	0.01 / -2.41	0.48 / -.28
* Significant at 0.05				

Table 6: Results of the independent sample t-tests for the aggregated IS impact measures

7.2 Observations

It is observed that Experts differ with Novice in their views of IS impact for all four dimensions. At the item level, Experts have a different opinion to Novice on 75% of the measures. Their views are different across all four measures of Individual Impact. Similarly, when Expert views are compared against the Intermediates, there are statistically significant differences for Individual Impact and Organization Impact constructs.

8   CONCLUSION

This study attempted to define the salient characteristics of expertise in the discipline of Information Systems. A comprehensive literature review was conducted of analogous disciplines and then a formative research model with three main constructs (Knowledge, Experience and Socio-behavioural factors) was derived. This model was then tested using data collected (220 responses) from three medium sized organisations. A series of statistical analyses were conducted in order to validate the model. We observed that 'socio behavioural factors' was the highest contributor to 'expertise' followed by 'knowledge'. Years of experience showed negligible contribution to 'expertise'.

Following this, three groups were identified, novice, intermediate and expert. In order to do this we followed two methods (standard deviation and cluster analysis). This triangulation provides further support for the groupings of the three groups. T-tests were conducted on items and dimensions of ISI; identifying some significant differences between the cohorts. This too provides further evidence to the three groups that were identified.

It is observed that Experts differ with Novice in their views of IS impact for all four dimensions. At the item level, Experts have a different opinion to Novice on 75% of the measures. Their views are different across all four measures of the Individual Impact construct. Similarly, when Expert views are compared against the Intermediates, there are statistically significant differences for Individual Impact and Organization Impact constructs.

These results then support the hypothesis of this study, "When evaluating an operational IS (using the IS-impacts measurement instrument), users classified according to Expertise (varying degrees of proficiency) would make statistically different assessments".

9   APPENDIX A

Proactive self-learning

1   I refer to corporate database before processing some tasks

2   I try to document and store expertise and guidelines on new tasks and policies

3   I extensively search through customer and task-related databases to obtain knowledge necessary for the tasks

4   I can learn what is necessary for new tasks

Willingness to adapt

1   I can refer to best practices and apply them to my tasks

2   I can use the Internet to obtain knowledge for the tasks

3   I obtain useful information and suggestions from brainstorming meetings without spending too much time

4   I search information for tasks from various knowledge sources administered by the organization

5   I am ready to accept new knowledge and apply it to my tasks when necessary

Knowledge Competencies

1   I fully understand the core knowledge necessary for my tasks

2   My knowledge of SAP is more than enough to perform my day-to-day tasks

3   I have colleagues and workmates helping me with SAP related problems and issues (inversely worded)

4   I rarely contact SAP helpdesk for software related problems

5   I rarely make mistakes when completing my tasks in SAP

6   I have an in-depth knowledge of the tasks that I must do on a day-to-day basis

7   I have a good knowledge of the organizational goals, procedures and guidelines

Knowledge Sharing

1   I regularly share my knowledge of tasks with my colleagues

2   I suggest work improvements to my managers / colleagues often

3   My colleagues come to me for assistance when they are faced with a work related issue

4   I regularly contribute to knowledge sharing forums within my organization

Training

1   I have received appropriate formal training on the business processes in my department

2   I have received adequate SAP training on my tasks and processes

3   I have received formal introduction on the organization, its goals and objectives

Individual Impact

1   I have learnt much through the presence of SAP

2   SAP enhances my awareness and recall of job related information

3   SAP enhances my effectiveness in the job

4   SAP increases my productivity

Organization Impact

1   SAP is cost effective

2   SAP has resulted in reduced staff costs

3   SAP has resulted in cost reductions (e.g. inventory holding costs, administration expenses, etc.)

4   SAP has resulted in overall productivity improvement

5	SAP has resulted in improved outcomes or outputs
6	SAP has resulted in an increased capacity to manage a growing volume of activity (e.g. transactions, population growth, etc.)
7	SAP has resulted in better positioning for e-business
8	SAP has resulted in improved business processes

System Quality

1	SAP is easy to use
2	SAP is easy to learn
3	SAP meets requirements of my department
4	SAP includes necessary features and functions
5	SAP always does what it should
6	The SAP user interface can be easily adapted to one's personal approach
7	SAP requires only the minimum number of fields and screens to achieve a task
8	All data within SAP is fully integrated and consistent
9	SAP can be easily modified, corrected or improved

Information Quality

1	SAP provides output that seems to be exactly what is needed.
2	Information needed from SAP is always available.
3	Information from SAP is in a form that is readily usable.
4	Information from SAP is easy to understand.
5	Information from SAP appears readable, clear and well formatted.
6	Though data from SAP may be accurate, outputs sometimes are not.
7	Information from SAP is concise.

Overall

1	….the impact of SAP on the department has been positive.
2	….the impact of SAP on me has been positive.
3	....Overall, the SAP System Quality is satisfactory.
4	....Overall, the SAP Information Quality is satisfactory.
5	....In my organization, my colleagues recognize me as someone with high expertise.
6	....I believe that I have a high level of expertise based on my experience, skills, abilities and knowledge.

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