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A knowledge mapping approach to facilitate strategic human resource and knowledge management

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Keywords

knowledge, mapping, approach, facilitate, strategic, human, resource, knowledge, management

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A Knowledge Mapping Approach to Facilitate Strategic Human Resource and Knowledge Management

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Abstract

A key challenge facing organisations is how to effectively connect employees who seek knowledge with those who have the necessary knowledge. From case studies conducted in three separate knowledge intensive organisations, briefly introduced in this paper, we found that locating and measuring expertise were major challenges with no current satisfactory solutions. We offer a method to map intellectual capital within organisations distinct from previous expertise location methods in several significant ways. First, it includes the measurement of knowledge value within the context of the organisation's strategy and activities. Second, it addresses concerns with existing methods such as subjectivity associated with self-reporting, currency, and validation by incorporating several innovative techniques such as 360 degree peer review, data mining, and feedback loops. Thirdly the mapping approach incorporates all types of knowledge including tacit and explicit knowledge.

Keywords

Knowledge management, strategic human resource management, expertise registers, tacit knowledge, codified knowledge

INTRODUCTION AND BACKGROUND

An organisation's most valuable resources are its people and the knowledge they hold. A key challenge facing organisations is how to effectively connect employees who seek knowledge with those who have the necessary knowledge. Increasingly, strategic human resource management (SHRM) researchers are examining knowledge management (KM) tools and techniques (e.g. Snell, 1999; Youndt et al, 2004) for ways to increase strategic capability (Lengnick-Hall and Lengnick-Hall, 2003). KM creates value through sharing essential knowledge within the organisation; this is embodied through the concept of connectivity, which ensures knowledge seekers find knowledge providers (Kluge et al., 2001).

Despite the existence of various KM tools and recognition of the value of managing human resources, during 2004-2006 we conducted three separate case studies which confirmed the need to manage and measure expertise and revealed shortcomings in existing techniques. The approach offered in this paper extends the work begun in those case studies and is our response to the outstanding issues identified. The first study was conducted with the Royal Australian Navy in 2004 and produced theoretical frameworks and methods for measuring the value of knowledge resources (Massingham, 2005). The second study involved interviews with 17 personnel in late 2006 within a Defence R & D organisation that is expertise intensive. This research revealed that people and projects, and to a lesser extent, tools and groups, play central roles in identifying who is an expert. The structure of the organisation also played a major role in being able to find and access an expert. The third study was conducted in late 2007 within one of our institutions; being another expertise intensive organisation and identified several search requirements including specific issues relating to levels of knowledge. From these studies, issues relating to access to experts, incentives for providing the needed information, expertise currency, trust and validation were raised. Our main findings from each of these studies are briefly outlined next.

Case study 1

The Pilot Study formed the basis of a current Australian Research Council Linkage Project. Based on a series of lengthy questionnaires with 40 civilian employees within the RAN's NAVSYS Branch, the study developed a range of ideas which are extended in the method outlined in this paper. First, it developed a taxonomy of tacit knowledge which highlights the most valuable tacit knowledge in any organisation. This begins with human capital. The constructs of tacit social capital (organisational memory), tacit structural capital (learning organisation contribution), and tacit relational capital (knowledge tied to the individual rather than the position) are then introduced. Second, an index for identifying the most valuable employees is introduced, based on a novel combination of extant measurement constructs, which represents a set of objective observable criteria, particularly when validated by 360 degree peer review.

The Pilot Study produced a range of human capital value measurements as indicators of productivity and output (e.g. profitability in financial terms). Based on a scoring system derived from the taxonomy, individuals are aggregated to derive an overall knowledge level, explaining how well the firm is using its human capital. Knowledge facilitator levels identify whether the firm's capability is increasing. Unsatisfactory scores may suggest that employees are not competent to do their work and/or that there is a lack of knowledge sharing. These are red flag signals just like profitability indicators such as operating margin in financial statements. This will have a significant indirect impact on the three tacit capitals. Social capital value measurements are indicators of knowledge flow (e.g. cash flow in financial terms). The network tie and social relationship score explains the degree of connectivity. The social attitude and dependence score identifies whether employees are motivated to share tacit knowledge. Unsatisfactory scores may suggest that knowledge is being hoarded and/or that the organisational culture is unhealthy (e.g. does not support a learning organisation). This will result in a lack of organisational memory. Structural capital measurements are indicators of wealth (e.g. assets in financial terms). The codification attitude score identifies the organisation's degree of ownership of its knowledge. The learning organisation attitude score explains employees' level of organisational commitment. Unsatisfactory scores may suggest that there is high risk of valuable knowledge loss which threatens the organisation's future. This will result in lack of learning organisation capability. Relational capital measures are indicators of market position (e.g. shareholders' equity in financial terms). The relational score identifies the vulnerability of the organisation's external relationships. Unsatisfactory scores may suggest that key inter-organisational relationships are fragile. This will result in relationships based on individuals rather than positions.

Case study 2

We conducted interviews with seventeen personnel during the months of September and November 2006 within a Defence R & D organisation which is expertise intensive. A series of questions was presented to our interviewees in an attempt to get them to present their experiences on accessing expertise in each of their fields. The questions were also designed to elicit barriers they faced to gaining expertise as well as assessing the quality of the expertise they were provided. It is this last parameter that is the most difficult to assess.

It is clear from our initial investigations in 2006 within the organisation concerning how expertise is currently located, that a fully automated approach which advises who to contact, or a semi-automated approach using techniques such as SNA to answer "who knows who" will not deliver an optimal or widely accepted solution. Currently, there are basically two ways of accessing 'know-how' within the organisation. One path takes the approach of drawing upon one's social networks (a people-centric approach). The alternative but somewhat less used method is through a more academic approach of reading publications, and determining from there, who has the relevant expertise (a more algorithmic/automated type of approach). Key issues that emerged included Issues that we have identified as critical regarding any method to locate experts include:

- Establishing trust and quantifying levels of trust
- Turnover of experts and thus loss of expertise within the organisation
- Access to experts across organisational boundaries
- Currency of expertise and the impact of currency on relevancy of expertise
- Short timeframes (hours/days) for decision making related to forming a new team and project.
- Information is typically classified and only available on a need to know basis.

It was clear that people and projects, and to a lesser extent, tools and groups play central roles, in identifying who is an expert. We conjecture that the purpose of expertise location/recommender systems for this R&D organisation equates to how to answer the question "how do you find someone to work on a particular project". The structure of the organisation also played a major role in being able to find and access an expert.

Case study 3

The third case study was conducted at Macquarie University in late 2006, being another expertise intensive organisation. Macquarie University had an existing expertise recommender system known as XPertNet which was primarily designed for use by journalists but suffered from incomplete and out-of-date data. We interviewed groups and individuals from four key areas that were interested in finding experts: Research Office (RO); Development and External Relations Division (DERD); Marketing and Public Relations (MPR) and Teaching and Learning (TL). By this stage we had already identified the importance of providing feedback from previous searches, handling trust and currency issues (which our interviewees confirmed to be of importance) and thus the requirements below can be seen as additional and in some cases organisation specific requirements.

- The age of an expert should be included in the system and the system should be able to search for experts based on age (suggested by DERD for offering age-specific awards).
- Users should be able to search for expertise in general as well as expertise in a particular field (Suggested by DERD for offering non-domain-specific awards).
- The system should store the details not just of well-established and/or recognised experts, such as professors, but also of PhD or Masters students, as well as non-academics performing relevant research. (Suggested by DERD as they have found that people studying towards a higher degree were more likely to be interested in applying for an award).
- The system should hold information about an expert's teaching awards, publications, and grants, as well as information about the type of teaching skills they possess (e.g. if they have experience in student centred learning, or team teaching). (Suggested by TL as a method of in judging the quality of the expert's teaching skills and finding out, for instance, if they would be suitable to give guest lectures or mentor new staff members).
- The system should contain a model showing the relationships between experts (Suggested by RO as useful in showing joint research grants and publications)
- Certain flags to restrict searches on grant applications that are confidential (suggested by RO).
- Experts who are registered in the system should be allowed to nominate how often they are available to be contacted and how willing they are to be contacted by various different expert-seekers. For example, they should be able to indicate whether they are willing to give television or radio interviews (suggested by MPR as they found that the response time of an expert was an important issue. Often journalists who use the MPR office for expert recommendations require a response in as little as an hour).

ADDRESSING THE CHALLENGES

To meet the requirements and challenges outlined above, we propose an examination of the intersection between SHRM and KM by developing and validating an approach which manages the knowledge stocks within an organisation, including the nature, context, source and currency of the knowledge to increase the effectiveness of tacit and explicit knowledge sharing in organisations. Our knowledge mapping method seeks to provide effective connectivity that aligns the needs of knowledge seekers with appropriate knowledge providers by capturing and utilising the knowledge and search context. Our model differs from existing methods by identifying levels of knowledge by activity, supported by a triangulated validation method. The innovation in our model is that it encompasses both tacit knowledge and codified knowledge, and its multi-layered method ensures that seekers find people with the type of knowledge they are looking for at a level they can understand. In this way we will improve organisational innovation through strategic alignment of knowledge resources.

Traditionally, SHRM was defined as 'the pattern of planned human resource deployments and activities intended to enable an organisation to achieve its goals' (Wright & McMahan, 1992, p.298). More recently, SHRM is being seen in terms of the development of intellectual capital, particularly human capital, and its role is to develop capability via the knowledge, skills, talents and know-how of individuals in organisations (Mouritsen et al., 2005). Human capital is measured in terms of the activities it enables employees to perform and the tacit knowledge resources available to the organisation to create new knowledge, solve problems, or develop employee capability (Dess and Shaw, 2001). Our model will assist SHRM to create value for organisations by providing a KM tool that effectively connects knowledge seekers with knowledge providers' tacit knowledge, thereby facilitating the sharing and growth of valuable human capital. Intellectual (IC) capital theorists distinguish between human capital (HC) (tacit knowledge), structural capital (SC) (codified knowledge) and relational capital (RC) (knowledge embedded in relationships) (for example, see Bontis, 2002). KM researchers also identify a specific form of human capital called social capital (SC), which is the ability to draw on social status and reputation to access remote, rare and valuable knowledge resources (Granovetter, 1992; Nahapiet & Ghoshal, 1998).

Expertise is part of HC as it is the knowledge possessed by employees and aggregated at the organisational level in terms of their combined competence and experience (Dess & Shaw, 2001). HC in turn, is a component of IC, which is the organisation's stock of knowledge (Bontis, 1998). Intellectual capital is not restricted to HC, as employees are valuable sources of SC, the knowledge embedded in organisational routines as well as RC, the knowledge connecting personnel. Expertise location is an important strategy for accessing and sharing this organisational knowledge. To that end, our research aims to answer the following questions:

1. How can the value of knowledge be measured?

2. How can automatic identification of expertise be validated to ensure relevant results and appropriate outcomes for those seeking an expert?
3. At what stage of the knowledge hierarchy do {techniques/tools/methodologies/ practices/approaches} convey the most effective articulation of {tacit/procedural} knowledge aligning with the strategic directions of the firm?
4. Through what means does an organisation's intellectual capital shape the creation of expertise?
5. How does the organisation's pool of expertise deliver value to the structural, social and customer capital of a firm?

A wide range of tools and techniques have been designed to help store and distribute knowledge about employees' skills such as recommender systems that greatly speed up and simplify a search process (whether the search is for a book, film or person) and also expert registers (Alwert & Hoffmann, 2003; see also Mertins et al, 2003), sometimes referred to as yellow pages directories. Sociology researchers view expert registers in terms of the democratization of knowledge, providing access to a wider range of employees than would normally be the case (see Fuller, 2002). Tool designers aim then to provide efficient connectivity, by greatly speeding up and simplifying the search process, yielding increased reach in terms of knowledge sharing (Montano, 2005). While existing register models provide efficiency, i.e. speed of access to experts, they are not effective because they rely on the honesty and effort of the experts to maintain accuracy.

The expertise location method offered maintains user profiles, in order to match experts with service requesters, and takes into account the value of the knowledge resource being sought and supplied. Firstly the creation, maintenance and validation of the user profiles, and secondly the estimated value and cost of resources necessary to provide efficient and effective system recommendations, will be achieved using a combination of automated and human-based techniques, which combine and reinforce these two main approaches that individually have numerous weaknesses. The method outlined in this paper examines these issues by developing a knowledge map, which allows navigation of an organisation's codified and tacit knowledge (Alwert & Hoffmann, 2003). The work draws together research into knowledge-based systems, data mining and knowledge discovery; tacit knowledge management; and knowledge resource measurement. We envisage that the research findings will be applicable across a broad range of industry sectors and disciplines.

APPROACH

Our approach focuses on, although not exclusively, human capital - the way knowledge creates value for the organisation. Knowledge, in whatever form, lies idle unless an individual takes action, and this occurs through human capital. We agree with a growing number of researchers (for example, Tsoukas, 2003) that tacit and codified knowledge are not binary constructs; rather, they are complementary, two sides of the same coin. We believe that the management of knowledge is embedded in the tasks, tools and personnel that shape the organisation. In turn, the organisation is shaped by the tacit knowledge embedded in the skills, experiences, expertise and relationships of the staff, coupled with the articulated knowledge embodied in knowledge or information and entrenched in the processes and tasks (formal and informal) which combine staff and tools to produce the outputs of the organisation (Argote & Ingram, 2000). Identifying human capital, therefore, requires the assessment of an individual's tacit knowledge (that is, the knowledge in their head); which typically measures their skills, competencies, qualifications and experiences (Liebowitz & Wright, 1999). Our approach also requires us to assess the individual's structural capital, relational capital and social capital; which is non-intuitive, and has received scant attention from researchers because of previous confusion about the binary nature of tacit and codified knowledge. If we accept that tacit and codified knowledge are complementary, then expertise location models must take into account the interaction between human capital and the other capitals (see Massingham, 2008).

Our model seeks to address weaknesses in existing expert registers which tend to fall into one of two categories: 1) experts are responsible for entering and maintaining their own data which we refer to as *self reporting* or 2) automated computer-based techniques such as data mining are used to uncover expertise within the organisation. Our method uses a combination of 1) human-based techniques including self-reporting but also a feedback loop between knowledge seeker and knowledge provider and 2) automated techniques which use existing artefacts such as publications to identify areas of expertise. Individually these two techniques have limitations. For example, data mining is an automated technique requiring highly structured data sets that may not be easily found in the domain, and the results produced will vary significantly depending on the algorithm. On the other hand, relying on self-reporting by individuals of their expertise is prone to numerous biases and depends on individual motivation. The result is incomplete, inconsistent and out-of-date information that fails to capture, validate and/or maintain levels of expertise within an organisation. However, there are limits to these tools. Knowledge mapping approaches currently lack efficacy for a number of reasons: (a) process problems created by the knowledgeable getting in each other's way (too many people trying to capture or act on knowledge

simultaneously); (b) content problems created by more knowledge being available than can be assimilated (see Fuller, 2002); and (c) application problems created by knowledge seekers not finding the correct knowledge provider. Our method focuses on the third problem. This will represent breakthrough research in this area by developing an expertise location method.

The framework offered seeks to provide guidance and structure in measuring, assigning and locating levels of expertise. Several elements of our research approach are particularly significant and innovative. The supporting system to be developed is based on a triangulated approach that draws together automated/technology-centred and manual/human-centred approaches, and also seeks to close the loop through extensive cross-validation and feedback mechanisms. As Figure 1 illustrates, data mining is the foundation from which our initial data is captured and against which our data is regularly crosschecked. The use of the self-reporting technique to expertise identification is a supporting dimension, within which we allow for others to nominate/refer another person, hence the label 'self-referral'. Data from both sources are used to cross-validate the other, together with explicit feedback regarding the usefulness, timeliness and so on of the assistance provided by both the system and the expert. Collectively this information will also be used in search query formation and determining recommendations.

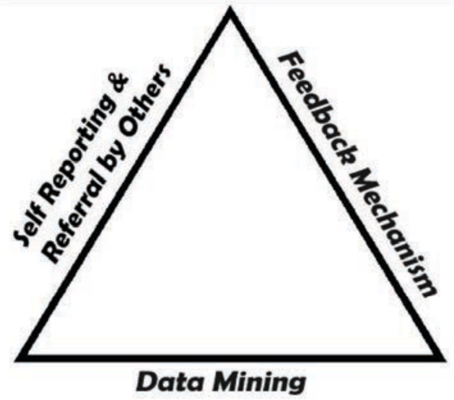

Figure.1.Triangulated approach

Previous methods fail because they mix types of indices and measure learning organisation capacity rather than knowledge resources (e.g. human capital). Our triangulation method (Figure 1) allows levels of expertise to be identified (mined) based on observable phenomena (artefacts) and cross-validated against self-reported expertise, which on their own suffer from biased, missing, irrelevant and non-validated data) together with feedback mechanisms regarding the value/usefulness/timeliness of the expertise provided. Triangulation is commonly used as a method to increase research validity; we adopt its principles to address the need for observable phenomena. More information about our triangulated approach and the results of two studies (with 28 and 19 participants) evaluating the triangulated approach can be found in (Richards, Taylor and Busch, 2008).

We are currently seeking to incorporate the triangulated approach into a more extensive theoretical framework for measuring intellectual capital (for example, expertise). Part of this will involve identifying the range of tools and techniques for storing and sharing knowledge resources and expertise location (for example, recommender systems) spanning current research in the fields of artificial intelligence, information systems, and the knowledge-based view of the firm (KBV). The integrated framework will encompass a knowledge mapping tool, including processes, methods and models, which addresses the major weaknesses with existing tools and techniques. We intend to evaluate the framework within a number of case study organisations.

The research adopts an organisational-level approach to the problem of expertise location. Previous research on the topic tends to privilege the individual by providing tools that assist employees find help (i.e. expertise). While our knowledge map will facilitate individuals in their knowledge search, we want to place this within the context of organisational behaviour (i.e. why people seek knowledge), organisational culture (i.e. barriers to knowledge sharing), organisational structure and systems. In doing so, we will look at the value of expertise location tools to the organisation, within the context of strategic human resource management (SHRM). The value of our framework is best seen within the context of strategic alignment of activity and expertise (Mouritsen et al., 2005). A tool that enables organisations to evaluate whether they have sufficient stocks of human capital to achieve strategic objectives has significant theoretical and practitioner utility. Finally, the research matches activity with human capital, through best practice techniques from the fields of artificial intelligence and information systems to automate effective and efficient knowledge search behaviour.

THE KNOWLEDGE MAPPING MODEL

In order to manage the difficult and complex problem of measuring expertise and intellectual capital, we have developed a systematic, detailed and integrated approach to creating a knowledge map for the organisation. The flow chart in Figure 2 is designed to specifically address the need for data integration and to ensure that all types of knowledge are mapped within the context of specific business strategies and activities. We will use this model to map levels of expertise in several case study organisations. These organisations will be drawn from a group currently working with the authors, and might include the Royal Australian Navy, DSTO and BlueScope Steel. As appropriate, other organisations with which we have contacts, such as Honeywell, Optus and CISRA, may also be invited to participate.

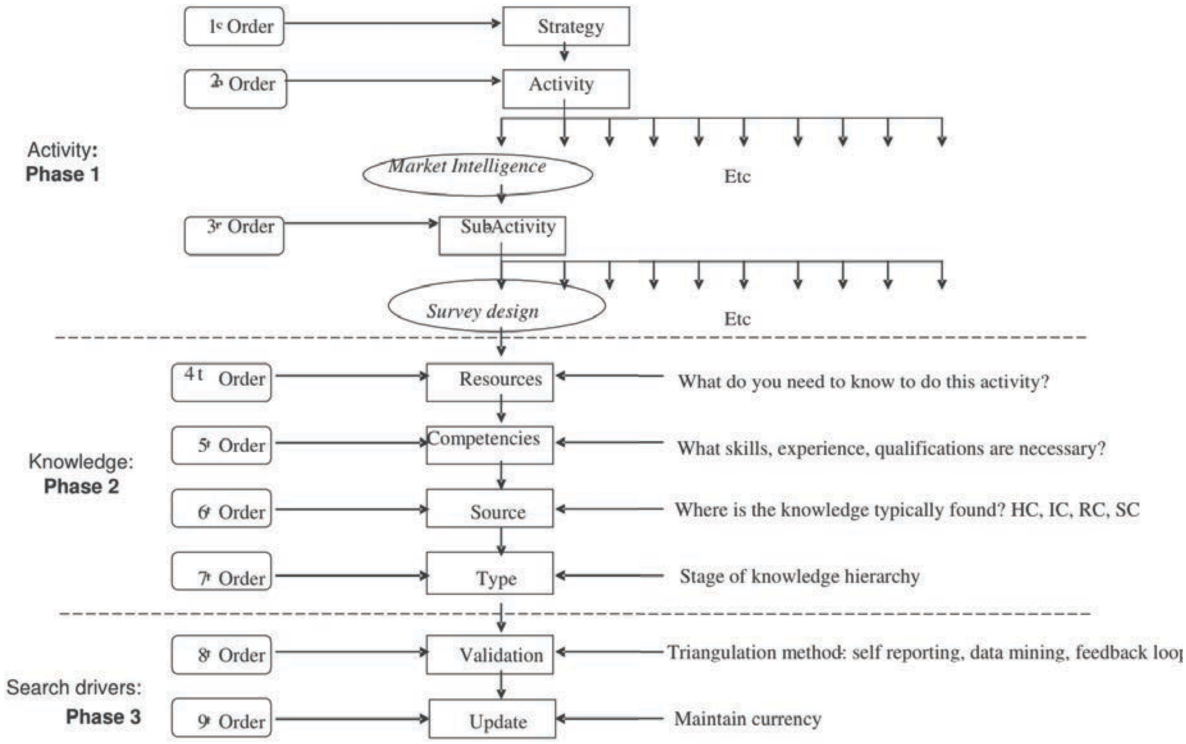

Figure 2: Knowledge Map and Process

As shown in Figure 2, our approach contains three phases representing discreet bundles of activities that combine to allocate an expertise value measurement. Each phase has a number of constructs. Each construct is a level of analysis. Bontis (1998) uses a similar approach to disaggregate intellectual capital into the constructs of human capital, structural capital, and relational capital. Each construct represents a sub-set of the previous construct, i.e. **activity** (*2nd order construct*), is a sub-set of strategy (*1st order construct*). Thus, Figure 2 has a tree structure. At the top of the tree is strategy. There are multiple activities necessary to achieve an organisation's strategy and, therefore, activity has multiple branches (thus the horizontal line with vertical arrows to illustrate). In Figure 2 we have included only one vertical path, i.e. market intelligence and the **sub-activity** (*3rd order construct*) of survey design. It should be clear that the number of tree branches (or nodes) expands as we move down Figure 2. Therefore, the model has multiple vertical and horizontal paths, bounded only by the complexity of the activity and knowledge resources necessary to achieve the organisation's strategy. For the purposes of operationalising this research and to make it manageable, we limit the number of vertical paths explored in each case study organisation. Modelling and collecting data for constructs 1-3 (strategy, activity and sub-activity) are performed in Phase 1. Figure 2 shows one vertical path for the *Survey Design* sub-activity within the *Market Intelligence* activity.

Phase 1 is grounded in the knowledge-based view of the firm (KBV) (e.g. see Grant, 1996) theory. This phase performs data collection for 1st – 3rd order constructs. This is a relatively straightforward process involving: 1. searching each organisation's strategic plans and other documents (e.g. job descriptions) to clarify strategy, and key activities and sub-activities performed by the organisation; 2. validation using an on-line survey of staff and 3. management will be asked to verify the outcomes of Phase 1 and to nominate a few activities to explore further (i.e. Phases 2 and 3). Phase 1 will identify a list of sub-activities for further examination in Phases 2 and 3.

In the second phase we identify the nature and location of expertise necessary to perform the activities and sub-activities selected from Phase 1, which uses theory from a variety of fields.

The *4th order construct* – **resources**- is grounded in the KBV, which explains how knowledge creates value for the organisation, thereby connecting the 3rd and 4th order constructs. We will also use knowledge management tools, such as Tiwana's (1999) eight step levels of knowledge typology, to differentiate expertise. Each organisation will nominate recognised experts for each sub-activity. Secondly, experts will participate in a focus group to discuss the (levels of) knowledge necessary to perform the sub-activity, classifying knowledge as

either: basic, competent, or best practice. Q-Methodology (e.g. see Brown, 1996) will be used to rank knowledge levels. Third, participants will be asked to validate the outputs of discussion.

The *5th order construct* – **competencies** – is grounded in strategic human resource management, which defines human capital in terms of skills, experience, and qualifications. We use this to classify work (i.e. the sub-activity) according to levels of competence.

The *6th order construct* – **source** – is grounded in intellectual capital theory (e.g. Bontis, 1998), which defines the necessary knowledge in terms of human capital, structural capital, relational capital, and social capital. We use this to classify the location of the knowledge in broad terms.

The *7th order construct* – **type** – is grounded in knowledge management theory (e.g. see Tsoukas, 2003) and a knowledge hierarchy (Busch, 2008) which includes five stages of knowledge starting with tacit knowledge (TK) at stage 1 from which some articulable tacit knowledge (aTK) can be extracted (stage 2) eventually leading to codified knowledge (CK) (stage 3). In due course knowledge becomes categorised (Stage 4) and thereafter formalised for example into rule sets, mathematics, formulae (stage 5). The overwhelming majority of research (and development) to-date has focussed on stage 3 codified knowledge or above. Our approach takes a more holistic view by using the knowledge hierarchy to identify the type of knowledge needed/possessed and addresses the epistemological problem in expertise location we previously identified, which is the distinction between codified and tacit knowledge. We use this knowledge hierarchy to distinguish the difficulty in locating the knowledge; e.g. stage 1 in the knowledge hierarchy is the most difficult to locate, and stage 5 is the easiest. Furthermore, We will use Q methodology to manage the 'messiness' of truly valuable tacit knowledge, which the assessor identifies as a potential barrier. Q methodology will be used to engage teams of experts to help us map knowledge levels by domain in a democratic way, resulting in validated taxonomies.

To identify competencies, source and type (5th, 6th and 7th order constructs), we will firstly examine job descriptions for staff who perform the sub-activities selected for study to identify whether there are formally required levels of competence. Second, we will use an on-line survey to gather information regarding competencies, source and type related to each subtask. For example, the possible competence levels will include: basic, competent or best practice. Third, we will examine search cycle behaviour using intellectual capital theory to identify where knowledge is typically found, e.g. HC, IC, RC and SC.

Phase 2 will produce information about the nature of the expertise necessary to perform each sub-activity and its location. The 4th order construct distinguishes knowledge resources, while the 5th order construct differentiates levels of competence. Classifying expertise in this way allows the searcher to locate expertise that fits the task and the searcher's needs. For example, if you have been asked to perform a task for the first time, you should start with basic knowledge, rather than best practice. The 6th and 7th order constructs explain the difficulty in locating the expertise. The results of searches using the 4th and 5th order constructs might indicate you need best practice knowledge and an expert. The 6th and 7th order constructs will tell you whether you can access this knowledge or if you need to modify your search.

Phase 3 covers a major part of the method. The goal of the phase is deliver the framework for identifying levels of expertise that will include a validated process and supporting tools. A challenge for any research that tries to measure the value of knowledge is subjectivity (e.g. see Bontis, 1998). We address this through the triangulation validation method (see Figure 1).

The *8th order construct* – **validation** – is grounded in three literatures. Data mining is grounded in computer science research and will use data inputs such as emails, web pages, project/grant repositories, citation indexes (e.g. CiteSeer http://citeseer.ist.psu.edu/) and publications databases. Self-reporting is grounded in psychology HRM research and will use quantitative/psychometric approaches such as 360º feedback (e.g. Antonioni, 1996). Finally feedback loops will provide a number of means for ensuring the validity and currency of the knowledge, such as employing learning adaptation processes from domain models of expert finding systems (e.g. Yimam-Seid & Kobsa, 2003).

As part of the process of validation we will conduct a number of interviews to develop an inventory of knowledge usage/searching behaviour scenarios: This task will validate and supplement the literature, address the issues raised by our pilot studies (e.g. trust, turnover, access, currency and timing), validate the outputs from Phases 1 and 2 and ground our model within the reality of day-to-day work knowledge search behaviour (i.e. what people do when they need expertise) by capturing knowledge-in-action (Richards and Busch, 2002). Our technique is a psychology-based approach (Wagner & Sternberg 1991) using short (one paragraph) workplace-based descriptions of a situation designed to elicit an ethical (should do) and realistic (will do) 7-point Likert scale response to a number of (up to a dozen) possible responses to the problem posed. Similar to the approach utilised by (Richards and Busch, 2008) to identify innovators, specific sub-activity experts will be invited via interview to present their 'war stories' on accessing expertise. The questions will be designed to elicit barriers they faced to gaining expertise as well as assessing the quality of the expertise they were provided. Additionally,

we will ask the expert to identify the resources (4th order construct), competencies (5th order construct), source (6th order construct) and type (7th order construct) for the knowledge required in the particular scenario. Next the key aspects of the problems and solutions described will be used to develop an edited online inventory of scenarios. Finally, using our online tool the experts will be asked to provide responses to the scenarios and classifications related to their sub-activity area to calibrate the instrument and provide cross-validation with the outputs of phase 2. This inventory will be used again later to maintain currency (see 9^{th} order construct).

According to our triangulated approach we will provide automated validation using data mining techniques and manual approaches using self-reporting. Data mining will involve a search for expertise via codified forms. The key inputs to data mining will vary across organisation type. Data mining can provide the basis for expertise profiles including areas of expertise, statistics on numbers of teams led, publications written, currency/recency of expertise and collaborators. The output of the data mining step will be provided to each person included in the expertise database. Self-reporting will involve on-line questionnaires to ask respondents to rate themselves in the knowledge domains relevant to their work using a series of questions with rating scales (e.g. Tiwana, 1999) to identify levels of expertise. The results will be moderated and validated by two follow up questionnaires: a psychological profile that will allow us to moderate for personality that over-estimates and under-estimates self-reporting of competence; a 360° peer review which asks supervisors, peers, and subordinates to rate respondents in terms of their expertise using tools such "Development Advantage Profile" for assessing managerial competencies (www.concepsys.com) and PROFILOR for assessing different types of staff (http://www.personneldecisions.com.sg).

The *9th order construct* – **update** – involving the extensive use of feedback loops and the development of a unified tool to maintain currency.

Feedback loops form the third support in our triangulated method to ensure that the outputs from data mining and self reporting are consistent. Firstly a personal profile with inconsistencies and missing data highlighted by the system will be provided to the expert for correction. Secondly, based on our findings from elicited search behaviours and scenarios, we will develop a scheme for accessing and measuring the usefulness of the expertise. The approach proposed in Richards, Taylor and Busch (2008) is envisaged, which gives both parties the opportunity to comment on such things as their availability and appropriateness (on the side of the expert) and whether the expertise was helpful.

A unified tool will be used to integrate and keep the knowledge current. The data gathered and instruments created and/or used in phases 1 and 2, such as surveys and the scenario inventory, will be brought together with portals to the other components generated from data mining, self-reporting and feedback loops to provide a comprehensive toolkit. For example, the data mining component will allow the selection of a specific data mining algorithm (including association, classification, clustering and neural network algorithms) or output of results in various forms such as the profile sent to experts. The self-reporting component will include screens for self-analysis and for peer review. The system will perform crosschecking of results from data mining and self reporting, create and maintain user profiles using the available data and various statistics such as availability and user satisfaction with the assistance given, and provide simplified and convenient opportunities for reviewing and updating the system via techniques such as automated emails, reports and formatted screens. The toolkit will provide assistance with searching, using the profiles the search behaviours identified in Phase 3 to recommend experts and advise users about the appropriate automatic and/or manual method/s to use and how to combine them.

A third and significant form of feedback that will serve to crossvalidate the findings in the reports from phase 2 will be completion of scenarios in our inventory of search behaviours relevant to the individuals' subactivities. Analysis of this data will be used to modify the models we have developed for each subactivity. To test the toolkit and approach they will be deployed in subunits within the participating organisations to provide a proof of concept and suggested enhancements. Phase 3 will produce a framework and toolkit that ensures the expertise located by Phases 1-2 is validated and current and which supports a range of search behaviour and needs identified within this phase.

By grounding the value measurement framework in activities, the model is a tool useful at the organisational level, rather than simply the individual level. Previous recommender systems explicitly help individuals to locate expertise. Our model seeks to create organisational benefits through improved strategic alignment — fit between business and HRM strategy — and knowledge management — efficiency and effectiveness gained through knowledge search behaviour. The model's multiple constructs contain powerful potential for scenario modelling ('what if' situations) to analyse the organisation's stock of knowledge. The intended outcomes are a framework and toolkit that ensures IC located by Phases 1-2 is validated and current and which supports a range of search behaviour and needs identified within this phase.

CONCLUSION

Through greater access to and uptake of valuable tacit knowledge the project seeks to improve knowledge worker efficiency and effectiveness. A KM-based methodology that ensures appropriate levels of expertise can be quickly located within organisations, represents a major contribution with widespread application across industry sectors; this is particularly important as Australia develops its capability as a knowledge economy.

From an academic perspective, the research seeks to produce a validated framework for locating levels of expertise within organisations, a significant topic for several reasons. First, it will contribute to the intersection of of research in computer science, information systems, SHRM and KM by addressing important theoretical questions about the value of tacit knowledge, the complementarities of tacit and codified knowledge, how human capital contributes to other capitals, and how to account for weaknesses in conventional expertise location methods, for example, currency, motivation and subjectivity.

We anticipate that the research will make significant theoretical contributions to advancing our understanding of knowledge resources (for example, expertise), and examine how to store and share these resources. The ability to measure human capital resources will provide SHRM researchers and practitioners with a method for developing and demonstrating the field's value, particularly in terms of the need to manage, support and develop human capital. The argument that 'our people are our strength' may become clearer but it may also reveal that they are not. The measurement of this capability represents an exciting set of research ideas.

The project's practical focus explores these theoretical questions within the context of the working environment at our case study organisations. For example, we examine barriers to effective knowledge and expertise sharing which may exist and explore approaches for handling organisational, cultural and behavioural issues underlying the identified barriers and finally propose a knowledge map toolkit as a sustainable, low-cost expertise location method. This research will equip Australian organisations to compete in the knowledge economy with a tool that increases knowledge search efficiency and effectiveness, and improves the strategic fit between business and human resource strategy.

The inter-disciplinary nature of the work and the methodology that has been conceived seeks to address weaknesses with existing expert registers. The project has potential to make breakthrough contributions to our understanding of expert registers in three areas. First, the research specifically addresses weaknesses in conventional expert/recommender systems, such as data mining's variability and subjectivity, and self-reporting's inaccuracy and lack of currency. We will achieve this with a triangulated validation method. Second, the research contributes to one of strategic management's 'black boxes': the measurement of knowledge resource value, by differentiating levels of knowledge or expertise through examination of the type of knowledge from several perspectives. Third, the research combines these issues to design an entirely new approach to expert recommender systems that matches the knowledge resource with the activity.

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