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User Expertise in Contemporary Information Systems: Conceptualization, Measurement and Application

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INTRODUCTION
An organization’s human resources are being recognized as a significant competitive advantage and one of the hidden forces behind profits, growth and lasting value [1, 2]. As Torraco and Swanson [3] assert, “Business success increasingly hinges on organization’s ability to use its employee’s expertise as a factor in shaping of its business strategy” (p 11). It is the knowledge, the skills, and the experience of the organization’s human resources – in short expertise of their employees – that has gained recognition and prominence in providing true competitive advantage. Thus, developing employee expertise is a strategic imperative for organizations in hyper-competitive economic environments. In parallel with the continuing investments in complex and costly contemporary Information Systems (IS) – Enterprise Systems (ES) being the quintessence – there has been a growing recognition of the importance of user expertise, competence and user quality on the effective adoption of contemporary IS.

User expertise, however, is not a simple reflection of one’s innate abilities and capabilities, but rather a combination of acquired complex skills, experience and knowledge capabilities [4-7]. Eriksson et al., [8], demonstrate that both extended deliberate practice and deliberate learning of skills have a strong positive relationship with expertise. Simon and Chase [9], demonstrated that in certain disciplines it takes approximately 10-years of intensive deliberate practice to attain a high degree of proficiency. In Information Systems, research on user competence [e.g. 10] and computer self-efficacy [11-14], provide a wealth of knowledge on how to conceptualize and measure ‘staff computing ability’ [10]. Yet, as Marakas et al., [15] observed, “[past studies on both self-efficacy and user competence] have focused heavily on models in very distinct domains”, predominantly using simple information systems (e.g. spreadsheets, word processing) and lacking emphasis on user expertise
in contemporary IS. At a time where organizations are in a transition from in-house, custom-made, stand-alone applications to integrated, complex, customizable, user-centric software packages [16], it is vital that we re-visit the notions of User Expertise in Contemporary Information Systems\(^1\). User expertise in contemporary IS could answer why some users employ only the bare minimum of system features and functions, while others engage in optimal use of a contemporary IS through value-adding usage [17, 18].

This paper conceptualizes User Expertise in Contemporary Information Systems as a multi-dimensional formative construct, with each construct measured using several reflective measures. Through a robust, multi-method study design, which includes three separate studies, 244 respondents in total, representing three organizations in India, we develop a model for evaluating expertise. Our approach employs theoretical foundations of computer self-efficacy and user competence, perceptual measures, its aim being to offer a common instrument that addresses requirements of a contemporary IS in a holistic way. Such a validated and widely-accepted expertise construct has both academic and practical value. Furthermore, using two complementary methods, we offer a classification method to place users on a continuum based on their expertise, as expert, intermediate or novice. Finally, we demonstrate the application of our expertise construct in Information System evaluations (IS success), demonstrating that users of different expertise levels evaluate systems differently.

**USER EXPERTISE IN CONTEMPORARY IS**

There has been a growing recognition of the importance of using contemporary IS appropriately for the lifecycle-wide health and longevity [19, 20]. For example, Momoh et al. [21] attribute a lack of ES benefits to lack of appropriate ES use / lack of user expertise. Furthermore, a recent study by the Standish Group reports that only fewer than 10% of ES installations succeed in using the intended full ES functionality in the early phase of the ES lifecycle due to lack of employee skills. Moreover, contemporary system users experience a steep learning curve after ‘going-live’ at the shakedown phase, gaining knowledge of the system features and functions through

\(^1\) Given the unwieldy expression ‘User Expertise in Contemporary Information Systems’ further reference to this concept is simply ‘Expert/ies’, where the contemporary nature of the system and user expertise are implied.
exploration and undergoing training to add value to their business processes at the later parts of the system lifecycle (i.e. onwards/upwards phase) [22, 23]. Concomitantly, there have been reports of organizations achieving high levels of success with ES by focusing on effective use of the system [24], where users’ expertise with Information Systems has been recognized as crucial of its effect on workplace productivity [25-28].

Information Systems research addressed this issue of productivity through user expertise, focussing on the adoption and use of IS by end-users [e.g. 29, 30], through studies of computer self-efficacy, end user computing and user competence. This past research has made at least two substantial contributions to the IS discipline: (i) recognition of the central role of the end user in deriving value from systems, and (ii) derivation of several frameworks and measurement models to understand fundamental characteristics of end users. Yet, as Marakas et al [15] pointed out, the current conceptualizations of these topics have not evolved beyond the simple information systems like word processing and spreadsheets – what McAfee [31] calls as functional IT. McAfee, in addition to Functional IT (e.g. word processing; spreadsheets), identified two other types of systems: Network IT (e.g. Emails, WiKis) and Enterprise IT (e.g. ERP, CRM systems), classifying systems based on what McAfee calls the ‘complements’. Complements are defined by McAfee [31] (p 142) as “organizational innovations or changes”. Examples of complements that allow performing technologies include ‘re-design of processes’ and ‘new decision rights’. Thus, McAfee argued that Functional IT (e.g. word processing) can be adopted without substantial organizational innovation, changes and they do not entail process re-designs or new decision rights. On the other hand, Enterprise IT imposes complements throughout the organization, defining tasks, sequences, and mandates its use. Moreover, the advent of Enterprise IT leads to continuous process re-designs and changing decision rights throughout the lifecycle. The salient differences between Enterprise IT and Functional IT relating to the current topic are summarized in Appendix A.

Thus, considering the fundamental differences between functional IT systems verses Enterprise IT systems, a new conceptualization, constructs, measures and evaluation models of expertise are required to gauge the user expertise of users in complex systems like Enterprise Systems [15, 16]. Nonetheless, most current studies continue
to rely on instruments and measures that had been validated and derived from simple Functional information systems. In example, Munro et al. [10] observed end user computing using word processing applications, while Marakas et al. [15] observed computer self-efficacy using spreadsheets and word processing applications.

DEVELOPING A CONCEPTUAL FRAMEWORK FOR CONTEMPORARY IS EXPERTISE

In developing the expertise construct for contemporary IS, we synergize the constructs of Theory of Self-Efficacy and studies of User Competence for contemporary IS. The constructs of the two theoretical foundations jointly help us derive the new expertise construct that we argue are better fitting to contemporary IS expertise. High-level attitudes and beliefs important for ES expertise are derived from the theory of self-efficacy and, akin to learning theory, the constructs of user competence on specific cognitive competence and skill-based constructs are derived through user competence studies.

As researchers note that, becoming an expert in the 21st century professional workplace involves a complex array of knowledge and skills as well as processes [5, 32]. Past research contend that, this new workplace emphasises on such things as the need for dealing with deep understanding, the ubiquity of change and novelty, the simultaneous occurrence of processes, the interactiveness and interdependence of processes and people, the demand for customisation/particularisation in both products and procedures, non-hierarchical-linear management structures and the like [33]. Our intension herein is to employ Bandura’s and related work of Marcolin et al as the foundation and then to develop constructs and measures related to contemporary Information Systems expertise considering both cognitive skills as well as their ability to adapt and adopt to new situations. The section below, not intended to introduce each theory in full, provides an overview of the conceptual framework for contemporary expertise.

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2 Munro et al (1997) defines user competence stating that “...end users essentially need to know about, and able to use, three things: EUC software, hardware, and concepts and practices. These, then, are the three major EUC “domains (p 47)”. The Marakas et al (2007) instrument of computer self-efficacy on seven task related constructs focusing on: general efficacy, Windows Efficacy, Spreadsheet Efficacy, Word-Processing Efficacy, Internet Efficacy, Database Efficacy and a test on Task Performance.
Bandura [34] defined self-efficacy as “people’s judgments of their capabilities to organize and execute courses of action required to attain designated types of performances. It is concerned not with the skills one has, but with judgments of what one can do with whatever skills one possesses” (p. 391). Therefore, the concept of self-efficacy was context specific, or the valuing of self through specifically defined situations. The definition of self-efficacy provided by Bandura [34] highlighted the importance of distinguishing between component skills and the ability to perform actions. Further studies by Bandura discussed the psychological construct of self-efficacy as a concept that referred “to beliefs in one’s capabilities to mobilize the motivation, cognitive resources and courses of action needed to meet situational demands” [35] (p. 506). In general, the self-efficacy construct reflects ones’ perceived skills and ability, including motivational and ability to adapt for the work environments as well [35, 36]. Originally conceptualized at the task-specific level, computer self-efficacy can be hypothesized to be far more complex than previously suggested [cf. 37], where the self-efficacy construct captures not only the competence of completing a task, but also socio-behavioural aspects important in completing the task. Self-efficacy has been studied at both the application-specific level (word processing, spreadsheets, etc.) and at a more general computing level [34, 38].

On the other hand, User Competence studies specify specific constructs that are directly related one’s employment. Past studies measured user competence employing “Skill-Based” and “Cognitive Competence” [e.g. 39]. Stated in User Competence is that the construct is measured employing the “known” tasks or activities. For example, Marcolin et al. [39] observed user competence of Spreadsheets and Word Processing, focusing on specific functions that users perform within the software (e.g. formatting). In derivation of items and measurement too the approaches of Self-Efficacy and User Competence have similarities. In designing measures for self-efficacy too, Bandura [14] (p. 207) states “…there is no all-purpose measure of perceived self-efficacy. The “one measure fits all” approach usually has limited explanatory and predictive value because most of the items in an all-purpose test may have little or no relevance to the domain of functioning. Moreover, in an effort to serve all purposes, items in such a measure are usually cast in general terms
divorced from the situational demands and circumstances. This leaves much ambiguity about exactly what is being measured or the level of task and situational demands that must be managed. Scales of perceived self-efficacy must be tailored to the particular domain of functioning that is the object of interest”. Thus the measures of ‘affective’ were derived using the key high-level premises of Enterprise Systems, observing whether the users are able to withstand and are motivated to change and evolve with the evolution of the Enterprise System.

Observing past research in Information Systems [e.g. 10, 14, 15], Psychology [e.g. 40, 41], and Sociology [e.g. 8, 42], we identify three salient considerations for developing constructs and measures for contemporary IS user expertise: (i) type of system, (ii) measurement constructs/ domain, and (iii) evaluation method. Our approach is similar to the one reported in Marcolin et al. [39], wherein their discussion of User Competence of Spreadsheets and Word Processing, included: (1) Measurement Method – self-report, paper-and-pencil test, Hands-on, observer assessment, (2) Knowledge Domain Areas – Software and Hardware Knowledge, and (3) Conceptualization of Competence\(^3\) – Cognitive, Skill-based and Affective. We agree that Measurement method, Conceptualization and Knowledge Domain areas are still important in understanding ones expertise; the essential difference being our inclusion of the type of the system.

We argue that one could conceive expertise using any combination of these three considerations. In figure 1, cells marked with ‘A’ denote where past studies of computer self-efficacy and user competence concentrate on, which cells marked as ‘B’ provide the scope for this research. The scope (i.e. cells) must be selected with care, understanding the intent of the study context, acknowledging that some combinations of cells are less realistic and less informative. We recommend that the

\(^3\) The definitions for the three constructs are derived using the learning theory of Kraiger et al 1993. Their definitions of the three constructs have been later employed in User Competence Studies of Marcolin et al. 2000. We define the constructs of ‘Cognitive’ or ‘Knowledge Domain’ using the learning Theory (Kraiger, Ford and Salas 1993; Anderson 1980) as a class of variables related to the quality, quantity and types of knowledge for an end user. Marcolin et al (2000) employs the aforementioned definition specific to Information Systems, stating that Cognitive outcomes refer to the knowledge that users have about what a technology and how to use it. Kraiger et al (1993) define Skill-Based outcomes in relation to the users’ ability to move from procedural knowledge to automaticity through proactive self learning. The Affective outcomes, according to Kraiger et al are defined as an attitude and motivation as outcomes of learning.
primary consideration herein should be the ‘type of the system’. Thus, as a rule-of-thumb, we suggest that the selection of cells be based, first on the system, next the on the domains, and finally selecting the measurement approach. One should then commence developing measures appropriate to the selected context [18].

![Figure 1: Expertise Framework](image)

**Type of the System**

In order to understand how expertise of one type of a system could be different to another, we use the simple system classification provided by McAfee [31], where systems were grouped into: Functional IT, Network IT[^5] and Enterprise IT. Appendix A presents a summary of differences between these three systems. According to McAfee [31], Functional IT assists only with the execution of discrete tasks. Examples of Functional IT include word Processing, spreadsheets, and computer aided design statistical software. McAfee also outlines that Functional IT can be adopted without complements[^6], and argue that most contemporary Functional IT operates within the same operational framework (e.g. almost identical menu paths between Microsoft Word and Microsoft Excel). Moreover, users of Functional IT

[^4]: The variable Affective is later narrowed down to capture only ‘Motivation’. See discussion later in this paper

[^5]: We will not discuss Network IT herein. Network IT facilitates interactions without specifying their parameters. Examples of Network IT include: Emails, instant messaging, wikis, blogs and mash-ups.

[^6]: Complements are defined by McAfee (2006, p. 142) as “organizational innovations, or changes in the way companies get work done”. Examples of complements that allow working performing technologies, according to McAfee (2006, p. 143) are “better-skilled workers”, “higher levels of teamwork”, “redesigned processes”, and “new decision rights”. 
would attain a reasonable expertise with the basic (and essential) functionality of Functional IT and even a novice user could easily adapt to changes of the Functional IT without much exertion. Given the nature of Functional IT, it is essential that an employee is required to use more than one application for the daily work, changing between one Functional IT to another. As an example, most Functional IT users are likely to use a spreadsheets, presentation and word processing applications in a single day. Thus, required skills, knowledge and the ability to switch between applications (commonly known as the ‘switching effort’) are minimal. Yet, most computer self-efficacy and user competence studies report the ability to switch between Functional IT applications as the ‘competence’ [e.g. 39]. We differ here and argue that a contemporary IS user, given their familiarity with Functional IT applications, can adopt from one Functional IT application to another relatively easily.

On the other hand, Enterprise IT is ‘new’ to most IS users and they specify business processes and impose complements throughout the organization [31]. The processes and the task sequences of the processes, data format and, in most cases use of an Enterprise System are mandated by the organization. Furthermore, Enterprise IT users – unlike Functional IT – are rarely required use more than one Enterprise System. This means that the ability of a user to adopt new technological applications, as employed in computer efficacy studies is less relevant to the context of Enterprise IT. Instead, the focus must be on how well a user evolves from being a novice user, presumably at the ‘go-live’ time, then developing their expertise over the lifecycle. Furthermore, given the process nature of Enterprise Systems, Enterprise IT users must focus on the business processes expertise, not task expertise [e.g. 16, 43].

**Measurement Construct / Domain**

Studies of learning and training theories [44, 45] identify three different outcomes associated with learning: Cognitive, Skill-Based and Affective. Cognitive outcomes – commonly referred to as declarative knowledge – refer to the knowledge users have of the technology. Marakas et al [15] suggest that the cognitive knowledge measures must be derived through a full understanding of the context of the study, rather than simply adopting from past studies. Skill-based outcomes capture the user’s ability to adapt and adopt into novel situations. Herein, most past computer self-efficacy and
user acceptance studies measure user’s ability to generalize procedures at simple tasks. Marcolin et al [39] (p. 39) note “those learning word processing might proceed from the knowledge that applying bold formatting to text can be accomplished by highlighting the text and then, selecting “bold” from a menu or toolbar, and that applying underline is accomplished in the same way, to the recognition that most character formatting is applied in this fashion”. We argue that ‘moving beyond the knowledge’ in a contemporary corporate-wide system should entail a more fluid and a holistic approach, where the user shows the ‘ability’ to learn continuously. Contemporary thinking is that, ‘proactive self-learners’ excel in dynamic contexts [46], like in the case of Enterprise Systems. Affective outcomes relate to attitude and motivation (including aspects of self-efficacy) on users’ willingness to adapt.

In defining the construct ‘affective’, we employ Kraiger et al. [44] definition. Kraiger et al. defined affective using pioneering work of Bloom [47] and Gagne [48], in association with learning theories. Therein, Kraiger et al. [44] defined affective in using a composite of ‘attitude’ and ‘motivation’ constructs. We concur with Marcolin et al. in their use of Kraiger et al. [44] definition of affective in their study of user competence. In that Marcolin et al argue that most Information Systems studies measure affective solely using attitude as a dimension, ignoring motivation. Marcolin et al. [39] state that “…it should be noted that the term affective, as used in this [their] model, is much broader than the term as used in Information Systems literature… The IS literature focuses affective as a component of attitude…” (p 40).

Furthermore, Gagne [48] define attitude as an internal state that influences the choice of personal action. Researchers, therefore argue that attitude contributes to one’s expertise in more social environments, like in the law enforcement and amongst fire fighters [49], where attitude impacts on individuals’ levels on aspects in relation to group norms [49], tolerance for diversity [50] and recognition of what is important to learn. Motivational aspects on the other hand, include such aspects like motivational disposition and goal setting behaviour [48]. Moreover, Kraiger et al. citing [51] and [52] note that motivation can be conceived through mastery or performance orientation; where mastery refers to the intention to do well and to gain recognition, and the later refers to the abilities and skills to adopt and adapt in a changing environment. Kraiger et al. note that mastery of orientation allows people to achieve
higher levels of learning [akin to expertise] making changes to internal attributes to suit the changing situations. Considering all, it is logical that attitude be dropped from our conceptualization and only Motivation be retained as a construct of expertise, allowing it to be considered for deriving measures in study 1 and 2. A parallel notion has been identified in the study of Germain [46, 53, 54] who included ‘willingness to adopt and adapt’ as a construct of expertise.

In addition, ‘Years of Experience’ is also considered as having a positive influence on expertise. For example, Simon and Chase [9] initiated a series of observations in disciplines ranging from tennis [55], mathematics and [56], music [57] observing that it takes approximately 10 years for one to become an expert from the time at which practice was initiated. Despite its wide adoption, Simon and Chase 10-year expertise-based-on-experience rule has never been empirically tested in IS research.

### Evaluation Method

Three types of measurement methods have been employed in past expertise / competence; (i) self-reported measures [e.g. 58], (ii) classical method [e.g. 37, 42], and (iii) observer assessment [e.g. 59]. Self-reported measures are provided by individuals assessing their own abilities, while in classical approach expertise is measured by the investigator based on how well one responds to a set of questions. In general, the classical approach is appropriate when expertise can be measured using a set of finite questions that are not subjected to external / contextual factors (e.g. in mathematics). The observer assessment method involves rating of skills of an individual by an independent observer, in most cases by the colleagues. Studies have shown that all three methods provide a reasonable assessment of an individual’s skills, knowledge and in general, expertise [53]. In particular, Germain and Ruiz [53] observed a strong correlation between expertise measured using the self-assessment method and the classical approach. The method of measurement must be selected with care, paying close attention to its suitability to the phenomena of measurement. For example, Mann [60] and Moskal [61] note lesser-skilled are more likely to exaggerate their skills and colleagues could rate their superiors’ expertise high. Germain [46] and

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7 The classical approach can be further divided into hands-on and paper-and-pencil tests.
Germain and Ruiz [53] note that the classical method cannot be employed in studies where there is no finite answer, and the answer is moderated by the context [46, 53].

The conceptual model in figure 2 is derived through the cells marked with ‘B’ in figure 1, which illustrate the scope of this research, informing the development of the a-priori model. Our choice of considerations (marked as ‘B’) was guided by theoretical and pragmatic considerations. Our system of interest is Enterprise Systems, domains including Cognitive, Motivation, and Skill-Based outcomes, using the self-evaluation measurement approach. Our decision with respect to choosing the self-reported measures follows closely our conceptualizations of the type of the system and measures of expertise derived through a three-phased study design (figure 3 and related discussion). Moreover, the classical measurement approach (using ‘paper-and-pencil’ and ‘hands-on’ testing) was deemed inappropriate for measuring expertise in this context, where knowledge is non-declarative and influenced by the context [e.g. 45].

![Figure 2: The Conceptual Model](image)

**RESEARCH DESIGN**

This study employed a multi-method research design, using the research cycle proposed by MacKenzie and House [62] and McGrath [63] for developing and validating a measurement model. Despite a wealth of research on computer self-efficacy and user competence, this exploratory approach was deemed necessary, mainly due to the purported differences between Functional IT and Enterprise IT.
The research design entailed two main phases and three studies as shown in figure 3: (i) phase 1: a qualitative, exploratory phase, facilitated by two studies to identify specific measures of the four a-priori constructs of the formative expertise model, and (ii) phase 2: a quantitative confirmatory phase, to test the hypothesized model against survey data gathered. Study 1 and study 2 of the exploratory phase adhere to the two-step approach advocated by Burton-Jones and Straub [18] for operationalizing constructs and identifying appropriate context specific measures. The aim is to adequately account for the context of large, contemporary IS (in our study, Enterprise Systems) and to ensure model completeness and an appropriate choice of measures and constructs.

Figure 3: Research Design

All three studies employed data collected from users of the ‘Procurement and Order Fulfilment’ processes at three large organizations that had implemented SAP Enterprise System. In order to minimize influence of extraneous factors, all three organizations were selected from the same industry sector (manufacturing), use the same Enterprise System (SAP), same country (India), and had implemented their SAP systems around the same time – thus assume to be at the same phase of the ES lifecycle. The selection of the procurement and order fulfilment process too was deliberate and logical: (i) the procurement and order fulfilment are two of the most commonly automated ES business processes in most industry sectors allowing wider generalizability, (ii) the process involves a representative cross-section of the organization, from sales, purchasing and financial accounting, (iii) the processes involve both management and operational staff, (iv) the steps in the processes reflect adequate variance to be used at ‘near mandatory’ levels as well as ‘value-adding’ optional levels, and finally, (iv) akin to Burton-Jones and Straub [18], the knowledge
of the research team of the procurement and order fulfilment business processes and SAP, allowing us to develop survey items and better interpret their results. Table 1 summarizes the three data collections conducted in this study.

<table>
<thead>
<tr>
<th>Study</th>
<th>Purpose</th>
<th>Organization/s</th>
<th>Method</th>
<th>Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study 1</td>
<td>Identify themes and possible measures of expertise</td>
<td>Glass Co</td>
<td>Semi-structured interviews</td>
<td>12</td>
</tr>
<tr>
<td>Study 2</td>
<td>Specify domains, themes and measures of expertise</td>
<td>Pharma 1 Co</td>
<td>Semi-structured interviews</td>
<td>12</td>
</tr>
<tr>
<td>Study 3</td>
<td>Validate the expertise model</td>
<td>Glass Co, Pharma 1 Co, Pharma 2 Co</td>
<td>Survey</td>
<td>220</td>
</tr>
</tbody>
</table>

Table 1: Details of the three studies

**Study 1**

Study 1 is qualitative and aims to generate a set of starting domains, themes and measures that represents expertise of an ES user that could be used for measure development\(^8\) [64, 65]. Herein, we strive to develop a good formative index – one that exhausts the entire domain of the construct completely, meaning that the constructs should collectively represent all the relevant aspects of the variable of interest [66-68]. Its purpose, akin to the function phase of the Burton-Jones and Straub [18] approach, is to justify the a-priori salient measurement domains as per figure 2 (i.e. Cognitive, Skill-Based and Motivation) and identify appropriate themes and measures for each dimension of expertise. While a common approach to identifying a-priori measures is to select from the existing literature, based on conceptual arguments, we believe this is inadequate given study objective of extending to the new Enterprise Systems context.

Study 1 canvasses how expertise is conceived in the minds of the ‘experienced’ and ‘expert’ users of a contemporary IS, yields qualitative data to substantiate the constructs from the literature, thereby ensuring that (i) the referent constructs are not only conceptually, but also empirically relevant in the contemporary IS context, and (ii) identify measures (and possibly constructs) not already identified in the literature but possibly of significance in that environment. The constructs and measures

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\(^8\) As noted by Hinkin (1995), this step further enhances the content validity of our measures, as this process allowed us to refine and / or replace items before preparing and administering a questionnaire. As per Hunt (1991), an inductive approach is used, also called ‘grouping’ or ‘classification from below’ is appropriate when the theory is extended to a different or new context.
substantiated and discovered in study 1 subsequently, validated again through in study 2, became the basis of an a-priori model that was operationalized in the specification survey\(^9\).

Study 1 consists of a field study of 6 management and 6 operational staffs of the Procurement and Order Fulfilment processes of Glass Co, conducted using individual\(^10\), remote, semi-structured interviews lasting between 40-50 minutes each. In total, our interviews transcribed to approximately 09 hours and 20 minutes. Two non-probability sampling techniques, purposive and snowball were utilized in the selection of interview participants to ensure that they were appropriate opinion leaders with well-developed views on the research topic [69]. Given the generative purpose of the interview, the sample size did not have to be large since “the validity, meaningfulness, and insights generated from qualitative inquiry have more to do with the information-richness of the cases selected and the observational/analytical capabilities of the researcher than with sample size” [70, p 185]. At the beginning of the meeting, the participants were briefed about the objective of the study.

From each participant study 1, we asked two questions: (i) “How do you describe an expert in your organization, in the business process that you are involved in?” (ii), “What are the salient characteristics of an expert (in general)?” One of the co-authors of this paper and two research assistants conducted the interviews and recorded responses. The study 1 analysis yielded a total of 214 citations on 24 unique themes (Table 2 illustrates the ‘citations by User-Group’, with a ‘summary’ and the percentage of agreement on each citation between the two User-Groups – stated as ‘between agreement’). Decomposition of the textual responses was straightforward, simply involving the extraction of contiguous phrases, without modification. In order to minimize individual errors of judgment, two researchers participated in the mapping exercise, each person mapping approximately 20 citations and comparing results. Comparison of the individual classifications revealed an average inter-coder

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\(^9\) Each measure has a corresponding perceptual question in the survey questionnaire.

\(^{10}\) Our decision to gather data individually (instead of gathering data through a single panel of 12 participants) was motivated by: (i) lack of peer influence on selecting categories, (ii) less frivolity and thus (iii) better concentration of the participants.
agreement of 80 percent\textsuperscript{11}. Discrepancies were discussed until a consensus was reached and formal criteria for classification were documented. Next, for each of the 24 themes, the research team developed a simple description of 2-3 lines.

<table>
<thead>
<tr>
<th>Theme</th>
<th>Managers (n=6)</th>
<th>Operational (n=6)</th>
<th>Summary</th>
<th>Between Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ability to learn related aspects about the corporate structure</td>
<td>5</td>
<td>4</td>
<td>9</td>
<td>4.2%</td>
</tr>
<tr>
<td>Must be thorough with company policies and guidelines relevant to</td>
<td>4</td>
<td>6</td>
<td>10</td>
<td>4.7%</td>
</tr>
<tr>
<td>Ability to find better ways of doing my their business process in</td>
<td>4</td>
<td>5</td>
<td>9</td>
<td>4.2%</td>
</tr>
<tr>
<td>Eager to learn improvements, updates of the SAP system</td>
<td>5</td>
<td>4</td>
<td>9</td>
<td>4.2%</td>
</tr>
<tr>
<td>Can adapt to any changes to the SAP system</td>
<td>6</td>
<td>6</td>
<td>12</td>
<td>5.6%</td>
</tr>
<tr>
<td>Can adapt to changes in my their business process</td>
<td>5</td>
<td>6</td>
<td>11</td>
<td>5.1%</td>
</tr>
<tr>
<td>Can adapt to changes in their department, related to their</td>
<td>3</td>
<td>2</td>
<td>5</td>
<td>2.3%</td>
</tr>
<tr>
<td>Can absorb any changes in their organizational structure, related</td>
<td>6</td>
<td>6</td>
<td>12</td>
<td>5.6%</td>
</tr>
<tr>
<td>Can accept new roles and responsibilities related my their</td>
<td>4</td>
<td>5</td>
<td>9</td>
<td>4.2%</td>
</tr>
<tr>
<td>Can adapt to changes in their department, related to their business</td>
<td>3</td>
<td>6</td>
<td>9</td>
<td>4.2%</td>
</tr>
<tr>
<td>Knowledge of SAP is adequate to perform their day-to-day functioning</td>
<td>5</td>
<td>4</td>
<td>9</td>
<td>4.2%</td>
</tr>
<tr>
<td>Rarely make mistakes when completing a business process using</td>
<td>6</td>
<td>6</td>
<td>12</td>
<td>5.6%</td>
</tr>
<tr>
<td>One with in-depth knowledge of the functions of the business process</td>
<td>4</td>
<td>4</td>
<td>8</td>
<td>3.7%</td>
</tr>
<tr>
<td>One with excellent knowledge of the organizational goals, procedures</td>
<td>4</td>
<td>6</td>
<td>10</td>
<td>4.7%</td>
</tr>
<tr>
<td>Years of experience in the business</td>
<td>6</td>
<td>6</td>
<td>12</td>
<td>5.6%</td>
</tr>
<tr>
<td>One who shares their knowledge of SAP with colleagues ^</td>
<td>5</td>
<td>6</td>
<td>11</td>
<td>5.1%</td>
</tr>
<tr>
<td>One who suggest improvements of the business processes to their</td>
<td>5</td>
<td>6</td>
<td>11</td>
<td>5.1%</td>
</tr>
<tr>
<td>One who assists when others are faced with a work related issue ^</td>
<td>5</td>
<td>5</td>
<td>10</td>
<td>4.7%</td>
</tr>
<tr>
<td>Has been recognized as someone with high expertise ^</td>
<td>5</td>
<td>6</td>
<td>11</td>
<td>5.1%</td>
</tr>
<tr>
<td>One who is ethical in their conduct *</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1.4%</td>
</tr>
<tr>
<td>One who is hard working *</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>1.9%</td>
</tr>
<tr>
<td>One who has worldly knowledge *</td>
<td>3</td>
<td>2</td>
<td>5</td>
<td>2.3%</td>
</tr>
<tr>
<td>One who is skilled in all aspects *</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>1.9%</td>
</tr>
</tbody>
</table>


Table 2: Themes of expertise derived through study 1

**Study 2**

Study 2 was formed to content validate the domains, themes and our descriptions thereof. It too was qualitative and followed the same data collection procedure (remote, semi-structured workshop/interviews lasting between 40-50 minutes each, with 6 operational and 6 management staff of Procurement and Order Fulfilment). Study 2, was conducted at a Pharmaceutical company (Pharma 1 Co). Herein, we did not specify the sample needed to be composed of ‘experts’. Anyone who works in the procurement and order fulfilment business processes using SAP was deemed appropriate and eligible as a participant. Moreover, since the purpose of the scale was
to measure expertise at various levels in an organization, the participants had to match the expected target population. The sampling was purposive and convenient\textsuperscript{12}.

The sample in study 2 observed the degree to which each theme reflects (and perhaps operationalizes) its nominated construct. To facilitate this evaluation process, the domain definition, description of the theme in lay terms and a survey item per theme were provided. Following the suggestions of Grant and Davis [72]\textsuperscript{13}, each participant was asked to address the representativeness, comprehensiveness, and clarity examining the 24 themes of expertise and their descriptions in table 2.

**Representativeness:** Each participant was given the (i) 24 themes, (ii) their description, (iii) a corresponding survey item, and (iv) the names of the four constructs. Next, each participant was asked to indicate the extent to which they perceived each individual theme (that is i, ii and iii) to be representative of the domain (that is iv) with which it was associated, by selecting the most appropriate domain. This first element forms the quantitative part of the content validation process. Hence, study 2 members examined the questions and identified whether the questions captured the theme and the closeness of the items to the constructs / domain [76]. This also served as a pre-test of survey items.

**Comprehensiveness and Clarity:** The second task was to evaluate the comprehensiveness of the entire instrument by identifying items which they perceived to be incongruent with its nominated domain and, subsequently, assigning them to an alternative domain with which the items were better matched.

**Deriving the a-priori model**

Results of study 1 and study 2 helped us form the expertise a-priori model constructs and measures. Specifying a parsimonious a-priori model for expertise involved: (i)
elimination and consolidation of domains; (ii) introduction of new domains or measures; and (iii) revisiting the relevance of the domains identified in study 1. Respondents in study 2 highlighted that themes 21-24 in table 2 are too broad for measuring user expertise. They identified that those themes narrate the general characteristics of a ‘good person’, and are less relevant for specific expertise of Information Systems that we seek in this study. Similar observations on one’s ‘ethical conduct’, ‘worldly knowledge’ and ‘skilled in all aspects’ were recognized as too broad for the domain specificity by and Dweck [51]. Furthermore, study 2 identified that themes 17, 18, 19 and 20 are about how experts share knowledge – a possible consequence of expertise. Thus, in the interest of parsimony, and consistent with formative index development procedures [77-80], those 8 themes were not included as measures in the expertise a-priori model. The remaining themes and a single measurement item for each theme were included in the a-priori model.

Figure 4 depicts the a-priori expertise model, including themes and constructs (henceforth referred to as measures and constructs respectively) conceived through our expertise framework and validated using results of study 1 and study 2. The a-priori model is in alignment with our conceptual model (figure 2) and the expertise framework in figure 1.

The a-priori model consists of four formative constructs: Cognitive, Skill-Based, Motivation and years of experience. The 15 reflective measures of Cognitive Competence, Skill-Based and Motivation constructs, within each construct, have a strong association with the broader topics business processes, software, organization, application of software to business processes.

Our model conceptualization is also consistent with the observations of Marakas et al [15] (p. 21) who state that “…we argue that validation of CSE [computer self-efficacy] and GCSE [general computer self-efficacy] instruments must use techniques appropriate for formative constructs rather than the commonly adopted techniques associated with reflective constructs”14.

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14 See Marakas et al. (2007) for a discussion of why CSE and GCSE constructs must be conceived as formative. Marakas et al. also discuss (table 1, page 20) the key differences between formative and
The a-priori model does not purport (is not concerned with) any causality among the constructs; rather the constructs are posited to be formative constructs of the multidimensional concept – Expertise. As per the guidelines for identifying formative variables, constructs 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 [77, 78, 80]. Moreover, use of formative constructs in this case provide a ‘specific and actionable attributes’ of a concept [81], which is particularly interesting from a practical viewpoint as the weight of the construct can be used to draw practical implications on the importance of specific details and therefore guide practical enforcement on the characteristics [See details in 82].

![Figure 4: The a-priori model]
(Measures correspond with survey items in Appendix B)

**Study 3**

The purpose of study 3 (the survey) was to empirically test and specify the a-priori model based on constructs and measures derived from study 1 and 2. A survey instrument was designed to operationalize the 15 measures of the three domains / reflective constructs under 4 properties: direction of causality, interchangeability of indicators/items, covariation amongst indicators, and nomological net. This study employs all of four properties.

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19
constructs (See Appendix B), plus 2 demographic questions to establish years of experience. Each item was designed in consideration to the key differences of Function and Enterprise IT and their reflections on expertise stated in Appendix A.

Section one of the survey instrument gathered demographic data (respondent’s name, employment title, employment description, the number of years with the organization and years in the industry sector). The 15 questions in section two included; 4 questions of Skill-Based, and 5 questions on Motivation, and 6 questions on Cognitive Competencies. The instrument’s instructions requested that their, “...answer should relate to [your process] experiences and perceptions of the SAP system in your organization.” All questionnaire items (except the two questions on the years of experience, which are ordinal) were measured using seven-point Likert scales with the end values (1) “Strongly Disagree” and (7) “Strongly Agree”, and the middle value (4) “Neutral”.

In addition to the 15 measures of expertise, the survey instrument of study 3 included 38 additional questions: 5 questions on knowledge sharing (our consequence of expertise to test its nomological net), 27 questions on IS success (to apply expertise construct on IS success), and 6 criterion items (4 for IS success and 2 for expertise). Once the expertise model is specified, we employ the ‘knowledge sharing’ construct to further validate the expertise construct in its nomological net (as per formative construct validation guidelines). IS success construct is then employed to apply the expertise classification that we derived to understand whether groupings based on different levels of expertise demonstrate significant differences in their success evaluation. These discussions are forthcoming in the paper. In attention to reducing Common Method Variance, items for expertise, knowledge sharing and IS success were not grouped under their construct headings.

The draft survey instrument was pilot tested with a sample of 21 staff (11 operational staff and 10 managers) of the two organizations participated in study 1 and 2, resulting only minor cosmetic changes to the instrument format. Next, the survey instrument was circulated to 350 direct operational and management users in the three participating organizations. The survey received 220 valid responses, yielding a response rate of 63%.
DATA ANALYSIS

Our data analysis results are presented in the following manner; (i) first, we validate the expertise construct, (ii) next, we employ the derived expertise construct to identify mutually exclusive groups based on one’s degree of expertise and finally, (iii) we explore whether those groups derived in step two demonstrate significant differences in relation to their assessment of IS success.

Therefore, results of the data analysis are arranged under 3 headings: (i) model and construct validation established through content validity, discriminant and criterion validity, structural model testing and nomological net testing; (ii) developing a classification of respondents based on their levels of expertise, using two complementary methods (the classical method and cluster analysis); and (iii) application of the expertise model and expertise groups on IS success. To the extent that the respondent classification derived in ii is meaningful and that the expertise groups in iii demonstrate significant differences in their success evaluation will provide further validity and reliability to our expertise construct derived in step i.

Model and Construct Validation Model and construct validation in this research are reported under four headings: (i) content validity reported using content validity ratio, (ii) construct validity established using composite reliability, average variance extracted, and factor analysis, (iii) outer model tested using partial least squares and finally, (iv) structural model tested using knowledge sharing as the immediate consequence of expertise.

Content Validity

We paid close attention to content validity through analyses of study 1 and study 2. Data yielded from study 1 and 2 derived themes and items that appear logical, consistent with prior research and relevant to the ES context. As a further test of this association of items with constructs and their completeness, we followed the guidelines of McKenzie et al. [83] for establishing content validity, which entailed four steps: (i) using guidelines of Lynn [84], we created an initial draft of the

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15 The four-step approach followed here is analogous to the Q-sort approach suggested by 73. Tractinsky, N. and S.L. Jarvenpaa, Information systems design decisions in a global versus domestic context. MIS Quarterly 1995. 19(4): p. 28, 74. Kendall, J.E. and K.K. E., Metaphors and methodologies: Living beyond the
survey instrument through canvassing related literature available in self-efficacy and user competence domains deriving its domains / constructs; (ii) following the guidelines of the American Educational Research Association [85], we established a panel of reviewers (study 2) to evaluate possible survey questions, where the panel had necessary training, experience, and qualifications; (iii) had the panel (also known as a ‘jury’) critique the survey constructs (our themes and constructs) of both study 2 and pilot-test by a sample of respondent staff; and (iv) had the ‘jury’ conduct a review of the questionnaire, assessing how well each item represented as a reflective measure of the construct. In this fourth step, a quantitative assessment was made, establishing the Content Validity Ratio (CVR) for each item/question based on the formula of Lawshe [86]. Based on 21 pilot tests, the minimum CVR value of .77 was observed at statistical significance of $P<.05$. Feedback from the pilot round respondents resulted in minor modifications to wording of survey items [83, 84, 86], and endorsement of the research model its constructs and measures. Next, using data from study 3, we test the a-priori model and related instrument items for validity.

**Construct Validity**

As mentioned earlier, the formative constructs of the expertise model are measured with reflective items. The 15 items/measures distilled from study 1 and 2 now serve as the starting point for the construction of the measures of each formative construct. Note that ‘Years of experience’ was measured as a continuous variable, therefore was not included in the analysis of validity and reliability. We employed IBM SPSS version 25 and SmartPLS 2.0 [87] in our data analysis. For partial least squares tests [88] - a structural model technique that is well suited for highly complex predictive models [88, 89] - SmartPLS was used together with the bootstrap resampling method (500 resamples) to determine the significance of paths within the structural model [77, 90].

First, the reflective measurement model was assessed by estimating internal consistency, as well as discriminant and convergent validity, following similar studies [e.g. 91].
First, strong and significant composite reliability was observed with all constructs, reporting above 0.85 [92], with alpha values for Motivation = 0.917, Skill-based = 0.931, and Cognitive Competence = 0.867. Convergent validity was next established through Average Variance Extracted (AVE). Although the intercorrelations between Motivation and Skill-based was high (0.616), the items demonstrated satisfactory convergent and discriminant validity. Convergent validity is adequate when constructs have an AVE of at least 0.5 [93]. For satisfactory discriminant validity, the AVE of the construct should be greater than the variance shared between the construct and other constructs in the model [89]. Table 3 demonstrates the correlation matrix, with correlations among constructs and the square root of AVE on the diagonal. In all cases, the AVE of each construct is larger than the correlation of that construct with all other constructs in the model.

<table>
<thead>
<tr>
<th></th>
<th>Skill-Based</th>
<th>Motivation</th>
<th>Cognitive Competence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skill-Based</td>
<td>0.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Motivation</td>
<td>0.616</td>
<td>0.91</td>
<td></td>
</tr>
<tr>
<td>Cognitive Competence</td>
<td>0.312</td>
<td>0.461</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Table 3: Correlations of Latent Variables

Next, we demonstrate discriminant and convergent validity through factor analysis, where the individual items load above 0.5 on their associated factor and when the loadings within constructs are higher than those across constructs. Appendix D contains the loadings and cross-loadings for items used in this study; all items loaded on their constructs as expected. The measures of expertise demonstrated satisfactory reliability as the reflective factor loadings all above the 0.64, which is well above the proposed threshold level of 0.5 [94]. Also, we did not observe substantial cross factor loadings. Also, Appendix D includes the SmartPLS cross item loadings, indicating that there are no major cross factor loadings.

The Outer Model

As suggested by Diamantopoulos and Winklhofer [95] (p. 272), in testing the outer model, we employ global items that “summarizes the essence of the construct that the

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16 A major cross item loading in SmartPLS is where one of the loadings is less than 0.2 away from the loading of its primary factor (Ringle 2005).
index purports to measure” and examine the extent to which the items associated with the index correlate with this / these global item/s. For this purpose, we employ the two criterion measures of expertise that were included in a separate section of the survey instrument as stated below. It is also noted that the first criterion item reflects a quasi third party evaluation of expertise (See appendix B for the survey items and figure 1 for the measurement approaches).

- “In my organization, my colleagues recognize me as someone with high expertise [of the business process]”
- “I believe that I have a high level of expertise based on my skills, abilities and knowledge [of the business process]”

Correlating the 15 items with the two global measures demonstrated significant correlation coefficients at the 0.001 level.\textsuperscript{17}

Our results show that the four constructs – Skill-Based (0.442, \( t = 5.3 \)), Motivation (0.405, \( t = 4.4 \)) and Cognitive Competence (0.124, \( t = 1.6 \)) – were all significantly related to the Expertise construct and they collectively account for over 70% of the variance, demonstrating external validity. The 70% explanation exceeds variances reported in comparable similar papers in the literature [e.g. 96] and adequate considering model parsimony.

From figure 5, we can establish the convergent and discriminant validity of the model constructs. Convergent validity of Cognitive Competence, Motivation and Skill-Based confer to the heuristics of Gefen and Straub [97], where all t-values of the Outer Model Loadings exceed the one-sided\textsuperscript{18} cut-off of 1.645 levels\textsuperscript{19} significant at 0.05 alpha protection level. However, loading for ‘years of experience’ on the expertise construct was weak and insignificant. Yet, this construct is retained for nomological

\textsuperscript{17} It is noted that a single reverse-coded item was appropriately correlate negatively with the criterion items.

\textsuperscript{18} One-sided test is appropriate because we only hypothesize a positive contribution of the formative components of expertise. Use two-sided cut-off of 1.96 otherwise.

\textsuperscript{19} The t-values of the loadings are, in essence, equivalent to t-values in least-squares regressions. Each measurement item is explained by the linear regression of its latent construct and its measurement error.

assessment (reported next), since ‘years of experience’ did not display excessive collinearity.

**The Structural Model: Nomological Net Testing**

Finally, we assess the structural model, focusing on the nomological aspects, by linking the index to other constructs with which it would be expected to be linked. According to Jarvis et al. [78], these other constructs can be either antecedents or consequences of the phenomena under investigation. Thus, consistent with Jarvis et al. [78] and Bagozzi [98], and with the (third) guideline of Diamantopoulos and Winklhofer [95] for validating formative constructs in a nomological network, we test the relationship between expertise and ‘knowledge sharing’, where ‘knowledge sharing’ is an immediate consequence of expertise.

The précis below of knowledge sharing is not intended to provide an in-depth overview of knowledge sharing and its associations with expertise, rather to present the argument for this seemingly tautological scenario, where experts share knowledge with their peers. First, experts’ willingness to sharing knowledge was suggested in our study 1 (table 2) by the participants. Therefore, the reflective measures of knowledge sharing were developed based on the themes of table 2 and are listed in Appendix B.

In addition, numerous studies have identified that knowledge sharing is an essential part of knowledge management, and it is imperative to ES success [e.g. 99, 100]. Studies of several disciplines; IS [e.g. 101, 102], business [e.g. 103], and psychology [e.g. 104, 105, 106]; suggest that experts, are willing, able and motivated to convey their superior knowledge and skills to novices.

The test of the structural model includes estimates of the path coefficient, which indicate the strength of the relationship between the independent and dependent variable, and the $R^2$ values, which represent the amount of variance explained by the independent variable/s. Together, the $R^2$ and the path coefficient (loadings and significance) indicate how well the data supports the hypothesized model [91].

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20 Bagozzi, R., *Structural equation models in Marketing Research: Basic Principals*, in *Principals in Marketing* R. Bagozzi, Editor. 1994, Blackwell: Oxford. p. 317-385. suggests, “After all, the substantive reason behind index construction is likely to be how the index functions as a predictor or predicted variable” (p. 332).
Figure 5 depicts the structural model with path coefficient ($\beta$) between Expertise and knowledge sharing, $R^2$ for knowledge sharing significant level of 0.005 alpha. Supporting our prepositions, further validating the construct, results show that expertise is significantly associated with knowledge sharing (path coefficient ($\beta$) = 0.733, $p < 0.005$, $t = 15.56$); the squared multiple correlation coefficient ($R^2$) of 0.537 indicating that expertise explains almost 54% of the variance in the endogenous construct.

In summary, our results of the analyses confirm the validity and reliability of our measurement of expertise, using Cognitive Competence, Motivation and Skill-Based constructs. However, despite its prominence in the past literature as a determining factor of one’s expertise, ‘years of experience’ does not make a significant contribution. This may be attributed to the dynamic nature and the high rate of evolution in contemporary Enterprise Systems, when the pace of technology evolution outstrips the expertise gained solely through the years of experience. It is evident that, unless the other facets of expertise (e.g. Motivation) are fulfilled, one’s experience alone does not contribute to expertise of IS. On the other hand, ‘Motivation’, ‘Skill-Based’ and ‘Cognitive Competence’ constructs are strong indicators of IS expertise.

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21 The reliability of the Knowledge Sharing measures was 0.855 (at 0.005 confidence level).
THE CONTINUUM: NOVICE, INTERMEDIATE AND EXPERT

Having validated the constructs and measures of the IS expertise, we now attempt to group respondents of the survey (study 3) according to their degree of expertise. We attempt to derive a simple classification of expertise using a commonly used groupings in a continuum of: (i) novice, (ii) intermediate and (iii) expert [42, 106], where a user can be placed in any one of the phases of the expertise continuum.

We employ two separate methods to derive the classification of the expertise continuum. Method 1 – the classical method – has been employed in the past in socio-psychology studies [4-7]. Method 2, exploratory in nature, employs a cluster analysis to uncover natural groupings of respondents based on their expertise.

Method 1 – The Classical Method

Anecdotal evidence (and common sense) suggests that an expert would have ‘better’ knowledge, skills and adaptability, as compared to an intermediate or a novice. Yet, the derivation and their boundaries between the three groups in a continuum are less clear. Social science researchers employ the classical approach to group respondents using standard deviations and mean scores of the constructs measurement in expertise. Here, a respondent is considered as an ‘expert’, if the respondent’s mean for the measurement construct is above the sum of standard deviation and the mean of the sample of the measurement construct. Similarly, a respondent is considered a novice, when the respondent’s mean is less than the subtraction of standard deviation from the mean of the sample.

Applying this notion to our study constructs, we first calculate the mean scores of each construct, for every respondent. Next, the sample mean and the sample standard deviation are calculated for each construct. The classification in table 4 is derived using the following simple equations: Novice = Respondent’s mean \( \text{construct} \) < (sample mean \( \text{construct} \) - sample standard deviation \( \text{construct} \)), while an Expert = Respondent’s mean \( \text{construct} \) > (sample mean \( \text{construct} \) + sample standard deviation \( \text{construct} \)). The remainder are considered intermediates. Table 4 shows the expertise classification derived for each of the 4 constructs. Furthermore, we derive a ‘composite construct of expertise’ using the three variables of Motivation, Cognitive and Skill-based. This
approach is deemed appropriate especially when the constructs were conceived as formative and can be added to derive the overarching construct of expertise. The composite classification is then employed to compare results in the forthcoming cluster analysis.

<table>
<thead>
<tr>
<th>Motivation</th>
<th>Cognitive</th>
<th>Skill-Based</th>
<th>Composite</th>
<th>YoE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#</td>
<td>%</td>
<td>#</td>
<td>%</td>
</tr>
<tr>
<td>Novice</td>
<td>33</td>
<td>15%</td>
<td>30</td>
<td>14%</td>
</tr>
<tr>
<td>Intermediate</td>
<td>175</td>
<td>80%</td>
<td>180</td>
<td>81%</td>
</tr>
<tr>
<td>Expert</td>
<td>12</td>
<td>5%</td>
<td>10</td>
<td>5%</td>
</tr>
</tbody>
</table>

**Table 4: Results of Classification Method One**

The distribution of percentages derived using the classical method for the groupings of novice, intermediate and experts is almost identical across the three measurement constructs of expertise and the composite classification, with approximately 15% of novice, 80% of intermediates and 5% of experts.

**Method 2 – Cluster Analysis**

The objective of cluster analysis is to explore whether measurement items lead to a *natural* classification of expertise. Through step-wise clustering on the criterion item – “In my organization, my colleagues recognize me as someone with high expertise” – yielded a three cluster solution, with the goodness of cluster quality indicating ‘good’ – where cluster 1 having 30 respondents, cluster 2 with 176 and cluster 3 with 14 respondents. Intrigued by the three cluster solution, we then sought a relationship between the composite result of Method 1 and results of Method 2. Here, we compared the results of method 1 and method 2, going through record-by-record (for each respondent). We observed that respondents in cluster group 1 matching 99% with respondents in composite group Novice (using method 1), 100% matching with Intermediates and 100% matching with results of Experts. This high overlap between results of method 1 (composite) and method 2 provides further strength to our classification of respondents and in turn on constructs and measures of expertise.

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23 As stated earlier, this criterion item relates to a quasi third-party evaluation of one’s expertise (akin to observer evaluation method of expertise in figure 1).
Application of Expertise Classification

Having arrived at an expertise classification to groups respondents into three groups based on their expertise, we now explore whether the experts, intermediates and novices demonstrate significant differences in their evaluation of an Enterprise System. The reasons for selecting IS success as the ‘application’ area are several; (i) the natural alliance between success evaluation and expertise, where in practice, ‘expert views’ are frequently sought in system evaluations, (ii) respondents having different views of system success is a key challenge in IS success studies, yet according to many [e.g. 108, 109, 110], a notion rarely explored and (iii) the popularity of IS success studies [e.g. 111, 112-114] suggesting that this application is relevant and meaningful to a greater community.

To measure IS success, we employ the 27 measures of the IS success model of Gable Sedera and Chan [16] in Appendix C. Data was collected using respondents of study 3\textsuperscript{24}. The Gable et al. (2008) IS Success model too is conceptualized as a formative, multidimensional index comprised of four dimensions – Individual Impact, Organizational Impact, System Quality and Information Quality. Their multidimensional conception of success has garnered some endorsement in recent literature; in example, Petter et al. [114] cite Gable et al. [16] model as one of the most comprehensive, and comprehensively validated IS success measurement models to-date.

In order to explore the purported differences in perceptions in relation to the four dimensions of system success across the three groups of expertise continuance, a series of independent sample t-tests were conducted. Table 5 shows results of the independent sample t-tests for at aggregated IS success constructs level.

\textsuperscript{24} All 27 measures were subjected to formative validation followed in study 3. Their VIF scores were less than 4.1.
<table>
<thead>
<tr>
<th></th>
<th>Information Quality</th>
<th>System Quality</th>
<th>Individual Impact</th>
<th>Organization Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sig / t-value*</td>
<td>Sig / t-value*</td>
<td>Sig / t-value*</td>
<td>Sig / t-value*</td>
</tr>
<tr>
<td>Expert Vs.</td>
<td>0.02 / -2.41</td>
<td>0.01 / -2.86</td>
<td>0.01 / -3.35</td>
<td>0.03 / -1.89</td>
</tr>
<tr>
<td>Novice</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expert Vs.</td>
<td>0.01 / -2.85</td>
<td>0.86 / 0.25</td>
<td>0.00 / -4.41</td>
<td>0.03 / -2.65</td>
</tr>
<tr>
<td>Intermediate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Novice</td>
<td>0.02 / -2.38</td>
<td>0.10 / -5.8</td>
<td>0.01 / -2.41</td>
<td>0.02 / -2.39</td>
</tr>
</tbody>
</table>
| * significant at 0.05

Table 5: Results of the independent sample t-tests

From Table 5 we see significant differences between the Experts, Intermediates and Novices, in relation to Information Quality, System Quality, Individual Impacts and Organization Impacts (with the exception of System Quality). These observed differences concur with our proposition that users with different levels of expertise evaluate the same system differently.

**SUMMARY AND CONCLUSIONS**

This study sought to conceptualize, measure and then apply the notions of User Expertise for the Contemporary Information Systems. Our discussion on the conceptual framework, together with information in Appendix A, highlighted the need to revisit the notions of user expertise in Contemporary IS. Most past studies of computer self-efficacy and user competence focus on functional IT (e.g. spreadsheets and word processing as common examples), highlighting the need to re-conceptualize user expertise of a complex, contemporary, and organizational-wide Information System (where Enterprise System is an archetype of). As Marakas [15] highlight “...for business and information systems, real world tasks are neither simple nor single domain focussed. Rather, they often draw on multiple skill sets and require an individual to be able to perform tasks that span several skill domains... (p. 40)”. Our conceptualization, measurement and application of Contemporary Information Systems User Expertise are driven to address this gap in research.

This research conceived the model constructs as formative and their respective measures as reflective, manifested in extensive attention to the completeness and necessity of constructs of expertise. In order to ensure this, the expertise model specification and validation proceeded from an inclusive view of expertise, commencing with the three theoretical constructs of the theories of learning (Kraiger et al., 1993), as employed in past studies. Conceived primarily through a ‘system
centric’ viewpoint, the study presented a conceptual framework for which IS expertise can be understood (figure 1).

Our primary evidence collection in study 1 validated the domains of IS expertise, which later were further qualified through findings of study 2. Conceptual arguments that drew on past research, combined with this citation analysis, suggested the sufficiency of the three constructs to develop specific measures for contemporary IS user expertise. We also included years of experience, to explore and test its relevance and its contribution to contemporary Information Systems user expertise. The a-priori model was tested using survey data of 220 operational and managerial users representing three SAP using companies, conforming to all formative data analysis techniques, corroborating evidence of multiple data analysis methods. In addition, we investigated the nomological relationship between expertise and one of its immediate consequences of knowledge sharing – demonstrating further validity of our expertise construct.

We next sought to derive a simple, yet useful classification of expertise. The study classified the respondent sample into three groups based on their expertise, employing the classical method (using standard deviations and mean scores) and method two employing an exploratory cluster analysis, yielding almost identical results. The classification of user expertise into three groups, by itself useful, provides further credibility to the constructs and measures of our expertise model. Next, we applied the expertise model and the classification of users according their expertise to the IS success domain, exploring whether experts, intermediates and novices perceived information system success differently.

The three-phased data collection approach employed in this study was designed specifically to minimize the impact of extraneous factors on constructs and measures user expertise. Thus, our data collection sought homogeneity through country, industry sector, Enterprise System, and business processes. Our constructs are similar to those employed in the theories of learning and self-efficacy and are consistent with prior studies on User Competence and Self-Efficacy. Thus, we believe, with further testing, the user expertise measures in Appendix B can be useful beyond the current scope of the study.
Implications, Limitations and Follow-on Research

This study, model and approach contribute to several areas (relevant stages of the study indicated in parentheses). This research: (i) provided a system centric conceptual framework to conceptualize and measure user expertise, (the framework of expertise), (ii) developed new measures in attention to the characteristics of contemporary Enterprise Systems, exceeding past notions of computer self-efficacy and user competence (the framework, study 1 derivation of themes, study 2 qualifying themes and measures), (iii) conceives and tests the expertise model as a formative model, using strict guidelines of formative construct validation (study 3 and related analysis), (iv) establishes a generalizable classification of expertise using two complementary methods (developing the expertise continuum), and (v) demonstrates the application and usefulness of such a classification for system evaluations (application in IS success). Moreover, (vi) in attention to calls by researchers (e.g. Marakas et al., [15] (p. 40) to use ‘real data’ using ‘using real world tasks’ to develop a better understanding of competence of users, all three study phases were conducted using ‘real data’ from respondents from three companies using the SAP Enterprise System.

To the extent that the expertise model and its constructs are robust across other contemporary systems, contexts, and lifecycle phases, user expertise may serve as a validated dependent / mediating / moderating variable in ongoing research. As an independent variable, user expertise may aid in understanding the relationship between IT and organizational performance. Across systems and user groups in an organization, user expertise measure may lead to a complete measure of user quality. Though our results are heartening, measures developed in this study must be tested for their utility in other contexts and provide the foundation for deriving new measures in other research contexts (e.g. customer relationship management systems, early lifecycle phases).

25 Recognizing that most past studies focussing on user competence and self-efficacy had employed classroom experiments using college graduates.
For the practice, our study makes several contributions. First, (i) our study provides a meaningful way of understanding expertise in a contemporary IS. (ii) Practitioners could employ the model to emulate ‘expert qualities’ to assist novices and intermediates to perform at higher levels and ultimately become experts. (iii) It too highlights that, since one’s IS expertise does not necessarily depend on their innate abilities and years of experience, thus, productivity improvements sought through IS can be achieved by appropriate interventions. (iv) Our study also highlighted, that any program geared toward improving performance would require interventions focussed not only on enhancing systems related skills, but on more behavioural aspects (in this study Motivation and Skill-Based). Finally, (iv) for those practitioners engaged in system evaluations, our study provides evidence that experts, intermediates and novices perceive system success differently.

Despite having extended the rigorous approach adopted from MacKenzie and House [62], and despite validity demonstrated, we recognize several limitations of the study model requiring attention beyond the scope of this study and paper. First, the model was developed and validated with data collected from only three organizations, using the same Enterprise System (i.e. SAP) representing the same industry sector (i.e. manufacturing). All these raise questions about whether the initial list of constructs and measures used in the development of the a-priori model was complete and representative of contemporary IS in general, and whether the final list of measures and constructs are, indeed, generalizable.

In conclusion, an extensively validated and widely-adopted IS expertise model would facilitate cumulative research, while providing a benchmark for organizations to track their user expertise. These study results offer a significant step in this direction.
### APPENDIX A - ENTERPRISE IT VS. FIT / NIT

Appendix A demonstrates the differences between the Enterprise IT vs. Functional and Network IT as defined by McAfee [31] and how user expertise differs in the two types of systems. The table below, derived using McAfee [31], compares the three types of systems. In addition, we demonstrate how such differences between the types of systems reflect on user expertise.

<table>
<thead>
<tr>
<th>Category</th>
<th>Function IT</th>
<th>Network IT</th>
<th>Enterprise IT</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Definition</strong></td>
<td>Assists with the execution of discrete tasks</td>
<td>Facilitates interactions without specifying their parameters</td>
<td>IT that specifies business processes</td>
</tr>
<tr>
<td><strong>Characteristics</strong></td>
<td>Can be adopted without complements. Impact increases when complements are in place.</td>
<td>Does not impose complements, but lets them merge over time. Does not specify tasks or sequences. Accepts data in many formats. Use is optional.</td>
<td>Imposes complements throughout the organization. Defines tasks and sequences. Mandates data formats. Use is mandatory.</td>
</tr>
<tr>
<td><strong>Examples</strong></td>
<td>Spreadsheets, computer aided design, statistical software</td>
<td>Emails, instant messaging, wikis, blogs and mash-ups</td>
<td>ERP, CRM and SCM</td>
</tr>
<tr>
<td><strong>Automation</strong></td>
<td>Some degree of automation (e.g. Spell check)</td>
<td>Very low level of automation</td>
<td>High level of automation</td>
</tr>
<tr>
<td><strong>Key-User-Groups</strong></td>
<td>More likely to have a single Key-User-Group</td>
<td>More likely to have a single Key-User-Group</td>
<td>Multiple Key-User-Group using the same system very differently</td>
</tr>
<tr>
<td><strong>Considerations for Expertise</strong></td>
<td>Most users would remain proficient with the basic system features. Potential to improve performance through deeper and exploratory use</td>
<td>Limited work-oriented functionality. Access to system features is equal across all key-user-groups. Depth of use would not result in substantial improvements</td>
<td>High automation of business processes. Many key-user-groups have different types of uses. Must consider mandatory and non-mandatory uses. For processes with high automation, frequency of use will only provide observations of efficiency</td>
</tr>
</tbody>
</table>

We outline four salient differences between Enterprise IT (EIT) and Functional IT (FIT) along the following aspects that justify the need to develop a better understanding for Enterprise IT expertise.
1. **Enterprise IT cannot be adopted without complements:** Complements are defined by McAfee (p. 142) as “organizational innovations or changes”. Examples of complements that allow performing technologies include ‘re-design of processes’ and ‘new decision rights’. Thus, McAfee argued that Functional IT (e.g. word processing) can be adopted by the user without any substantial organizational innovation, changes and the use of Functional does not entail process re-designs or new decision rights (as opposed to Enterprise IT). For example, an SAP Enterprise System software needs to be ‘configured’ as per the organizational requirements, leading to different configurations in organizations. Therefore, an Enterprise IT user faces with a range of options in their business process executions, where the process of execution depends on his/her organizational knowledge, business process knowledge and or knowledge of the system features. For example, when procuring material for the organization, a user must know the organization specific purchasing strategies, whether to create a purchase order using a contract or requisition, and how to select the best vendor through a vendor evaluation completed through the system. Such process oriented variances in tasks require far deeper knowledge of the system, business processes and organization specific procedures.

**Reflections on Expertise:** The success of an Enterprise System depends largely on how well users adopt that system in parallel with organizational innovations and changes. Thus, an expert Enterprise System user should possess the ability to swiftly adapt the system with complements of the environment. As such, the ability of the user to adapt to organizational and system changes is an important aspect of Expertise of the Enterprise IT user. Our model construct ‘motivation’ captures ones willingness to adapt to organizational and system changes. For example, item M1 [I can easily adapt with any changes to the SAP system required for the [name of the business process] captures the respondent’s ability to adapt to the changes in the system, while item M3 [I can easily adapt to changes in my department, related to my [name of the business process] observes the respondent’s ability to adapt to organizational changes.

2. **Extensions to Learning is essential**

As stated above, Enterprise Systems are always adopted with complements. Such complements are dynamic in nature and they change the way that systems are adapted from one organization to another. As a result, for example, two organizations using the same business processes implemented through the same Enterprise System software will be used differently. Therefore, organizations are required to engage and encourage their users to continuously up-skill and re-skill.

**Reflections on Expertise:** Most organizations using Enterprise Systems do not have specific resource allocations for training and up-skilling continuously. Organizations therefore encourage and facilitate self-learning of skills through creation of corporate databases, system sand-pits and make their policy documents easily accessible to their employees. As such, the expert user takes advantage of such opportunities and extends their knowledge through learning and applying the changes brought-to-bear through complements. Our model construct ‘skilled-based’ captures proactive self-learning of employees
using four questions. For example, S1 [I regularly refer to corporate database (e.g. intranet) for updates and gain new knowledge of my [name of the business process]] observes whether users are proactively seeking knowledge in corporate databases, while S3 [I try to find better ways of doing my [name of the business process] in the SAP system.] observes whether the users explore new / better ways of doing their work using the system.

3. **Prior knowledge and Knowledge Types:** Another difference between Function IT and Enterprise IT relates to the prior knowledge that users are required to have before using a system. Unlike Function IT, users seldom have prior knowledge of the system features and functionality of an Enterprise IT. Yet, given the proliferation Function IT (word processing and spreadsheet applications) as a day-to-day application at the individual/personal levels, users in general are knowledgeable about Functional IT applications before they start using them at a work place. This also means that users of Functional IT in general have similar expertise throughout their use of an application – whereas, the users of Enterprise IT will have different levels of expertise. Moreover, given the complements outlined in point #1, users of Enterprise IT must also know about the business processes and organizational rules and policies. This too differentiates Enterprise IT with Function IT, where Function IT use does not change due to business processes or organizational rules and policies.

**Reflections on Expertise:** We argue that an expert Enterprise IT user must possess all three types of knowledge; business process, software and organizational. As such they are able to use the system for a particular business process, adhering to the organizational goals procedures and guidelines. Our model construct ‘cognitive competence’ employs six questions to capture this unique aspect of Enterprise IT cognitive competence. For example, C2 and C3 [e.g. My knowledge of SAP is more than enough to perform my day-to-day functioning of the [name of the business process]] captures the software knowledge, while C5 [I have an in-depth knowledge of the functions of the [name of the business process] that I must do on a day-to-day basis.] and C6 [I have a good knowledge of the organizational goals, procedures and guidelines.] measure business process knowledge and organizational knowledge necessary for Enterprise IT expertise.

4. **Proficiency of Enterprise IT changes over time / across user cohorts:** Users of all IT, regardless of their classification, are expected to differ in their proficiency over time. Yet, the extent of such changes varies across the user cohorts and the years of experience. In Enterprise IT, the breadth of functionalities available in a system allows users to commence using the system with minimal (and perhaps essential) knowledge of system features and functionality. Over a period, they enhance their use through better knowledge of business process, software and organization, and through skill-based and motivation. Moreover, different user cohorts use Enterprise IT differently. For example, the system functional requirements of an operational user are vastly different to the system functional requirements of a
management user. Such differences in evolution and diversity of use across user cohorts are rare in Functional IT.

**Reflections on Expertise:** In light of aforementioned arguments, we argue that expertise of an Enterprise IT user changes over a period of time. Though we acknowledge that user expertise of Functional IT could change (presumably improve) over a period of extensive use, such changes assumed to be minimal. For example, a user of a spreadsheet application may also spend time observing (learning), adapt to changes of new versions, and perhaps even make fewer mistakes in using them. Furthermore, the distinction between the competency of a ‘novice’ user and an ‘experienced’ user in Functional IT is minimal. Moreover, the degree of proficiency required by each key user group (i.e. operational staff, managers and strategic) too is substantially different for Enterprise IT. Whereas in Functional IT, user expertise of an application (e.g. for word processing) largely remains the same across multiple user groups.
APPENDIX B – EXPERTISE SURVEY ITEMS

SKILL-BASED [PROACTIVE SELF LEARNING]
S1: I regularly refer to corporate database (e.g. intranet) for updates and gain new knowledge of my [name of the business process].
S2: I regularly observe at changes to company policies and guidelines through information repositories relevant to my [name of the business process].
S3: I try to find better ways of doing my [name of the business process] in the SAP system.
S4: I am eager to learn improvements in the SAP system related to my [name of the business process].

MOTIVATION [WILLINGNESS TO ADAPT]
M1: I can easily adapt with any changes to the SAP system required for the [name of the business process].
M2: I can easily adapt to changes in my [name of the business process].
M3: I can easily adapt to changes in my department, related to my [name of the business process].
M4: I can easily absorb any changes in my organizational structure, related to [name of the business process].
M5: I am ready to accept new roles and responsibilities related my [name of the business process] when necessary.

COGNITIVE COMPETENCE [KNOWLEDGE REQUIREMENTS]
C1: I fully understand the core knowledge necessary for [name of the business process].
C2: My knowledge of SAP is more than enough to perform my day-to-day functioning of the [name of the business process].
C3: I rarely contact SAP helpdesk for software related problems in relation to the [name of the business process].
C4: I rarely make mistakes when completing my [name of the business process] using SAP.
C5: I have an in-depth knowledge of the functions of the [name of the business process] that I must do on a day-to-day basis.
C6: I have a good knowledge of the organizational goals, procedures and guidelines.

KNOWLEDGE SHARING
1. I regularly share my knowledge of SAP with my colleagues.
2. I often suggest improvements of [name of the business process] to my managers / colleagues.
3. My colleagues come to me for assistance when they are faced with a work related issue.
4. I have colleagues and workmates helping me with using SAP for my [name of the business process] (inversely worded).
5. I regularly contribute to knowledge sharing forums within my organization.

EXPERTISE CRITERION ITEMS
1. In my organization, my colleagues recognize me as someone with high expertise.
2. I believe that I have a high level of expertise based on my experience, skills, abilities and knowledge.
APPENDIX C – IS SUCCESS ITEMS (from Gable et al. (2008; p 405))

**Individual-Impact** is concerned with how [the IS] has influenced your individual capabilities and effectiveness on behalf of the organization.
1. I have learnt much through the presence of [the IS].
2. [the IS] enhances my awareness and recall of job related information
3. [the IS] enhances my effectiveness in the job
4. [the IS] increases my productivity

**Organizational-Impact** refers to impacts of [the IS] at the organizational level, namely improved organisational results and capabilities.
5. [the IS] is cost effective
6. [the IS] has resulted in reduced staff costs
7. [the IS] has resulted in cost reductions (e.g. inventory holding costs, administration expenses, etc.)
8. [the IS] has resulted in overall productivity improvement
9. [the IS] has resulted in improved outcomes or outputs
10. [the IS] has resulted in an increased capacity to manage a growing volume of activity (e.g. transactions, population growth, etc.)
11. [the IS] has resulted in improved business processes
12. [the IS] has resulted in better positioning for e-Government/Business.

**Information-Quality** is concerned with the quality of [the IS] outputs: namely, the quality of the information the system produces in reports and on-screen.
13. [the IS] provides output that seems to be exactly what is needed
14. Information needed from [the IS] is always available
15. Information from [the IS] is in a form that is readily usable
16. Information from [the IS] is easy to understand
17. Information from [the IS] appears readable, clear and well formatted
18. Information from [the IS] is concise

**System-Quality** of the [the IS] is a multifaceted construct designed to capture how the system performs from a technical and design perspective.
19. [the IS] is easy to use
20. [the IS] is easy to learn
21. [the IS] meets [the Unit’s] requirements
22. [the IS] includes necessary features and functions
23. [the IS] always does what it should
24. The [the IS] user interface can be easily adapted to one’s personal approach
25. [the IS] requires only the minimum number of fields and screens to achieve a task
26. All data within [the IS] is fully integrated and consistent
27. [the IS] can be easily modified, corrected or improved.

**IS-Impact** (criterion measures)
28. Overall, the impact of SAP [Financials] on me has been positive.
29. Overall, the impact of SAP [Financials] on the agency has been positive.
30. Overall, the SAP [Financials] System Quality is satisfactory.
31. Overall, the SAP [Financials] Information Quality is satisfactory.
### APPENDIX D

**Factor Analysis: Loadings and Cross Loadings**

<table>
<thead>
<tr>
<th>Construct</th>
<th>Motivation</th>
<th>Cognitive Competence</th>
<th>Skill-Based</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>.163</td>
<td>.083</td>
<td>.844</td>
</tr>
<tr>
<td>S2</td>
<td>.246</td>
<td>.129</td>
<td>.872</td>
</tr>
<tr>
<td>S3</td>
<td>.338</td>
<td>.123</td>
<td>.852</td>
</tr>
<tr>
<td>S4</td>
<td>.395</td>
<td>.126</td>
<td>.831</td>
</tr>
<tr>
<td>M1</td>
<td>.790</td>
<td>.174</td>
<td>.214</td>
</tr>
<tr>
<td>M2</td>
<td>.845</td>
<td>.204</td>
<td>.192</td>
</tr>
<tr>
<td>M3</td>
<td>.815</td>
<td>.258</td>
<td>.184</td>
</tr>
<tr>
<td>M4</td>
<td>.695</td>
<td>.219</td>
<td>.488</td>
</tr>
<tr>
<td>M5</td>
<td>.722</td>
<td>.181</td>
<td>.458</td>
</tr>
<tr>
<td>C1</td>
<td>.025</td>
<td>.798</td>
<td>.003</td>
</tr>
<tr>
<td>C2</td>
<td>.083</td>
<td>.760</td>
<td>.014</td>
</tr>
<tr>
<td>C3</td>
<td>.218</td>
<td>.715</td>
<td>.252</td>
</tr>
<tr>
<td>C4</td>
<td>.280</td>
<td>.644</td>
<td>.072</td>
</tr>
<tr>
<td>C5</td>
<td>.183</td>
<td>.803</td>
<td>.033</td>
</tr>
<tr>
<td>C6</td>
<td>.098</td>
<td>.658</td>
<td>.157</td>
</tr>
</tbody>
</table>

**SmartPLS Item Cross Loadings**

<table>
<thead>
<tr>
<th>Construct</th>
<th>Cognitive Competence</th>
<th>Motivation</th>
<th>Skill-Based</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>0.3737</td>
<td>0.8148</td>
<td>0.5003</td>
</tr>
<tr>
<td>M2</td>
<td>0.4069</td>
<td>0.8705</td>
<td>0.4912</td>
</tr>
<tr>
<td>M3</td>
<td>0.4373</td>
<td>0.8655</td>
<td>0.4854</td>
</tr>
<tr>
<td>M4</td>
<td>0.4118</td>
<td>0.8867</td>
<td>0.4837</td>
</tr>
<tr>
<td>M5</td>
<td>0.3818</td>
<td>0.8747</td>
<td>0.6571</td>
</tr>
<tr>
<td>C1</td>
<td>0.7561</td>
<td>0.2243</td>
<td>0.1277</td>
</tr>
<tr>
<td>C2</td>
<td>0.7056</td>
<td>0.2733</td>
<td>0.1487</td>
</tr>
<tr>
<td>C3</td>
<td>0.8201</td>
<td>0.466</td>
<td>0.3644</td>
</tr>
<tr>
<td>C4</td>
<td>0.7133</td>
<td>0.3974</td>
<td>0.265</td>
</tr>
<tr>
<td>C5</td>
<td>0.8017</td>
<td>0.3617</td>
<td>0.213</td>
</tr>
<tr>
<td>C6</td>
<td>0.7158</td>
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<td>S2</td>
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<tr>
<td>S3</td>
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<td>0.4499</td>
<td>0.9388</td>
</tr>
<tr>
<td>S4</td>
<td>0.3137</td>
<td>0.6888</td>
<td>0.935</td>
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REFERENCES


