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MOTIVATION FOR LEARNING IN INFORMATION TECHNOLOGY EXPERTS: PROFILES OF MULTIPLE GOALS

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MOTIVATION FOR LEARNING IN INFORMATION TECHNOLOGY EXPERTS: PROFILES OF MULTIPLE GOALS

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF EDUCATIONAL PSYCHOLOGY

BY

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Table of Contents

Index of Tables

Index of Figures

Abstract

This study describes the motivational characteristics of developing experts in information technology (IT). Experienced IT workers (*N* = 203) who were users of online technology discussion groups completed surveys about perceived competence and goals (learning/mastery goals, performance-approach goals, intrinsic and extrinsic rewards, and future-oriented perceived utility goals) for continued expertise development. The sample as a whole scored higher on intrinsic motivators than on extrinsic motivators, and scored high on perceived competence, as would be expected for developing experts. A cluster analysis was performed on standardized scores in order to create profiles of multiple goals. Three groups were found: Cluster 1 scored relatively low (as compared to others) on all goal variables and on perceived competence; Cluster 2 scored relatively high on intrinsic goals and perceived competence and relatively low on extrinsic goals; and Cluster 3 scored relatively high on extrinsic goals and relatively low on intrinsic goals and perceived competence. Therefore, while the participants reported that their expertise development was motivated more intrinsically than extrinsically, some depended relatively more on extrinsic rewards and had lower perceived competence than their peers. This may cause their expertise development to have a lower trajectory, in which they progress more slowly and with less satisfaction and enjoyment.

Chapter One: Introduction and Literature Review

The body of research on the nature and development of expertise is large. In the literature, researchers have addressed the question of why some who set out to develop expertise achieve it and others do not, but most of these studies concern only a single factor. Those who advocate, for example, practice as key to expertise contend with those who advocate ability. Whatever their differences, however, these researchers acknowledge that developing experts must be motivated, because expertise takes years of time and effort to acquire; those who lack motivation will not persevere to the level of expertise. Because the development of expertise is likely to be a more complicated issue than can be explained by a single factor, I first will review the literature to describe the multiple factors that might lead to individual differences in developing expertise, and then propose a model of how these factors interact. Next I will list research questions arising from the model, and describe a study focused specifically on the nature of the motivation factor because it is among the least-explored components of expertise development. Although motivation is a major topic of research concerning K-12 and postsecondary students, more work is needed specifically on motivation for expertise.

The purpose of this study was therefore to connect expertise theory to motivation theory by describing more precisely what types of motivation are important to people developing expertise. It follows on a qualitative study (Beesley, 2004) of information technology (IT) experts in which interviewees reported being motivated toward expertise by a variety of achievement goals (see Appendix A). The connection between motivation and expertise is not just under-researched—it is important as well. In much of teaching and learning, expertise rather than lower-level functioning is the ultimate objective, even if really achieving expertise will necessarily occur far in the future. Therefore it is essential that the factors leading to development of expertise, including motivation, be well understood so that expertise can be effectively fostered.

Because expertise often requires many years of preparation, expertise research should not neglect adults whose formal schooling has ended but whose expertise development, especially in their careers, will continue possibly for decades. This study addressed these working adults by focusing on IT workers. IT is a demanding field with an extensive body of knowledge. Those who seek expertise in this field not only have to master this knowledge, but continue to learn more in order to keep up as technology changes—in effect they are continually developing experts. This requires a great deal of motivation throughout the career span; therefore IT professionals make good candidates for studies of motivation and expertise, and their goal profiles could have implications for other types of professionals.

While all developing experts require some kind of motivation to continue in their field, the precise nature of their motivation may not be the same for everyone. The cluster analysis described in this study allowed participants to express multiple goals for continued domain learning and enabled a comparison of how the goals differed between groups.

Experts and Novices

Much research has been done on the nature of expertise, and the differences between novices and experts in several domains. According to Anderson (2000), skill acquisition has a cognitive phase in which people learn the steps of a procedure, an associative phase in which the method is worked out and errors are reduced, and an autonomous phase in which skill becomes rapid and automatic. Experts tend to have declarative knowledge about their domain proceduralized for greater efficiency of performance, and remember information about their domain in chunks rather than as individual items. They tend to reason forward from the givens of problems rather than backward from the problem statement, and can focus on the constructs underlying problems (bottom-up reasoning) rather than on surface features such as knowns and unknowns (top-down reasoning). When making decisions, as with chess players, for example (Horgan, 1990), experts do not require the exhaustive evaluations of alternatives that novices do, because their experience, memory, and domain-specific knowledge help them narrow the range of choices quickly.

Studies of experts in different domains have diversified the view of expertise. For example, expert computer programmers use top-down reasoning, as thinking about the breadth of their programs before the depth of each component leads to better-designed systems (Anderson, 2000). In a study of genetic counselors and biology professors, the genetic counselors focused more on surface features such as knowns and unknowns than did the professors, but still outperformed them on genetic problem-solving (Smith, 1992). The nature of particular domains, and the context in which skills are used, influence what expertise looks like in terms of problem representation and solution techniques.

Alternative views of expertise have also appeared in the literature. Alexander's (2003) Model of Domain Learning (MDL), for example, addresses three components that are involved in the development of expertise in academic domains: knowledge, strategic processing, and interest. The model describes how, as students move through the stages of domain learning—acclimation, competence, and proficiency—they organize and use domain knowledge in increasingly sophisticated ways, use deeper processing strategies, and progress from situational interest, which is aroused by events or surroundings, to individual interest, which is one's enduring investment in a domain. According to Alexander, this model differs from previous models in that it is more focused on academic domains and on motivational and affective dimensions of expertise, and is more concerned with the journey from novice to expert than on dichotomous comparisons between novices and experts.

Individual Differences in the Development of Expertise

However, while aspects of the nature of expertise are becoming known, more difficult to explain are individual differences in the development of expertise. Why does one serious violinist or tennis player become more accomplished than another? Why does one employee become expert in the use of a company's new financial software system, while another who attended the same training and works in the same job keeps making mistakes? The research on explanations for differences in people's rate and level of expertise development is sparser than that examining how experts differ from novices (Alexander, 2003). Conclusions range from differences in deliberate practice, talent/ability, and motivation to differences in metacognition and cultural surroundings.

I will discuss the major explanations offered in the literature for individual differences in the development of expertise, propose a model including several factors that produce differences in expertise development, and describe the present study. Motivation is an important and neglected (Alexander, 2003) aspect of expertise development, so this model includes goals, flow, and self-efficacy. However, their relation to individual differences in expertise development is best understood in the context of other factors, so the origin of the entire model is included.

Deliberate Practice

People may watch an Olympic athlete or concert pianist and marvel at the "talent" these individuals possess. Some researchers, however, write that the extraordinary expertise of these accomplished performers is not proof of superior talent (Howe, Davidson, & Sloboda, 1998; Sloboda, 1996). Ericsson (1996; 2002) advocated *deliberate practice*, versus either talent or mere participation, as the explanation of differences in the development of expertise. In his studies of domains such as music, sports, and dance, where competitions can help identify and measure clearly superior performance, he concluded that expert performance is primarily acquired through many thousands of hours of deliberate training and practice, because he found direct positive correlations between hours of practice and achievement. Ericsson defined deliberate practice as periods of intense concentration and work that constantly push the limits of current capacity, four to five hours per day, preferably guided by the best teachers or coaches. This type of practice leads to cognitive, psychological, and physiological changes that produce expert performance. Ericsson wrote that in order to reach an international level of competition, people need at least 10 years of this type of guided deliberate practice, rather than special talent. Expert performers tend to start practicing two to five years earlier than less-accomplished performers, so over time tend to accumulate more hours of deliberate practice (Ericsson & Charness, 1997).

Anderson (2000) also stressed the role of practice, writing that chess masters, for example, were not more generally intelligent than other people; they just had practiced more. In his view, the improvement from practice was continuous, if at an ever-diminishing rate, and was virtually unlimited for cognitive skills. According to Ericsson (2002), Anderson's three-step model of expertise applies to everyday skills, but once performance reaches the third stage of automaticity, one risks stagnation. To be truly expert, deliberate practice and specially designed training activities are necessary. In this way, performers can develop skill but retain cognitive control over aspects of the performance, allowing them to adjust to a new instrument, weather conditions, or audience preferences, for example, which would be impossible if behavior were totally automated.

Underlying deliberate practice are motivation and the acquisition of domain-specific knowledge that can help one monitor learning activities (Ericsson, 1996), although Ericsson did not explore these factors extensively. Innate ability is a trivial consideration. Ericsson noted that athletes do not have better simple reaction time, memory, or perception of stimuli than other people. Although he acknowledged that musicians are more likely to have perfect pitch and that better typists can tap their fingers faster, he asserted that these abilities can be skills acquired through training and deliberate practice rather than being precursors to expertise.

Facilitating deliberate practice

Ericsson studied elite musicians and athletes who were guided intensely by coaches and teachers. Davidson, Howe, Moore, and Sloboda (1996), however, studied the involvement of parents with young musicians to see precisely how motivation and deliberate practice (and thereby expert performance) could be facilitated by parents. They interviewed parents about their role in their children's musical studies. The children were divided in to five groups: Group 1 were students in a selective music school, Group 2 had applied to the school but were rejected, Group 3 had inquired about the school but not applied, Group 4 studied music in school, and Group 5 had started musical study but had quit. Their performance was evaluated by the Associated Board and Guildhall School of Music Grades, and the expected performance differences were found among all five groups. Although children across all groups experienced some parental involvement in practice, such as their listening to or requesting practice, successful children were found to have the most parental involvement in lessons as well, across an entire learning period of 12-15 years. When parents attended lessons and found out what the teachers were asking for, they were better able to guide practice at home. The most skilled students in Group 1 had parents who were very interested in music, although not necessarily as performers. Davidson et al. (1996) speculated that parents who were performers might be overly critical of students' early efforts, while nonperforming parents might have been more impressed and encouraging.

Davidson et al. (1996) acknowledged that children with greater talent might elicit greater parental involvement, but wrote that this would not explain the difference in rate of improvement over time, nor would it increase parental involvement in lessons. They envisioned a cycle in which parental behavior enhances achievement, which motivates further parental support, which in turn enhances achievement, and so on.

Côté (1999) studied parents' involvement in the development of their children into expert athletes. Following qualitative interviews with four families of elite athletes, he identified three phases of the children's participation: sampling (ages 6-13), specialization (ages 13-15), and investment (ages 15 and up). In each phase, the parents played a somewhat different role. During the sampling years, parents provided opportunities for children to get involved in sports, encouraged them to try numerous activities, and identified what they called "gifts" in the children. During the specialization years, parents emphasized both sports and academics, made a greater financial and time commitment to the child's sport, and developed a growing interest in the child's sport. The investment years find parents exhibiting great interest in the child's sport, helping the children fight setbacks, and possibly treating the child athlete differently than their other children (investing more money in the athlete, for example). Over time, the parents made greater and greater efforts to support, both emotionally and practically, the kind of deliberate practice that Ericsson (1996; 2002) described.

While Ericsson (1996; 2002), Davidson et al. (1996), and Côté (1999) studied experts whose development was fostered by parents and teachers, Charness, Krampe, and Mayr (1996) studied chess champions. While they found that deliberate practice carried the most weight in determining skill level, they also discovered that tutoring was relatively unimportant in this group. Although coaches early on might have helped to provide motivation and set up practice schedules, most champions studied and practiced alone. There was a significant correlation between the number chess books owned and achievement rating. At least in some domains, it may be possible to establish self-learning situations that facilitate expertise development at least as well as teachers and coaches do.

Ability and Talent

Studies of deliberate practice would seem to confirm the old joke about how to get to Carnegie Hall: "Practice!" Anyone who has seen a child who appears to be a music or math prodigy, however, may question the possibility that motivation and deliberate practice are all that underlie individual differences in expert performance. Indeed, there are dissenting voices against the deliberate practice research.

In his Differentiated Model of Giftedness and Talent (DMGT), Gagné (2004) described a process through which people can develop expert-level skills. The DMGT begins with natural abilities that, through practice and with the assistance of catalysts such as environmental support, can develop into a talent in a particular domain. Elsewhere, Gagné (1998) wrote that deliberate practice proponents ignored research on the high correlations between general intelligence and school achievement. Detterman, Gabriel, and Ruthsatz (1998) referred to the deliberate practice research as "absurd environmentalism" (p. 411). Like Gagné (1998) they emphasized the impact of general intelligence on achievement, and they pointed out research on its genetic transmissibility. The Minnesota Study of Twins Reared Apart (MISTRA) is one well-known example of this research. Because the twins in the study were genetically identical yet were not raised in the same environment, similarities between them, including intelligence, were likely to be due to a shared genotype (Bouchard, 1997).

Sternberg (1996) wrote that much of the deliberate practice research is fundamentally flawed. According to him, it ignores contradictory findings, such as work in behavior genetics. He also cited cases in which students who perform better have worked less; for example, in one of his statistics courses, students who reported studying longer made lower midterm scores, which he took to mean that practice without ability does not produce rewards. In addition, Sternberg pointed out that studies of deliberate practice involve correlation, not causation, and do not use control groups, making it difficult to compare experts with those who have had as many hours of deliberate practice but have not become experts. Deliberate practice studies, according to Sternberg, ignore the fact that many people who seek a high level of expertise in a domain often drop out due to dissatisfaction with their performance, so naturally those who remain display a correlation between expertise and practice. Finally, Sternberg argued that deliberate practice studies ignore common sense. What Mozart accomplished as a child is seldom matched by those who accumulate as much practice as he had had at that time, for example. Some graduate students are better teachers after one semester than are professors who have taught for many years, despite their inexperience. Deliberate practice, therefore, is responsible for only part of expert performance.

According to Sternberg (1996), trying is not enough, even when it takes the form of deliberate practice. It is likely that Winner (1996) would agree. In a study of children’s drawings, she found evidence to support the existence of an innate talent in the domain of the visual arts. Although she agreed that hard work is necessary, she argued that it is not sufficient, and moreover it is difficult to separate hard work and ability. They are confounded because we are likely to want to work hard at something that we can do easily. In any case, Winner found it illogical to ascribe mental retardation to biological bases yet claim that high performance is due only to hard work.

In her study of young children drawing, Winner (1996) compared the work of children who drew using advanced techniques at very young ages, without instruction and without having to work at it, with the artwork of those who practiced drawing without seeming to have the ability of the others. She found that children who have high ability at a young age tend to learn more rapidly in the domain, are intrinsically motivated because of the ease of their learning, make artistic discoveries, such as perspective, without scaffolding from adults, and tend to do creative things that ordinary children do not think to do. These children tended to draw constantly without being told, with progressively better results. "Regular" children may work hard, but their progress over the years was much slower than that of artistically gifted children. Winner pointed out that the talented children she has studied tend to be left-handed, with visio-spatial strengths but linguistic deficits. According to Winner, this, taken together with the existence of drawing savants (children who are accomplished artists but who are severely delayed in other ways), may be evidence pointing to biological markers of artistic talent.

Other empirical studies that examine direct links between innate ability or talent and expert performance are difficult to find, perhaps because it is hard to measure innate ability and to completely avoid confounds with environment.

Metacognition

Apart from the debate over deliberate practice versus the role of ability, other factors contribute to individual differences in the development of expertise. Sternberg (1998) wrote that along with abilities, metacognition contributes to the development of expertise. Reasoning that metacognition operates independent of domain, intelligence, and knowledge (as mere knowledge does not always lead to action), Veenman and Elshout (1999) investigated the role of metacognition along with intelligence, to see whether metacognition would contribute separately toward developing expertise. They measured the general intellectual ability and prior physics knowledge of introductory psychology students, and identified students with high intelligence and novice physics experience (as measured by the number of courses taken), students with low intelligence and novice physics experience, students with high intelligence and advanced experience in physics, and students with low intelligence and advanced physics experience. They had them study an introductory thermodynamics text and take a pretest. Afterward the students used a computer-aided instruction module of thermodynamics problems that included a "help" feature, and then took a posttest. Metacognitive skillfulness was measured by having the subjects think aloud. Veenman and Elshout found that the advanced students had higher metacognitive skillfulness in comparison to novices of both intelligence levels. However, highly intelligent novices nearly reached the metacognitive level of advanced students, and tended to rapidly gain knowledge in the physics domain. For both novices and advanced students, metacognition contributed on its own, apart from intelligence.

When Veenman and Elshout (1999) had novice and advanced students solve thermodynamics problems with different levels of complexity, they found that novices could only solve problems within three levels of complexity. For advanced students, differences in intelligence were not a factor during easy and complex problems, but were important with very complex problems, as these were solved by the high-intelligence students only. At that high level, metacognitive skillfulness was no longer helpful for problem solving. The authors concluded that routine metacognitive skills are more important than intelligence for routine problems but not for very difficult problems, perhaps because at that point problems no longer concern students' proceduralized knowledge but rather require knowledge at the conceptual level, which higher-intelligence students may be better able to use. Therefore, although Veenman and Elshout (1999) were able to demonstrate the contribution of domain experience and metacognition to differences in the development of expertise in physics, when problems got very difficult intelligence still made a difference.

Cultural Factors

In considering how and why experts are motivated to work longer and harder than others, thus acquiring knowledge, skills, and the useful psychological and physiological changes that come from practice (e.g. Ericsson, 1996), Gleespen (1996) sought other sources of motivation support than the aforementioned parents and coaches. His cultural theory of expertise development states that the cultures of experts tend to support learning and development, and are replete with resources and opportunities in the relevant domain. This can include teachers and parents where children are concerned, or colleagues and communities of practice for adults. In a setting in which experts and learners acknowledge each other’s skills, collaborate and critique each other’s performance, and share advice, an attractive environment for achievement is created. When people are separated from this environment, their performance levels are likely to drop. This theory of environmental and cultural support for performance shares some similarities with Ogbu’s (1991; 1998) writings about the community forces that contribute to Black students’ academic lagging as involuntary minorities. Because of Blacks’ and other minorities’ disillusionment with their job outlook regardless of education, and identification of school as an element of the dominant White culture, their environment does not tend to support academic domains of expertise, thus leading to individual and group differences with those who are not involuntary minorities and whose environments are more supportive.

The idea of community support leading to expertise in certain domains may also apply to those who study relatively alone, such as the chess players observed by Charness, Krampe, and Mayr (1996). While these chess champions generally did not have coaches or live in communities of other chess players, they participated regularly in tournaments that allowed them to receive feedback with which to gauge their progress, and learning opportunities that may have helped to refine their future solitary practice. In addition, with the Internet it may now be easier than ever for people who had pursued a passion in relative isolation to create a lively virtual community that provides all the expertise-supporting advantages mentioned by Gleespen (1996), and that is less sensitive to changes in a participant's physical location than is the neighborhood in which one lives or the workplace in which one is employed. Now that cultural support is more accessible and portable for many domains, it remains to be seen whether levels of participants' expertise, or the number of existing experts, has risen.

A Multifaceted Model of Differences in Expertise

A unitary model (deliberate practice only, talent only, for example) is too simplistic to capture the range of factors underlying differences in the development of expertise. Sternberg (1999) proposed that intelligence is the same as developing expertise, and while ability affects the rate and asymptote of development in a domain, expertise has five elements: metacognitive skills, learning skills (ability to distinguish relevant from irrelevant information, for example), thinking skills (creativity, critical thinking, practical and applied thinking, etc.), declarative and procedural knowledge, motivation, and context (familiarity of material, importance to the student, for example).

Presumably individual differences in any of these factors could lead to individual differences in expertise development itself.

Sternberg's multifactorial explanation of expertise is welcome in the face of overly simplified models. However, it does not explain how these elements may be related, and does not elaborate on the motivation component. That motivation is required on the path to expertise is unsurprising; those with no motivation for developing expertise are unlikely to persist in the domain. However, what form this motivation may take still remains to be explored. Despite the paucity of research, theories of goals, self-efficacy, and flow suggest connections to other factors in expertise development.

Motivational Factors

Goals

People may describe developing experts as "goal-oriented." Because of the amount of time and work involved in the complex task of becoming an expert, it is reasonable to think that experts might be motivated by several types of goals, each one playing a part in their development over the years. Some possible goals related to expert performance are learning goals, performance goals, intrinsic valuing, extrinsic rewards, and perceived instrumentality for future goals.

In Dweck's study of adaptive and maladaptive motivational patterns (1986), she described goal-oriented activity with two factors, learning and performance goals. Individuals with learning goals "seek to increase their competence, to understand or master something new," while those with performance goals "seek to gain favorable judgments of their competence" (p.1040). According to Dweck, one's theory of intelligence is the factor underlying goal orientation. Those who believe that intelligence is fixed tend to adopt performance goals because they see achievement situations as tests of this fixed trait, so they want to get positive ratings of their competence, or at least avoid negative ones. In situations in which their perceived competence is high they prefer a challenging task and persist in their efforts, because when they accomplish it others' impressions of their ability improve. However when their perceived competence for a task is low, they avoid true challenge. When possible, they will either choose easy tasks they think they can complete, or very difficult ones that few people could complete, so that failure does not seem to indicate that their ability is low. When faced with obstacles, they do not persist in the task, because outright failure would mean that they have low ability. People with learning goals, however, believe that intelligence is malleable and strive to develop competence. According to the theory, people with learning goals tend to choose challenging tasks that develop mastery, even in situations where their self-perception of ability is low, because they are concerned with mastering the task rather than with others' perceptions of their ability. They persist when faced with obstacles, expending effort and trying new strategies. When they succeed, or even when they fail, they report satisfaction because of their effort.

In their work, Elliot and his colleagues have further divided performance goals into performance-approach and performance-avoidance goals. Those with performance-approach goals wish to do better than others, while those with performance-avoidance strive to avoid doing worse than others (Elliot & Church, 1997; Elliot & Thrash, 2001). Performance-approach goal regulation can include either a need for achievement, in which people eagerly approach the task, or a fear of failure, in which people approach the task and work very hard (overstrive) because they do not want to fail (Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002). Performance-avoidant people may try to avoid the achievement situation, or as Dweck (1986) also described, choose very easy or very difficult tasks.

Because achievement goal studies often focus on subjects who are not necessarily experts, it is difficult to hypothesize about the specific goals of experts by relying on previous research. However, the expectation of high self-efficacy in experts, and the fact that experts are people who perform well on challenging domain-related tasks, imply that experts are likely to hold learning goals as well as performance-approach goals. Because performance-avoidant people prefer to avoid achievement situations, it is unlikely that experts would hold performance-avoidance goals in their expertise domains. Research has addressed the possibility that people may not be dominated by either learning or performance goals, but may endorse multiple goals, and that a combination of learning and performance-approach goals is beneficial to achievement. Pintrich (2000) found that students with high mastery (learning) and low performance goals and those with high mastery and high performance goals performed equally well on most outcomes, and that on some outcomes the high-mastery/high-performance students performed better. Harackiewicz, Barron, Tauer, Carter, and Elliot (2000) studied college students over three semesters, and found that performance-approach goals predicted short- and long-term academic performance and that mastery goals predicted short-term interest in the course and enrollment in subsequent related courses. Therefore they suggested that optimal goal adoption consists of both performance-approach and mastery goals, because both grade performance and continued interest are important to success in college. When the researchers followed some of these students to graduation (Harackiewicz, Barron, Tauer, & Elliot, 2002), they found the same predictive pattern, although the effects of performance goals weakened over time.

Accepting that practice is one factor leading to expertise, and that deliberate practice involves intense concentration and continuous striving for progress, it would seem that learning/mastery goals would be effective in expertise development, since learning goals tend to foster persistence, effort, and improvement (Dweck, 1986). Because expertise requires years of involvement in a domain, the interest-sustaining properties of learning goals (Harackiewicz et al., 2000; Harackiewicz, Barron, Tauer et al., 2002) would also be important. However, many expertise domains, such as music and athletics, are dominated by the need to perform for others, and even in settings such as the workplace one must be concerned with performance and others' judgments of one's ability. It is also possible that people with little inclination to demonstrate their competence to others would not become known as experts. Therefore, those who have been successful in developing expertise are likely to have both learning goals and performance-approach goals to some degree, similar to the successful college students in Harackiewicz et al. (2000; 2002).

As important as learning and performance-approach goals are to expert development, on their own they may not be sufficient to describe the motivational picture of developing experts, because the arduous and complex process of becoming an expert over many years is likely to be related to multiple types of motivations. It is difficult to imagine people bothering to achieve expertise in domains for which they have no intrinsic motivation. Therefore the enjoyment and satisfaction of domain activities should play some role in intrinsically motivating expert performance as it does in motivating school performance (Csikszentmihalyi & Nakamura, 1989; Miller, DeBacker, & Greene, 1999). Deci and Ryan (1985; Ryan & Deci, 2000) further described intrinsic motivation to include a tendency to seek challenge and develop one's abilities, a characterization that should be particularly useful for experts given the advanced nature of their skills. They also wrote that people motivated intrinsically show more interest and confidence as well as more persistence than those motivated extrinsically, which would tend to support the intense domain involvement that expert development requires.

While developing experts may find learning and practicing to be enjoyable and interesting, they may also be aware that the skills they develop will result in rewards that are external to the work itself. In many workplaces, tangible rewards such as raises, bonuses, new titles, or better offices are frequently used to reward or "motivate" employees. The winners of competitions might obtain medals or prize money. In other situations, the rewards are not tangible, but are still external and outward rather than internal, such as recognition from others or renown. The importance and effects of these types of extrinsic rewards is likely to vary with the individual. In some cases extrinsic rewards might be the reason for developing expertise, but this approach carries a potential risk to developing experts. The more they focus on external rewards the less they may focus on the task itself, which could ultimately undermine their interest in the domain and their self-efficacy for domain tasks (Wolters, Yu, & Pintrich, 1996). In other cases extrinsic rewards might be completely unrelated to one's true motivation for engaging in the domain and therefore ignored or acknowledged only as subgoals that facilitate reaching more meaningful goals (Maehr, 1984). Nevertheless, extrinsic rewards should be included in the model, as they indicate the extent to which the external rewards of domain expertise actually influence experts.

What are these more meaningful goals? People developing expertise might have future goals that involve not tangible rewards but rather the fulfillment of long-held dreams of becoming the person they always wanted to be. This type of goal might be years away or never fully achieved, but once people determine what are the proximal tasks and subgoals that get them closer to their future goal, their investment and engagement in these proximal activities increase (Miller & Brickman, 2004; Miller et al., 1999). Therefore the deliberate practice of developing experts could be motivated in part by the perceived instrumentality of their present actions to this personally valued future goal. Activities that might not be intrinsically enjoyable at the time are invested with meaning because of their relationship to a meaningful future.

Self-efficacy

Perceived competence for a task, also known as self-efficacy (Bandura, 1994), interacts with achievement goals, as mentioned above. When perceived competence is high, people tend to persist when challenged regardless of goal type, but when perceived competence is low, they give up quickly if driven by performance goals, which is incompatible with the development of expertise. High self-efficacy also leads people to set higher goals, which in turn raises the level of motivation for and attainment of the task (Bandura, 1989), all of which would contribute to expert performance.

However, self-efficacy also affects expert performance directly (Bandura, 1989, 1994). In a difficult performance situation, people with high self-efficacy believe that they can cope with challenges, and therefore are not unduly bothered by them and can remain task-oriented. However, people with low self-efficacy become consumed with self-doubt during a challenging performance. The self-doubt is distracting, causing anxiety and interfering with thinking and concentration, thus leading to a lower quality of performance. The lower quality of performance then leads to lower self-efficacy for the future, and the cycle continues. In the road to expertise, then, self-efficacy exerts an influence on motivation by interacting with goals, but also has a direct connection to task performance itself.

Flow

Given the importance of deliberate practice as a component of expertise development (Ericsson, 1996; 2002), and given that deliberate practice is characterized by intense concentration that pushes the boundaries of capacity, it is possible that individuals engaged in deliberate practice experience flow (Csikszentmihalyi, 1990). Individuals in flow are in a self-chosen and optimally challenging environment in which their ability and the task challenges are well matched. The task is difficult enough to require some skill, and the performer is no longer a complete novice (or her skill level would be too low to be able to perform well enough to achieve flow). During flow, self-efficacy is high, so intrusive feelings of self-doubt do not interrupt the performance of the task. The task has a clear goal, and the task environment provides feedback that is comprehensible to the performer and to which he is able to react appropriately. The intense concentration drives out distracting extraneous thoughts and worries, and leads the performer to lose track of time. In this state the performer has a sense of control and competence but is still challenged. While during flow the performer loses the habitual sense of self-consciousness, afterward people often feel a stronger sense of self. At the time the flow experience may be too intense to feel pleasurable (or people are too engaged in it to stop and think about whether it is pleasurable), but later one looks back on it with happiness, accomplishment, and satisfaction, which is rarely the case with more relaxing pursuits.

In the context of expertise, flow and deliberate practice may sometimes be one and the same, or flow may be a particularly rewarding component of practice and performance that in turn motivates further practice. Flow may also overlap with intrinsic valuing, because of the enjoyment component (at least in retrospect) and the focus on challenge.

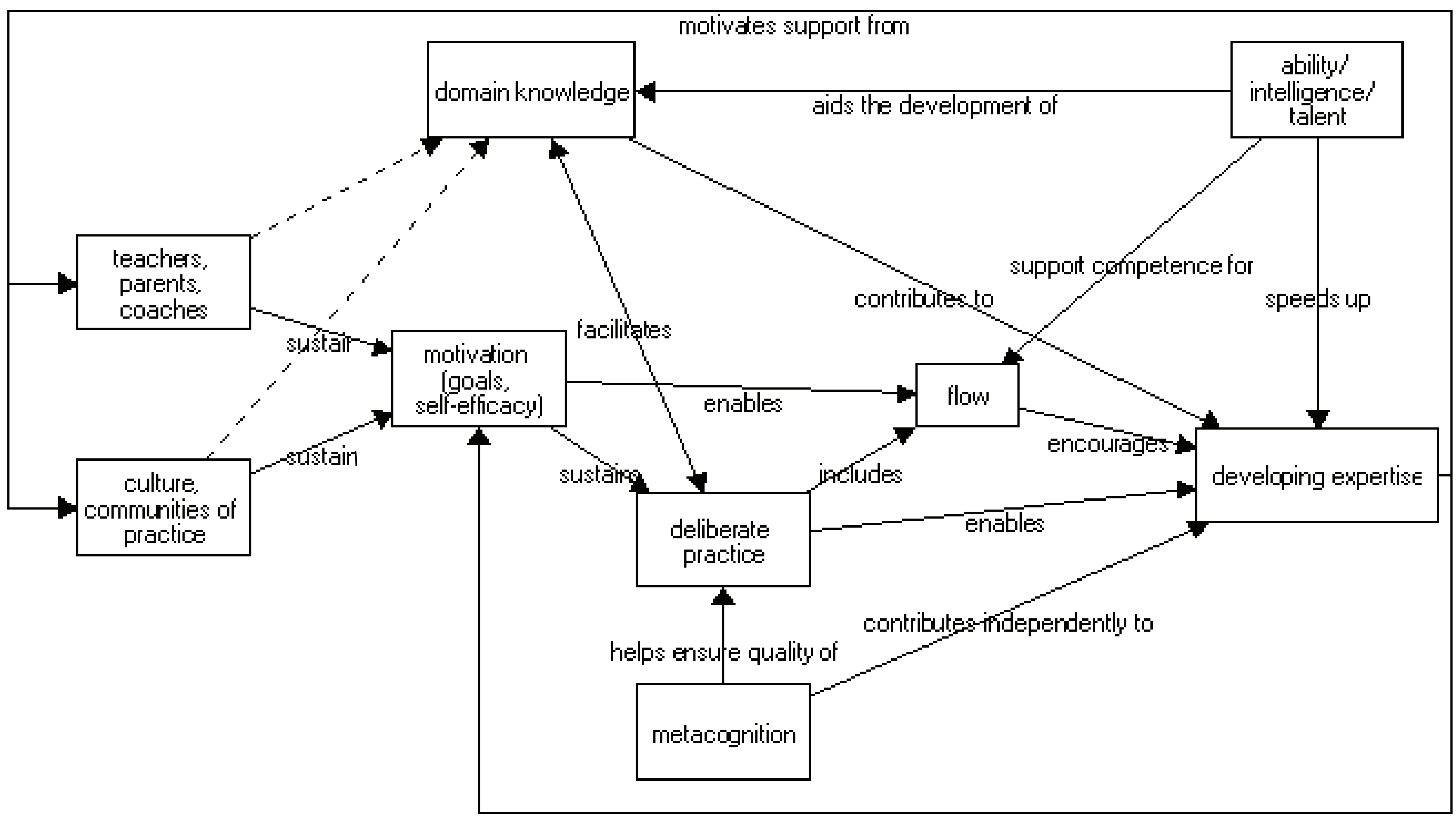
A Model of Factors Encouraging Expertise Development

In Figure 1, "Factors Encouraging Expertise Development (FEED)," I propose a set of relationships between aspects of expert performance described in the literature summarized above, such as deliberate practice, motivation, support from teachers and coaches, support from culture and communities of practice, metacognition, domain knowledge, and talent/intelligence. I also include factors not previously linked explicitly to individual differences in the development of expertise, such as goals, self-efficacy, and flow.

In the model, two primary elements lead to motivation (goals and self-efficacy): support from teachers, parents, and/or coaches and support from one's culture or community of practice. Support from teachers, parents and coaches would tend to be individualized and more intense than that from culture and communities of practice, but both serve to add to domain knowledge and sustain motivation. Motivation in turn sustains the work of deliberate practice, necessary for expert achievement. Deliberate practice may include periods of flow that encourage developing expertise. In the model, ability/intelligence/talent helps expert performance develop faster and farther. It also aids in the faster accrual of domain knowledge, and supports flow, because a fairly high level of competence is necessary to achieve flow. Domain knowledge contributes to the effectiveness of deliberate practice and in turn is increased by it, and also contributes to expert performance directly. Metacognition supports the quality of deliberate practice and contributes independently to expert performance. Finally, developing expertise starts the cycle again, as it tends to foster further support from teachers and the like, along with cultures and communities of practice to whom one's accomplishments become known. Successful performance also supports high self-efficacy and validates and strengthens the original goals that led to motivation for the domain in the first place.

This model can help to illustrate some of the ways in which individuals may differ from one another in the development of expertise. A failure in any node of the structure has the potential to imperil or delay expertise development. For example, lack of support from one's culture or lack of proper instruction diminishes motivation and domain knowledge. Failure to engage in deliberate practice detracts from performance, but also fails to develop domain knowledge. Low talent or intelligence puts domain knowledge, the possibility of flow, and expert performance at risk. Just as expert performance is the result of many related factors, differences in the achievement of expertise can be due to one or more of several causes.

Figure 1. Factors Encouraging Expertise Development (FEED)



General Research Questions Arising from the Model

"Factors Affecting Development of Expertise" is a preliminary model. The specific nature and direction of relationships between the elements that have previously been researched, such as ability, deliberate practice, metacognition, and domain knowledge, have yet to be established. The function of flow and the roles of goals and self-efficacy as components of motivation in the development of expertise (and to individual differences in that development) have also not been investigated extensively. Opportunities for research in the model may lead to its revision and refinement, and perhaps to interventions.

The motivation and flow aspects of the model present some research options. What is the motivational profile of an expert? Does it differ by domain? Do experts represent goals differently from novices, and if so, how do they change as they gain expertise? Do goals tend to be distal or proximal, mastery or performance-approach? In performance-oriented domains, do developing experts hold both learning and performance-approach goals? Do those who gave up before reaching expert level tend to differ in their goal orientation from those who did not? Do learning goals support the motivation that sustains deliberate practice, and how do experts measure their performance against their goals, especially in the absence of formal competitions? Does the experience of expert performance strengthen and validate goals and self-efficacy, and does it change them over time? What effect does self-efficacy have on the performance of experts? Are flow states common during learning or performing in the domain for those who are developing expertise? Is there a relationship between ability/talent and the occurrence of flow in practice and performance, or does prior deliberate practice alone predict flow states? For those who experience flow, does it tend to foster continued motivation for deliberate practice? Did those who continue on to expertise experience flow during their development more often than those who quit?

Some aspects of the relationships between elements of expertise development in the model could be fruitful lines of inquiry. Veenman and Elshout (1999) established that metacognition contributed independently to expert performance, but does it also contribute independently to the quality and effectiveness of deliberate practice in a domain? Do people with greater general intelligence (or innate talent, as described in Winner, 1996) tend to accumulate knowledge in a valued domain at a faster rate than those with lesser general intelligence, and do they proceduralize it more quickly? If amount of deliberate practice correlates positively with expert performance, as Sloboda (1996) and Ericsson (1996; 2002) found, does it also correlate to domain knowledge, or are there those who have domain knowledge as extensive as that of expert practitioners who nevertheless do not actually perform as well?

In studies of deliberate practice, Ericsson (1996; 2002) and Sloboda (1996) studied advanced athletes and musicians, as frequent competitions and rating systems made it relatively easy to determine expertise. In their studies, expertise was facilitated by coaches and teachers who worked intensely with students. However, there is a need to evaluate whether their findings about elite competitors are applicable to domains that are more common and less rarefied but nevertheless complex, and in which people seldom have access to extensive individual teaching and coaching. How can expertise be facilitated in the workplace, for example, through deliberate practice? What conditions in workplace culture or communities of practice tend to foster expertise in their domains? Is "deliberate practice" an appropriate term for the domains of expertise found in the workplace or other everyday settings? Unlike musicians or athletes, accountants or architects, for example, are seldom likely to practice in their domain simply for practice's sake, because they express their expertise in work-related tasks. However, as with deliberate practice, these experts are likely to improve and develop only if they engage in their domain intensely and reflectively, making the best possible use of feedback on their performance and constantly striving for improvement. Perhaps another term, such as "reflective engagement," would serve them better than "deliberate practice."

Charness, Krampe, and Mayr (1996) found that chess players did not generally use coaches, preferring to learn on their own and then measure their ability at tournaments. They took advantage of resources available in their domain, such as chess books. Other domains, information technology for example, are also known for experts who are largely self-taught (Hilton, 2001). In addition, in many workplaces employees are expected to adapt to the pace of technological change without extensive training, as hardware and software are replaced. How do those who become experts on their own find and utilize appropriate resources to support their development? How do they measure their progress? Do their self-study situations somehow replicate the motivational and knowledge-development functions of teachers and coaches? What role do communities of practice have in independent learning? If methods of effective self-study can be identified, can they be explicitly taught in an effective manner?

Considering a multifactorial model of factors encouraging the development of expert performance complicates the issue of individual differences. However, a model that includes aspects of motivation, experience and environment along with ability may help end the cyclical fluctuation between extreme genetic and environmental views that Sternberg (1996) criticizes, in favor of a more varied and realistic—if more complex—structure of developing expertise. One logical place to begin research is to determine whether there is evidence that the lived experience of experts actually includes the elements in the model. An initial qualitative study was conducted (Appendix A; Beesley, 2004) with self-taught IT workers to investigate their learning experiences as developing experts. In the study, the workers reported episodes of flow, described the influences of several types of goals, and discussed self-efficacy. Research should now focus on the least-researched part of the model, the motivation component.

Purpose and Research Questions for the Present Study

Multiple studies have been conducted on goals and other motivational aspects of students in classrooms from elementary school through college (e.g., Ames, 1992; Anderman & Anderman, 1999; Barron & Harackiewicz, 2001; Elliot & Harackiewicz, 1996; Harackiewicz, Barron, & Elliot, 1998; Harackiewicz et al., 2000; Harackiewicz, Barron, Tauer et al., 2002; Middleton & Midgley, 1997; Miller, Greene, Montalvo, Ravindran, & Nichols, 1996; Pintrich, 2000; Pintrich & De Groot, 1990; Wolters et al., 1996). Although these studies contribute to the understanding of aspects of motivation in schools, their applicability to the motivation that leads to expertise is unknown. We cannot assume that students in a classroom are necessarily becoming experts, or even that they have the goal of doing so (Alexander, 2003). Because the motivational aspects of the expertise model are the least researched, this would be a logical place to focus new research.

In the qualitative pilot study (Appendix A), IT experts reported high self-efficacy and flow experiences during their technology learning experiences, as expected. Because experts gain their expertise through years of study and practice in their domains, they naturally would be expected to have high self-efficacy for learning in that area; they would also have a record of past successful experiences upon which to draw (or else they would not be experts), including incidences of expert performance that would have been difficult if they had been distracted by self-doubt. However, in the qualitative study descriptions of goals differed from respondent to respondent. Because goal perceptions are the motivational area in which these experts are likely to differ, it is reasonable to focus on goal variables in a study in expert motivation. It may be that the experts share similar motivational characteristics, or that they remain idiosyncratic, or that they cluster in a set of types.

This study is intended to describe the motivational characteristics of developing experts. It is based on the motivation element in the model "Factors Encouraging Expertise Development," shown in Figure 1, and focuses specifically on profiles of multiple goals: learning/mastery goals, performance-approach goals, intrinsic and extrinsic rewards, and future-oriented perceived utility. The research questions are:

1. What types of goals are held by adults developing expertise in a domain?
2. To what extent do the developing experts hold multiple goals, and what are the relationships between the goals?
3. Do the developing experts cluster into groups that hold similar patterns of multiple goals, and if so, what is the nature of the groups?
4. What other non-goal variables predict group membership?

As discussed earlier, research has supported the adoption of both learning/mastery and performance-approach goals for sustaining students' achievement and continuing interest in a domain (Barron & Harackiewicz, 2001; Harackiewicz et al., 2000; Harackiewicz, Barron, Tauer et al., 2002; Pintrich, 2000). Because experts must sustain that performance and interest to a degree far surpassing that of the secondary and college students in those studies, I expected that the IT experts would also endorse both learning/mastery and performance-approach goals in some combination. As with flow, however, there may be some causes for individual differences in goals among experts, even within a domain. Developing IT experts would probably continue to hold learning goals over time, because learning goals may be at the heart of what drove them to become experts in the first place; however, as their position in their field becomes more secure they may become less driven by other's opinions of their abilities. They may feel they have already proven themselves in the eyes of others, and no longer need pay attention to continuing to demonstrate ability. Therefore, at any given time the influence of performance-approach goals may have diminished for some experts in the study, as it did with the college students in Harackiewicz et al. (2002).

Experts are likely to report intrinsic valuing of their domain, because it is difficult to imagine people pursuing a skill to expertise that they do not enjoy at least somewhat. The pressures of the workplace may undermine intrinsic learning motivation for some, however. The challenge aspect of intrinsic motivation (Deci & Ryan, 1985; Ryan & Deci, 2000) may also suffer for information technology workers who have advanced to a point where they do not experience substantial new challenge at work.

Experts' reactions to extrinsic rewards in the workplace are difficult to predict, because they depend both on the reward structure of the workplace and the experts' reactions to it (Amabile, Hill, Hennessey, & Tighe, 1994). Extrinsic rewards may be meaningful and motivational to some and ignored or devalued by others (Maehr, 1984). The context of the rewards may be influential as well. According to some researchers, extrinsic rewards, at least in school, may undermine intrinsic motivation (Deci, Koestner, & Ryan, 2001; M. R. Lepper & D. Greene, 1978), while others reported that they may not be harmful if they reflect competence rather than mere participation (Cameron & Pierce, 1994). The type of extrinsic reward may matter also; computer programmers have indicated being motivated by compensation in the workplace (Amabile et al., 1994), which they may take as a mark of their skill.

I expected that IT experts would report future-oriented perceived instrumentality, as they did in the qualitative study. They are likely to know enough about their profession and their own place in it to have some notion of their future, and to have enough experience to determine what current learning will be instrumental for that future. Here again, however, personal and contextual factors could mute the influence of perceived instrumentality. If the IT experts feel that their knowledge about the future of their jobs is doubtful, perceived instrumentality for learning would not be a major motivator, nor would it be if they are nearing retirement.

Because the five types of goals are likely to vary between IT experts depending on their personal characteristics as well as their response to their work environment, the intent of the study was to reduce the complexity of the multiple-goal situation into a series of profiles, or clusters. Therefore I performed a cluster analysis, and then used discriminant analysis to predict cluster membership with other variables not used in the clustering. Because of the risk of burnout in IT occupations (Hilton, 2001) and possible changes in goals over years of experience, time in field was expected to be the most useful predictor of goal profile, although due to the exploratory nature of the study and the focus on relating expertise to motivation, I also examined the usefulness of self-rating of expertise as a predictor.

Chapter Two: Methods

Participants

One persistent difficulty in expertise research is identifying participants who can with reasonable confidence be called experts. The snowball method described in the qualitative study (Appendix A) for identifying expert self-taught IT workers would have been rather unwieldy in locating the greater number of participants that a descriptive quantitative study would require. The number of developing experts required for the present study was at least 140, which would provide enough subjects for the goal clusters (Hair & Black, 2000). The challenge of identifying experts is likely what drove previous researchers toward domains with competitions and ranking systems, such as chess, music, and sports, where the responsibility for supporting the claim of expertise would not fall upon the researcher.

However, there are ways to obtain a sample of likely experts in domains that are not as systematically ranked. In this study, participants were sought from technology user groups with online discussion forums. These user groups are usually dedicated to a single type of software, programming language, or development platform, although some large groups have many divisions dedicated to different technologies. In these forums, user group members post their questions or comments, and other members respond with solutions or suggestions. The members of these user groups are likely to be developing experts: if they were novices they would not be using the relatively advanced technology, and if they were uninterested in developing their expertise they would not spend their time participating in these voluntary user groups dedicated to furthering knowledge about the technology. To help ensure that the IT workers had had sufficient time to develop their expertise, I analyzed data only for participants who reported working in the field for at least five years.

Variables and Measures

The Work Preference Inventory (WPI) by Amabile et al. (1994) is a 30-item measure of intrinsic and extrinsic motivational orientations in the workplace. It can be used as a two-factor (intrinsic valuing and extrinsic valuing) or a four-factor (intrinsic challenge, intrinsic enjoyment, extrinsic compensation, and extrinsic outward) scale. According to the authors, the intrinsic aspects were based on Deci and Ryan's cognitive evaluation theory (1985) and Csikszentmihalyi's flow theory (1990), while the extrinsic aspects were based on the work of Kruglanski (1978), Lepper and Greene (1978), and Calder and Staw (1975). It was validated with large samples of workers from a variety of work settings and was found to have "meaningful factor structures, adequate internal consistency, good short-term test-retest reliability, and good longer term stability" (p. 950). I used it as a four-factor scale, both because this configuration had better reliability and because computer programmers were found by Amabile et al. (1994) to differ in their scores on each type of intrinsic and extrinsic motivation, a nuance that would be lost by combining the subscales. The items are in Appendix B. I used the items as is, although my directions also asked the respondents to think about when they are learning new technology for their work. The WPI resulted in four variables for clustering: Challenge, Enjoyment, Compensation, and Outward (described by Amabile et al. as "oriented toward the recognition and the dictates of others," p. 955).

For the remaining goal variables—learning, performance-approach, and future-oriented perceived instrumentality—I adapted relevant items from the versions of

Approaches to Learning (ATL) found in Miller, DeBacker, and Greene (1999), Brickman, Miller, and Roedel (1997), Miller et al. (1996), and Greene and Miller (1996). Because they were intended for use with students in a classroom setting, I adapted their wording for adults in the workplace. The original items are found in Appendix C, and the adapted items are in Appendix D. In modifying the items, I first changed "I do the work assigned in this class" to "I learn new technology" and changed "students" to "co-workers." "Smart" was changed to "competent" to better match how adults might describe themselves and to be consistent with the theory, which involves demonstrating competence to others. An item that referred to scoring higher was replaced with one related to demonstrating competence.

The perceived competence variable, the eighth one used for clustering, was measured with Deci and Ryan's (2004) four-item Perceived Competence Scale (PCS). I adapted their Perceived Competence for Learning version to suit the developing technology experts by mentioning learning new technology skills. For example, the item "I feel confident in my ability to learn this material" was changed to "I feel confident in my ability to learn new technology skills for my job." The perceived competence items are in Appendix E.

In addition to the measures described above, I added a demographic survey. Because I wanted to know the characteristics of the survey sample, I included items about their age, sex, race/ethnicity, education level, job category, job title, time in current job, and time in field; these variables could also be used to predict cluster membership in a discriminant analysis following the cluster analysis. Because the IT sector has a large number of job titles, I used job concentrations listed by Tech Career Compass, an organization founded by several technology companies to assist job-seekers and employers in developing IT careers (Computing Technology Industry Association, 2004). In addition, I included an item asking respondents to rate on a 10-point scale their own expertise as compared to others in their department, and added an open-response box asking for the respondent's source for this information. This created a variable of self-rating for expertise, along with a measure of where they looked for expertise information (e.g., to themselves or to others' judgments). The demographic survey is found in Appendix F. A screenshot of part of the online survey is included as Appendix G.

Data Collection

In order to attract people who worked in IT, I targeted user group sites dedicated to technology usually used in the workplace, such as advanced enterprise-level database or server software, rather than technology often employed also in home use or by novices, such as Windows personal computer operating systems. I chose the forums based on recommendations from experienced programmers, database administrators, systems analysts, and network administrators. Typically the online forums of the user groups were divided into several subsections, each covering one specific aspect of the relevant technology. In order to avoid interrupting a technical discussion with an off-topic posting about the research study, I looked for subsections that were described as being non-technical in nature; these were called, for example, "Free for All" or "Café." The posters here were still members of the technical user group and viewed this area often (in fact, in some forums the off-topic subsection was one of the most active), but would be more receptive to a research-related posting here than in an area where they expected posts of only a technical nature. I did not post in forums that did not have an off-topic subsection. I entitled my post "Learning motivations of IT pros," gave a short description of the study, and included a link to the online version of the anonymous survey consent form (Appendix H), which in turn had a link to the online survey itself.

I posted notices about the study on 12 user group off-topic forums over a period of five months in 2005. At the end of December 2005 I downloaded the data from the server database. At this time the number of responses was 228.

Data Analysis

I downloaded the data into a spreadsheet and renamed the variables for easier importation into SPSS. I deleted entries I had made myself in order to test the functionality of the online survey system, as well as a few obvious duplicates (repeated identical cases, from the same Internet Protocol address, entered at exactly the same time) and blank entries. Although the Likert-type scales were numbered from 1 to 6 onscreen, the survey system recorded the data from 0 to 5 in the database, so I adjusted the data to reflect the intended 1-6 scale. After that I imported the data into SPSS and added value labels to categorical data and reversed the necessary items in the WPI. Because I intended to include only people who had been in their IT field for five years or more, I filtered out people who reported working in their field for less than five years.

I then categorized items with open-ended answers. The Race category was open-ended because I could not be certain that all respondents were from the United States, and terms used to describe race and ethnicity differ between countries; I also wanted to allow participants to describe themselves in the way they preferred. Academic majors, job titles, and source of self-rating of expertise were also open-ended because of the possible variety of responses.

I calculated Cronbach's alpha reliability coefficients for the subscales intended for clustering (intrinsic enjoyment, intrinsic challenge, extrinsic compensation, extrinsic outward, learning/mastery goals, performance goals, future-oriented perceived utility, and perceived competence), and then calculated subscale means for each. For categorical variables, I calculated frequencies and percentages and created bar charts. For continuous variables, I calculated frequencies, means, medians, and standard deviations, and created boxplots and histograms with normal curves. Finally, I computed correlations between the eight variables that would be used for cluster analysis as well as for variables that might predict group membership, such as age, time in the field, and self-rating of expertise.

Cluster analysis, a set of multivariate procedures, was performed to develop a series of motivational profiles for the IT experts. The goal of cluster analysis is to describe natural relationships in the data by forming groups with the minimum within-group variance and maximum without-group variance. It is similar to exploratory factor analysis, but essentially reversed; while factor analysis groups variables, cluster analysis groups cases. Although it is used often in market research, educational researchers and psychologists have also employed the technique (e.g., Alexander, Buehl, Sperl, Fives, & Chiu, 2004; Buehl & Alexander, 2005; Csizér & Dörnyei, 2005; Higgins, 2004; Marzillier & Davey, 2004). Cluster analysis itself is data-driven, exploratory, and dependent on subjective judgments at each step in the process, so the researcher must take care to include only variables that are expected to vary between cases in the sample and are theoretically meaningful, because the technique will result in clusters no matter what data are entered. I relied on Hair and Black's (2000) chapter on cluster analysis as a guide to the process described below.

First, I standardized the subscale variables in order to look for outliers, better depict the disparities between the resulting clusters, and moderate the effects of differences in standard deviation among the variables. Because outliers have a detrimental effect on cluster analysis, the cases were evaluated for extreme scores; cases with multiple extreme scores (>2.5 standard deviations) were dropped. Correlations between the subscales were evaluated for multicollinearity, with correlations above .85 considered multicollinear.

In determining a clustering procedure, the researcher must decide between hierarchical and nonhierarchical algorithms for grouping the cases. Hierarchical methods start by clustering the closest points and then adding new points to the original cluster or using them as bases for new clusters. The analysis continues until an optimal balance is reached between low in-group difference, high out-group difference, and number of groups. In hierarchical analysis, misleading early groupings may negatively affect the final cluster structure. With nonhierarchical methods, the researcher specifies the number of clusters; the other cases are then grouped into that number of clusters, using as many iterations as necessary to determine optimal cluster membership. Nonhierarchical methods, however, are dependent on the number of clusters selected by the researcher, and selecting different numbers of clusters usually results in different cluster structures. Therefore, just as researchers do a preliminary factor analysis to determine the optimal number of factors before calculating the rotated factor solution, one can run a hierarchical method to determine the number of clusters and further examine outliers (cases that resist classification into clusters) before using a nonhierarchical technique to determine ideal cluster membership.

In this analysis, I used Ward's method (hierarchical) to determine the number of clusters and a K-Means (nonhierarchical) method specifying the number of clusters resulting from Ward's method. I employed the squared Euclidean distance; it is the most commonly used distance method in cluster analysis and is similar to the sum of squares approach used in many statistical procedures ("Cluster Analysis," 2000). Ward's method minimizes the sums of squared distances between the clusters at each stage, and usually results in clusters with similar numbers of values. An agglomeration coefficient is calculated at each step in the hierarchical method; at the beginning, the number of clusters equals the number of cases, and at the end the all cases are in one cluster. As the number of clusters got into the single digits, I examined the agglomeration coefficient to look for points when it increased notably. When this occurs, it means that the members of the new cluster are relatively heterogeneous. Therefore, the number of clusters present *before* the large increase is a good candidate for an optimal cluster number, because at this point there is a balance between a manageable number of clusters and the relative similarity of the members of the clusters.

After determining the number of clusters, I conducted a K-Means nonhierarchical cluster analysis where *K* represented the number of clusters obtained from Ward's method. K-Means analysis starts with well-spaced cases equal to the number of clusters specified, and then adds cases to each cluster (and removes cases from clusters) through successive iterations until all cases are clustered into *K* number of clusters and no case needs to move to be closer to the centroid of another cluster.

Following the formation of the clusters, I computed means of the variables within each cluster in order to form goal profiles, and used a bar chart to depict the differences between the profiles. I also used a boxplot to examine the distance of the cases from their cluster centers, and calculated an ANOVA table to determine which of the variables contributed the most to the cluster solution.

The last step in cluster analysis was to validate the cluster solution ("Cluster Analysis," 2000; Hair & Black, 2000). One method of validating the cluster solution is to establish predictive validity by using discriminant analysis to compare the clusters on quantitative variables not used in the original cluster analysis. I conducted a discriminant analysis using time in field and self-rating of expertise as predictors of goal profile. I described and named the discriminant functions, and reported the accuracy with which they predicted cluster membership.

Finally, I created bar graphs and conducted two-way contingency table analyses to examine whether cluster membership was associated with other differences in the categorical descriptive variables.

Limitations

This study, like all others, has limitations. In this case, neither the WPI nor ATL was used in exactly the same way as in past research. The WPI (Amabile et al., 1994) is not intended explicitly for experts, although it was validated with over a thousand working adults, many of whom could be considered developing experts. Approaches to Learning (Brickman et al., 1997; Greene & Miller, 1996; Miller et al., 1999; Miller et al., 1996) was written for students rather than working adults, but it has been used with college students who were not much younger than some of the participants in the present study. Fortunately, both of these instruments are derived from the same theoretical foundations as the current model, "Factors Encouraging Expertise Development" (Figure 1), so they share conceptual foundations.

In addition, participants were asked to self-report their goals based on their involvement in a domain over the span of several years. Their memories of these events may be altered by the passage of time, or colored by their current perspective on their career or present conditions and events on the job.

The power of cluster analysis in this study is that it detects differences between groups of people that would not be obvious from simply looking at unstandardized means. However, cluster analysis is not an inferential technique in which statistical characteristics of the sample are assumed to correspond to population parameters (Hair & Black, 2000). Therefore, its usefulness for describing a population rests, even more than usual, in finding a sample that is truly representative of the population. A researcher's ability to do this is limited by a number of practical obstacles; it is not possible to obtain a complete, flawless list of the population of IT experts from which to draw a perfect sample. Therefore, a limitation of the study is that the motivational profiles obtained will be most applicable to those who most resemble the study sample.

Chapter Three: Results

Data Adjustments

After deleting test cases and accidental duplicates, the number of legitimate cases was 223. Filtering out people who had been in their field for less than 5 years removed 20 people, leaving 203.

I examined the open-ended responses to the Race item and grouped them into seven categories: Caucasian/White, Native American/American Indian, African American/Black, Latino/Latina, Asian (including Asian American), Middle Eastern, and Mixed. Some people chose not to answer this question, while others entered responses that were impossible to categorize in this way, such as "Human" and "British." For major in academic level reached and academic level completed, I found nine categories: IT-related, social sciences, law/criminal justice, math, business/communications, engineering/aviation, sciences, education, and humanities/arts. I identified ten categories of job titles: Chief Technology Officer/Manager, Consultant, Associate, Director/Lead, Analyst, Developer/Programmer, Engineer, Specialist, Trainer, and Database Administrator. Finally, I grouped the source of self-rating of expertise into nine categories: self/own opinion, comparing self with peers, certifications, formal evaluations, feedback from others, training/education, others asking them for help, experience, and level of responsibility.

Reliability Coefficients

Final Cronbach's alpha reliability coefficients for the eight subscales used in the cluster analysis are shown in Table 1. Initially the coefficient for Enjoyment (WPI) was .68. Item 9 in that scale, "No matter what the outcome of a project, I am satisfied if I feel

I gained a new experience," was alone responsible for lowering the alpha by .03, and had an item-total correlation of only .14, while the others were .30 to .47. With this group it may have tapped something different than did the other items in this scale, such as "What matters most to me is enjoying what I do" and "I enjoy doing work that is so absorbing that I forget about everything else." IT workers may feel enough pressure to complete projects successfully, or may believe that it is impossible to feel satisfaction over a failed project, that they respond differently to this item. Given the item's wording and its empirical behavior in this sample, I eliminated it from the subscale, leaving nine other items.

Table 1. Reliability coefficients for clustering variables

Subscale	Cronbach's α
Enjoyment (WPI)	.71
Challenge (WPI)	.70
Outward (WPI)	.60
Compensation (WPI)	.74
Learning Goals (ATL)	.87
Performance Goals (ATL)	.87
Perceived Instrumentality (ATL)	.77
Perceived Competence (PCS)	.85

Although the reliability coefficients for the WPI subscales are in some cases less than desirable, they are in much the same range (.62-.73) that Amabile et al. (1994) reported in validating the measure.

Descriptive Statistics

The study sample was 82% male (*n* = 166) and 18% female (*n* = 37). Most were White (78%, *n* = 159). The racial/ethnic characteristics of the sample are shown in Table 2.

Table 2. Racial/ethnic makeup of study sample.

Race/Ethnicity Category	Frequency	Percent
Caucasian/White	159	78.3
Native American	1	.5
African American/Black	4	2.0
Latino/a	1	.5
Asian	11	5.4
Middle Eastern	1	.5
Mixed	2	1.0
Did not respond	24	11.8
Total	203	100.0

Participants ranged in age from 23 to 66, with a mean of 41.82 years (*SD* = 9.81). The ages were fairly normally distributed around the mean, as can be seen in Figure 2. They had been in their field from 5.0 to 40.8 years; the mean time in field was 15.28 (*SD* = 7.50) years. The most frequently reported time in field was 10 years, so this variable was positively skewed (see Figure 3); considered together, however, age and time in field indicated that I had obtained an experienced sample. The mean time in current job was 5.33 (*SD* = 5.34), but this is a less important figure as IT workers tend to change jobs within their field (Hilton, 2001).

Figure 2. Age distribution of participants.

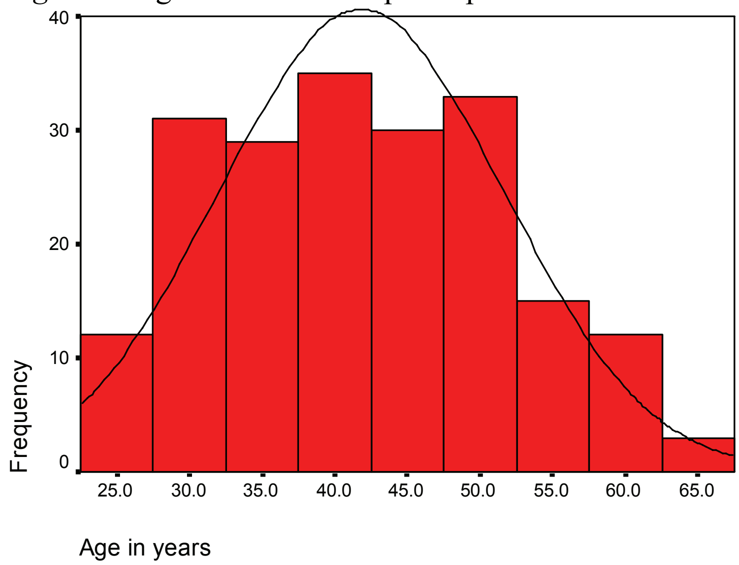
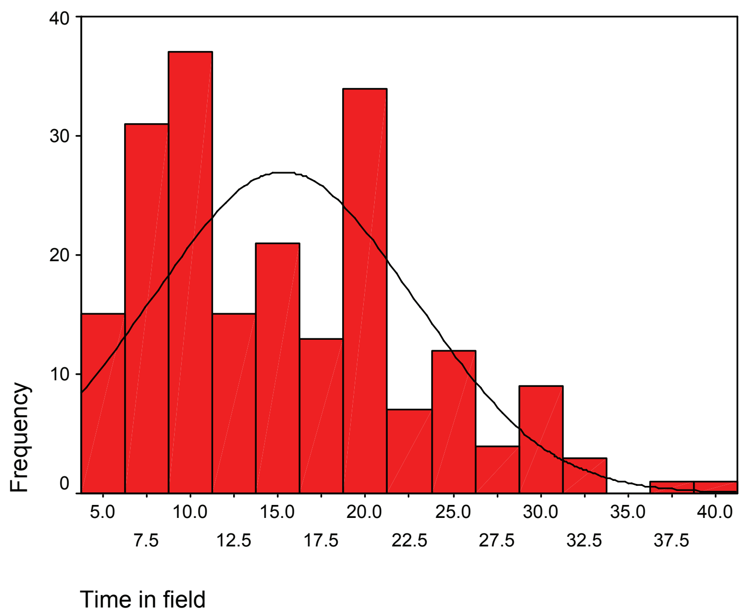


Figure 3. Time in field distribution of participants.



In the sample, most reported that the bachelor's degree was the highest academic level they had completed (46.3%). Next largest was those completing a master's degree (31.0%), followed by those with only a high school diploma (20.2%). Four had completed a doctorate, and one did not answer. However, only 13 reported that high school was the highest level they had reached, so the rest of those without a bachelor's degree likely had some college or other postsecondary experience.

As expected, the IT workers in this sample had completed degrees in a variety of majors, although most were in an IT-related field. Business was the next largest category, perhaps because many Management Information Systems classes are in business colleges. The majors of their completed degrees are listed in Table 3.

Table 3. Majors of completed degrees.

Major	Frequency	Percent
IT-related	76	37.4
Social sciences	11	5.4
Law/criminal justice	3	1.5
Mathematics	9	4.4
Business/communications	27	13.3
Engineering/aviation	18	8.9
Sciences	15	7.4
Education	5	2.5
Humanities/arts	5	2.5
Did not respond	34	16.7
Total	203	100.0

About the same number of respondents worked in the two most popular IT job areas, databases (37.4%) and programming (36.9%). These were followed by network infrastructure (12.3%), web development and administration (6.4%), network devices

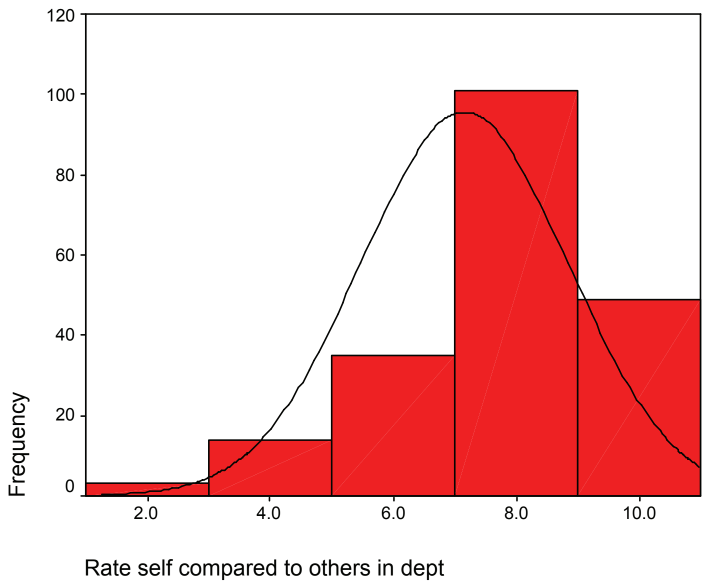
(1.5%), and digital media (1.5%). Eight people did not identify their job area. Statistics for their job title categories are shown in Table 4. As could be expected from the job areas, the most popular job titles were Developer/Programmer and Database Administrator. Many were analysts and engineers, and several were higher-level directors and CTO's. Overall, the participants represent a fairly wide range of job titles.

Table 4. Job title categories.

Job title category	Frequency	Percent
Chief Technology Officer/Manager	26	12.8
Consultant	18	8.9
Associate	7	3.4
Director/Lead	14	6.9
Analyst	25	12.3
Developer/Programmer	31	15.3
Engineer	28	13.8
Specialist	8	3.9
Trainer	5	2.5
Database Administrator	38	18.7
Did not respond	3	1.5
Total	203	100.0

When asked to rate their own expertise as compared to others in their department on a scale of 1 to 10, participants' responses had a mean of 7.16 (*SD* = 1.68). The distribution was negatively skewed (see Figure 4), which is not surprising for this experienced group.

Figure 4. Self-rating of expertise as compared to others in department.



As to the source of their self-rating of expertise, the largest number of participants cited themselves (39.4%, n = 80). Others compared themselves with peers (8.4%, n = 17) to determine their expertise level. Some relied on informal feedback from others (11.3%, n = 23) or formal workplace evaluations (6.4%, n = 13). The smallest groups relied on years of training and education (2.0%, n = 4) or technology certifications (1.5%, n = 3). Thirty-one (15.3%) did not respond to the question.

The means and standard deviations for the eight variables to be entered into the cluster analysis are shown in Table 5. Overall, participants scored highest in perceived competence, as expected, although scores ranged as low as 2.5 out of 6. The lowest means were for extrinsic variables such as outward, compensation, and performance-approach (referred to in tables and figures as "performance" to save space) goals. Performance-approach goals and compensation also had relatively higher variability.

Perceived instrumentality also had relatively higher variability, which could reflect the range of experience levels in this sample; those who are closer to retirement may be less likely to report this future-oriented goal.

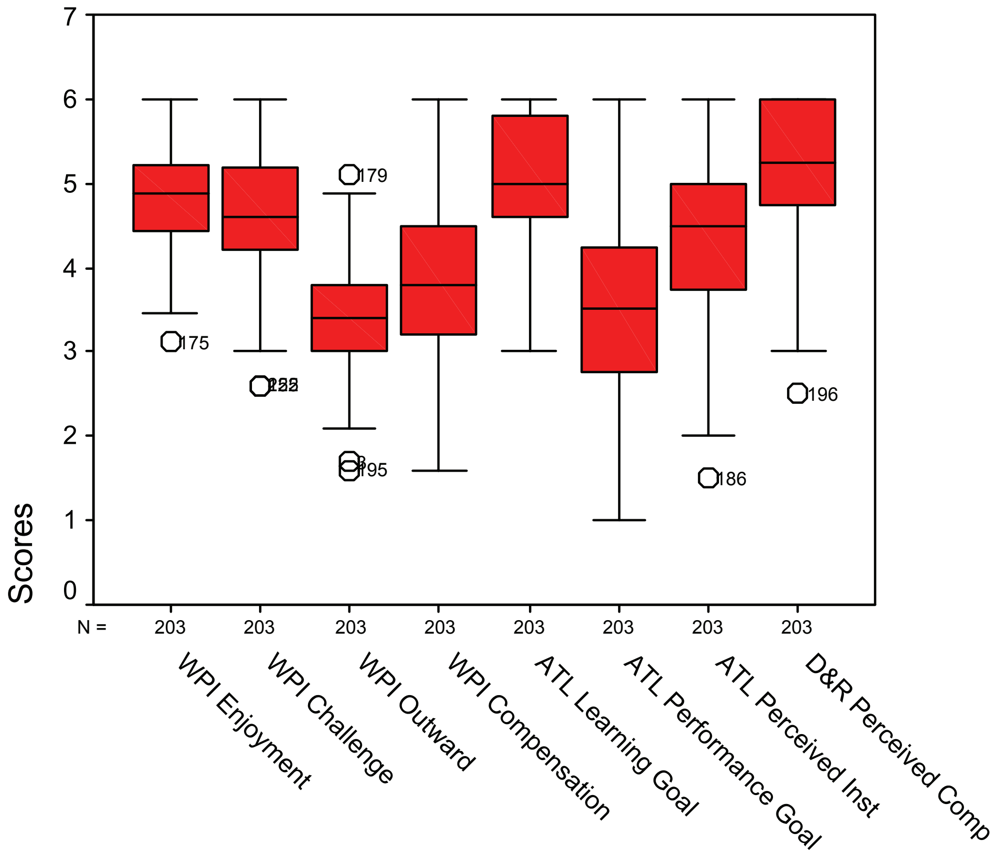
Table 5. Descriptive statistics for variables to be used in cluster analysis.

Variable[a]	M	Mdn	SD	Min	Max
Enjoyment	4.82	4.89	.54	3.11	6.00
Challenge	4.65	4.60	.69	2.60	6.00
Outward	3.43	3.40	.58	1.60	5.10
Compensation	3.83	3.80	.91	1.60	6.00
Learning Goals	5.05	5.00	.76	3.00	6.00
Performance Goals	3.44	3.50	1.12	1.00	6.00
Perceived Instrumentality	4.44	4.50	.94	1.50	6.00
Perceived Competence	5.23	5.25	.70	2.50	6.00

[a]n = 203 for each variable

A boxplot of the eight variables (Figure 5) reveals some cases that are statistical outliers on single subscales. The distributions of the variables are relatively normal, although perceived competence is negatively skewed, as is learning goals to a lesser degree.

Figure 5. Boxplot of variables to be used in cluster analysis.



Correlations

Intercorrelations between the eight clustering variables and the possible predictors of cluster membership are in Table 6. As expected, the intrinsic variables (enjoyment, challenge, and learning goals) were positively correlated with one another and with perceived competence. Perceived competence was also positively correlated with compensation, suggesting that those who feel confident about their skills may consider their compensation to be a reflection of their abilities. Learning goals and performance-approach goals were also positively correlated, which makes sense in a work environment where people who are mastery-oriented must still be concerned about others' perceptions of their competence. The extrinsic variables (outward, compensation, and performance-approach goals) were also positively correlated. Perceived instrumentality for the future was positively correlated with both intrinsic and extrinsic goals, so regardless of the source of achievement motivation participants related their present activities to their future goals.

Time in field, one of the possible predictors of cluster membership, was negatively correlated with outward, compensation, and perceived instrumentality for the future. Therefore, as time in field increased, the IT workers were less likely to care about what others think of them (perhaps because they have already made their reputations), what they get paid (they may be at the top of the pay scale) and the usefulness of new technical knowledge for their future (they may be near retirement). Self-rating of expertise naturally correlated positively with perceived competence—although not so highly as to be interchangeable, as self-rating of expertise measures current expertise while perceived competence applies to future technology learning—along with enjoyment, challenge, and performance-approach goals. This makes sense considering that some reported themselves as the source of their expertise rating; perhaps they consider how much they are enjoying their work (as opposed to being frustrated by it) or how well they meet the challenge of their work. Conversely, some participants relied on feedback from others in the workplace as the source of the expertise rating, an approach that would be consistent with performance-approach goals.

Table 6. Intercorrelations between clustering variables and possible predictors of cluster membership.

Variable	1	2	3	4	5	6	7	8	9	10
1. Time in field	—	.13	-.11	-.002	-.26**	-.17*	-.08	-.14	-.24**	-.05
2. Self-rating of expertise		—	.23**	.32**	-.08	-.01	.29**	.01	.12	.38**
3. Enjoyment			—	.56**	-.03	.10	.63**	.14*	.47**	.43**
4. Challenge				—	-.19**	.02	.56**	.02	.26**	.51**
5. Outward					—	.44**	-.06	.58**	.28**	-.01
6. Compensation						—	.06	.24**	.37**	.25**
7. Learning goals							—	.14*	.45**	.44**
8. Performance goals								—	.34**	.09
9. Perceived instrumentality									—	.29**
10. Perceived competence										—

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Hierarchical Cluster Analysis

Because cluster analysis is sensitive to cases with extreme scores, I planned to exclude cases with multiple extreme scores (standardized scores greater than ±2.5). This eliminated two cases, leaving $N = 201$ to be entered into the cluster analysis.

I conducted a Ward's method hierarchical cluster analysis using the squared Euclidean distance measure. The agglomeration coefficient table, used to determine the optimal number of clusters, begins when every case is its own cluster and ends when all cases are in a single cluster; in between are stages where the clusters are combined, totaling $N - 1$ number of stages. The table displays the number of the current stage, which clusters are combined in that stage, the agglomeration coefficient, the stage the combined clusters had first appeared, and the number of their next stage. I looked at the last ten stages in the table (shown in Table 7), when the number of clusters is in the single digits, to identify the point at which the agglomeration coefficient increases markedly.

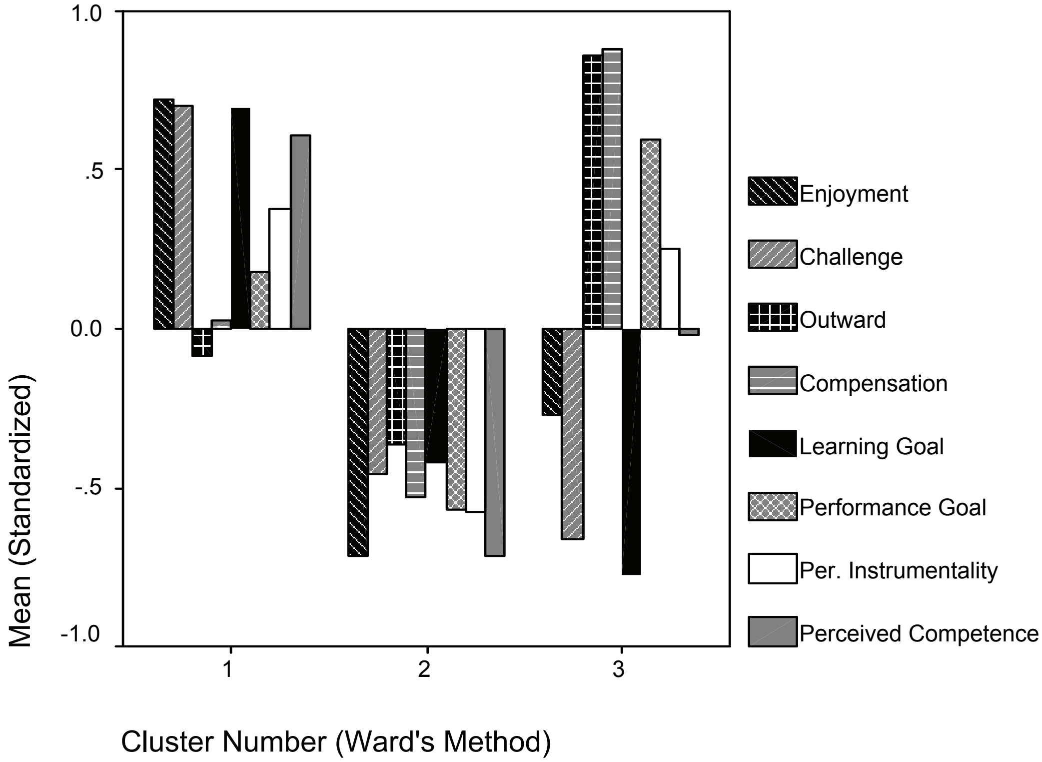
The agglomeration coefficient made its first comparatively large jump between stage 198 and stage 199, going from 1077.60 to 1250.45 for an increase of 172.85. Prior to that, the largest increase between stages was 83.97, between stages 197 and 198. Therefore I chose three as the optimal number of clusters, because at stage 198, before the large increase in the agglomeration coefficient, the cases were grouped into three clusters. At this point the number of clusters achieved a balance between parsimony in the number of clusters and relative homogeneity of cluster members.

Table 7. Last ten stages of Ward's method cluster analysis agglomeration table.

	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
Stage	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
191	2	42	719.828	153	170	194
192	17	30	747.611	184	162	198
193	3	11	779.012	187	189	196
194	1	2	821.313	188	191	197
195	5	13	870.176	185	190	199
196	3	8	921.146	193	183	198
197	1	22	993.630	194	178	200
198	3	17	1077.598	196	192	199
199	3	5	1250.448	198	195	200
200	1	3	1600.000	197	199	0

An examination of the standardized means of the three preliminary clusters formed by Ward's method shows them to differ in their goal profiles (see Figure 6). Cluster 1 (n = 92) had high means for the intrinsic variables and for perceived competence and a relatively high mean for perceived instrumentality. Its lowest means were for the extrinsic variables, although only outward is below the overall mean. The means for Cluster 2 (n = 69) were all below the overall means for the variables. People in Cluster 3 (n = 39) scored high on the extrinsic variables and somewhat high on perceived instrumentality. Their scores for the intrinsic variables were all below the overall means.

Figure 6. Characteristics of three clusters formed by Ward's method.



Non-hierarchical Cluster Analysis

I conducted a K-Means non-hierarchical cluster analysis, requesting three clusters because of the outcome of the Ward's method preliminary hierarchical analysis. The model converged quickly after only four iterations of adjusting the cluster centers. Table 8 displays the standardized and unstandardized means of the final cluster centers, along with the number of participants in each cluster.

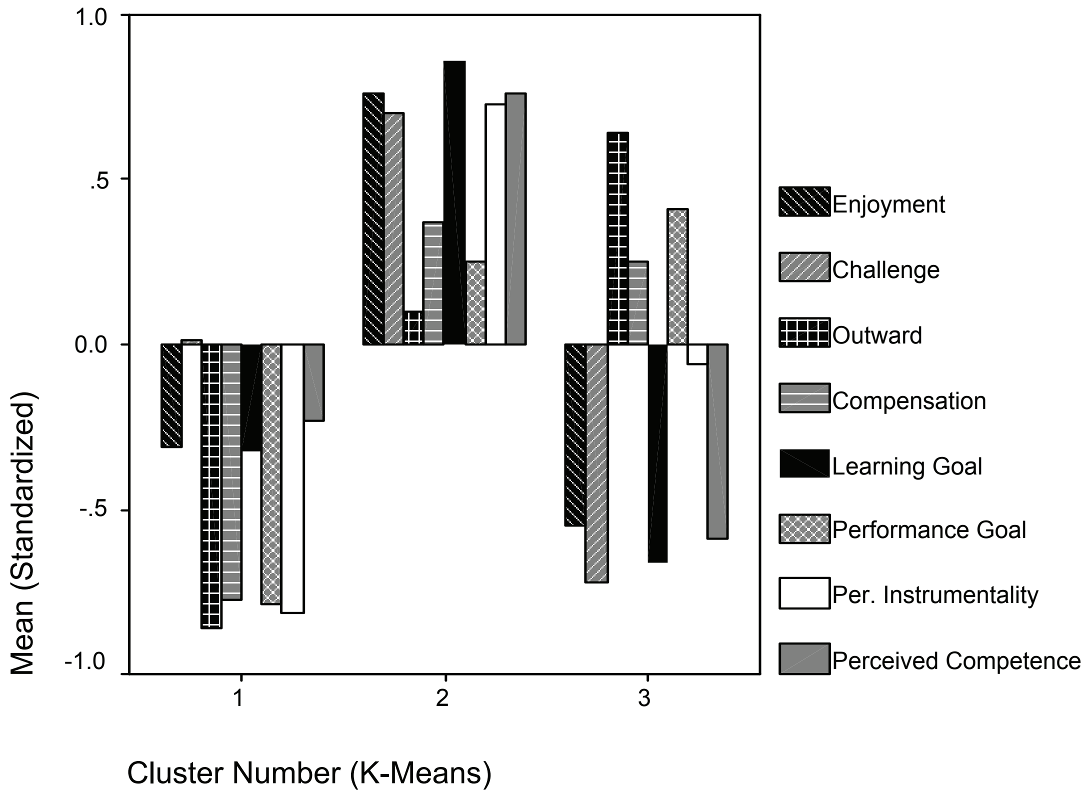
The K-Means analysis is intended to maximize the differences between the three requested clusters and determine optimum group membership. The bar chart (Figure 7) displays the differences between the resulting clusters. Cluster 1, the smallest group, was similar to Cluster 2 in the Ward's Method analysis in that its members had standardized means that were negative in almost all variables (the challenge mean was just above 0). I

Table 8. Standardized means (unstandardized means) of the final K-Means clusters.

Variable	Cluster number and *n*		
	1	2	3
	n = 58	*n* = 76	*n* = 67
Enjoyment	-.31 (4.65)	.76 (5.24)	-.55 (4.53)
Challenge	.02 (4.66)	.70 (5.13)	-.72 (4.16)
Outward	-.86 (2.93)	.10 (3.49)	.64 (3.81)
Compensation	-.77 (3.13)	.37 (4.17)	.25 (4.07)
Learning Goals	-.32 (4.81)	.86 (5.71)	-.66 (4.55)
Performance Goals	-.79 (2.55)	.25 (3.72)	.41 (3.90)
Perceived Instrumentality	-.82 (3.67)	.73 (5.13)	-.06 (4.38)
Perceived Competence	-.23 (5.07)	.76 (5.77)	-.59 (4.82)

labeled this group Low Overall. Cluster 2, the largest group, was like the earlier Cluster 1 in scoring high on the intrinsic variables of enjoyment, challenge, and learning goals. Like the earlier cluster this group also had high scores on perceived competence and perceived instrumentality; here these means were higher than in the Ward's method analysis. Another difference was that Cluster 2 had higher means for extrinsic variables as well, particularly compensation. Although the standardized means of all the variables were positive in this group, I labeled it High Intrinsic because those variables had the highest means. The present Cluster 3 was like Cluster 3 in the Ward's method analysis in that its standardized means were highest for extrinsic variables such as outward, compensation, and performance-approach goals. However in the present analysis this

Figure 7. Characteristics of clusters formed by K-Means cluster analysis.



group had comparatively low means on all intrinsic variables and on perceived instrumentality, and a comparatively low mean on perceived competence as well. I labeled this group High Extrinsic.

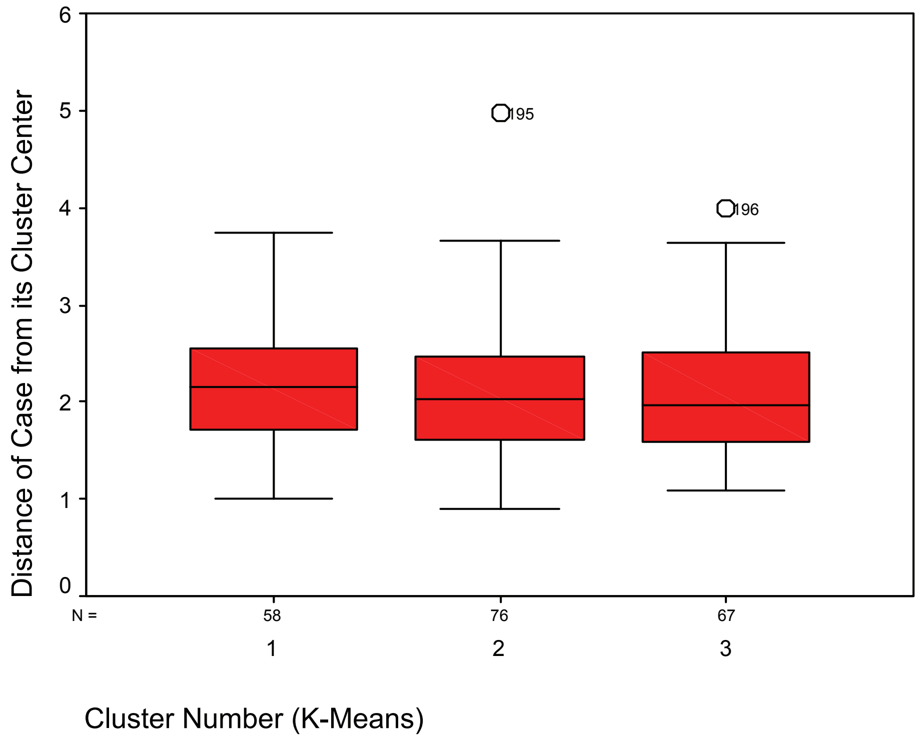
The ANOVA table (Table 9) describes how much each included variable contributed to the cluster solution. Because significance levels do not reflect the fact that the clusters were chosen to maximize between-group difference, they cannot be used to test the hypothesis that the clusters do not differ. However, the magnitude of the F statistic describes the strength of the variable's contribution to the cluster solution. In this case, learning goals contributed the most ($F(2,198) = 84.73$) and compensation ($F(2,198) = 32.17$) and performance goals ($F(2,198) = 34.57$) the least.

Table 9. ANOVA table of clustered variables.

Variable	Cluster		Error		*F*	Sig.
	Mean Square	*df*	Mean Square	*df*		
Enjoyment	35.065	2	.636	198	55.16	<.001
Challenge	35.929	2	.567	198	63.41	<.001
Outward	35.575	2	.659	198	53.99	<.001
Compensation	24.762	2	.770	198	32.17	<.001
Learning Goals	45.820	2	.541	198	84.73	<.001
Performance Goals	26.100	2	.755	198	34.57	<.001
Perceived Instrumentality	39.540	2	.578	198	68.36	<.001
Perceived Competence	35.067	2	.599	198	58.54	<.001

Examining the distance of classified cases from their cluster centers with a boxplot illustrates the amount of within-group variability and identifies outliers within clusters. In this analysis (Figure 8), clusters were shown to have a moderate amount of variability in relatively normal distributions, and an almost identical pattern of variability across clusters. Cases 195 and 196 were both identified as outliers. While Case 195 had high scores on intrinsic variables, typical of the High Intrinsic cluster, he also had very low negative standardized scores on extrinsic variables, which probably led to identification as a statistical outlier. Case 196 was classified into the High Extrinsic group, but he had negative standardized means on both the extrinsic and intrinsic variables. However, he recorded a very low standard score of -3.88 on perceived competence; this may have led to his placement within the cluster with the lowest perceived competence score.

Figure 8. Euclidean distances of cases from their cluster centers.



Discriminant Analysis

To determine what other variables might predict cluster membership, I conducted a descriptive discriminant analysis using time in field and self-rating of expertise as predictor variables. The means and standard deviations on these variables by group are shown in Table 10.

Table 10. Descriptives for predictor variables by group.

Group	Listwise	Mean		Standard deviation	
	n	Time in field	Self-rating	Time in field	Self-rating
Low Overall	58	17.35	7.31	6.65	1.60
High Intrinsic	75	14.26	7.72	7.23	1.21
High Extrinsic	67	14.91	6.42	8.26	1.69

Regarding the assumptions of discriminant analysis, there was evidence of non-normality. The Kolmogorov-Smirnov test was significant ($p < .001$), possibly as a result of the negative skew of the self-rating variable. Box's test of equality of covariance matrices was also significant ($p < .05$), although this may have been partly due to the non-normality. However, discriminant analysis is robust to these violations, especially since the group *n*'s are roughly equal.

In the discriminant analysis the overall Wilks' lambda was significant, $\Lambda = .86$, $\chi^2(4, N = 200) = 29.21$, $p < .001$, indicating that there were differences between clusters across the two predictor variables. The residual Wilks' lambda was also significant, $\Lambda = .97$, $\chi^2(1, N = 200) = 5.85$, $p < .05$, indicating that the predictors differentiated between the clusters after removing the effects of the first discriminant function. Therefore I interpreted both functions.

The within-groups correlations between the predictors and the discriminant functions and the standardized weights are in Table 11. The self-rating of expertise

Table 11. Coefficients and correlations of predictors with functions.

Predictors	Correlation coefficients with discriminant functions		Standardized coefficients for discriminant functions	
	Function 1	Function 2	Function 1	Function 2
Time in field	-.07	1.00	-.21	.99
Self-rating	.98	.21	1.01	.07

variable had the stronger relationship with the first function, and time in field had the stronger relationship with the second function, so I labeled the functions after their predominant variables. The High Intrinsic cluster had the highest standardized mean on the self-rating of expertise function ($M = .38$), the Low Overall cluster the next lowest mean ($M = .03$), and the High Extrinsic cluster the lowest mean ($M = -.46$). On the time in field function, the Low Overall cluster had the highest mean ($M = .27$), while High Extrinsic ($M = -.10$) and High Intrinsic ($M = -.12$) had lower means.

Despite the fact that there were two significant discriminant functions, less than half (46.5%) of the cases were correctly classified by the predictors. In order to assess how well the classification procedure would predict group membership in a new sample, I estimated the percentage of participants that would be correctly classified using the leave-one-out technique; this estimate was 45.5%.

Other Demographic Characteristics of the Clusters

Information about the other continuous demographic variables is presented in Table 12. The mean age for the Low Overall group is slightly higher than that for the other two groups, and people in the Low Overall group have been in their jobs, on average, almost two years longer. However, there is a relatively high amount of variability in "time in current job" for each group, indicating a wide range in job tenure.

Table 12. Age and time in current job by cluster.

Variable	Cluster and listwise *n*					
	Low Overall		High Intrinsic		High Extrinsic	
	$n = 57$		$n = 72$		$n = 67$	
	M	*SD*	*M*	*SD*	*M*	*SD*
Age	44.39	8.91	40.33	10.26	41.25	9.46
Time in current job	6.36	6.15	4.82	4.58	4.98	5.51

In order to examine differences between the clusters on the categorical demographic variables, I created a series of bar graphs. Not seeing any obvious differences on the bar graphs, I conducted two-way contingency table analyses to see if cluster membership was associated with differences on the categorical descriptive variables. The analyses were all nonsignificant with the exception of major in academic level reached ($\chi^2(16, N = 177) = 28.70, p < .05$) and major in academic level completed ($\chi^2(16, N = 167) = 29.24, p < .05$). It would have made sense if source of self-report of expertise had been associated with cluster membership (e.g., if High Extrinsic people, who scored higher in Outward, had indicated that feedback from others was the source of their expertise judgment), but it was not. I conducted follow-up pairwise comparisons to find the location of the differences I did find, but after applying the Holm's sequential Bonferroni method to control for Type I error at the .05 level across all three comparisons, none were significant. Aside from this, the only way the groups did differ was in the two variables entered into the discriminant analysis, and of course in the motivation variables that were used in the cluster analysis.

Chapter Four: Discussion

This study connects motivation theory to expertise theory by describing more precisely what types of goals are held by developing experts in IT when they learn new technology for their jobs. By doing so, this research elaborates on the motivation element of the theoretical model "Factors Encouraging Expertise Development." It also provides support for previous research on multiple goals, particularly regarding the types of goals that people are likely to hold simultaneously. The results provide two main areas of interpretation: the meaning of the relative characteristics of and differences between the clusters, expressed in the standardized cluster means; and the meaning of the magnitude of the scale scores, expressed in the unstandardized cluster means, for the theoretical model.

Characteristics of the Cluster Groups

Judging by the cluster solution, the developing IT experts did exhibit patterns of multiple goals. The agglomeration coefficients in the preliminary Ward's method cluster analysis did not indicate a cluster solution of more than three clusters, and those clusters either had several goals with relatively high means, or like the Low Overall group, none. Therefore, in this study there was no evidence that the participants were in single-goal clusters.

The three groups formed by the cluster analysis had clearly delineated patterns of goals. The High Intrinsic cluster had scores above their respective means on all variables, not just intrinsic ones, although the intrinsic ones were certainly highest. They scored higher on compensation than on other types of extrinsic motivators, as Amabile (1994) had previously found with computer programmers. This group also scored high on perceived instrumentality for future goals, so they saw their technology learning as instrumental to achieving the future they wanted. In addition, they were the most confident about their competence.

The High Extrinsic cluster had relatively high means only on extrinsic variables; enjoyment, challenge, and mastery were less important in motivating their technology learning. The fact that the High Extrinsic group also had relatively low perceived competence suggests that they are in a workplace situation in which they are more likely than the others to want their technology learning to have tangible rewards and to garner recognition from colleagues, while at the same time they are not as confident as others about their ability to meet the demands of the job. Their motivations and their feelings about their jobs, then, seem somewhat incompatible. The High Extrinsic group did not differ from the High Intrinsic group in terms of length of time in the field, so it is not likely that they are new to IT and still adjusting to its demands. However, judging by the standardized mean for perceived instrumentality for future goals, which was just under the overall mean and much higher than that for the Low Overall group, they do not necessarily plan to leave IT either. Perhaps some upheaval in the workplace has cast them into temporary doubt about their competence or undermined their intrinsic valuing of their work—at least in comparison to the people in the other two groups. It is also possible that the High Extrinsic people may have been participating in the online user groups in order simply to stay afloat on the job, and they are facing difficult challenges. On the other hand, their co-workers may not agree with their relatively low self-assessments; maybe they are being too hard on themselves and underestimating their skills. As I will discuss in the next section, while the High Extrinsic group scored lower on intrinsic valuing and perceived competence than did other groups, their scores are still not very low.

The Low Overall group presents a challenge to interpretation. While their means for all clustering variables were below the overall mean (except for challenge, which was just slightly above), their scores on outward, compensation, and performance goals were lower than those for more intrinsic variables. Therefore, intrinsic goals may be more salient to them then extrinsic ones, but they still score lower on them than the High Intrinsic group does. Their perceived instrumentality for future goals was relatively low as well, which could mean either that they do not find their current technology learning important to their future goals, or that they have been in the field long enough that they have achieved (as far as IT is concerned) what they had set out to achieve. Their perceived competence was below the overall mean, but higher than that for the High Extrinsic group. Are they burned out, or were their current goals not included in the study?

The results of the discriminant analysis begin to address this question, but leave much unanswered. As predicted, the longer participants had been in the field, the more likely they were to be in the Low Overall group. After their years of experience they may care less about the opinions of others and be less focused on their compensation. Although they still find learning new technology to be challenging to some extent, their enjoyment and mastery orientation are diminished in comparison to others. However, there is not enough information to determine whether this is the result of burnout, which is a risk in IT occupations (Hilton, 2001), or a result of a shift in goal orientation. At this point in their careers the Low Overall group might be more focused on managerial duties or on mentoring others in their workplace (there was no significant relationship between cluster membership and job title category, but job titles are not always indicative of one's responsibilities). If they had really lost interest in IT, they would probably not spend their time participating in online user groups. Their participation in the groups may be part of an effort to help the next generation develop expertise, rather than to continue focusing on their own achievement and technology learning.

Self-rating of expertise was also a significant predictor of cluster membership, and it followed the same pattern as perceived competence: the High Intrinsic group had the highest mean, followed by the Low Overall group and the High Extrinsic group. Even though self-rating of expertise concerns one's expertise as compared to others in the workplace, and perceived competence taps confidence in the ability to learn new skills, they both played out the same way in determining group placement.

The combination of the two predictors placed participants in groups with less then 50% accuracy. However, this is not surprising, because while the time in field variable was important in predicting the Low Overall group, there is no theoretical reason that it would distinguish between the High Intrinsic and High Extrinsic groups. These are more likely the result of relatively stable motivational orientations (Amabile et al., 1994), while Low Overall may be more influenced by external conditions such as career phase.

After conducting the qualitative pilot study, I had envisioned the motivation component of "Factors Encouraging Expertise Development" to most resemble the High Intrinsic group—confident about ability to learn new technology, interested in the applicability of current learning to future goals, high in learning goals, challenge, and enjoyment, while still somewhat influenced by extrinsic motivators such as performance goals and compensation. The High Intrinsic group is like that, but that is not the only way that motivation appeared in the developing IT experts. The High Extrinsic group persists in the IT field despite relative insecurity about ability and lower intrinsic motivation, while the Low Overall group may have other priorities than developing their own skills. This more diverse view of the motivations of experts adds nuance to how motivation works in "Factors Encouraging Expertise Development." While it would be tempting to conclude that the High Intrinsic group best represents developing experts and that the High Extrinsic and Low Overall groups have basically fallen off the path to expertise, this study provides no reason to think that this is the case, especially when considering the scale scores displayed in the unstandardized group means (Table 8, p. 57).

Scale Scores and Implications for the Theoretical Model

The High Extrinsic group may have scored lower than others on the intrinsic variables, but their scores were not low *per se*; the unstandardized means for enjoyment, challenge, and learning goals were all between 4 and 5, and the same was true for the Low Overall group. The High Extrinsic group scored higher on intrinsic variables than they did on extrinsic variables. It is only the fact that their scores on extrinsic were relatively high, and their scores on intrinsic relatively low, which put them in the High Extrinsic group. In the overall sample (Table 5, p. 50) the means of extrinsic scores (3.43-3.83) were lower than those of the intrinsic scores (4.65-5.05), so in general it was true that the IT experts were motivated more by intrinsic than extrinsic motives, as predicted. However, some were more extrinsic than others.

Likewise, although I was surprised at the presence of some low perceived competence scores (as low as 2.5 out of 6) and by the presence of some low scores on self-rating of expertise, as I expected most participants thought fairly highly of their expertise. Although there were differences between groups, those that scored lower than others were not absolutely low: for example, the perceived competence mean for the High Extrinsic group was 4.82 out of a maximum of 6, and their self-rating of expertise scores were only 1.3 points (out of 10) lower than those of the High Intrinsic group. The Low Overall group still averaged 5.07 out of 6 on perceived competence, and scored only .41 points below the High Intrinsic group on self-rating of expertise.

I had predicted that the developing experts were likely to hold both learning and performance-approach goals. This was essentially true for all groups, although those who were higher in performance-approach (the High Extrinsic group) were lower in learning goals than the other groups. As with other extrinsic goals, however, performance-approach scores for all groups were lower than learning goals and other intrinsic motivators.

Looking at the unstandardized means for the overall sample and for the three clusters it is possible to say that developing experts are motivated more intrinsically than extrinsically, that they have high perceived competence for learning new technology, and that they expect that their current technology learning will be instrumental to their future goals. This supports the conception of motivation in developing experts that I had expected to see. The cluster analysis, however, revealed that despite the fulfillment of these predictions, there are relative differences in the form that motivation takes in developing experts—differences that might have implications for expertise development over time.

The High Extrinsic (and Low Overall) participants are actively participating in the online user groups, so they are continuing to develop their expertise. They are doing it with less confidence than their High Intrinsic peers, but their unstandardized means reveal that they are nevertheless quite confident. Their relatively negative outlook may be an interaction of stable personality factors with situational uncertainly due to the frequent workplace disruptions that are characteristic of many IT jobs, as companies fail, merge, or are acquired. This kind of uneasiness may be dampening their intrinsic motivation, because concerns about job stability would prod employees to focus more on their compensation and the opinions of them held by others. Regardless of the cause, however, the relative dependence on extrinsic motivators and less powerful presence of intrinsic motivators would seem to make their progress in expertise more difficult, less enjoyable, and less sustainable for this group, even though they may persist on the path. They would have more difficulty than others entering into the flow state and engaging in effective deliberate practice because of their relatively lower task focus and higher outward focus; flow requires absorption into the task to the point where self-consciousness is suppressed, and deliberate practice requires effortful engagement at the edge of ability, both of which would be better supported over time by the High Intrinsic group. Therefore the High Intrinsic group would tend to experience more and faster growth in expertise. I would expect that the older Low Overall group would have an even flatter expertise trajectory than the High Extrinsic group, although for them developing personal expertise may be becoming less important than managing or mentoring others.

The motivational differences highlighted in the cluster analysis do not negate the predictions about the motivation element itself, but rather suggest different trajectories of the experts' path toward continually developing expertise. Those with relatively less intrinsic motivation or perceived competence may experience slower growth, less intensity, less happiness, and perhaps a lower level of expert performance during expertise development, as compared to those with relatively more intrinsic motivation. These different trajectories, then, are contributors to individual differences in the development of expertise. This rather subtle distinction would not have been observable without the cluster analysis of standardized scores.

Future Directions for Research

The first step for future research is to see whether the pattern of overall means and goal clusters observed here can be replicated with other groups of IT workers, and also with other samples of working adults who are developing experts in other domains.

This study raises questions about the nature of the Low Overall group. In order to find out more about why they scored the way they did on the motivation variables, it would be useful to explore issues such as level of burnout and interest in mentoring. Perhaps this group would divide into two if those variables were known.

For the High Extrinsic group, it would be interesting to probe why their intrinsic scores were relatively low and extrinsic scores relatively high, perhaps through a qualitative study that would allow them to express that in their own words. Comparing their perceived competence and self-rating of expertise scores with evaluations from their managers and co-workers would help determine whether they are rating themselves lower than they should, and interviewing them could investigate why. Also, given their lower levels of confidence, further research should measure performance-avoidance goals as well as performance-approach goals to see whether trying to avoid appearing incompetent motivates, in part, their technology learning. Research should also address their perceptions of their workplace environment to see if they differ in feelings about job security, for example.

Longitudinal studies might explore whether these motivational profiles tend to be stable over time (as Amabile et al. (1994) found with workers' motivational orientations). Because of the possibility that different motivational profiles lead to different expertise trajectories, longitudinal studies could be used to determine whether the High Extrinsic and Low Overall groups do indeed experience deliberate practice and/or flow differently than the High Extrinsic group does, and therefore slow down or stall on the continuing path to expertise.

Just as experts and novices within a domain have been compared in their problem-solving techniques, they should be compared in their motivational profiles. In this study there were not enough less-experienced workers to compare with the group that had over five years' of experience, but the way motivation changes as expertise increases is an issue worthy of study. The question of whether there is a difference between motivational profiles of experts in different domains is interesting as well, because it is an indication of the effect of the domain on the experts. Until these comparisons are made researchers cannot know how much of the nature of these profiles can be accounted for by the unique characteristics of work in IT.

Previous work in motivation has addressed the interaction between students' own goals and their classroom situation (Maehr, 1984). In this study, there were differences in participants' goals when learning new technology for their jobs, goals that would interact with their workplace environment. Future research should address people's motivations for expertise development on the job and how this is encouraged or discouraged by their perceptions of the values and rewards in their workplace.

Past expertise research had merely pointed out the necessity of motivation for those who would develop expertise, and then moved on to other aspects of expert development. In contrast, this study focused on the motivation issue and asked: what kind? The results were that developing IT experts are motivated more by intrinsic than extrinsic goals but yet they grouped into clusters whose technology learning motivation, as compared to others, was relatively intrinsic, relatively extrinsic, or relatively low overall. This indicates that there subtle differences in the way they are motivated toward expertise. The theoretical model helps predict how these motivational differences can lead to differences in the trajectories of expert development.

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Appendix A: Qualitative Pilot Study

Rationale for a Qualitative Study

Pursuing a new, complex model such as "Factors Encouraging Expertise Development" with quantitative methods first may be presuming too much about the experiences of experts. Therefore, I conducted an initial qualitative study of a group of experts in order to have a better understanding of if and how the hypothesized elements in the model exist in people developing expertise.

Although the nature and development of expertise in general have been widely studied, little work has been done on the motivational characteristics of developing experts, or on those who teach themselves to the level of expertise. Since there remains much to be learned about those who self-teach, a qualitative approach allowed for a full exploration of the phenomenon by allowing those who do it to explain and describe it as they experience it. A qualitative study can help identify categories and themes that will allow for further, more narrowly-focused quantitative work.

Purpose

For this purpose, any group of experts would arguably have been appropriate. At least in initial studies, however, the domain of expertise should be the same or similar for all members of the subject group, because the characteristics of the domain itself may influence the nature of its experts so much that the results of qualitative studies with experts from multiple domains may be difficult to interpret. I chose self-taught information technology (IT) experts for this study. Information technology is a complex and varied field that is constantly changing. Experts in this field must acquire and continuously update a large amount of domain knowledge, such as network structures and programming languages, and be able to use it effectively. Although the field is demanding and often stressful, information technology products and people are present throughout the economy (Hilton, 2001), so this domain of expertise is less exclusive than that of the elite athletes and musicians studied by other expertise researchers.

Unlike many other professions, the field of information technology is made up of people who come from a variety of educational backgrounds. Employers are more interested in the hands-on experience and technical knowledge of potential hires than in their degrees. One-third of IT workers have only a high school diploma or two-year degree, and of the two-thirds that have at least a bachelor's degree, less than half have a major or minor in a computer-related field (Hilton, 2001). Therefore, most IT workers have come by their knowledge from informal learning or self-teaching, similar to the chess players studied by Charness, Krampe, and Mayr (1996). Achieving expertise is effortful in all domains, but self-taught IT workers seem to have accomplished it with less formal support (teachers, coaches, degree programs) than have experts in areas where the path to success is less self-determined. Therefore self-taught IT experts might be exemplary in their ability to forge their own path to expertise, and their techniques illuminating to others who are attempting to do so, or to figure out how expertise development happens.

The purpose of this initial qualitative study was to explore the self-teaching strategies and behaviors of developing IT experts, and to see whether there was support in the data for the factors included in the expertise development model. The central questions of the study were:

1. What are the characteristics of self-taught IT workers?

2. How do those who become experts on their own find and utilize appropriate resources to support their development?
3. How do they measure their progress?
4. What sustains their motivation?

Since many other workers today must learn and adapt to new technology quickly, often without formal training, the strategies of self-taught IT experts could help others learn technology easier and more thoroughly.

Methods

A phenomenological approach describes the meaning of the experiences of a group of individuals who have undergone the same phenomenon. Its roots are in the philosophy of Husserl, Heidegger, Sartre, and Merleau-Ponty. Phenomenological study involves the search for the essence of the meaning of an experienced phenomenon. Data analysis in phenomenology aims to reduce the information into a set of themes (Creswell, 1998). Those who are participants in a phenomenological study must have experienced the phenomenon to be in the study group. Researchers allow the participants to explain their experience of the phenomenon from their own perspectives and in their own voices.

Participants and Sampling

Because a phenomenological approach requires participants to have experienced the phenomenon of interest, criterion sampling was used. In this study, the criterion was met if participants answered "yes" to both of the following questions: "Are you currently working in the information technology/computer science field? Is the knowledge of information technology that you are using in your work derived mainly from self-study (as opposed to formal university coursework or training classes)?"

However, another qualification was that the workers had to be well along the path to expertise. Testing the IT knowledge of the interviewees with some sort of task was impractical, not only because it would have been overly demanding of the time of the subjects but also because the IT workers can come from various subfields which may not share all of the same content (although according to Hilton (2001) they do share roughly the same percentage of informal learners). The best-performing IT workers, however, build communications with other IT colleagues and spend a lot of time gathering and sharing information (Hilton, 2001). IT work also has results that are easily observable by others—whether the application works, whether the database is useful, whether or not the servers run well—so workers' level of performance is not easily hidden, especially from other IT professionals. Through these methods IT workers can come to know the skill levels of others. Therefore a snowball sampling technique, in which knowledgeable people recommend other cases who in turn recommend other cases, and so on (Gall, Gall, & Borg, 2003), was appropriate in conjunction with the qualifying questions. The initial cases were experienced IT managers known to the researcher. Six people were interviewed for this study.

Data Collection and Instruments

Data collection included audiotaping interviews conducted with questions (see Table A1) derived from the elements of the model "Factors Encouraging Expertise Development." An initial interview was conducted with each participant, and followed up and verified as needed while data analysis continued. To ensure confidentiality, each participant chose a code name; in the results all participants are indicated by their code names. Other forms of qualitative data collection, such as observation, were less helpful in this specific study. When a learner sits at the computer, perhaps with a manual or some other study material, there is little in the way of conversation or interaction to observe. In future studies, however, conversations between IT workers, chat logs, or discussion board postings could be useful.

Table A1. Interview Questions in the Qualitative Study of IT Experts

Qualifying questions to determine participant eligibility
Are you currently working in the information technology / computer science field? If so, is the knowledge of information technology that you are using in your work derived mainly from self-study (as opposed to formal university coursework or a training program)?
If response is yes, ask the participant for a CODE NAME for use during the interview.
Guiding Questions for the Interview
Tell me about whether you feel you have a natural inclination or ability to work with computers and technology.
How long have you been working with computers and technology? How and when did you begin?
Describe your work: • Duties • Length of service • Feelings about job
Tell me about any work you do with computers in your spare time.
Think of a skill that you are currently using and that you had learned on your own. Focus on the experience of learning and developing this skill.

Please describe:

- The skill you learned
- How long ago you learned it
- How you are using it in your work

How would you describe your level of expertise in this skill?

How did you come to be aware of the need for this skill?

How long did you think it would take you to learn this skill and become proficient at it?

What information did you use to decide?

How difficult did you think it would be for you to learn this skill and become proficient at it?

What information did you use to decide?

Tell me about any prior knowledge you had that you knew would be useful in learning this new skill.

How did you choose resources and materials to learn this skill?

What activities helped you to learn this skill?

When you ran into a problem, what did you do?

At the time did you know other people who had mastered this skill?

Tell me about your communication with others while learning this skill.

- Without using names, who were they?
- How did you find them?
- How did you communicate with them?

Tell me about whether your communication with others was helpful to you in learning the skill.

Describe any memories, while learning this skill, of:

- Wanting to learn in order to master it?
- Wanting to learn it in order to demonstrate your expertise to others?
- While learning and practicing the new skill:

Describe how focused on the activity you were.

- What was your perception of the passage of time?
- What are your recollections of being distracted, or of being able to block out distractions?

What do you think motivated you to continue learning the skill?

While putting the skill to use, how did you measure your progress?

What were some of your short-term goals in learning the skill?

What were your long-term goals in learning the skill?

How did you decide on these goals?

Immediately after reaching a competent level with the skill, how did you feel?

Describe how accurate were your predictions about the time and difficulty of learning this skill.

In general, do you prefer teaching yourself new information technology skills or learning them in a class or from a teacher? Why?

Data Analysis

The modification of the Stevick-Colaizzi-Keen method for analyzing qualitative data in the phenomenological tradition, as described in Creswell (1998), was the model I used for handling the qualitative data. Beginning with transcripts from audiotaped interviews with the subjects, I listed out significant statements (sentences, clauses, or phrases) about how individuals experienced the phenomenon, giving them equal worth. Using statements instead of codes allowed for longer units of meaning, since some of the participants' thoughts could be adequately summed up in a word or two. I eliminated statements that were not relevant to the topic of interest, and removed or combined statements that overlapped with other statements. I grouped the statements into categories of meaning, and displayed them in tables. Finally I constructed a blended description of the overall meaning of people's experiences in each category, and then took the information back to the participants for verification.

Results

The following tables list some significant statements from interviewees on the categories that emerged from the data. Each category is labeled with its title and followed, in parentheses, by the element of the expertise model to which the category relates, or the topic of the research question (RQ) addressed. Each table is followed by a brief composite description.

Table A2. Curious about Technology Early On (Talent/Ability, RQ 1: Characteristics)

Subject code name	Statement
Bigglesworth	"Ever since I was a kid I pulled knobs off of things, pulled things apart."
	"I got curious about the operating system and I broke our brand-new computer."
Skippy	"When I was in 5^{th} or 6^{th} grade in elementary school...that was my first system administration gig."

	"They shipped them with books, and I read them and played around....Reading the manuals, and error and error."
Bub	"I always enjoyed building things, putting things together and seeing how they worked."
Robotech	"I started taking programming classes when I was in the eighth grade. I just kind of steered towards it. It was just a natural fit." "I've always been real gadgety, taking stereos apart, things like that."

The subjects reported (Table A2) being interested in taking things apart to see how they worked. They often began using computers in elementary school. Instead of merely running programs on them or playing with them, they examined their inner system structures, sometimes with unexpected results, and started programming them.

Table A3. Current Duties (RQ 1: Characteristics)

Subject code name	Statement
Bigglesworth	"I am an IT Analyst. My primary duties—I am lead programmer, so I am also assisting the other coders in my department, helping with direction and everything like that. My primary task is just to develop applications."
Skippy	"I'm the alpha geek."
	"I keep the machines running right, I write a bit of code here and there. I think my main responsibility is as the fallback guy in the office."
Bub	"It's largely user support. There's also network maintenance and some [database] design."
Robotech	"We do all the technical manuals....We've got our network servers, work stations, about 25 users...Right now I'm developing three training courses...I'm a system administrator."
Elroy	"Mostly administrivia, much to my chagrin."
	"Every chance I get…I'm either doing systems work, which is my home, or I tend to try to work on database and web applications of one kind of another."
Trogdor	"Systems administration...secondly, programming, because that's really what I enjoy most of all."

The IT workers (Table A3) came from different areas of the field, and had multiple duties. The current responsibilities of the IT workers include programming and systems administration, user support and training, database design, administration, and serving as a resource to less experienced workers.

Table A4. Reluctance to Ask Questions (Culture, RQ 1: Characteristics)

Subject code name	Statement
Bigglesworth	"I've worked on the same problem for about two weeks before I'd finally given up and asked."
	"If someone tells me something it kind of goes in one ear and out the other a lot of times."
	"I feel like in order for me to learn, I have to actually sit down and go through the process for me to be getting it."
Skippy	"The harder the question, the less likely it is that somebody else will know the answer off the top of their head."
	"You'd better be damn sure it's a good question."
	"It's about the worst thing you can do in the world, to waste a geek's time."
Robotech	"It's easier to go ask somebody and have them show you than it is to spend hours looking the answer up."
	"I only want to ask them if it's absolutely necessary. If I'm going to do something that I know will cause problems if I do it wrong, I might ask first."

While learning (Table A4), some of the IT workers tried to figure things out for themselves using sources such as books and the Internet, rather than asking someone a question. Even when the answer was not found quickly, they continued to search on their own—up to two weeks for Bigglesworth. The reasons for this reluctance to ask questions include the perception that the question is too difficult for someone else to answer easily, the desire not to waste another's time, the belief that getting answers from others diminishes one's own learning, and the satisfaction resulting from figuring it out oneself. Robotech was more willing to ask questions, but only when the task was important and the time savings were significant.

Table A5. Making Connections to Prior Knowledge (Metacognition, Domain Knowledge, RQ 1: Characteristics)

Subject code name	Statement
Bigglesworth	"If you've learned one language sometimes it translates into another. I was able to translate some of the knowledge I had previously in C to Perl."
Skippy	"It's as much of a shift between the old version and the new version as between Windows NT and 2000."
Bub	"The basics are always there, it's just new applications for them."
Robotech	"If it's a Windows-based product or an Apple product, I can pick it up within a couple of months."

The interviewees described (Table A5) how they used prior knowledge to help with the new learning task. In Skippy's case, he had experience shifting from one server version to another, and had used some of the components of the current system, such as Active Directory. Bigglesworth, who was learning a new programming language, found connections between it and a language he had previously mastered. Bub based his approach to computer security on the basics of how computers work, and Robotech used his knowledge of operating systems to understand new applications.

Table A6. Finding Resources with Help from Others (Culture, RQ 2: Finding Resources)

Subject code name	Statement
Bigglesworth	"[The book] was by recommendation, a lot of my friends that I know who are in IT."
Skippy	"Geeks talk about books a lot."
Bub	"There are a number of web sites that I check on a regular basis....We also have a mailing list here...of IT people, called Tech Support."
Robotech	"The course that they sent me to was helpful."
Elroy	"If I had seen someone swear by a book I would just order it or buy it."
Trogdor	"After Amazon.com, I'd say wait, let me check that book out. And everybody trashed that book. Aha! OK, it wasn't me, it was the book."

The interviewees (Table A6) got information from a variety of sources about which resources to use when learning new technology. When the technology is new, only the manufacturer's documentation is available. However, when there are multiple sources, information can be obtained from fellow "geeks," either in person, through the World Wide Web, through mailing lists, through e-mail, or on Usenet. Both interviewees mentioned books as an important source, and that other IT people make recommendations about good books. Trogdor followed the reviews on Amazon.com, while Robotech said that they vary too much to be useful.

Table A7. Learning Activities (Deliberate Practice, RQ 2: Using Resources)

Subject code name	Statement
Bigglesworth	"I came up with problems for myself."
Skippy	"The first thing I did was read the documentation front to back at a sitting."
	"You think of a configuration, 'Can I get it to do this?'"
Bub	"I will experiment with ideas at home on my smaller systems that might be translatable to the larger systems here."
Robotech	"Usually I sat there and hacked away at it."
Elroy	"Many, many, many nights of just staying in the server room until it got resolved in some way."
Trogdor	"Assembly language is the hardest language, except for maybe direct machine code...so if I could write in assembly language, then I was a real programmer."

When setting out to learn new software or a new language (Table A7), reading the documentation was an important first step. Then the learners moved to the keyboard to apply the knowledge, using problems or scenarios they made up that either teach general principals or resemble situations in the workplace. When difficulties are encountered, they often stay working on the problem for a long period of time until it is resolved, sometimes referring to documentation or the Internet for advice.

Table A8. Measuring Progress (Metacognition, RQ 3: Measuring Progress)

Subject code name	Statement
Bigglesworth	"I usually go back and look at what I've done before."
Skippy	"While learning, keep checking, 'OK, now what am I missing?'"
Bub	"The fact that we haven't had a major attack in a long time is probably the best indicator."
Robotech	"Hopefully I have people henpecking me a lot, because if they do it means they trust me to help them fix whatever it is....If I go in there in the morning and not get badgered every 30 minutes, I know something's wrong. Or everything's working really well."
Elroy	"Most of the time, my thought is really, am I enjoying it or not. And as long as it's yes, I keep going."

With these IT workers, the indicator of progress was idiosyncratic (Table A8). For Skippy, measuring progress with a new software package included repeatedly going through the options to see what has yet to be learned. For Bigglesworth, learning a new language involved looking at one's old code with more experienced eyes, to detect differences between what was done in the past and how much better it could be done now. For Bub, the absence of attacks on the system indicated that he was keeping up with security information. Robotech gauged his knowledge by the amount of questions other workers asked him. Elroy used a feeling of enjoyment as a barometer of how much he was learning.

Table A9. Enjoying Optimal Challenge, Learning (Flow, RQ 4: Sustaining Motivation)

Subject code name	Statement
Bigglesworth	"It's not so challenging it just drives you insane, but it's not so easy that you're bored."
	"When you conquer it you go, 'Cool, now I know how to do that.'"
	"It keeps you right on the edge."
Skippy	"Solving problems and making lights turn green, that's where it's at."
	"Not knowing how stuff works itches."
Bub	"Finding a solution is definitely a major relief."
Robotech	"I've conquered it. That's my biggest feeling. I've defeated it. I'm the master of the world."
Elroy	"I don't have any trouble blocking out distractions."
	"...Being happy about getting my mind around it."
Trogdor	"I get something to work, and it's like, 'Woooh, yay!' I probably get up and dance around."

The participants enjoy the challenge of problem-solving and learning how new technology works (Table A9). When they solve a problem or figure something out, they experience feelings of happiness, satisfaction, or relief. Some describe a state of optimal challenge, where they are working at the edge of their skill level and the task is neither impossibly difficult nor too easy, which is consistent with the concept of flow.

Table A10. Sense of Focus while Learning and Working (Flow, RQ 4: Sustaining Motivation)

Subject code name	Statement
Bigglesworth	"I'd come into work at 8 and wouldn't leave until 8, learning it."
	"I put headsets on and listen to music."
Skippy	"It's called larval stage. You just kind of shut out everything and turn completely inside, and you re-emerge later."
	"I don't hear people's voices and I don't hear the phone. I certainly don't see the clock."
	"On some level your mind is trying to protect your process."
Bub	"It can happen. It doesn't happen often, just because of the nature of this job. I wear so many hats."
Robotech	"I get there about 6:15 in the morning, and the next thing I know is it's already 2:00, and I leave at about 10 after 3:00."
Elroy	"A different manifestation of the theory of relativity....It literally seems like minutes and it's been hours. It applies to the high and low moments, the breakthrough and really frustrating moments. They both pass as part of one big continuum ...."
	"I don't have any trouble blocking out distractions."
Trogdor	"If the circumstances are right, I can definitely get sucked in, and get in the whole flow experience, however you pronounce that guy's name that wrote that book... In fact I'm very much influenced by that goal in choosing what I try to do."

The interviewees are capable of intense focus while learning new information technology (Table A10)—what Skippy called "larval stage." They block out external distractions, such as others' voices, and sometimes lose the sense of the passage of time. Trogdor (unprompted by the researcher) even used the word "flow" to describe his experiences, and mentioned that it was a motivator in choosing tasks. However, the nature of the job can interfere with this sense of focus; Bub reported that he is constantly getting interrupted.

Table A11. Goals for Self-Learning (Goals, RQ 4: Sustaining Motivation)

Subject code name	Statement
Bigglesworth	"Learning it because I needed to for a project or a problem that I needed to solve, that's definitely a big factor."
	"I also went above the knowledge I needed to learn. I went and learned more simply because you know it may come in handy later."
	"I enjoyed it."
	"But it's just one of those things that stimulates you to go and try to do more because you know you've … got to show off your skills in front of somebody else."
Skippy	"There's the utility of it, if you have this you can do this."
	"There's a little ego thing, being the guy in the office who can say yeah, actually that's done this way."
	"Mostly it's just fun digging around. It's a video game, it's a new toy at Christmas, take it apart, see how it works."

Bub	"It's keeping the information stores here safe that are entrusted to me, and making the computer and information resources available to the people that I serve without interruption."
Robotech	"The more I knew, the less stress I'd be under. That was the real thing, was just to make my job easier."
Elroy	"If it is something I'm just curious about...my goals would differ from something from work that I have to learn. Usually those are where you have to get to where you can satisfy the business need by this time."
Trogdor	"I almost see fun as a given." "I feel very, very motivated to constantly be making sure that I'm learning stuff." "So I also like technologies based on, how's this going to benefit my resume."

The participants' statements regarding their goals (Table A11) reveal many different goal types operating at the same time. They mentioned learning for perceived instrumentality for the future, solving current problems in the workplace but also learning more than is needed immediately because the knowledge might be useful later. In addition, they intrinsically enjoyed working with the new technology and learning new things. Some also reported concerns about others' opinions of their abilities, which could be characterized as performance goals. It is important to some of them that they are seen as a source of information on new technology, and that others realize what they have accomplished.

Discussion

Overall, the responses of the IT experts supported many of the elements in the proposed expertise model, even though they worked in different areas of IT. Participants reported having a talent for working with technology, getting support in their learning from others in their physical or virtual community, experiencing flow while learning, using metacognitive strategies, engaging in deliberate practice, and holding multiple goals. Self-taught IT workers had been using technology from an early age, linked new knowledge to prior knowledge when learning, and were reluctant to immediately ask questions. They found learning resources based on recommendations from friends or strangers in person or online, weighing the advice they got against their own experience. While learning they set up tasks for themselves and persisted in the face of problems or difficulties, but measured progress each in their own way. The challenge, focus, and satisfaction of the flow experience kept them motivated, especially when they had uninterrupted time. The IT workers acknowledged a variety of goals, including learning, performance, and future-oriented perceived instrumentality goals, either acting at different times or simultaneously; no one mentioned extrinsic rewards.

One limitation of the study concerns the difficulty of identifying experts in the domain, even though development of expertise, as opposed to a specific level of expertise, was the issue at hand. Although the snowball method identified IT workers who were at a level of expertise, they still might not have been at the same level of expertise. In addition, the IT experts studied may have learned in a variety of settings in the past, even if they were primarily self-taught. I eliminated from the study any IT worker whose undergraduate or graduate degree was in computer science, computer engineering, management information systems, or a related field. Eliminating those who had taken shorter-term training courses would have been impractical and probably unnecessary, as an IT worker with several years of self-taught experience along with a few one-week training courses is arguably more influenced by the self-teaching than the short courses. Therefore those whose formal training was limited to short courses were not excluded, but this training experience may still have affected the participants' descriptions of independent learning in information technology.

Appendix B: The Work Preference Inventory (WPI)

Work Preference Inventory Items (Amabile et al., 1994)

Item	Primary		Secondary			
	IM	EM	E	Ch	O	C
I enjoy tackling problems that are completely new to me.	X			X		
I enjoy trying to solve complex problems.	X			X		
The more difficult the problem, the more I enjoy trying to solve it.	X			X		
I want my work to provide me with opportunities for increasing my knowledge and skills.	X		X			
Curiosity is the driving force behind much of what I do.	X		X			
I want to figure out how good I can really be at my work.	X		X			
I prefer to figure things out for myself.	X		X			
What matters most to me is enjoying what I do.	X		X			
It is important for me to have an outlet for self-expression.	X		X			
I prefer work I know I can do well over work that stretches my abilities.	R			R		
No matter what the outcome of a project, I am satisfied if I feel I gained a new experience.	X		X			
I'm more comfortable when I can set my own goals.	X		X			
I enjoy doing work that is so absorbing that I forget about everything else.	X		X			
It is important for me to be able to do what I most enjoy.	X		X			

I enjoy relatively simple, straightforward tasks.	R	R	
I am strongly motivated by the money I can earn.	X		X
I am keenly aware of the promotion goals I have for myself.	X		X
I am strongly motivated by the recognition I can earn from other people.	X	X	
I want other people to find out how good I really can be at my work.	X	X	
I seldom think about salary and promotions.	R		R
I am keenly aware of the income goals I have for myself.	X		X
To me, success means doing better than other people.	X	X	
I have to feel that I'm earning something for what I do.	X	X	
As long as I can do what I enjoy, I'm not that concerned about exactly what I'm paid.	R		R
I believe that there is no point in doing a good job if nobody else knows about it.	X	X	
I'm concerned about how other people are going to react to my ideas.	X	X	
I prefer working on projects with clearly specified procedures.	X	X	
I'm less concerned with what work I do than what I get for it.	X	X	
I am not that concerned about what other people think of	R	R	

my work.		
I prefer having someone set clear goals for me in my work.	X	X

Note. An X indicates that the item falls on that particular scale. An R indicates that it is reverse scored. IM = Intrinsic Motivation Scale; EM = Extrinsic Motivation Scale; E = Enjoyment Scale; Ch = Challenge Scale; O = Outward Scale; C = Compensation Scale.

Appendix C: Approaches to Learning

Learning Goal, Performance Goal, and Perceived Instrumentality Items from "Approaches to Learning" (Brickman et al., 1997; Greene & Miller, 1996; Miller et al., 1999; Miller et al., 1996)

Subscale Name	Item
Learning Goals	I do the work assigned in this class because I like to understand the material I study.
	I do the work assigned in this class because I want to improve my understanding of the material.
	I do the work assigned in this class because I like to learn interesting things.
	I do the work assigned in this class because I like to understand complicated ideas.
	I do the work assigned in this class because I want to learn new things.
Performance-Approach Goals	I do the work assigned in this class because I like to do better than other students.
	I do the work assigned in this class because I want to look smart to my friends.
	I do the work assigned in this class because I can show people that I am smart.
	I do the work assigned in this class because I like to score higher than other students.

Perceived Instrumentality	I do the work assigned in this class because my achievement plays a role in reaching my future goals.
	I do the work assigned in this class because my achievement is important for attaining my dreams.
	I do the work assigned in this class because understanding this content is important for becoming the person I want to be.
	I do the work assigned in this class because learning the content plays a role in reaching my future goals.
	I do the work assigned in this class because learning this material is important for attaining my dreams.

Appendix D: Revised Goal Items from Approaches to Learning

Revised Goal Items from “Approaches to Learning” (Brickman et al., 1997; Greene & Miller, 1996; Miller et al., 1999; Miller et al., 1996)

Subscale Name	Item
Learning Goals	I tend to learn new technologies because I like to understand them.
	I tend to learn new technologies because I want to improve my understanding of them.
	I tend to learn new technologies because I like to learn interesting things.
	I tend to learn new technologies because I like to understand complicated ideas.
	I tend to learn new technologies because I want to learn new things.
Performance-Approach Goals	I tend to learn new technologies because I like to do better than other co-workers.
	I tend to learn new technologies because I want to look competent to my co-workers.
	I tend to learn new technologies because I can show people that I am competent.
	I tend to learn new technologies so that I can demonstrate my abilities to others.

Perceived Instrumentality	I tend to learn new technologies because my knowledge is important for attaining my dreams. I tend to learn new technologies because understanding this content is important for becoming the person I want to be. I tend to learn new technologies because they play a role in reaching my future goals. I tend to learn new technologies because mastering them is important for attaining my goals.

Appendix E: Perceived Competence Scale

Perceived Competence Scale items (Deci & Ryan, 2004)
I feel confident in my ability to learn new technology skills for my job.
I am capable of learning the technology skills I need.
I am able to learn what I need to keep up with the technology in my job.
I feel able to meet the challenge of learning the technology skills I need.

Appendix F: Demographic Survey

1. Age: ______ years _______ months

2. Sex (please check one): Female ___ Male ___

3. Race: ______________________

4. What is the highest academic level you have **reached** (please check one)?

    __ High School

    __ Undergraduate Major: ____

    __ Master's Major: ____

    __ Doctorate Major: ____

5. What is the highest academic level you have **completed** (please check one)?

    __ High School

    __ Undergraduate Major: ____

    __ Master's Major: ____

    __ Doctorate Major: ____

6. Length of time in present job (decimals are OK): ______ years

7. Length of time in the information technology field (decimals are OK): ______ years

8. What is your primary job responsibility (please check one)?

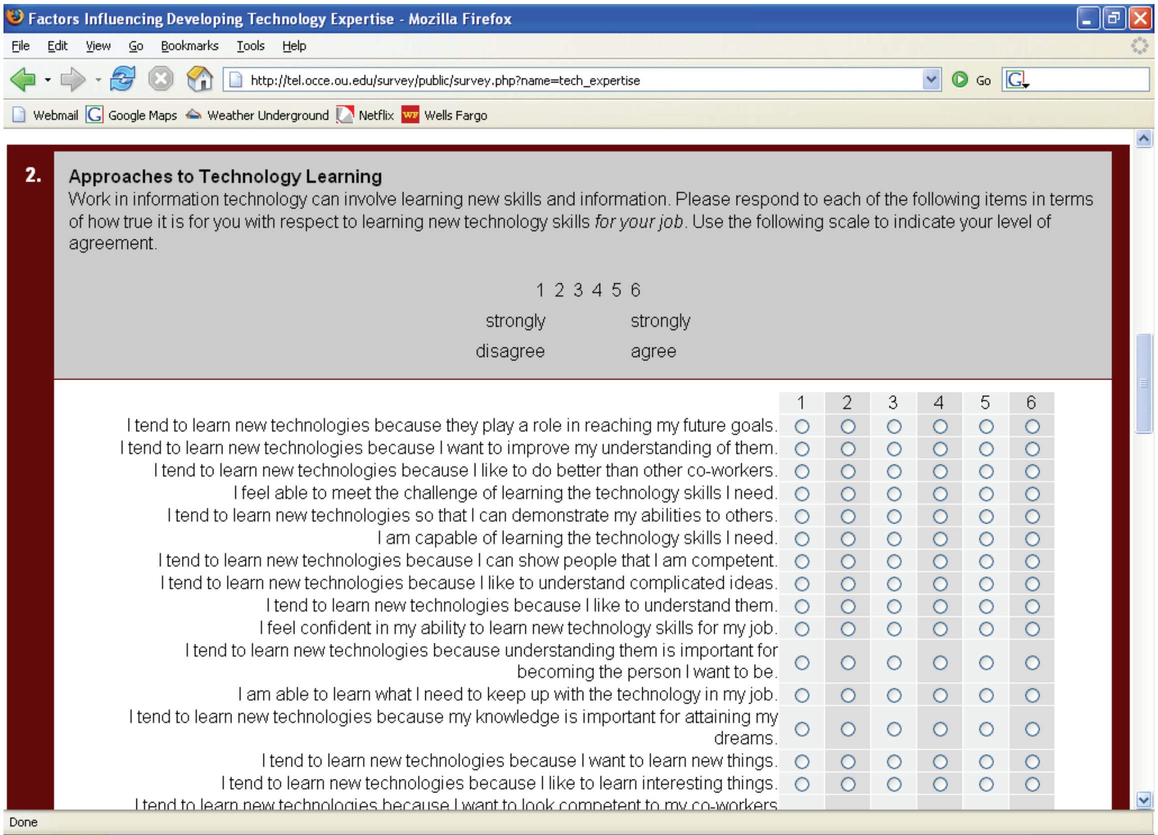
    __ Database Development and Administration
    __ Digital Media
    __ Network Devices
    __ Network Infrastructure
    __ Programming
    __ Technical Writing
    __ Web Development and Administration

9. What is your current job title? ____

10. Within your department, how would you rate your expertise as compared to others? Use a scale of 1 to 10 where 1 is the least expert and 10 is the most expert.

11. What is the source of this information? ___________________________________

Appendix G: Screenshot of Online Survey


Factors Influencing Developing Technology Expertise - Mozilla Firefox

File Edit View Go Bookmarks Tools Help

http://tel.occe.ou.edu/survey/public/survey.php?name=tech_expertise

Webmail Google Maps Weather Underground Netflix Wells Fargo

2. Approaches to Technology Learning

Work in information technology can involve learning new skills and information. Please respond to each of the following items in terms of how true it is for you with respect to learning new technology skills *for your job*. Use the following scale to indicate your level of agreement.

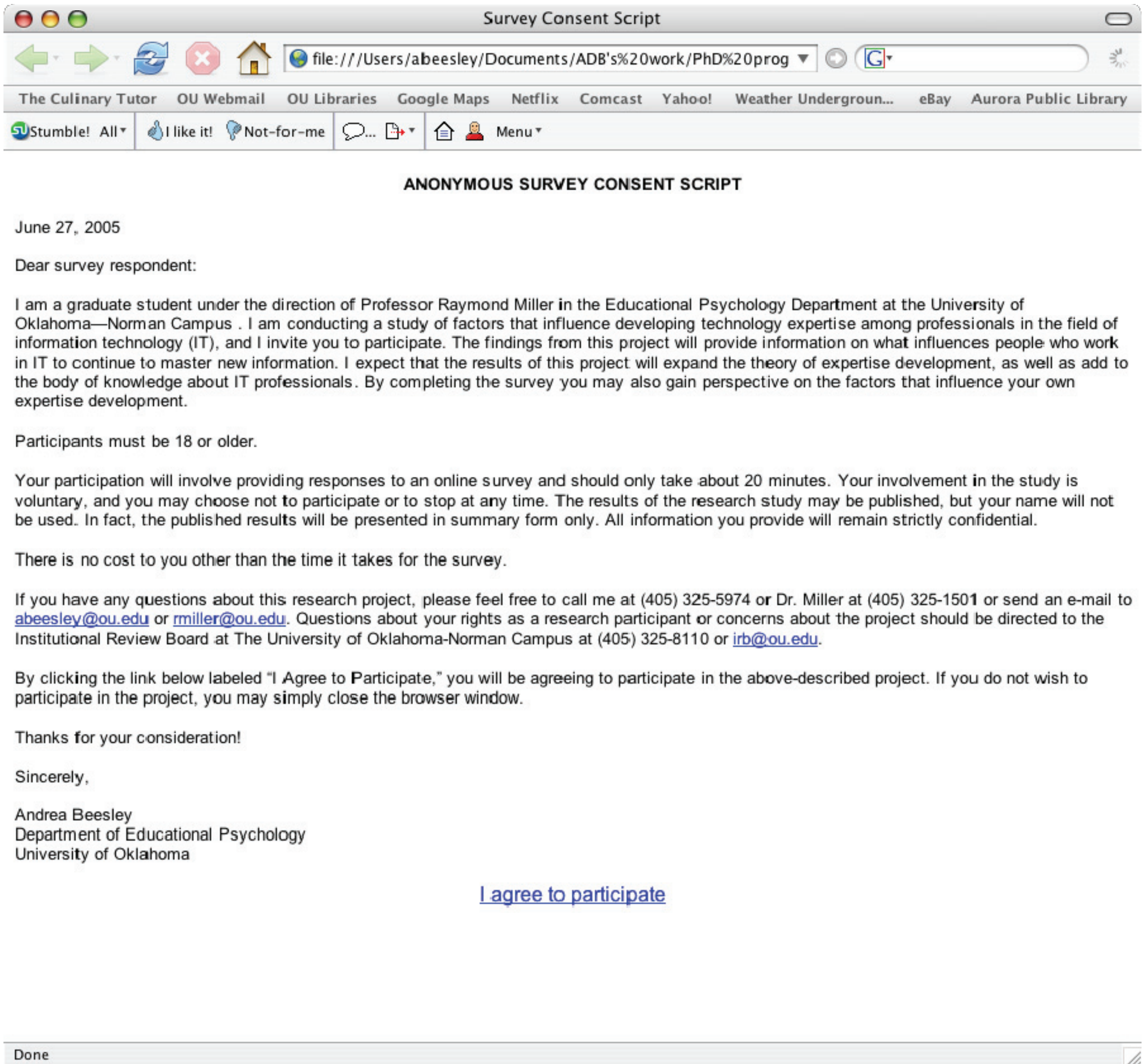
1 2 3 4 5 6

strongly disagree — strongly agree

	1	2	3	4	5	6
I tend to learn new technologies because they play a role in reaching my future goals.	○	○	○	○	○	○
I tend to learn new technologies because I want to improve my understanding of them.	○	○	○	○	○	○
I tend to learn new technologies because I like to do better than other co-workers.	○	○	○	○	○	○
I feel able to meet the challenge of learning the technology skills I need.	○	○	○	○	○	○
I tend to learn new technologies so that I can demonstrate my abilities to others.	○	○	○	○	○	○
I am capable of learning the technology skills I need.	○	○	○	○	○	○
I tend to learn new technologies because I can show people that I am competent.	○	○	○	○	○	○
I tend to learn new technologies because I like to understand complicated ideas.	○	○	○	○	○	○
I tend to learn new technologies because I like to understand them.	○	○	○	○	○	○
I feel confident in my ability to learn new technology skills for my job.	○	○	○	○	○	○
I tend to learn new technologies because understanding them is important for becoming the person I want to be.	○	○	○	○	○	○
I am able to learn what I need to keep up with the technology in my job.	○	○	○	○	○	○
I tend to learn new technologies because my knowledge is important for attaining my dreams.	○	○	○	○	○	○
I tend to learn new technologies because I want to learn new things.	○	○	○	○	○	○
I tend to learn new technologies because I like to learn interesting things.	○	○	○	○	○	○
I tend to learn new technologies because I want to look competent to my co-workers.						

Done

Appendix H: Screenshot of Consent Form



ANONYMOUS SURVEY CONSENT SCRIPT

June 27, 2005

Dear survey respondent:

I am a graduate student under the direction of Professor Raymond Miller in the Educational Psychology Department at the University of Oklahoma—Norman Campus . I am conducting a study of factors that influence developing technology expertise among professionals in the field of information technology (IT), and I invite you to participate. The findings from this project will provide information on what influences people who work in IT to continue to master new information. I expect that the results of this project will expand the theory of expertise development, as well as add to the body of knowledge about IT professionals. By completing the survey you may also gain perspective on the factors that influence your own expertise development.

Participants must be 18 or older.

Your participation will involve providing responses to an online survey and should only take about 20 minutes. Your involvement in the study is voluntary, and you may choose not to participate or to stop at any time. The results of the research study may be published, but your name will not be used. In fact, the published results will be presented in summary form only. All information you provide will remain strictly confidential.

There is no cost to you other than the time it takes for the survey.

If you have any questions about this research project, please feel free to call me at (405) 325-5974 or Dr. Miller at (405) 325-1501 or send an e-mail to abeesley@ou.edu or rmiller@ou.edu. Questions about your rights as a research participant or concerns about the project should be directed to the Institutional Review Board at The University of Oklahoma-Norman Campus at (405) 325-8110 or irb@ou.edu.

By clicking the link below labeled "I Agree to Participate," you will be agreeing to participate in the above-described project. If you do not wish to participate in the project, you may simply close the browser window.

Thanks for your consideration!

Sincerely,

Andrea Beesley
Department of Educational Psychology
University of Oklahoma

I agree to participate