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Abstract:

Extant research in information systems relies heavily on career anchor theory (CAS) as a lens to examine occupational choices and outcomes in information technology. Yet, the empirical results are inconclusive, and the power of the theory in predicting IT occupations is rather weak. With the growing demand for IT professionals, we need to examine other factors that can predict the IT occupational outcomes. In this paper, we draw on social cognitive career theory (SCCT) and examine self-efficacy as a complementary factor to career anchors in predicting whether seekers end up with technical, business, or managerial occupations in IT. Specifically, we propose and test a model that combines variables from both CAS and SCCT theories. We use multiple discriminant analysis to measure the extent to which variables from both theories discriminate the IT occupations. The results show that our model predicts occupations with an accuracy rate of 82.2 percent (compared to 75.2 percent for the original CAS model). Our results also show that individuals who hold a professional role that matches their profile are more satisfied than those who do not. Lastly, we discovered that, from individuals who hold a position that does not match their profile, business-IT professionals are most satisfied.

Keywords: Career Anchor Theory, Social Cognitive Career Theory, Discriminant Analysis, IT Occupations, IT Careers.

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1 Introduction

The information technology (IT) industry is one of the most rapidly changing and dynamic industries, which has resulted in a constant flux in the IT job market (Gefen, Ragowsky, Miller, Licker, & Stern, 2015). While old IT jobs begin to falter, new job titles and responsibilities that require novel skills seem to be in a steady demand worldwide, and the employability of IT professionals is among the highest in North America (Armstrong, Brooks, & Riemenschneider, 2015; Choudhury, Lopes, & Arthur, 2010; Luftman & Kempaiah, 2008; Luftman & Kempaiah, 2007). Nevertheless, attracting, developing, and retaining IT professionals continues to be a top concern for IT managers and executives (Downey, Bartczak, Young, & England, 2016; Luftman & Ben-Zvi, 2011; Luftman & Ben-Zvi, 2011). The decreasing number of graduates in science, technology, engineering and mathematics (STEM) compounds this problem (Fotache, Dumitriu, & Greavy-Serban, 2015; Luse, Rursch, & Jacobson, 2014; Li, Zhang, & Zheng, 2014), and academic institutions need serious reforms to graduate skilled professionals (Triche, Firth, & Harrington, 2016). Indeed, organizations continue to complain about the persistent deficiencies of IS skill sets (Levinson, 2012). They are going to great lengths to strengthen the IS skills of their workforce themselves (Poston & Dhaliwal, 2015). This unwavering IT job market is compelling researchers to pay closer attention to the career development of IT professionals and to examine IT career orientations, decisions, and outcomes (e.g., Ituma & Simpson, 2007; Summer, Yager, & Franke, 2005; Chang, Chen, Klein, & Jiang, 2011).

Extant research on IT careers has drawn heavily on the career anchor theory (CAT) (Schein, 1971, 1975) to explore the relationship between professionals' career orientations and their different career outcomes. According to Schein (1996), career orientations are anchors or patterns of self-perceived motivations, talents, and values that formulate individuals' decisions about their careers. Therefore, CAT rests on the foundation that a match between individuals' anchors and the respective work environment can lead to better career-development outcomes. CAT scholars have examined several related topics. For instance, many studies have focused on identifying the dominating orientations of professionals who work in the IT industry (Ituma & Simpson, 2007; Ginzberg & Baroudi, 1992; Crepeau, Crook, Goslar, & McMurtrey, 1992; Ramakrishna & Potosky, 2003), notably in terms of entrepreneurial innovation (Chen, 2014). Furthermore, many studies have explored the effects of different career orientations on individuals' professional experience and occupational attitudes (e.g., Igbaria et al., 1991; Summer et al., 2005; Jiang, Klein, & Balloun, 2001; Jiang & Klein, 2002; McMurtrey, Grover, Teng, & Lightner, 2002). A third and much smaller research stream has investigated the relationship between career orientations and the occupational roles that IT professionals hold (Igbaria, Greenhaus, & Parasuraman, 1991; Crook, Crepeau, & McMurtrey, 1991). Igbaria et al. (1991) found high correlations between technically oriented career anchors and technical occupational choices such as programming. Crook et al. (1991) found that technical competence, managerial competence, geographical security, service, and variety best discriminate occupational choices.

With this paper, we contribute to the third research stream that examines actual occupations in the IT industry. We argue that, in addition to the concepts examined in the CAT, other factors might discriminate the IT positions that professionals hold based on three primary reasons. Firstly, some empirical evidence suggests that career anchors are not sufficient to predict IT occupations accurately (e.g., Crook et al., 1991; Quesenberry & Trauth, 2007). Second, current IT occupations may span across a wide range of anchors and, thus, lead to potential inconsistencies between career anchors and the actual IT positions. Finally, we have conflicting empirical evidence about the dominance of certain career anchors of IT professionals. For instance, while some studies assert the dominance of the managerial, technical, and variety anchors (Crepeau et al., 1992; Igbaria et al., 1991; Quesenberry & Trauth, 2007), others have found that these anchors have a weak presence across IT occupations (Baroudi, 1988; Ginzberg & Baroudi, 1992). Similarly, some studies have found strong effects of the creativity, autonomy, and identity anchors (Summer et al., 2005); Crepeau et al., 1992), whereas others have negated these findings (Ginzberg & Baroudi, 1992; Crepeau et al., 1992). Given these diverging research outcomes and the fact that previous efforts to predict occupational outcomes have relied on correlational analysis (Igbaria et al., 1991) or used factors that had marginal discriminatory power (Crook et al., 1991), we need more research on the topic.

To address these issues, we argue that including self-efficacy as a second predictor would better discriminate IT occupations. More specifically, we investigate whether the joint consideration of career anchors (taken from the CAT) and self-efficacy (taken from social cognitive career theory, another widely used career theory) can better predict the type of IT occupations that individuals pursue.

Self-efficacy refers to an individual's perceived capability in performing necessary courses of action to achieve goals (Bandura, 1997). Self-efficacy determines whether one will pursue a given course of action or not, how much effort one will expand to pursue it, and to what extent one will sustain such efforts considering potential obstacles and problems (Lent, 2016; Hackett & Betz, 1981; Lent, Brown, & Hackett, 1994). Indeed, prior career research has shown that self-efficacy positively influences persistence in occupational pursuits (Lent et al., 1994) and successful attainment of occupational pursuits (Hackett & Betz, 1981). Researchers have developed the concept of self-efficacy in social cognitive career theory (SCCT) to explain different aspects of career development, such as career interest, choice, and actions (Lent, 2016; Lent et al., 1994). We include self-efficacy in this study as an additional predictor to the CAT based on the premise that an individual’s self-concept of values, needs, and motives (career anchors) cannot sufficiently determine that individual’s actual occupational outcomes. Therefore, we argue that, to achieve higher discriminatory power for predicting IT occupations, we need a model that combines individuals’ career anchors and their belief in their ability to perform the required work behaviors (i.e., self-efficacy).

This paper contributes to the literature in three ways. First, we develop a model that integrates insights from CAT and SCCT to improve the discriminatory power to predict what IT occupations individuals will pursue. Second, we close the discrepancy between the conceptual definition of career anchors that partly includes self-perceptions of talents and abilities (Schein, 1978) and the actual operationalization of career anchors in the IS literature, where no item captures such talents and abilities (e.g., Igbaria et al., 1991; Ginzberg & Baroudi, 1992; Jiang et al., 2001; McMurtrey et al., 2002; Chen, 2014). We do so by explicitly conceptualizing and operationalizing self-efficacy as a separate construct that reflects individuals’ self-perceptions of their talents and abilities. Finally, we guide academics and practitioners who are interested in helping individuals to select the best occupations that match with their needs, values, and perceived capabilities. This contribution is particularly valuable given the shortage of skilled IT professionals and the fast-changing developments in the IT discipline (Choudhury et al., 2010; Downey et al., 2016; Luftman & Ben-Zvi, 2011). Shedding light on these issues improves our understanding of the key attributes professionals need to possess in order to be attractive to several IT occupations.

This paper proceeds as follows: in Section 2, we describe the literature on career anchor theory and social cognitive career theory and highlight the theories’ key elements that are relevant to developing our model. In Section 3, we present the research model and define its components. In Section 4, we describe our empirical investigation of the research model. In Section 5, we present the results of the multiple discriminant analyses and, in Section 6, discuss them. In Section 7, we discuss the study’s implications. Finally, in Section 7, we discuss our study’s limitations and, in Section 8, conclude the paper.

2 Literature Review

2.1 Career Anchor Theory

Edgar Schein originally developed the concept of career anchors to describe a cluster of self-perceived motives, values, and talents that shape an individual’s career decisions (Schein, 1975; Igbaria et al., 1991). Schein (1978) originally introduced five anchors (autonomy/independence, security/stability, technical competence, managerial competence, and creativity/entrepreneurship). DeLong (1982) later extended those anchors to also include identity, service, and variety. Other research explored new theories to identify determinants of occupational choices. For example, Rodrigues, Guest, and Budjanovcanin (2013) built on Schein’s work to argue that career orientations might be more flexible to explain occupational choices than anchors. According to these authors, orientations are stable career preferences that emerge from the interaction between contextual factors such as the social environment, experience, and parental influence. Nevertheless, they found great overlap between Shein’s anchors and orientations. Indeed, CAT remains an important and influential theoretical model and serves as guidance for career decisions. Further, much contemporary research includes CAT and examines it against other models (e.g., Chapman, 2016) or employs it to study cross-cultural careers (e.g., Wechtler, Koveshnikov, & Dejoux, 2017; Costigan, Gurbuz, & Sigri, 2016).

In the IT career literature, CAT assumes a central role in explaining various career-development processes and outcomes. Broadly speaking, three streams of research have emerged. The first research stream focuses on identifying the dominant career anchors of IT professionals in various settings. For example, a survey of 321 IT professionals found three dominant clusters of career anchors: leadership, technical competence, and stability (Crepeau et al., 1992). Similarly, a study of 464 IT professionals in the US identified technical and managerial competence as the two most prevalent anchors (Igbaria et al., 1991). A study of female IT professionals found that technical and managerial competence were dominant career anchors (Quesenberry & Trauth, 2007). On the other hand, Ituma and Simpson (2007) conducted a cross-cultural study that identified various dominant anchors, including some that Schein's original taxonomy included (stability) and other new ones (e.g., being marketable).

The second research stream explores the impacts of individuals' career orientations on their attitudes towards a certain occupation and various aspects of their work experience. In line with CAT's core premises, this stream's main findings show that congruence between individuals' career anchors and occupations enhances their career satisfaction (Igbaria et al., 1991; Jiang & Klein, 2002; McMurtrey et al., 2002) and organizational commitment (Igbaria et al., 1991; Summer et al., 2005) and reduces their turnover intentions (Igbaria et al., 1991; Jiang & Klein, 2002). In one study, the authors reduced the initial discrepancy between career anchors and occupations by altering some of the occupational features to make them more congruent with the career anchors (McMurtrey et al., 2002). More specifically, after the authors made the core technology used more sophisticated, managerially oriented individuals perceived their occupations to be upgraded, which was in line with their managerial orientations.

The third stream, which we focus on in this study, examines the empirical relationships between career anchors and IT occupations. Amid a paucity of research in this area, Igbaria et al.'s (1991) seminal study of IT professionals established statistical correlations between career anchors and types of occupations. Particularly, technical occupations such as programmers were more significantly associated with individuals who were primarily technically oriented. Conversely, half of the computer managers and most project leaders were primarily managerially oriented. Consultants were more evenly split between the two career anchors. Going beyond statistical correlations, another study of 321 IT professionals examined the discriminatory power of career anchors among IT-occupation types (Crook et al., 1991). The result show that technical competence, managerial competence, geographical security, service, and variety best discriminated the types of occupations. However, the factors' discriminatory power was marginal.

Overall, we draw two main conclusions from the IT career anchor literature that pertain to our study. First, separate studies have identified various career anchors as the most dominant. In addition, studies lack consensus about career anchors' degree of dominance. Table 1 illustrates these conflicting empirical results.

Table 1. Dominance of Career Anchors in Predicting Occupations

Degree of dominance / **Career anchors**	**Dominant**	**Moderate**	**Weak**
Entrepreneurial creativity	Summer et al. (2005)		Ginzberg & Baroudi (1992); Crepeau et al. (1992)
Autonomy/independence	Summer et al. (2005), Crepeau et al. (1992)	Igbaria et al. (1991)	
Service/dedication	Baroudi (1988), Ginzberg & Baroudi (1992), Crepeau et al. (1992)		
Managerial competence	Igbaria et al. (1991), Crepeau et al. (1992), Quesenberry & Trauth (2007)		
Technical competence	Igbaria et al. (1991), Crepeau et al. (1992), Quesenberry & Trauth (2007)		Baroudi (1988), Ginzberg & Baroudi (1992)
Identity	Summer et al. (2005), Crepeau et al. (1992)		Ginzberg & Baroudi (1992)
Variety	Summer et al. (2005), Baroudi (1988), Crepeau et al. (1992)		
Security/stability	Ituma & Simpson (2007), Ginzberg & Baroudi (1992), Crepeau et al. (1992); Quesenberry & Trauth (2007)		
Lifestyle		Igbaria et al. (1991)	
Being marketable	Ituma & Simpson (2007)		
Challenge	Ginzberg & Baroudi (1992)		

Second, studies lack correspondence between how they conceptualize and operationalize career anchors. Schein originally conceptualized career anchors as a self-concept that comprises 1) self-perceived talents and abilities, 2) basic values, and 3) the evolved sense of motives and needs as they pertain to careers. Most studies on IT careers have used this conceptualization (e.g., Ginzberg & Baroudi, 1992; Ituma & Simpson, 2007; Quesenberry & Trauth, 2007; Ramakrishna et al., 2003; Summer et al., 2005). However, the operational measures of career anchors used in the employed career orientation inventory mainly tap into perceived values and needs but not talents and abilities (Igbaria et al., 1991; Ituma & Simpson, 2007; Ginzberg & Baroudi, 1992). Only a handful of studies have a correspondence between the conceptual definitions of career anchors and the career orientation inventory that they use to measure them (see McMurtrey et al., 2002; Jiang & Klein, 2002).

2.2 Social Cognitive Career Theory

Social cognitive career theory (Lent et al., 1994) is grounded in social cognitive theory (Bandura, 1986, 1997), which views a triadic reciprocal model of personal attributes (e.g., cognitive and affective states), behaviors, and environmental factors as determining an individual's choices, behaviors, and goal attainment. This model considers self-efficacy as the most influential predictor in this model. Another important predictor is outcome expectations (Bandura, 1997).

Social cognitive career theory (SCCT) also views self-efficacy as a key predictor of academic and occupational performance attainment (e.g., Sheu & Bordon, 2017; Tatum, Formica, & Brown, 2017). Occupational interest formation, choice intentions, and choice actions can mediate this path (Lent et al., 1994). For example, Lent et al. (1994) argue that individuals are unlikely to form an initial occupational interest in areas where they perceive themselves as lacking the requisite skills and capabilities (i.e., low self-efficacy). Self-efficacy also determines occupational choice intentions and career adaptability (Bocciardi, Caputo, Fregonese, Langher, & Sartori, 2017). Indeed, individuals are likely to adopt occupational and career goals and act towards the goals that they see themselves competent to achieve (Lent et al., 1994).

Career theorists have drawn on SCCT to investigate self-efficacy's impact on occupational interests, choices, and outcomes—albeit mostly in academic settings and with mixed results. For instance, some research has found that academic and barriers-coping self-efficacy were positively associated with academic interests and intentions to choose a major (Kim & Seo, 2014; Lent, Lopez, Sheu, & Lopez, 2011). Similarly, Cohen and Parsotam (2010) found that computer self-efficacy and occupational self-efficacy (IT skills) were associated with choice of major intentions and IT career intentions. Another study of individuals (both students and workers) involved in a cybersecurity competition found that subject-specific (cybersecurity) SE was positively related to occupational interests (Bashir, Wee, Memon, & Guo, 2017). Joshi and Kuhn (2011) examined three types of self-efficacy: computer self-efficacy, technical self-efficacy (software programming), and non-technical self-efficacy (IS soft skills). They found that computer self-efficacy and technical self-efficacy were associated with occupational interests (in IS career), whereas non-technical self-efficacy had a non-significant effect. In another investigation, Joshi et al. (2010) found that occupational self-efficacy (IT skills) was not significantly related to IT career intentions. In one of the rare studies conducted in a non-academic setting, Cunningham, Doherty, and Gregg (2007) examined occupational (head coaching) self-efficacy and head coaching intentions among 66 assistant coaches in Canada. They found differences between men and women in terms of their head coaching intentions and SE ratings. However, they focused only on intentions—as opposed to actual occupational outcomes—and did not explicitly test the association between self-efficacy and head coaching intentions.

Self-efficacy studies that have focused on actual outcomes have also reported mixed results and mostly considered academic outcomes. Among the studies that found support for this relationship, Zimmerman, Bandura, and Martinez-Pons (1992) found that self-efficacy for academic achievement was positively related to academic attainment (grades). In another study, computer self-efficacy indirectly influenced academic performance through academic goal-setting's mediation effect (Smith, 2002). In a meta-analysis of the social cognitive predictors of college students' academic performance and persistence, Brown et al. (2008) found that academic self-efficacy had a mostly positive relationship with academic performance (GPA and retention). In contrast to these findings, Stephen (2008) found support for the subject-specific self-effiacy–academic interest relationship but only mixed results for the relationships between self-efficacy and academic achievement (end of semester grades). Math self-efficacy had no direct effect on math achievement but did have an indirect effect through interest. By contrast, two other self-efficacy types (science and English) had no direct or indirect relationships with academic achievement. In a similar vein, Yang (2004) studied 1034 vocational college students in Taiwan and found a weakly significant association between general self-efficacy and academic achievement.

In sum, extant research has mostly focused on academic or occupational interests and choice goals as outcomes with little insights regarding self-efficacy's impact on actual job occupations. In addition, the empirical results are mixed or inconclusive. SCCT has also shown varying degrees of success depending on whether the self-efficacy measures were general (e.g., Kim & Seo, 2014; Yang, 2014) or task specific (e.g., Joshi & Kuhn 2011; Joshi et al., 2010). Below, we propose a theoretical model that focuses on task-specific self-efficacy and combines it with insights from career anchor theory (CAT) to predict actual IT occupational outcomes.

3 Research Model: Integrating the Two Perspectives

We follow the theoretical reasoning in El-Masri and Addas (2014). As our literature review shows, researchers have employed both SCCT and CAT to examine IT careers. However, these efforts have drawn on the theories separately without combining the two. The discriminatory power of career anchors in predicting actual IT occupations has been marginal (Crook et al, 1991). Therefore, we argue that we need to look beyond career anchors in order to better understand the factors that discriminate among IT occupations. While research has considered factors such as gender (Inda, Rodriguez, & Pena, 2013), education (Feldt, Kokko, Kunnunen, & Pulkkinen, 2005) and personality (Pulkkinen, Ohranen, & Tolvanen, 1999) as additional influential determinants of occupational choices, it has not amply examined abilities. Indeed, the way prior studies have operationalized career anchors does not reflect talents and abilities, which the self-efficacy construct of the social cognitive career model captures. Thus, we can see a discrepancy in how researchers have conceptualized career anchors to include self-perceptions of talents and abilities but operationalized it to not include them (see Igbaria et al., 1991; Jiang et al., 2001; McMurtrey et al., 2002). For instance, researchers have operationalized CAT's technical competence anchor in a way that captures only the attributes of occupations that satisfy individuals in technical occupations and attract them to pursue it. On the contrary, they have operationalized SCCT's technical efficacy in a way that measures individuals' perceived technical abilities in areas such as programming, networking, and databases. We examined how studies in the literature have operationalized the CAT's anchors and the different SCCT's competences and found that the former capture values and motives while the latter capture individuals' judgment of their own talents and abilities. Accordingly, we argue that we need to integrate these two perspectives (Figure 1). This position concurs with the original view of Schein (1971) that the perceived talents and abilities are important elements of an individual's career self-concept. Nevertheless, we capture this element in the separate construct of self-efficacy and restrict career anchors to aspects relevant to individuals' values and motives—an approach consistent with Alavi, Moteabbed, and Arasti (2012) who argue that career orientation is a motivational phenomenon and that one should ground it in theories of motivation and expectancy.

Our approach recognizes self-efficacy as a widely used construct in career theory. Its inclusion in the model enhances construct validity by maintaining consistency between how we conceptualize and operationalize career anchors, which we (along with McMurtrey et al., 2002) define in this study as the values, beliefs, and intentions that individuals perceive as important in their careers. Lent et al. (1994) have implicitly suggested that one could integrate both concepts—career orientation and self-efficacy. They claim that career interests—which is akin to career orientation—and self-efficacy each contributed uniquely to the prediction of occupational outcomes. In short, we propose that combining career anchors and self-efficacy can achieve higher power to predict IT occupations.

3.1 IT Occupation

IT occupation is the dependent variable in our model. We treat it as a categorical variable that comprises three dimensions or job types (Igbaria et al., 1991):

1. Technical occupations such as programmer, architect, and database administrator
2. Business occupations such as analyst, technical writer, and trainer, and
3. Managerial occupations such as project manager, project leader, and IT director.

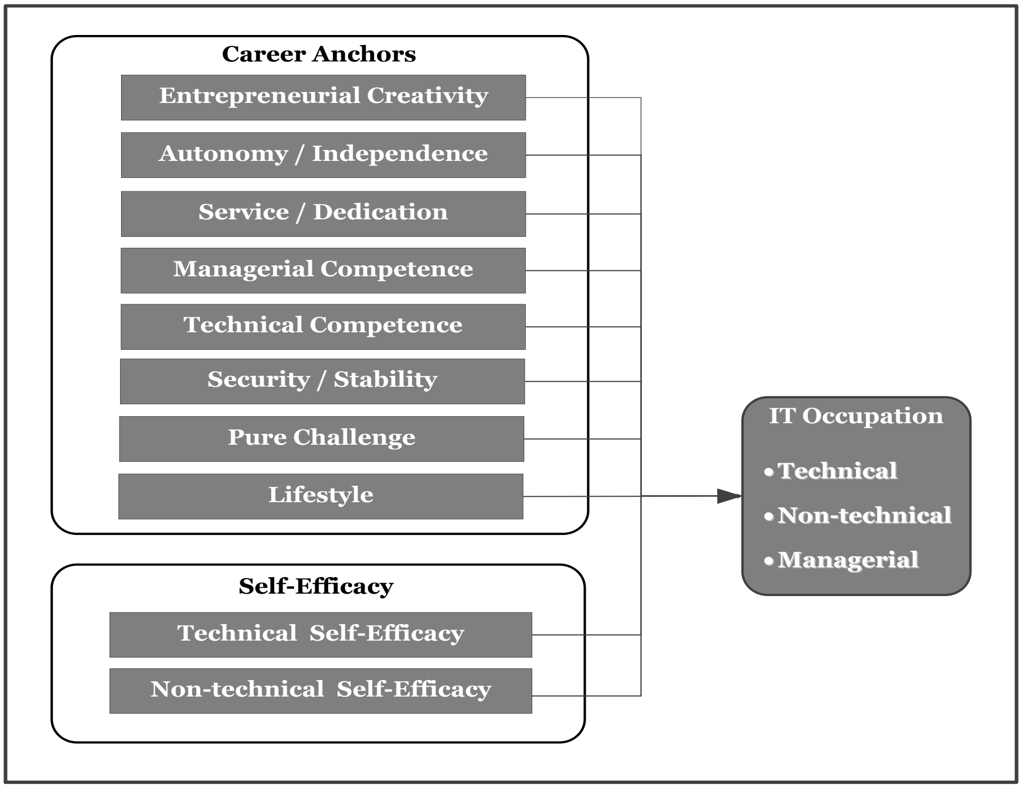

Figure 1. Research Model

3.2 Career Anchors

We conceptualize career anchors in terms of individuals' perceived values and needs regarding eight job dimensions (McMurtrey et al., 2002; Schein, 1996):

1. Entrepreneurial creativity: being motivated by the need to build something that is entirely their own.
2. Autonomy/independence: being motivated to be free of organizational constraints.
3. Service/dedication to a cause: being motivated to improve the world in some fashion; wanting to align work activities with personal values about helping society.
4. Managerial competence: feeling excited by the opportunity to analyze and solve problems under uncertainty.
5. Technical competence: feeling excited by the work content itself and preferring technical rather than managerial advancements.
6. Security/stability: being motivated by job security and valuing long-term attachment to their organization.
7. Pure challenge: being motivated to overcome major obstacles, solve almost unsolvable problems, or to win out over extremely tough opponents.
8. Lifestyle: being motivated to balance career with lifestyle; being highly concerned with such issues as paternity/maternity leave, day-care options, and so on.

3.2.1 Self-Efficacy

Following Joshi et al. (2010), we define self-efficacy as individuals' belief that they "can be proficient in skills necessary to becom[e] an IT professional" (p. 2). We conceptualize self-efficacy as a task-specific belief rather than a generalized belief (Osipow & Temple, 1996), which is closer to Bandura's (1997) original conceptualization of self-efficacy. Extant career studies show that the construct is a more consistent predictor of occupational outcomes when conceptualized according to an individual's career domain. For instance, Byars-Winston and Fouad (2008) found that the relationship between math/science-self-efficacy and career choices in mathematics/science was consistent with Bandura's original theorization. Joshi et al. (2010) decomposed self-efficacy into IT-technical and IT-non-technical self-efficacy. They found that the former dimension was positively related to students' intentions to pursue IT careers and that the latter dimension was negatively related to IT career intentions.

We examine two dimensions of self-efficacy (Joshi et al., 2010):

1. IT technical self-efficacy: includes technical skills such as programming and implementation.
2. IT non-technical self-efficacy: includes business/human skills such as adaptability and leadership.

4 Research Method

4.1 Measures

We adapted previously validated scales from the literature on career anchor theory and social cognitive career theory where they proved to be valid and reliable. We modified the questionnaire's wording to fit our study's context and pretested it with four PhD candidates. The unit of analysis focused on the individual. We used a 40-item scale to measure career anchors (Crepeau et al., 1992; Delong, 1982; Wood, Winston, & Polkosnik, 1985). We asked respondents to rate how true they found each item, and we anchored the response options on a five-point Likert scale that ranged from never true (1) to always true (5). Appendix A provides all the items in the questionnaire.

The self-efficacy scale, which we adopted from Joshi et al. (2010), included 12 IT non-technical self-efficacy items and 13 IT technical self-efficacy items. We asked respondents to rate their perceived level of ability/expertise in the areas described in each item. Specifically, we asked respondents to rate their level expertise in the areas technical and non-technical areas. We anchored the response options on a five-point Likert scale that ranged from not at all confident (1) to always confident (5).

To measure IT occupation, we relied on the job categories found in the Dictionary of Occupational Titles (see http://www.occupationalinfo.org). This database contains thousands of job titles that it organizes in mutually exclusive occupational categories similar to our classification (technical, professional, managerial). Accordingly, we asked respondents to choose one of the three occupation categories. We collected data on the type of IT occupation and the number of years in the current position. To allow for inter-group analysis, we also collected demographic information (gender, attainted education, and age).

4.2 Pretesting

We pretested the questionnaire during separate meetings with four PhD candidates. The candidates completed the questionnaire and made recommendations to improve it. They also suggested that we add a control variable to measure the respondents' career satisfaction. Accordingly, we added the career satisfaction construct that Greenhaus, Parasuraman, and Wormley(1990) developed. This construct can help explain whether the variations in the dependent variable arise due to factors other than the proposed ones, such as economic, social, or cultural factors. We used a five-item measure of career satisfaction that Greenhaus et al. (1990) developed.

4.3 Pilot Testing

We pilot tested the questionnaire online with 30 graduates of a Canadian university. The initial analysis of the data suggested that some of the respondents raced through the questionnaire (probably due to its length). We used two direct screening techniques to increase the trustworthiness of the collected data (Beam, 2012). To filter out respondents who were not careful when completing the questionnaire, we reversed the sense of two items. For instance, we reversed an item that starts with "I am always on the lookout for ideas" to "I am never on the lookout for ideas". Second, we added two extra throwaway questions about social media addiction (Beam, 2012). While we did not consider these two questions when analyzing our data, we used them to keep the respondents engaged in the survey given that it was relatively long.

4.4 Sample

We collected the empirical data using an online questionnaire administered to the alumni of two Canadian universities. Those universities have educational programs such as engineering, information systems, computer science, and software engineering. The alumni offices helped us contact the students by sending an email to those alumni who had graduated from IT-related programs in the past two years. Accordingly, our sample included all working individuals who graduated with IT-related degrees within two years without controlling for the type of the company they worked for. All participants volunteered, and we briefed them on the study's purpose and their rights not to participate or to withdraw from completing the questionnaire at any time. To encourage participation, we promised respondents that they would enter a draw to win a prize (one iPad Air 2 for each 100 participants). Participants took about 15 minutes to complete the online questionnaire.

Out of the 553 potential participants, 367 completed the survey (a 66.3% response rate). We excluded all respondents who had been working for four years or more to improve the likelihood that the respondents' technical and non-technical self-efficacies indeed helped them decide on their IT occupations and were not byproducts of those choices. We also excluded unemployed graduates and the ones who chose to continue their education. After screening for missing data and duplicate responses, we retained 242 surveys for data analysis. Among the sample, 59.5 percent were male and the mean age was 25 years. In terms of educational level, 8.3 percent had a certificate/diploma, 54.5 percent had a bachelor degree, and 37.2 percent had a graduate degree or above. As for the type of actual IT occupation, 78 had a managerial role (32.3%), 101 had a business role (41.7%), and 63 had a technical role (26%). Table 2 shows the demographic characteristics of the respondents.

Table 2. Description of the Respondents' Demographic Profiles

Category	Category	Frequency	Percentage %
Gender	Males	144	59.5
	Females	98	40.5
Occupational type	Technical	63	26.0
	Business	101	41.7
	Managerial	78	32.3
Educational level	Diploma	20	8.3
	Undergraduate	132	54.5
	postgraduate	90	37.2
Age	18-25	193	79.8
	26-35	40	16.5
	35-45	9	3.3
	>45	1	0.4
Years at current position	0-1 years	141	58.3
	2-3 years	101	41.7

4.5 Data Analysis

We analyzed the collected data following a four-stage procedure. First, and after cleaning the data from irrelevant responses and handling missing values, we conducted an exploratory factor analysis (EFA) using principal component analysis to check whether the instrument items loaded properly on their respective theoretical constructs. We individually applied EFA on the items that belonged to the eight CAT constructs and on those belonging to the technical self-efficacy and on-technical self-efficacy. We also applied EFA on the satisfaction construct. Items that belonged to the CAT and satisfaction constructs properly loaded on the eight corresponding constructs. As for self-efficacy, we derived three subfactors that belonged to technical self-efficacy and another three that belonged to non-technical self-efficacy, which we present in Section 5.

Second, we conducted validity and reliability tests on all the theoretical constructs and the newly derived factors to ensure that the instrument employed served its purpose and reported correct and reliable information. We also performed these tests to establish that the two self-efficacy constructs had reflective measurement models.

Third, we employed a multiple discriminant analysis (MDA) to measure the degree to which each of the 14 (eight from CAT + three from technical self-efficacy + three from non-technical self-efficacy) independent variables contributed to a linear function that best discriminated the three IT occupation types. Scientific research has long used MDA as a statistical technique. It has its roots in biological and behavioral sciences and, in the past three decades, has become widely used in finance (e.g., Kumar & Bhattacharya, 2006), HR (e.g., Santos, Ferreira, & Gonçalves, 2014), accounting (e.g., Deakin, 1972), marketing (e.g., Jayasankaraprasad, 2014), and information systems (e.g., Chang & Wong, 2010; Li & Sun, 2011).

Essentially, one uses MDA to classify an observation into one of several a priori groups given the observation's individual characteristics. This method can accommodate mixed independent variables (Kohli & Devaraj, 2003) and is suitable in situations with a categorical dependent variable (Lee, 2004). MDA can explain relationships between multiple independent variables and one categorical dependent variable (Kohli & Devaraj, 2003). With discriminant analysis, one can derive a linear combination of independent variables that will discriminate best between predefined groups (Hair, Anderson, Tatham, & Black, 1992). Note that a primary advantage of MDA in dealing with classification problems is the way it analyzes the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics.

Fourth, we investigated whether the average satisfaction rates across the three occupations significantly differed for the cases that were correctly predicted in the previous stage from those that were wrongly classified.

5 Results

5.1 Exploratory Factor Analysis and Tests of Validity and Reliability

We subjected all items that related to the eight CAT constructs and those that belonged to satisfaction to EFA. Results of the principal component analysis revealed nine factors. Except for two constructs (autonomy (AU) and security/stability (SS)), every construct's item loadings exceeded 0.5, and most also exceeded 0.7. We removed one item from AU and two items from SS with poor loadings after ensuring that doing so not cause a loss in the content domain of the constructs.

We also conducted EFA on the technical and non-technical self-efficacy constructs; technical self-efficacy (TSE) had 13 items and non-technical self-efficacy (NTSE) had 12. The results of the EFA show that each construct, TSE and NTSE, had three subdimensions:

- TSE subdimensions: systems analysis and design skills (SAD), technical development skills (TDS), and business domain knowledge (BDK).
    - SAD had four items: business analysis, system auditing, design, and system implementation).
    - TDS had six items: programming, Web development, IT architecture, IT security, networking, and database.
    - BDK had two items: enterprise applications and process analysis skills.
- NTSE subdimensions: interpersonal skills (IPS), creative self-efficacy (CSE), and code of conduct awareness (CCA).
    - IPS had three items: ability to work in teams, adaptability, and communication skills.
    - CSE had three items: openness to new experiences, critical thinking, and creativity.
    - CCA had two items: sensitivity to organizational culture and politics and professionalism.

To ensure adequate factor loading scores, we removed one item from the TSE construct and three items from the NTSE construct. Factor loadings were all above 0.6 (see Appendix B).

Subsequently, we tested the validity and reliability of the scale we used. We conducted convergent and discriminant validity tests using the average variance extracted (AVE) and composite reliability (CR). As Table 3 shows, all constructs had AVE and CR values above the threshold of 0.5 and 0.7, respectively, which suggests that each construct had significant convergent validity. Similarly, the square root of the

AVE of each construct significantly exceeded all correlation scores with other constructs, which suggests the constructs exhibited discriminant validity. The only exception was technical competence (TF): its AVE was 0.41. We then examined the internal consistency for each construct by obtaining the respective Cronbach's alpha measures. Note that the Cronbach's alpha for most of the constructs exceeded 0.7. The only values under the 0.7 threshold were for the two non-technical self-efficacy constructs: creative self-efficacy (CSE) and of code of conduct awareness (CCA). However, we retained these factors given their adequate AVE and CR values and the fact that they tap into an important part of the content domain of NTSE.

Table 3. AVE, CR and Cronbach's Alpha Values

Construct	Number of items	AVE	CR	Cronbach's α
Managerial competence (GM)	5	0.62	0.9	0.88
Service/dedication (SV)	5	0.65	0.9	0.9
Entrepreneurial creativity (EC)	5	0.64	0.9	0.9
Pure challenge (PC)	5	0.62	0.89	0.86
Lifestyle (LS)	5	0.6	0.88	0.86
Autotomy/ independence (AU)	4	0.63	0.87	0.86
Technical competence (TF)	5	0.41	0.78	0.8
Security/stability (SS)	3	0.73	0.9	0.86
Business domain knowledge (BDK)	2	0.7	0.82	0.78
Systems analysis and design skills (SAD)	4	0.53	0.82	0.81
Technical development skills (TDS)	6	0.56	0.88	0.88
Interpersonal skills (IPS)	3	0.64	0.84	0.77
Creative self-efficacy (CSE)	3	0.58	0.79	0.66
Code of conduct awareness (CCA)	2	0.66	0.66	0.56
Satisfaction	5	0.6	0.88	0.82

Table 4 shows the descriptive statistics of the constructs. All means were above the midpoint of 2.5 and ranged from 2.67 to 4.35, standard deviations across all constructs ranged from 0.6 to 1.0, and the skewness statistics ranged between -1.5 and 0.15. Appendix C depicts the inter-construct correlation matrix.

Table 4. Descriptive Statistics

Variable	Mean	St. dev.	Skewness	Kurtosis
Entrepreneurial creativity (EC)	3.47	0.98	-0.29	-0.84
Autotomy/ independence (AU)	3.81	0.77	-0.58	-0.18
Service/dedication (SV)	3.87	0.82	-0.93	0.55
Managerial competence (GM)	3.12	0.88	0.11	-0.80
Technical competence (TF)	3.65	0.76	-0.40	-0.66
Security/ stability (SS)	3.52	0.89	-0.36	-0.37
Pure challenge (PC)	3.80	0.76	-0.79	0.53
Lifestyle (LS)	3.96	0.73	-0.59	0.09
Interpersonal skills (IPS)	4.35	0.65	-1.5	3.51
Creative self-efficacy (CSE)	4.25	0.6	-0.6	0.09
Code of conduct awareness (CCA)	4.15	0.71	-0.63	-0.17
Business domain knowledge (BDK)	3.8	0.8	-0.79	1.3
Systems analysis and design skills (SAD)	3.4	0.9	-0.54	-0.02
Technical development skills (TDS)	2.67	1.0	0.15	-0.75
Career satisfaction	3.55	0.80	-0.71	0.48

5.2 Discriminant Analysis

Before we generated the discriminant functions, we verified the MDA assumption of equality in the predictor variables within-group covariance matrices using the Box's M statistic. Even though Box's M statistic rejects the null hypothesis of equal covariance matrices, discriminant function analysis is robust against this violation when the logs of determinants are relatively close to each other (they ranged from -8.5 to -10.58) and the dataset is relatively large. We calculated the composite score for each construct using the arithmetic mean value of the scores of its respective and valid items.

We employed a multiple linear discriminant analysis using the step-wise Mahalanobis distance. We performed classification based on prior probabilities computed from the sample group sizes. In order to ensure the robustness of the test against the inequality of the independent variables' covariance matrices, we performed discriminant analyses based on both within- and separate-groups covariance matrices. Both tests produced similar results in terms of predictive power, and the discriminating variables were the same.

Given that we had three groups (i.e., technical, business, and managerial), the discriminant analysis generated two linear discriminant functions, and the Wilk's lambda statistic for both functions had a p-value of less than 0.001. This result rejects the null hypothesis that the functions had no discriminating abilities. Table 5 summarizes the MDA analysis. In addition to the group centroids, Eigenvalues, variances and Wilks' lambda for the discriminant functions, Table 5 lists the standardized canonical coefficients and the tolerance of each independent variable in the classification process. The coefficients and tolerance values highly contributed in the selection process of the discriminating independent variables. The higher the total of the absolute values of coefficients, the higher the importance of the independent variable in classifying the dependent (i.e., the higher the discriminating abilities of that independent variable). Similarly, for tolerance values, the higher the tolerance of an independent variable, the higher its variance not accounted for by any other variable.

Table 5. Standardized Canonical Coefficients

<table>
<tr><th rowspan="2">Variable</th><th colspan="3">Standardized canonical discriminant functions coefficients</th><th rowspan="2">Tolerance</th></tr>
<tr><th colspan="2">Function 1</th><th>Function 2</th></tr>
<tr><td>Technical competence (TF)</td><td colspan="2">.588</td><td>-.311</td><td>.955</td></tr>
<tr><td>Managerial competence (GM)</td><td colspan="2">-.591</td><td>.25</td><td>.917</td></tr>
<tr><td>Autotomy/independence (AU)</td><td colspan="2">.243</td><td>.266</td><td>.954</td></tr>
<tr><td>Technical development skills (TDS)</td><td colspan="2">.357</td><td>.624</td><td>.972</td></tr>
<tr><td>Interpersonal skills (IPS)</td><td colspan="2">-.131</td><td>-.535</td><td>.936</td></tr>
<tr><td>Code of conduct awareness (CCA)</td><td colspan="2">-.157</td><td>-.206</td><td>.929</td></tr>
<tr><td>Security/stability (SS)*</td><td colspan="2">-.189</td><td>-.060</td><td>.944</td></tr>
<tr><td>Pure challenge (PC)*</td><td colspan="2">.176</td><td>.028</td><td>.854</td></tr>
<tr><td>Lifestyle (LS)*</td><td colspan="2">.093</td><td>.066</td><td>.843</td></tr>
<tr><td>Business domain knowledge (BDK)*</td><td colspan="2">-.043</td><td>.021</td><td>.942</td></tr>
<tr><td>Entrepreneurial creativity (EC)*</td><td colspan="2">.133</td><td>.284</td><td>.765</td></tr>
<tr><td>Systems analysis and design skills (SAD)*</td><td colspan="2">.082</td><td>.214</td><td>.802</td></tr>
<tr><td>Creative self-efficacy (CSE)*</td><td colspan="2">-.083</td><td>-.128</td><td>.839</td></tr>
<tr><td>Service/dedication (SV)*</td><td colspan="2">0.49</td><td>.094</td><td>.784</td></tr>
<tr><th>Discriminant functions</th><th colspan="2">Function 1</th><th colspan="2">Function 2</th></tr>
<tr><td rowspan="3">Group centroids</td><td>1 (technical)</td><td>1.4</td><td>1 (technical)</td><td>.827</td></tr>
<tr><td>2 (business)</td><td>.511</td><td>2 (business)</td><td>-.715</td></tr>
<tr><td>3 (managerial)</td><td>-1.793</td><td>3 (managerial)</td><td>.258</td></tr>
<tr><td>Eigenvalue</td><td colspan="2">1.676</td><td>.418</td><td>1.676</td></tr>
<tr><td>% of variance</td><td colspan="2">80.0</td><td>20.0</td><td>80.0</td></tr>
<tr><td>Wilks' lambda</td><td colspan="2">.263 (sig. <.001)</td><td>.705 (sig. <.001)</td><td>.263 (sig. <.001)</td></tr>
<tr><td colspan="5">* Variable not used in the classification analysis.</td></tr>
</table>

Six independent variables out of 14 proved to be necessary and sufficient to discriminate the observations and classify them in one of the three job categories. Three of these variables belonged to the CAT: technical competence, managerial competence, and autonomy. The remaining three variables belonged to the technical and non-technical self-efficacy constructs: technical development skills, interpersonal skills, and code of conduct awareness.

Discriminant analysis shows that our model predicted jobs based on the selected independent characteristics with an accuracy rate of 83.3 percent (see Table 6). For every job type, correct predictions overtook errors to reach an accuracy of almost 90 percent for managerial jobs, 83 percent for business, and almost 78 percent accuracy for technical jobs.

Table 6. Summary of the MDA Analysis

Occupational type	Predicted group membership			Total
	1 (technical)	**2 (business)**	**3 (managerial)**	
1 (technical) 2 (business) 3 (managerial)	49 (77.8%) 10 (9.9%) 2 (2.6%)	11 (17.5%) 84 (83.2%) 6 (7.7%)	3 (4.8%) 7 (6.9%) 70 (89.7%)	63 101 78
The model correctly classified 83.9 percent of original grouped cases.				

We also conducted a series of tests to ensure the superiority of our theoretical model—especially against models that belong to the original theories from which we formed our model. Note that, if we used only the independent variables that belong to the CAT to classify the same cases, the discriminatory power dropped to 77.7 percent accuracy. On the other hand, if we used only self-efficacy for the classification, the prediction accuracy dropped to 56.6 percent. This finding basically indicates that none of the theories accurately determine a group outcome when applied separately; however, the combination of both boosted the prediction accuracy by 6.2 percent as compared to the CAT alone and by more than 27 percent compared to self-efficacy alone.

As a final step in the discriminant-analysis procedure, we compared the average values (on a scale from 1 to 5) of the six discriminating variables across the three job types to understand how these indicators vary by job type. As Table 7 shows, relatively high technical competence, autonomy, and technical development skills coupled with relatively low managerial competence and non-technical self-efficacy clearly identified individuals with technical jobs. In contrast, relatively high technical competence and interpersonal skills, relatively low managerial competence and autonomy, and moderate technical development skills and code of conduct awareness identified people with more business-related roles. Finally, relatively high managerial competencies, interpersonal skills and code of conduct awareness and relatively low technical competence, autonomy, and technical development skills identified people with managerial positions. Satisfaction was almost identical across the three jobs.

Table 7. Mean Values of the Six Discriminating Variables

	Technical	Business	Managerial
Technical competence (TF)	4.1	4	2.9
Managerial competence (GM)	2.8	2.7	3.9
Autonomy/independence (AU)	4.2	3.4	3.3
Technical development skills (TDS)	2.7	2.4	2.3
Interpersonal skills (IPS)	3.9	4.5	4.5
Code of conduct awareness (CCA)	3.8	4.2	4.3
Satisfaction	3.5	3.5	3.6

5.3 Career Satisfaction based on Discriminant Analysis

Notwithstanding the improved predictive power of our model, we compared the satisfaction level of the groups that our model predicted correctly with those that it did not and examined whether correct predictions were associated with higher satisfaction rates. Specifically, we examined whether we could find a relationship between the prediction of jobs selection, based on our classification model, and employees' satisfaction. Such a relationship would answer the question of whether the classification model not only relates to job types but also can give some indicators on satisfaction consequences. To answer this question, we calculated the average satisfaction score three times for each job type: once when the classification was correct (i.e., prediction matched the actual outcome) and twice when it was not (one for each wrong group classification). Table 8 below shows the results.

Table 8. Comparison between Satisfaction of Groups Correctly and Wrongly Predicted

	Correctly predicted	Wrongly predicted	
Technical	3.62	Business	Managerial
		3.71	2.15
Business	3.55	Technical	Managerial
		3.61	3.28
Managerial	3.74	Technical	Business
		2.56	1.85
Satisfaction	3.63	3.17	

We can see that groups whose occupations matched the predicted profile were more satisfied with their careers (3.63 out of 5) than those who were not (3.17 out of 5). For professionals identified as having technical characteristics in their professional profile, we found no statistical significant difference in satisfaction when our model correctly predicted their job type as technical or wrongly predicted it as business; however, we found a serious drop in satisfaction when a person with technical characteristics held a managerial position. For professionals with characteristics that matched a business job such as business analysts, we found no significant difference between their satisfaction scores whether they held a business position (correctly predicted), a technical position, or a managerial job. Thus, the results show that professionals who fall in the business profile are flexible in terms of the IT profession they practice. On the other hand, the results show that professionals with managerial profiles are significantly less satisfied when they work in positions other than managerial ones; however, when correctly predicted, individuals who hold a managerial position have higher satisfaction than their professional peers who work in technical or business positions. We tested these results for statistical significance using ANOVA and t-test statistics and confirmed them at a 0.001 significance level.

6 Discussion

Young IT professionals and fresh graduates with IT-related degrees can take many different paths. In this regard, IT occupational types complement each other they though may significantly differ in terms of required skills, the nature of the daily tasks, and career progression. We integrated concepts from two distinct theories (namely, the career anchor theory and the social cognitive career theory) into a single model. The model identifies the main characteristics' values that predict professional profiles that match the IT occupational categories (technical, business, and managerial). Furthermore, the model associates career satisfaction with the occupational profiles it predicts. In other words, career satisfaction enhances the model's utility so it can not only simply descriptively predict professional profiles but also help prescriptively recommend types of IT occupations based on the predicted profiles.

6.1 Prediction of IT Professional Profiles

In analyzing the data we obtained from young IT professionals, we shed light on several important issues. The discriminant analysis results show a clear advantage in favor of the model we propose as compared to a model taken from each theory separately. Our model's overall discriminatory power attained 83.3 percent accuracy in its classification, whereas the model based on the eight anchors of the CAT attained 77.7 percent accuracy and the model based on self-efficacy attained only 56.6 percent accuracy. These results confirm our proposition that the self-efficacy constructs complement career anchors to better predict professional profiles in the IT industry. We argue that prior research has conceptualized the CAT concepts in a way that mainly focuses on professionals' motivation and the potential vision to achieve their objectives. However, this operationalization does not explicitly stress the required skills or self-confidence in these skills to attain those objectives. We included the self-efficacy constructs, which we took from the SCCT, in our model to bridge this gap by injecting indicators to identify the types and levels of the perceived skill set a person possesses.

Our results show a higher success rate in predicting managerial professional profiles as compared to the other two profiles, which we can attribute to two factors. First, professionals with leadership features and managerial responsibilities tend to have more concerns about their future career path and, hence, can clearly converge in a common CAT anchor (Hölzle, 2010). The second reason lies in the differences between the natures of the managerial and the technical skills required in their respective occupations in the IT industry. We can express these differences in terms of types, levels, and the number of skills a manager needs to have compared to a technical professional. The specificity of those skills and how individuals gain and sharpen them over time differ in managerial occupations from in technical occupations. The skills managers tend to have include a large number of common management abilities that they learn once and then sharpen with experience (e.g., leadership, inter-personal communication, and conflict management). In contrast, IT technical professionals tend to have technical knowledge that they gradually accumulate/update in response to specific needs. Consequently, technical professionals tend to have a smaller number of specific skills that they have mastered at a higher level and gained from a quasi-constant learning process (e.g., network engineering, graphics design, and programming). In other words, a successful IT project manager may have a certain level of communication skills and all other general management-related skills that evolve with time; however, a good mobile applications developer needs to constantly learn about new libraries and APIs specifically related to mobile programming, while they are not explicitly expected to know much about, for example, database administration. Our model reflects these differences well as the operationalization of the CAT constructs predicts managerial profiles to a very satisfactory level, whereas the self-efficacy construct that we took from the SCCT plays a major role in predicting technical profiles due to how straightforwardly the self-efficacy items address specific skills along with the subjects' confidence in their levels of knowledge.

Regarding non-technical business professionals such as business analysts and technical writers, they fall in the sweet spot having characteristics from both technical and managerial professional profiles. Interestingly, when conducting an MDA for a model that comprised only the CAT constructs, its discriminatory power was 60 percent, and it fell to 36.6 percent when it employed only self-efficacy constructs. Therefore, both models that comprise constructs that pertain to only the CAT or only the SCCT fail in classifying business professionals into their respective profiles. Therefore, the balance that our model, which integrates career orientations and skills, provides significantly contributes in shaping the prediction trend of the business professional profile.

6.2 Prediction vs. Satisfaction

While our model does not include satisfaction as a primary construct, we used it as an indicator to validate the prediction results that it produced. The results show that, on average, subjects who held a professional role that matched their predicted profile were more satisfied than subjects whose role the model did not predict correctly. Therefore, one can also regard our model as a recommendation tool for selecting occupations based on the predictions it produces.

Our results show that the correctly predicted business professionals were the most flexible subjects in terms of satisfaction if they did not hold a position that matched their professional profile. Undoubtedly, their skillset with both managerial and technical elements greatly contributes to their adaptation. For instance, business professionals are commonly good managers given their interpersonal skills and have some technical knowledge such as programming or database design. Furthermore, the nature of non-technical tasks requires business analysts and other business roles to regularly interact with managers and technical people and to serve as an intermediary between them. As a result, these subjects refine their skills so that, when their skills reach a certain level, they may be able to fulfill any other non-business role. Technical professionals only partially had the same flexibility. Our results show that people predicted to have a technical profile were mostly satisfied when holding either technical or business positions. Thus, these results support our interpretation that the technical and business regular interaction brings these two profiles closer together, which minimizes dissatisfaction when a non-technical person holds a technical position and vice versa. This finding advocates our previous discussion about the huge difference between the nature of skills that technical and managerial profiles require. Finally, the results suggest that professionals predicted to have a managerial profile will only be satisfied if they work in a position that matches their managerial profile and, likewise, that people predicted to have a technical occupation will experience dissatisfaction if they hold a managerial position. However, the results suggest that the satisfaction a business person may still have in working on a managerial position does not apply vice versa (i.e., that a managerial person will not have satisfaction in working in a business position). We can attribute this result to the presence of some technical aspects in the business profile that managers would not feel comfortable with.

As a last note, the results highlight that managers who have their profile correctly predicted exhibit the highest rate of satisfaction (followed by technical profiles and business profiles in that order). This finding suggests that, when managers are satisfied with their careers, they are more satisfied than their peers who belong to the other profiles. On the other hand, the scattered satisfaction of business professionals due to their high flexibility results in their being the least satisfied with their careers no matter what position they hold.

7 Implications

In this study, we suggest a new model that integrates constructs from both the CAT and the SCCT. While researchers have extensively used both theories—separately—to examine research questions related to careers (notably in IT), our integrated model provides strong prediction accuracy. The results of the empirical tests we conducted indicate a higher discriminatory power than any model taken from both theories separately. Thus, our work contributes to previous studies that have reported a marginal discriminatory power of career anchors in predicting actual IT occupations (e.g., Crook et al., 1991).

Our work brings significant value to the IT careers' literature and may form a basis for further prediction models and instruments that may extend to other career fields and industries. Furthermore, our including satisfaction in our study enriched the findings we obtained from our prediction model. In analyzing the satisfaction data and comparing it to the results that our model generated, we found that satisfaction was positively correlated with the match of occupations and actual professional profiles. Further, we explain the matching between the different professional profiles and the types of IT occupations in terms of satisfaction. That is, we explain how our model may help recommend occupations for IT professionals based on their profiles and may estimate their future levels of satisfaction when holding a role that differs from their professional profile.

Our work also provides important practical contributions. One can regard our model as a tool for identifying IT people's professional profiles. Based on the predicted profiles, professionals may have a clearer vision of their career orientation and their selected IT occupation, which is particularly significant given the myriad occupational types and titles that currently exist in the IT industry. Therefore, graduating IT students, professionals, and career advisors who assist professionals in the IT discipline can use our model.

8 Limitations and Future Research

Our work has several limitations that can form avenues for future research. First, our prediction model focuses on actual IT occupations as an outcome. However, researchers have also used the CAT and SCCT constructs we examined to predict occupational interests and choice goals. Future studies could incorporate these intermediate outcomes in addition to our more ultimate outcome of IT occupations.

Second, we collected data only from individuals in North American who may have particular cultural attributes and perceptions toward technology and IT. Future research could apply the model in other geographical or cultural contexts and potentially model different cultural effects. We can reasonably expect that certain anchors are more dominant than others in predicting occupational choices and outcomes in different regions.

Third, we tapped only into the careers of young professionals who have recently pursued IT occupations, which leaves open opportunities to examine the model's validity for IT professional with varying ranges of tenure (e.g., in the early, middle, and later career stages).

Finally, and for parsimony, we took only the self-efficacy concept from the SCCT. We chose this concept by itself given the weight it puts on individuals' specific technical and non-technical skills and on their degree of confidence in these skills. Future investigations could incorporate other SCCT variables, such as outcome expectations and personal goals.

9 Conclusion

The IT job market remains highly vibrant. In such a market, organizations can find it difficult to develop and retain IT professionals. Our study sheds light on the factors that help IT professionals to advance their careers. We combine concepts from social cognitive career theory and career anchor theory into a single model that can predict the suitable occupational outcomes according to individuals' profiles.

We conducted this study due to our observation that researchers have used the most widely used career theory—career anchor theory—to extensively measure occupation seekers' motivations and values but less so their skills and talents. This state of affairs conflicts with the original conceptualization defined by Schein (1996), who explicitly recognized that individuals' perceived skills and talent plays a role in their IT occupational choices and outcomes. We expect that the inclusion of self-efficacy—both technical and non-technical—as an integral component of the career model will provide clarity about why people pursue one IT career over another. Additionally, we believe that our model can help explain the conflicts in the extant literature regarding the dominance of various career anchors in predicting IT occupational outcomes.

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Appendix A: The Survey Instrument

We measured the items for the satisfaction construct on a five-point Likert scale from “not at all” to “very much”. We measured the items for career orientation construct on a five-point Likert scale from “never” to “always true for me”. We measured the items for self-efficacy construct on a five-point Likert scale from “not at all confident” to “always confident”.

Demographics

Job type:

- Technical: software engineer, systems analyst, architect, designer, etc.
- Professional business: business analyst, etc.
- Managerial: project manager, functional manager, development manager, etc.
- Other (specify):

Years at current position:

0-1 years	2-3 years	4-10 years	10+ years

Respondents’ age:

18-25	26-35	36-45	46-55	> 55

Career satisfaction

1. I am satisfied with the success I have achieved in my career
2. I am satisfied with the progress I have made toward meeting my overall career goals.
3. I am satisfied with the progress I have made toward meeting my goals for income.
4. I am satisfied with the progress I have made toward meeting my goals for advancement.
5. I am satisfied with the progress I have made toward meeting my goals for the development of new skills.

Career anchors

Autonomy/independence

1. I dream of having a career that will allow me the freedom to do a job my own way and on my own schedule.
2. I am most fulfilled in my work when I am completely free to define my own tasks, schedules, and procedures.
3. I will feel successful in my career only if I achieve complete autonomy and freedom.
4. The chance to do a job my own way, free of rules and constraints, is more important to me than security.
5. I would rather leave my organization than accept a job that would reduce my autonomy and freedom.

Entrepreneurial creativity

1. I am always on the lookout for ideas that would permit me to start my own enterprise.
2. Building my own business is more important to me than achieving a high-level managerial position in someone else’s organization.
3. I am most fulfilled in my career when I have been able to build something that is entirely the result of my own ideas and efforts.
4. I will feel successful in my career only if I have succeeded in creating or building something that is entirely my own product or idea.
5. I dream of starting up and building my own business.

General managerial competence

1. I am most fulfilled in my work when I am able to integrate and manage the efforts of others.
2. I dream of being in charge of a complex organization and making decisions that affect many people.
3. I will feel successful in my career only if I become a general manager in some organization.
4. Becoming a general manager is more attractive to me than becoming a senior functional manager in my current area of expertise.
5. I would rather leave my organization than accept a job that would take me away from the general managerial track.

Lifestyle

1. I would rather leave my organization than to be put in a job that would compromise my ability to pursue personal and family concerns.
2. I dream of a career that will permit me to integrate my personal, family, and work needs.
3. I feel successful in life only if I have been able to balance my personal, family, and career requirements.
4. Balancing the demands of personal and professional life is more important to me than achieving a high-level managerial position.
5. I have always sought out work opportunities that would minimize interference with personal or family concerns.

Pure challenge

1. I dream of a career in which I can solve problems or win out in situations that are extremely challenging.
2. I will feel successful in my career only if I face and overcome very difficult challenges.
3. I have been most fulfilled in my career when I have solved seemingly unsolvable problems or won out over seemingly impossible odds.
4. I seek out work opportunities that strongly challenge my problem solving and/or competitive skills.
5. Working on problems that are almost unsolvable is more important to me than achieving a high-level managerial position.

Security/stability

1. Security and stability are more important to me than freedom and autonomy.
2. I would rather leave my organization altogether than accept an assignment that would jeopardize my security in that organization.
3. I seek jobs in organizations that will give me a sense of security and stability.
4. I am most fulfilled in my work when I feel that I have complete financial and employment security.
5. I dream of having a career that will allow me to feel a sense of security and stability.

Service/dedication to a cause

1. I will feel successful in my career only if I have a feeling of having made a real contribution to the welfare of society.
2. I am most fulfilled in my career when I have been able to use my talents in the service of others.
3. Using my skills to make the world a better place to live and work is more important to me than achieving a high-level managerial position.
4. I dream of having a career that makes a real contribution to humanity and society.
5. I would rather leave my organization than accept an assignment that would undermine my ability to be of service to others.

Technical/functional competence

1. I dream of being so good at what I do that my expert advice will be sought continually.

2. I will feel successful in my career only if I can develop my technical or functional skills to a very high level of competence.
3. Becoming a senior functional manager in my area of expertise is more attractive to me than becoming a general manager.
4. I would rather leave my organization than accept a rotational assignment that takes me out of my area of expertise.
5. I am most fulfilled in my work when I have been able to use my special skills and talents.

Self-efficacy inventory

Non-technical self-efficacy

1. Communication skills
2. Ability to work in teams
3. Adaptability
4. Ability to work under pressure
5. Openness to new experiences
6. Creativity
7. Critical thinking
8. Ability to engage in independent learning
9. Problem solving skills
10. Sensitivity to organizational culture and politics
11. Ethics
12. Professionalism

Technical self-efficacy

1. Domain knowledge
2. Integrating enterprise application
3. Process analysis
4. Design skills
5. System implementation skills
6. System auditing and information assurance
7. Programming skills
8. Business analysis skills
9. Database management skills
10. Networking skills
11. Web development skills
12. IT security
13. IT architecture infrastructure

Appendix B: Factor Loading of Technical and Non-technical Self-efficacy Items

Table B9. Factor Loadings of the Technical Self-efficacy Items

Technical self-efficacy items	Technical development skills (TDS)	Systems analysis and design (SAD)	Business domain knowledge (BDK)
IT security	0.872	0.067	0.088
IT architecture infrastructure	0.797	0.081	0.202
Networking	0.748	0.128	0.041
Web development	0.741	0.277	-0.020
Programming	0.691	0.388	-0.142
Database management	0.612	0.472	-0.136
System implementation	0.161	0.766	0.311
Business analysis	0.100	0.741	0.028
System auditing and information assurance	0.220	0.716	0.251
Design skills	0.278	0.690	0.204
Integrating enterprise application	0.068	0.211	0.844
process analysis	-0.022	0.189	0.828

Table B2. Factor Loadings of the Non-technical Self-efficacy Items

Non-technical self-efficacy items	Interpersonal skills (IPS)	Creative self-efficacy (CSE)	Code of conduct awareness (CCA)
Ability to work in teams	0.855	0.081	0.127
Adaptability	0.800	0.144	0.092
Communication skills	0.732	0.223	0.115
Critical thinking	0.210	0.820	0.011
Creativity	0.043	0.778	0.154
Ability to engage in independent learning	0.180	0.677	0.128
Sensitivity to organizational culture and politics	0.056	0.112	0.844
Professionalism	0.207	0.123	0.778

Appendix C: Inter-construct Correlations

Table 10. Inter-construct Correlations

	TF	GM	EC	SV	PC	LS	AU	SS	TDS	SAD	BDK	IPS	CSE	CCA
Technical competence (TF)	1	-.537**	.185**	.160*	.372**	.199**	.147*	-.256**	.209**	.199**	0.068	-.167**	-0.05	-.158*
Managerial competence (GM)	-.537**	1	0.12	.132*	-0.065	-0.101	0.046	.184**	-0.074	-0.041	0.031	0.052	0.09	.180**
Entrepreneurial creativity (EC)	.185**	0.12	1	.407**	.239**	.257**	.408**	-.141*	.281**	.154*	0.062	-0.124	.151*	-0.051
Service/dedication (SV)	.160*	.132*	.407**	1	.384**	.302**	.257**	0.06	0.062	0.053	0.118	-0.027	.131*	.265**
Pure challenge (PC)	.372**	-0.065	.239**	.384**	1	.200**	.256**	-0.057	.154*	.249**	0.121	-0.06	0.058	-0.093
Lifestyle (LS)	.199**	-0.101	.257**	.302**	.200**	1	.331**	0.03	-0.058	0.096	.131*	0.028	0.055	0.08
Autonomy/ independence (AU)	.147*	0.046	.408**	.257**	.256**	.331**	1	-0.079	.213**	.210**	0.096	-.155*	0.019	-0.027
Security/stability (SS)	-.256**	.184**	-.141*	0.06	-0.057	0.03	-0.079	1	-.198**	0.017	.205**	.228**	0.111	.210**
Technical development skills (TDS)	.209**	-0.074	.281**	0.062	.154*	-0.058	.213**	-.198**	1	.493**	0.118	-.151*	0.007	-0.028
Systems analysis and design skills (SAD)	.199**	-0.041	.154*	0.053	.249**	0.096	.210**	0.017	.493**	1	.402**	-0.007	0.124	0.013
Business domain knowledge (BDK)	0.068	0.031	0.062	0.118	0.121	.131*	0.096	.205**	0.118	.402**	1	-0.085	0.062	.165*
Interpersonal skills (IPS)	-.167**	0.052	-0.124	-0.027	-0.06	0.028	-.155*	.228**	-.151*	-0.007	-0.085	1	.371**	.297**
Creative self-efficacy (CSE)	-0.05	0.09	.151*	.131*	0.058	0.055	0.019	0.111	0.007	0.124	0.062	.371**	1	.282**
Code of conduct awareness (CCA)	-.158*	.180**	-0.051	.265**	-0.093	0.08	-0.027	.210**	-0.028	0.013	.165*	.297**	.282**	1

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

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