INVESTIGATING THE EMERGENCE OF COGNITIVE WORK: TOWARD A NEW JOB CLASSIFICATION SCHEME FOR CROSS-CULTURAL ENVIROMENTS

ABSTRACT

Job analysis and its by-product job classification are foundational tools for Human Resource Management. Current job analysis techniques were developed a century ago. In the interim dramatic change has occurred in the structure of the economy and the jobs that define it. This paper tests the proposition that a new category of work, i.e. "Cognitive Work," has emerged. Experiments were performed in two countries to investigate construct validity. One hundred participants completed a coding exercise sorting thirty-nine job descriptions into one of three job categories. Analysis provided preliminary support for the validity of this new classification scheme.

Keywords: Job Analysis, Job Classification, Knowledge Worker, Cognitive Worker

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INTRODUCTION

Since first introduced to management at the turn of the 20st Century (Ghorpade & Atchison, 1980), job analysis has become indispensable to both the theory and practice of Human Resource Management (HRM). Job analyses are the basis for a core number of HRM processes (Aguinis, Mazurkiewicz & Heggestad, 2009; McEntire, Dailey, Osburn & Mumford, 2006; Prien, Goodstein, Goldstein, Gamble, 2009; Sanchez & Levine, 2000; Singh, 2008) and are critical in legal matters concerning employee rights under the law (Ash, 1988; Brannick, Levine & Morgeson, 2007; Levine, Thomas & Sistrunk, 1988). Due to the significant role job analysis plays, organizations are consistently advised to take the time to properly conduct up-do-date job analyses (Aguinis et al., 2009).

A primary function of the job analysis is to generate the data required to create job classifications (Brannick et al., 2007; Cornelius, Carron & Collins, 1979; McCormick, 1979). Job analysis data is typically obtained via interviews, questionnaires, observations, diaries, incumbent self-reports and expert checklists (Ghorpade & Atchison, 1980). Different job analysis methods (e.g. Position Analysis Questionnaire, Job Element Method, Functional Job Analysis and Critical Incident Technique) require different combinations of these techniques (Primoff & Fine, 1988; Singh, 2008; Van Wart, 2000). Despite there being many different job analysis methods, what they have in common is the production of grouping of jobs in the form of job families, job clusters, job categories, and job ladders.

Traditional job analysis and associated job classification models are based on three assumptions (Singh, 2008): 1) that individual jobs are discrete and the building block for both organizational and broader labor market classification schemes, 2) that jobs form into naturally occurring hierarchies and 3) the notion that jobs remain constant over time.

These assumptions have held sway for more than a century despite the fact that the nature of the modern economy, and the jobs that define it, has changed dramatically. In 1870, approximately 50% of the United States (US) workforce worked in agriculture (Carter et al., 2006). At the start of the 21st Century agricultural jobs still dominated the US workforce, with 41% of workers in the US employed on farms in 1900 (US Department of Commerce Bureau of the Census, 1976). However, by 1950 only 12% of US workers were employed in agricultural jobs, and by 1970 there were only 2% of US workers were employed in agricultural jobs (US Department of Commerce Bureau of the Census, 1976).

As early as 1959, when Peter Drucker (1959) coined term "knowledge worker", indications of what was ahead began to appear. Most recently, the US Department of Labor (2010a; 2010b) reported there being 11,730,000 (9%) persons employed in manufacturing occupations, 90,445,000 (69%) persons employed in service-providing occupations and only 1,091,000 (less than 1%) persons employed in farming, fishing and forestry occupations.

Given the fast-evolving character of the global economy, HRM tools and practices are challenged to keep apace. It is the purpose of this paper to contribute to that effort by testing the premise that a new "category" of worker has emerged as a defining element in the 21st Century economy. Toward this end we begin with a brief history of job analysis and its outcomes, such as job classifications. We then propose and report on an early effort to produce a new method of classifying contemporary jobs. This will be followed by an explanation of the study conducted, its associated results, a discussion of the findings, and their implications for the future.

HISTORY OF JOB ANALYSIS

As noted, job analysis is the foundation for the majority of HRM activities (Aguinis et al., 2009; McEntire et al., 2006; Prien et al., 2009; Sanchez & Levine, 2000; Singh, 2008; Thompson & Thompson, 1982). A quality job analysis paves the way for effective organizational recruitment, selection, training, performance evaluations, promotions, job design and redesign, workforce planning and payroll classification (Brannick et al., 2007; Gael, 1983; Van Wart, 2000). Because it so dramatically influences the effectiveness of the organization's HRM Department it is widely accepted that organizations need to take the time to properly conduct a job analysis for each job in the enterprise (Aguinis et al., 2009).

Job analysis is the means by which the organization identifies a job's essential functions (Felsberg, 2004; Gael, 1983; Levine, Ash, Hall & Sistrunk, 1983; Sanchez & Levine, 2000) and the knowledge, skills and abilities required to successfully perform the job (Thompson & Thompson, 1982; Van Wart, 2000). It is the tool used to differentiate jobs, so that what people do at work can be properly explained, guided and assessed (Brannick et al., 2007). Common elements of a good job analysis include a job's roles, tasks, traits, work environment, standards and levels (Van Wart, 2000).

Job analyses are of particular importance because the information collected is directly transformed into a job description (Ghorpade & Atchinson, 1980; McCormick, 1979; Prien et al., 2009). A job description is the brief document describing the essence of a job by stipulating its purpose, primary tasks, duties and responsibilities, performance objectives, and reporting relationships (Brannick et al., 2007; Heery & Noon, 2001a).

The idea of job analysis was first introduced very early in the Industrial Revolution by the French philosopher, art critic, and writer Denis Diderot (1713–1784), who used observation to perform a systematic task analysis to organize jobs in the fields of different trades, arts, and crafts, while working on his *Encycloepedie* (the project began in 1746 and did not end until 1772) (Furbank, 1992; Primoff & Fine, 1988; Singh, 2008; Van Wart, 2000). However, it was not until over 150 years later, in 1903, when the modern job analysis process first appeared in the management literature. Frederick W. Taylor, the world's leading proponent of Scientific Management, made it central to his studies (Primoff & Fine, 1988; Singh, 2008; Wilson, 2007) by naming "work analysis" as the first of his four key principles (Ash, 1988).

Taylor's job analyses were focused in the manufacturing and construction industries (Van Wart, 2000) and, more specifically, on time-motion studies aimed at improving work efficiency and effectiveness (Brannick et al., 2007). This sparked an interest in the field of job analysis which prompted Uhrbrock to compose the first book on the history of job analysis in 1922 (Ash, 1988; Signh, 2008; Wilson, 2007; Uhrbrock, 1922). Today there are numerous methods of job analysis, five of the most common are: Position Analysis Questionnaire (McCormick, Jeanneret & Mecham, 1972; McCormick & Jenneret, 1988), Job Element Method (Primoff, 1957; Primoff & Fine, 1988), Functional Job Analysis (Fine, 1955; 1988; Fine & Cronshaw, 1999), Critical Incident Technique (Flanagan, 1949; 1954), and Task Inventory (Christal, 1974; Christal & Weissmuller, 1988; Gael, 1983).

Early forms of job analyses were of particular interest to the political reformers behind passage of the US Classification Act in 1923. Techniques developed as a consequence of this legislation required extensive job analysis (Primoff & Fine, 1988; Singh, 2008; Van Wart, 2000) and created now familiar labels such as department, position, employee, grade, class, service and compensation. This process was particularly influenced by the appointment of Ismar Baruch as Chief of the Division of Personnel Classification of the US Civil Service Commission (Baruch, 1937; 1941; Johnson & Libecap, 1994). He and his new staff of HR professionals were charged with the responsibility to create a classification scheme for jobs based on their associated salaries as a means to determine comparable pay between jobs (Primoff & Fine, 1988).

Levine et al. (1988) observed that a job analysis, particularly in the public sector, is effectively the "legally mandated cornerstone upon which many human resource management applications must be built" (p. 340). Although in the U.S, there are no specific federal laws that directly require the use of job analyses, there are important laws surrounding pay and personnel selection that require information which is generally inaccessible without conducting a proper job analysis (Brannick et al., 2007; Primoff & Fine, 1988; Sparks, 1988). In order to ensure that an organization is properly complying with certain employment laws (e.g. Equal Pay Act, the Civil Rights Act and the American with Disabilities Act, Fair Labor Standards Act, etc.), it is in the organization's interest to conduct thorough and accurate job analyses (Brannick, Brannick & Levine, 1992; Brannick et al., 2007; Thompson & Thompson, 1982). For example, a job analysis can determine the "essential functions" of a job that are of importance in determining whether or not an organization is violating the American with Disabilities Act of 1990 (Brannick et al., 1992; Brannick et al., 2007; Wilson, 2007). Similarly, a job analysis can help define what "equal work on jobs the performance of which requires equal skill, effort and responsibility," which is of importance in assessing organizational compliance with the Equal Pay Act of 1963 (Brannick et al., 2007; Levine et al., 1988).

With respect to civil rights law, in *Griggs v. Duke Power* (1971), the Supreme Court established the principal of "job-relatedness" (Ash, 1988; Sparks, 1988). Although the court did not explicitly state that job analyses are necessary to establish job relatedness, their decision strongly implied the need for a job analysis to establish and adhere to valid selection procedures

(Ash, 1988; Brannick et al., 2007; Thompson & Thompson, 1982). This case set the precedent for the use of job analyses as support in later court cases surrounding employment practices. However, there are court cases (e.g. *Kirkland v. New York State Department of Correctional Services*, 1975; *Jones v. New York City Human Resource Administration,* 1975; *Greenspan v. Automobile Club of Michigan*, 1980) holding that simply conducting a job analysis does not necessarily mean that the organization is complying with the law. In order for a job analysis to withstand court challenge (e.g. *Washington v. Davis,* 1976; *Guardians Association New York City Police Department v. Civil Service Commission of New York,* 1980) the job analysis must follow the established Equal Employment Opportunity Commission's (1978) "Uniform Guidelines on Employee Selection Procedures" (Brannick et al., 2007; Field & Holley, 1982; Thompson & Thompson, 1982). A set of standards meeting these guidelines includes the job analysis being performed regarding the specific job for which candidates are being selected, the analysis being presented in written form, and the data being collected from multiple current data sources, including an expert job analyst (Ash, 1988; Levine et al., 1988; Thompson & Thompson, 1982). Following these guidelines helps to establish the job analysis' validity and enhances its value to an organization (McCormick, 1979).

While essentially similar in most respects (Levine et al., 1983; Van Wart, 2000), different types of job analysis can lead to different results and associated job classifications and groupings (Clifford, 1996; Cornelius et al., 1979; McCormick, 1979). Thus, an inappropriate technique or an inappropriately conducted analysis results in ineffective HRM practices and a waste of an organization's resources (Aguinis et al., 2009, Sanchez & Levine, 2000). Due to this, it is important to define the purpose of the job analysis and then determine the appropriate method by which the jobs will be analyzed (Baruch, 1937; 1941; Gael, 1983; Levine et al., 1988;

McCormick, 1979; Stutzman, 1983; Theologus, 1969; Wilson, 2007). The most common methodologies focus on the human worker's aptitudes and/or by the job's tasks performed (Brannick et al., 1992; Cornelius et al., 1979; Dierdoff & Wilson, 2003; Hartman, Mumford & Muller, 1992; Pearlman, 1987; Stutzman, 1983; Wilson, 2007).

The work or task-based models concentrate on what the worker actually does. It is this conventional approach that tends to be used more frequently (Cornelius et al., 1979; McCormick, 1979; Prien, Prien & Gamble, 2004). In task-based analyses, the worker's tasks, equipment needed, machines used and work context is recorded, and proper analyses are based on these observations (Brannick et al., 1992; Brannick et al., 2007).

In contrast, worker-based models focus on what characteristics the person doing the job must possess in order to successfully accomplish the work they are responsible for (Brannick et. al., 1992; Brannick et al., 2007). This type of model tends to look more into an individual's knowledge and mental capabilities. Worker-based models describe a job from the worker's point of view, leading it to be a more subjective assessment in comparison to the task-based models (McCormick, 1979).

Macro Job Classifications as an Answer to the Changing Organizational Landscape

Whereas job analysis is a process of identifying the key components of a job, job classification is a process for clustering jobs in terms of their attributes as discovered via job analysis (Brannick et al., 2007; McCormick, 1979). Absent a job analysis, an organization cannot move on to create job classifications because the job analysis data from individual jobs needs to be compared and combined in order to produce the general job classifications (Cornelius et al., 1979).

Job classifications act as the lens through which society views any specific job and attempts to understand the job's required work behavior (Hartman et al., 1992). Common job classifications are based on pre-selected criteria, such as tasks or general work activities, knowledge, skills and abilities (KSAs), worker behavior requirements, or lines of authority (Brannick et al., 2007; Pearlman, 1987). As an example of such job classifications, The United States Equal Employment Opportunities Commission Job Classification Guide (1996) established nine job categories the government uses in their compliance assessments: officials and managers, professionals, technicians, sales, office & clerical, skilled craft workers, semi-skilled operatives, unskilled laborers and service workers.

Jobs can be classified at many different levels, from very specific and small classification groups (i.e. tasks, duty, position) to very broad and large classification groups (i.e. industry) (Brannick et al., 2007). Similarly, before beginning the classifying process, one must determine if the classification is to be either monothetic or polythetic. Monothetic classifications consist of an exclusive set of characteristics that must be exhibited by each member of the group in order to be included, such that all items within the classification are in essence the same (Bailey, 1973; McCormick, 1979; Sokal, 1974; von Eye, Mun & Indurkhya, 2004). In contrast, polythetic classifications group together items based on their overall similarity, such that not all items must be the same (Bailey, 1973; McCormick, 1979; Needham, 1975; Theologus, 1969). These later classifications consider many more variables and the members of the classification share a large percentage of the same characteristics (Sokal, 1974; von Eye, 2004). Due to the nature of polythetic classifications, they are inherently more general than monothetic classifications, which encourage their wider use (McKelvey, 1978; Needham, 1975; Sokal, 1974).

Traditional job analysis models assume that jobs remain constant over time. Although this may have been the case when the idea of job analysis was introduced, researchers have begun to acknowledge that this assumption no longer holds true (Singh, 2008). The changing nature of the way that work is conducted has led to complications in the job analysis process such that it is now financially prohibitive for organizations to keep up-do-date job analyses (Singh, 2008; Wilson, 2007). Although, specific classifications can be quite useful, this is only in the rare instances when the unique characteristic that defines the classification is of particular interest (McKelvey, 1979). Specific or monothetic classifications are not the wise choice when analyzing the overall nature of a job or group of jobs.

A possible solution to this problem of obtaining up-to-date job analyses is to base analyses on a broader, or more polythetic level, such as by the general characteristics required by a particular job rather than the specific tasks a job entails (Brannick et al., 2007). Broad job classifications increase the range of the job allowing for greater managerial discretion in the assignment of tasks (Van Wart, 2000). This allows for a simpler job analysis. However, it also means jobs are not defined as well (Van Wart, 2000), creating room for greater ambiguity.

The changing nature of the workforce and organizational practices impacts how types of work are classified. Hartman et al. (1992) concluded that in the future, the formation of general job groupings may prove useful due to their ability to span across alternative descriptive systems and thus hold a valuable purpose. Introduced below is a new broad classification system that has been developed based on the cognitive requirements of individual jobs.

TOWARD A COGNITIVE JOB CLASSIFICATION SCHEME

At the turn of the twentieth century, males comprised the majority (81.9%) of the compensated workforce (United States Department of Commerce Bureau of the Census, 1976) and the jobs they held were typically on the floor of a manufacturing plant (Parker, Wall & Cordery, 2001). In the 100 plus years since, we have witnessed a dramatic decrease in industrial work as a percentage of the economy and a dramatic increase in the workforce in the service sector (Osterman, 1997). According to the US Department of Labor Statistics (2010a), in June 2010, 11,730,000 (8.9% of employees in nonfarm industries) persons were employed in the manufacturing sector, whereas 90,445,000 (68.8% of employees in nonfarm industries) were employed in the service sector. These numbers confirm the dominant position of the service sector in today's economy.

The service sector revolves around supplying customers/clients with intangible services, as opposed to tangible product goods. As the service sector expanded, so too did the number of employees, both male and female, that many have begun to label "knowledge workers" (Parker et al., 2001).

For the purpose of this research, we propose that that the label "service worker" is insufficient to the task of capturing and describing the substantive diversity of jobs included in this category. More specifically, we propose that there are three major categories of work type: Conventional, Knowledge and Cognitive.

Conventional Work

Conventional work consists of jobs that are often referred to as "blue-collar" or manual work, and are typically industrial jobs requiring physical labor or physical presence. The conventional worker may be skilled or unskilled, but a college degree is typically unnecessary. The absence of a required advanced formal education is one of the major attributes differentiating conventional from knowledge or cognitive work. For both knowledge and cognitive work, college degrees are most often a prerequisite for employment. Conventional work composed the majority of the workforce beginning in the late 19th century and continued through the middle of the 20th century (Carter et al, 2006). Importantly, it was the type of work that most defined the workforce when the job classification tools we continue to depend upon were invented and institutionalized.

Knowledge Work

As noted by a number of observers, the transition to a service dominant economy has led to an increase demand for knowledge workers (Bell, 1973; Cortada, 1998; Drucker, 1999; Janz, Colquitt & Noe, 1997). An observation consistent with the popular *Resource Theory of the Firm*, where employee knowledge is treated as a unique organizational asset in that it can be used and reused, without being depleted, and it helps to define an organization's competency (Penrose, 1959; Barney, 1991). Organizations seek to leverage employee knowledge, both individually and collectively, as a means of increasing productivity and securing strategic differentiation (Blackler, 1995; Drucker, 1999).

Discovery of the knowledge worker began as early as the late 1950s when researchers began to recognize that brainpower was replacing human muscle power as the engine of firm success (Bell, 1973; Porat, 1998). Accordingly, Peter Drucker (1959) coined the term "knowledge worker" to describe those who work with intangible resources. He would later elaborate on this description of knowledge workers to define them as higher-level employees who apply theoretical and analytical knowledge, acquired through formal education, to develop new products or services (Drucker, 1999) and that these workers will come to dominate the workforce (Drucker, 2001). Currently, knowledge work, using this broad and still emerging definition, stands as the fastest growing workforce sector (Cortada, 1998).

Upon closer examination, many knowledge jobs, despite the requirement of higher intellectual preparation, often revolve around routinized processes. For example, an accountant routinely fills out itemized tax returns, or an information technology specialist repeatedly installs system software. Or, consider the role of a pharmacist, who must adhere to established compounding procedures to fill doctor ordered prescriptions. The commonality among these jobs is that there are detailed protocols dictating how the employee must proceed; once learned, the primary responsibility of the employee is to follow the protocol. Employees in this group have little discretion; they are rewarded for reliable implementation, not creative invention.

When taking into consideration this dynamic environment it is important to mention that knowledge worker takes into consideration changes in the environment and adjusts and bents accordingly keeping the standards of profession. They keep with standards of profession, ethical conduct and within the same business model they started from at the first place. The idea or change comes from environment and they implement it within the existing set of rules, frame of mind and standards.

Cognitive Work

To address the defining limitation of classic knowledge work, we introduce the term "cognitive worker" to capture jobs demanding a broader and more elastic response to the non-physical demands of work. In contrast to routinized procedures of knowledge work, cognitive work requires job incumbents to exercise cognitive fluidity and creativity to confront unknown and non-routinized tasks. Consider for example, a research scientist searching for new pharmaceuticals, or a university professor developing a new theory of workplace justice.

In today's society, organizations increasingly strive to gain competitive advantages through continuous innovation and creativity (Mohrman et al., 2002). This has led to the importance of employees using their minds to overcome problems not before been seen. In our formulation, a job labeled “cognitive” has three major components: a) the employee is required to have cognitive fluidity, b) the employee is expected to exhibit high-level thinking skills, and 3) the job is such that it cannot be machine automated or routinized through protocol or procedure.

Cognitive work requires employees to not only access a defined knowledge base, it requires that they rearrange and expand their personal knowledge to address novel situations. In other words, the thoughts being processed in cognitive work make more stops during the cognitive process than that of knowledge work. Instead of completing routine tasks with one's mind moving from point A to B to C to D, cognitive worker's minds are expected to be more fluid and may move from point C to Z to B to M to L to Y to A to D to T, before making a final decision. In cognitive work, the employee’s mind is constantly engaged as it considers different options to reach with the best alternative to the problem. They strive to come up with context-sensitive and customized solutions to the problem at hand as opposed to a one-size-fits all solution (Martin, 2007). Their work is highly idiosyncratic, the employee is expected to tailor or adapt potential solutions to unstable job requirements. Additionally, evidence suggests that, due to these cognitive demands, this type of work spills over into the personal, home context of the individual. Occasionally this may have adverse effects on the quality of rest and personal domain interactions of cognitive workers (Ezzedeen, & Swiercz, 2003; 2007; Sonnetag, & Kruel, 2006).

High-level thinking skills, involving the use of naturalistic decision making and integrative thinking, are required by cognitive work. Naturalistic decision making describes experts making intuitive decisions based on cognitive skills developed on patterns formed from previous experiences (Kahneman & Klein, 2009; Lipshitz, Klein & Carroll, 2006). The basis of naturalistic decision-making rests in the intuition of the decision maker and oftentimes a naturalistic decision maker is unable to articulate the process or rationale for their decision choice. This type of decision-making process rejects the idea of choosing amongst alternatives (Lipshitz et al., 2006). Instead, naturalistic decision makers mentally evaluate options generated from their analysis of certain environmental cues related to past experiences; if they believe an option will work they implement it, otherwise they will modify it or go on to evaluate the next plausible option (Kahneman & Klein, 2009). These integrative thinkers also take into account the less obvious and seemingly irrelevant factors, welcome complexity, and question how all factors impact each other. Martin (2007) describes the integrative thinker's ability to assess relationships by holding multiple parts of the puzzle in their mind at once, as their having an opposable mind providing them with the ability to resist simplistic and innate ways of learning.

Machines have replaced many human workers, particularly in industrial jobs. Cognitive work, by definition cannot be performed by a machine until machines become true thinking machines as minimally defined by the Turing Test (Turing, 1950). Currently, a machine cannot replicate the level of intelligence and brain use required of cognitive workers in accordance to this test. Since cognitive work revolves around the unknown, there are no fixed routines cognitive workers follow in any given situation. Cognitive workers may not even be able to articulate the process they are going through in their minds as they make decisions, and thus, machines cannot yet be programmed to think in the same way.

Cognitive work requires an employee to consistently complete non-routinized tasks, these individuals are constantly using new knowledge and abilities to complete the tasks assigned to them, which increases the demand for the skill variety of their job as defined by Hackman and

Oldham in their Job Characteristics Model (1975; 1980). The level of task significance is also increased with cognitive work, due to its predominance in the service sector and its direct effect on other individuals. As cognitive work is idiosyncratic and cognitive workers find themselves in a role such that they are the only one, or one of a few, that can effectively complete the task at hand. This increases the employee's ability to maintain task identity and feedback. Since the cognitive worker is the only one dealing with the task, they complete the process from start to finish, and are accordingly the only one that the success/failure of the project will be attributed. Furthermore, because these tasks involve the employee tackling not previously experienced problems, there are no specific rules or processes they have to follow to complete them, which leads these jobs to have an increased level of autonomy.

The aforementioned attributes of conventional, knowledge and cognitive work signify that there are substantive differences between these three different categories of work. It is the appropriateness of this broad classification of jobs into three groups (Conventional, Knowledge and Cognitive) that is the focus of this study. In line with the differences between these three types of work, we anticipate that jobs will be able to be classified, by their given job description, into one of these three categories and that there will be a consistency in how jobs are classified across different coders.

Due to the fact that he/she creates a new business model or standard for certain business area it is not possible to follow work performance recipes. Cognitive workers have an idea and work progresses until this idea or innovation becomes reality in the environment of constraints and barriers.

Hypothesis 1: Jobs will be classifiable as being either conventional, knowledge or cognitive.
Hypothesis 2: There will be consistency in how jobs are classified across different coders.

METHODS

The empirical portion of this paper is divided in two sections. Each of the sections was deliberately designed differenly in order to increase validity of the study. Both of the sections are designed as a complimentary pilot research projects testing the plausability of the arguments. Section I data collection was secured in US. Section II data was secured in Europe, Croatia.

SECTION I

Research Design

For this study, participants were given a packet containing thirty-nine 4x6 index cards, each labeled with a job title and job description obtained from the Occupational Information Network (2006).

Subjects were given three envelopes, each labeled with a description associated with a category of job labeled on it. To minimize response bias, the three categories of jobs were identified as Folder Alpha, Folder Beta and Folder Gamma; respondents were not aware of the actual classification titles of conventional, knowledge and cognitive.

Participants were instructed to carefully read the job descriptions and the job category definitions. They were then instructed to sort the thirty-nine job descriptions into the three categories of jobs, place the sorted index cards into the appropriate envelope and return to the researcher.

Participants

In total thirty working professionals participated in this study. Fourteen participants were Senior HR professionals and sixteen were younger professionals across a variety of occupations. This total sample was comprised of 17 females (56.67%). The age breakdown of respondents was as follows: four under the age of 25 years, twelve 25-30 year olds, seven 31-40 year olds, three 41-50 year olds and four 51-60 year olds.

Participant job titles varied widely, including Certification Officer, HR Administrator, HR Consultant, HR Director, HR Manager, HR Regulatory Analyst, HR Representative, Full-time MBA Student, Law Clerk, Management Analyst, Personnel Analyst, Program Managers, Recruiters and Vice President of HR. These jobs were housed in a variety of industries, including government (eight), health care (three), non-profit (three), finance (two), technology development (two) and one person working in each of the following industries: banking, consulting, distribution, education, energy, entrepreneurship, law, public relations, software, telecommunications, retail, and utilities.

The tenure of participants in their jobs ranged from: four in their position for less than one year, fourteen for between one and three years, seven for between four and five years, one between six and ten years, two between eleven and twenty years and two for over twenty-one years.

Regarding the educational background of respondents: one earned a Technical Level Certificate, seventeen earned an undergraduate diploma, eleven obtained a Masters and one obtained an EdD. The amount of global experience among participants was also wide ranging: eleven people reported having no global experience, two having between four and twelve months' global experience, four people having between one and three years' global experience, and nine having more than three years' global experience.

Measures

Job Descriptions: Respondents were provided thirty-nine job titles and their associated job description[1]. The thirty-nine jobs used in this study are presented in Table 1.

Insert Table 1 about here

Categories of Jobs: Three categories of jobs were identified for analysis and testing: conventional, knowledge and cognitive, which were identified as Alpha, Beta and Gamma to the study's participants. The Conventional category (labeled as Alpha) was defined to participants as *"Jobs in both manufacturing and service industries that typically require, but not always, manual labor. These jobs may be semi-skilled or unskilled. Formal advanced education is not required and on-the-job training tends to be of relatively short duration"*. The Knowledge category (labeled as Beta) was defined to participants as "*Jobs that require employees to apply theoretical and analytical knowledge to formal routinized procedures. These jobs require employees to accumulate, process, and interpret data and information within a specific subject area. They are particularly evident in situations where employees interact with people and/or intangible products"*. The Cognitive category (labeled as Gamma) was defined to participants as *"Jobs that require employees to use intellect and high-level thinking skills to situations they have not previously experienced, in order to solve problems and complete non-routinized tasks. This is done by the employee exploring all possible options to craft a context-sensitive and customized solution to the problem at hand. These jobs are often highly idiosyncratic, such that they are often personalized to the specific individual doing the job."*

[1]Job descriptions are available from the authors.

Controls: Demographic variables including age, gender, education level, industry in which they work, the number years in their current job role, and the number of years of global work experience were controlled for during the analysis.

To ensure participant anonymity, all names were removed from the returned information sheet and coded material and replaced with an identification number ranging from one to thirty. All information sheets and coded materials were kept strictly confidential and were viewed only by the two researchers.

RESULTS

The data collected was analyzed using the frequency statistic in SPSS and by calculating Fleiss' kappa. Fleiss' kappa is a statistical measure of agreement between raters ranking items on a set nominal scale. It is similar to Cohen's kappa, except that whereas Cohen's kappa can only be used assess inter-rater reliability between a pair of raters, Fleiss' kappa works for any number of raters (Fleiss, 1971). This statistic allowed us to determine the amount of inter-rater agreement relative to how each job description was assigned to one of the three types of job categories. Table 2 presents the breakdown of the number of coders, the associated percentage of total coders, and the estimate of classification agreement among coders (Fleiss's kappa), per job title.

As will be noted, there were six job descriptions in which all thirty coders were in complete agreement, five job description in which there was more than 80% estimated coder agreement, ten job descriptions had more than 60% estimated coder agreement, seventeen job descriptions had more than 40% estimated coder agreement, and one job description with 38.2% estimated coder agreement. Each job was classified into one of the three categories with at least 50% (fifteen) coders identifying it as belonging in that category.

Insert Table 2 about here

Fleiss' kappa assesses the relative strength of inter-rater agreement for categorical data, above the level of agreement expected by chance. The recommended level for Fleiss' measure of agreement strength is between .8 and 1 for almost perfect agreement, between .6 and .79 for substantial agreement, between .4 and .59 for moderate agreement and between .2 and .39 for fair agreement (Landis & Koch, 1977). For this study, the kappa value assessing overall inter-rater consistency of coder classifications of the thirty-nine job descriptions was .785. With a Fleiss kappa of .785, this study reveals substantial agreement between coder classifications falling just short of the .8 threshold of the perfect agreement guideline. The high score nonetheless highlights the potential classification power of our three-category job classification scheme.

SECTION II

RESEARCH DESIGN

The second study was carried out in groups on four occasions. A PowerPoint presentation containing 39 job titles (presented in Table 1) was presented through the projector onto the big screen.

Insert Table 1 about here

Each job title was presented on different slide for the period of 15 seconds. This period was shown in the pre-study to be long enough for participants to categorize it in one of the groups. Respondents' task was to write the presented job title in one of the three tables presented to them on the piece of paper. Each table contained category name and description of jobs that fall under that category. There were in total six combinations of names and description of the category, so that each category name was paired with each job description to control for the copying of the “lazy” participants. Before the start of the research participants were presented and read the instructions stating the general purpose of the research and the that there are not correct and incorrect answer but they should categorize according to their own discretion. Their anonymity was guaranteed because we did not ask for any personal information.

Participants

The presentation was provided to 70 respondents, of which 10 of the participants did not categorize all of the jobs so they were excluded from further analysis. Every participant was a student at the Faculty of Economics and Business, University of Rijeka, Croatia ranging from third year of the undergraduate studies to the second year of graduate studies.

Measures

As in Study #1 respondents were provided thirty-nine job titles from U.S. Bureau of Labor Statistics – Standard Occupational Classification (SOC) job classification (presented in table 1). Job titles were translated to Croatian by two experts. In order not to confuse our participants all jobs were presented as male jobs (for example “Actor” and not “Actress” was used).

Categories of Jobs: Three categories of jobs were identified for analysis and testing: conventional, knowledge and cognitive, which were identified as Category A, Category B and Category C to the study’s participants with no specific label.

Due to various limitations we were unable to use control variables aside from different pairing of category name and job descriptions.

RESULTS

The data collected in study #2 was also analyzed using the frequency statistic in SPSS and by calculating Fleiss' kappa. Fleiss' kappa is a statistical measure of agreement between raters ranking items on a set nominal scale. It is similar to Cohen's kappa, except that whereas Cohen's kappa can only be used assess inter-rater reliability between a pair of raters, Fleiss' kappa works for any number of raters (Fleiss, 1971). Fleiss' kappa assesses the relative strength of inter-rater agreement for categorical data, above the level of agreement expected by chance. The recommended level for Fleiss' measure of agreement strength is between .8 and 1 for almost perfect agreement, between .6 and .79 for substantial agreement, between .4 and .59 for moderate agreement and between .2 and .39 for fair agreement (Landis & Koch, 1977). For this study, the kappa value assessing overall inter-rater consistency of coder classifications of the thirty-nine job descriptions was .40. With a Fleiss kappa of .40, this study reveals moderate agreement between coder classifications.

We also calculated the coders agreement on each of the jobs by formula:

Where *n* in Formula represents number of participants and *m* refers to number of time that particular job was grouped under particular category.

This statistic allowed us to determine the amount of inter-rater agreement relative to how each job description was assigned to one of the three types of job categories. Table 1 presents the breakdown of the number of coders, the associated percentage of total coders, and the estimate of classification agreement among coders, per job title. Jobs are ordered by the size of the agreement for each of the category. Criterion for including a job to particular category was that at least 50% of participants categorized it in that category.

Insert Table 3 about here

There are couple of jobs that were perfectly categorized (exclusively to the first category). Also, jobs categorized in the first category were more similar in the size of the agreement between coders in comparison to the second and third category.

In order to present our results more clearly, we employed two additional techniques: Cluster analysis and Multidimensional scaling. Using R programming language, we conducted Wards clustering with 3 cluster. According to this technique, clusters are formed in a way that more similar items are grouped together according to "distances" between them. A Dendogram is presented on the Picture 1.

Insert Picture 1 about here

The dendogram confirms the observed clear distinction between the first category and the other categories. Evidence in favour of this conclusion is observed via the length of the horizontal lines. Items that are similar fall under one "umbrella" and we can assert that the second and third category are starting to diverge much later than first category.

Although helpful in visualizing the data, the dendogram shows how the groups are different in one dimensional space. Multidimensional scaling (MDS) is a technique that can be used to plot the results in multidimensional space (the most often used number of dimensions is two). The purpose of MDS is to present items as points in space in a way that the distance between them represent their differences/similarities as good as they can. Instead of trying to picture and imagine how do results plot based on various matrices and numbers, the relations between items are presented in much more clear fashion (Groenen & Borg, 2013). MDS model fit was assessed by a stress test. According to Kruskal (1964) stress test values below .05 are considered good fit while values below .1 are considered moderate fit. Stress value in our research was .06 which is between the two, afore mentioned, values. Thus, we conclude that the use of MDS was justified.

Insert Picture 2 about here

Combination of MDS and cluster analysis is presented in the Picture 3. The job titles were grouped according to the results of cluster analysis.

Insert Picture 3 about here

Both Picture 2 and Picture 3 provide much more information than a mere dendogram. It is easy to see the distinct grouping of Category A compared to other categories. The one thing that dendogram does not show in this, much more salient, way is the individualization of jobs such as *Artist, Actor, Writer, Fashion Designer, Coach* and *News Anchor* from their "native" Category B. Jobs such as *Firefighter, Hair Stylist* and *Automotive Technician* although members of the Category A seem distant from the "core" of the category.

DISCUSSION

In this paper, we argued for a new three-category job classification scheme to investigate the continued utility of current job classification schemes in light of the dramatic structural change in the composition of the workforce. Our goal was to assess the value in organizing jobs by way of this non-conventional job classification scheme, which categorizes job types as being either Conventional, Knowledge or Cognitive.

Hypothesis 1 asserted that jobs could be classified as either conventional, knowledge or cognitive. This hypothesis was strongly supported in the study. Every coder was able to classify each job and associated description into one of these three classifications; no jobs were reported as being unclassifiable.

Hypothesis 2 explored the consistency in how jobs were classified. High levels of consistency were observed. Hypothesis 2 was supported in the study.

The Section I analysis estimated the level of agreement per job title in accordance with the standard set forth by Landis and Koch (1977). It revealed were six job descriptions with perfect agreement between coders, five job descriptions with almost perfect agreement, ten jobs with substantial agreement and seventeen jobs with moderate agreement. There was only one job description failing to meet the threshold for a fair strength of agreement between coders.

Of the twenty-one job descriptions that were perfectly, almost perfectly or substantially classified with agreement, eleven were classified as conventional, seven as knowledge and three as cognitive. The seventeen jobs with moderate agreement were classified with two as conventional, eight as knowledge, six as cognitive and one job description being split between knowledge and cognitive. The job classified with only moderate agreement was classified as a conventional job. Importantly, there was no job description that was not classified into one of the three categories with less than 50% of the coders' support for it belonging to that category.

It is interesting to note how the six job descriptions in which all thirty coders were in complete agreement, were classified as conventional (alpha) jobs. Conventional work being the job category that was most consistently agreed upon by coders may indicate that this job category was clearly distinguishable from the knowledge (beta) and cognitive (gamma) job categories. There were six job descriptions classified as a mixture of either conventional or knowledge, and fourteen job descriptions coded as a mixture of either knowledge or cognitive, and thirteen job descriptions that were coded as a mixture of all three classifications.

It was expected that the most difficulty would occur when separating knowledge jobs from cognitive jobs, since both categories require higher cognitive demands, in comparison to conventional jobs. The key distinction between knowledge and cognitive work is the indication that knowledge work revolves around completing routine processes, whereas cognitive work requires the development of unique or new processes to deal with non-routinely encountered situations. Having fifteen jobs classified as knowledge and nine jobs classified as cognitive, with at least moderate consistency, suggests that there is a noteworthy difference between these two job categories and that the development of the new cognitive work category has the potential to significantly influence both research and practice.

The results in Section II revealed a deeper level explanation. The MDS graphic allowed us to again observe three distinctive groups of job. The first group of job categorized the simple/conventional jobs, mostly repetitive in their nature. The characteristic of this group of jobs is that the impetus for any activity comes from outside and employee has to adjust and manage the needs and find a way how to meet the demand in the most appropriate way.

The second distinctive group of jobs are more knowledge-based type of activities. They demand for more specific type of specialist knowledge. The distinctive subgroup for jobs like *Fashion designer, Actor, Artist, Writer, News anchor and Professional coach* are all job titles that we can describe as “visible” jobs. In a way that people come across these kinds of jobs on a daily basis and presumably all of us have our own perception of those jobs. Additionally, they came across the embedded need for creativity, artistry and non-repetitive type of work when dealing with the problem, project or client.

The third distinctive group of jobs is characterized by the high complexity of problem they have to deal with. They function in the world where the impetus for any activity is their own idea, innovation or creation which they materialize in the world of obstacles and constraints. It is contrary to the first group in a way that in the third group they have to create and image a new solution, a new method or a new project. The main difference between the second and third group of job is that the second group of jobs is less cognitively demanded and consist of the repetitive activities (with the exemption) of the subgroup of several creative jobs.

Limitations

There are potential reasons that some job descriptions were classified with lower levels of agreement between coders. First, there may have been problems with the implementation methodology used. Instructions given to the coders were intentionally brief, opening up the potential for uncertainty of the coders on how to proceed. Different interpretations of the instructions may have impacted the results and influenced the differences amongst the coders' classifications. Second, the three job categories may have been insufficiently articulated to the coders. If coders found the job category definition to be ambiguous, they may have interpreted the category differently than their peer coders. Again, this could have impacted their ability to place the job descriptions into consistent categories.

This study used only thirty-nine job descriptions. Considering there are 12,099 different job titles listed in the Dictionary of Occupational Titles (US Department of Labor, Employment & Training Administration, 1977), this is a very slim selection of jobs represented. Although we strove to choose a variety of jobs to well represent the workforce, if different job descriptions had been chosen for the study there could have been different results.

Using a limited number of job descriptions also limits the generalizability of the study's results and the ability to categorize all jobs into one of our three established job categories (Conventional, Knowledge, and Cognitive). Similarly, having only thirty participants in the Section I is a small sample size, which could also lead to a lack of generalizability to the greater population.

Practical Implications and Future Research

The relationships examined in this paper offer significant contributions to the literature in three primary ways. First, following an extensive review of the job analysis literature, the "Cognitive Work" construct was introduced. As this is a newly developed concept, it should continue to be explored and examined for the importance that it has in the organization, the workforce, the associated literature, and whether or not there is a need for enhanced specification of this work category.

Second, with the introduction of cognitive work a new three-category job classification scheme was developed. This new classification scheme allows for the recoding of an organization's workers according to the type of mental requirements their job demands. As suggested by the results this could have a significant impact on the presently over-populated category of service workers.

Third, the proposed classification scheme would also allow researchers to compare classifications of workers in two different organizations within the same industry, across industries and across nations. Doing this is often difficult when classifications are based on compensation, unions, or department because these classification schemes are not consistent between organizations. However, this new macro-level of job classification can be used globally and across organizations in a variety of industries.

There are several consequences of implementing this new classification scheme into organizations. In 2009 the American Society for Training and Development estimated that $134.07 billion was spent in the US during 2008 on employee learning and development. This money would be better spent if the training and development programs were aligned with the type of work employees were doing on a daily basis. To incorporate this classification scheme into organizations would imply an increase of investment in training and development, selection, and appraisal systems so that these HRM systems include cognitive workers. Also, along the lines of training, it could have implications for Executive Development and MBA programs as to what degree these students are trained as knowledge (technicians) and cognitive (leaders) workers.

There are also implications the introduction of cognitive workers may have on work-life balance, the cognitive intrusion of work and managing part-time workers. These potential implications should be explored in future research.

The intitial study was conducted in the US, and included only thirty respondents and a second study was conducted in Croatia with 70 respondents. Such a limited group was targeted and used so that this could act as an initial study to see if the claims made were valid and if future research regarding this topic and the emergence of cognitive work is worthwhile. In order to further evaluate the propositions made in this study, future research should be conducted using a much larger sample, perhaps via an internet survey or computer application which has the ability to target a much larger set of respondents.

Finally, considering the level of global work experience by respondents and small sample size, these findings may not be valid globally. Although the pilot was performed in both the US and a European country, there is a chance that these results are not as applicable to the workforce in countries other countries. In order to assess this, further research should be conducted across the globe.

REFERENCES

Aguinis, H., Mazurkiewicz, M. D., & Heggestad, E. D. (2009). Using web-based frame-of-reference training to decrease biases in personality-based job analysis: An experimental field study. ***Personnel Psychology***, 62(2), 405-438.

American Society for Training and Development. (2009). ***State of the industry report***. [online], available: http://www.astd.org/content/research/stateOfIndustry.htm [accessed 23 September 2010].

Ash, R. (1988). Job analysis in the world of work. In S. Gael (Ed.), ***The job analysis handbook for business, industry and government*** (Vol. I) (pp. 3-13). New York: John Wiley and Sons, Inc.

Bailey, K. D. (1973). Monothetic and polythetic typologies by the heuristic method. ***The Sociological Quarterly***, 14(3), 291-308.

Baruch, I. (1937). ***Facts and fallacies about position-classification. Civil service assembly of the United States and Canada pamphlet no. 10***. Chicago, Illinois: Civil Service Assembly of the United States and Canada.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*, 99-120.

Baruch, I. (1941). ***History of position-classification and salary standardization in the federal Service 1789-1941***. Washington, DC: US Civil Service Commission Personnel Classification Division.

Bell, D. (1973). ***The coming of post-industrial society: A venture in social forecasting***. New York, NY: Basic Books.

Blackler, F. (1995). Knowledge, knowledge work and organizations: An overview and Interpretation. ***Organization Studies,*** 16(6), 1020-1046.

Brannick, M. T., Brannick, J. P., & Levine, E. L. (1992). Job analysis, personnel selection and the ADA. ***Human Resource Management Review***, 2(3), 171-182.

Brannick, M. T., Levine, E.L. & Morgeson, F. P. (2007). ***Job and work analysis: Methods, research, and applications for human resource management*** (2nd ed.). Thousand Oaks, CA: Sage Publications, Inc.

Carter, S. B., Gartner, S. S., Haines, M. R., Olmstead, A.L., Stuch, R. & Wright, G. (Eds.). (2006). ***Historical statistics of the United States: Earliest times to the present*** (Vol. 2). New York, NY: Cambridge University Press.

Christal, R. E. (1974) ***The United States Air Force occupational research project***. No. AFHRL—TR-73-75. Brooks Air Force Base, TX: Air Force Human Resource Laboratory.

Christal, R. E. & Weissmuller, J. J. (1988). Job-task inventory analysis. In S. Gael (Ed.), ***The job analysis handbook for business, industry and government*** (Vol. II) (pp. 1019-1035). New York: John Wiley and Sons, Inc.

Clifford, J. P. (1996). Manage work better to better manage human resources: A comparative study of two approaches to job analysis. ***Public Personnel Management***, 25(1), 89-102.

Cornelius, E.T., Carron T. J. & Collins, M. N. (1979). Job analysis models and job classification. ***Personnel Psychology***, 32, 693-708.

Cortada, J. W. (1998). Where did knowledge workers come from. In J. W. Cortada (Ed.), ***Rise of the Knowledge Worker*** (pp. 3-22). Boston, MA: Butterworth-Heinemann.

Davenport, T. H. (2017) The rise of cognitive work (re)design, Deloitte Review, 21, July, pp. 108-120.

Dierdoff, E. C. & Wilson, M. A. (2003). A meta-analysis of job analysis reliability. ***Journal of Applied Psychology***, 88(4), 635-646.

Drucker, P. F. (1959). ***Landmarks of tomorrow***. New York: Harper & Row.

Drucker, P. F. (1999) Knowledge worker productivity: The biggest challenge. ***California Management Review***, 41(2), 79-94.

Drucker, P. (2001). The next society. ***Economist***, 361(8246), 3-5.

Equal Employment Opportunity Commission, U. S. Civil Service Commission, U. S. Department of Labor & U. S. Department of Justice. (1978). ***Uniform guidelines on employment selection procedures.*** Federal Register, 43, No. 166, 38290-38309.

Ezzedeen, S. R., & Swiercz, P. M. (2003). Cognitive consequences of overwork. ***Human Resource Planning,*** 26(3), 7-8.

Ezzedeen, S. R., & Swiercz, P. M. (2007). Development and initial validation of a cognitive-based work-nonwork conflict scale. ***Psychological Reports,*** 100(3), 979-999.

Felsberg, E. J. (2004). Conducting job analyses and drafting lawful job descriptions under the Americans with Disabilities Act. ***Employment Relations Today***, 31(3), 91-93.

Field, H. S. & Holley, W. H. (1982). The relationship of performance appraisal system characteristics to verdicts in selected employment discrimination cases. ***Academy of Management Journal***, 25(2), 392-406.

Fine, S. A. (1955). A structure of worker functions. ***Personnel and Guidance Journal***, 34, 66-73.

Fine, S. A. (1988). Functional job analysis. In S. Gael (Ed.), ***The job analysis handbook for business, industry and government*** (Vol. II) (pp. 1019-1035). New York: John Wiley and Sons, Inc.

Fine, S. A., & Cronshaw, S. F. (1999). ***Functional job analysis: A foundation for human resources management***. Mahwah, NJ: Erlbaum.

Flanagan, J. C. (1949). Critical requirements: A new approach to employee evaluation. ***Personnel Psychology***, 2, 419-425.

Flanagan, J. C. (1954). The critical incident technique. ***Psychological Bulletin***, 51, 327-358.

Fleiss, J. L. (1971). Measuring nominal scale agreement among many raters. ***Psychological Bulletin***, *76*(5), 378-382.

Furbank, P. N. (1992). ***Diderot: A critical biography***. New York, New York: Alfred A

Knopf, Inc.
Gael, S. (1983). ***Job analysis: A guide to assessing work activities***. San Francisco: Jossey-Bass.
Ghorpade, J., & Atchison, T. J. (1980). The concept of job analysis: A review and some suggestions. ***Public Personnel Management***, 9(3), 134-144.
Griggs v. Duke Power Company, 401 U.S. 424 (1971).
Greenspan v .Automobile Club of Michigan, 495 F. Supp. 1021 (1980).
Groenen, P.J. i Ingwer B. (2013). The Past, Present, and Future of Multidimensional Scaling., Econometric Institute Report EI 2013-07.
Guardians Association New York City Police Department v. Civil Service Commission of New York, 630 R. 2d 79 (1980).
Hackman, J. R., & Oldham, G. R. (1975). Development of the job diagnostic survey. ***Journal of Applied Psychology,*** 60 (2), 159-170.
Hackman, J. R., & Oldham, G. R. (1980). Motivation through the design of work. In J. R. Hackman & G. R. Oldham (Eds.), ***Work redesign*** (Chapter 4, pp. 71-97). Reading, MA: Addison-Wesley.
Hall, E. J. (1993). Waitering/waitressing: Engendering the work of table servers. ***Gender and Society,*** 7(3), 329-346.
Hartman, E. A., Mumford, M. D. & Muller, S. (1992). Validity of job classifications: An examination of alternative indicators. ***Human Performance***, 5(3), 191-211.
Harvey, R. J. (1986). Quantitative approaches to job classification: A review and critique. ***Personnel Psychology***, 39, 267-289.
Heery, E., & Noon, M. (2001a). Job Description. ***A dictionary of human resource management*** (pp. 186). Oxford, New York: Oxford University Press.
Heery, E., & Noon, M. (2001b). Job Family. ***A dictionary of human resource management*** (pp. 187). Oxford, New York: Oxford University Press.
Janz, B. D., Colquitt, J. A., & Noe, R. A. (1997). Knowledge worker team effectiveness: The role of autonomy, interdependence, team development, and contextual support variables. ***Personnel Psychology***, 50, 877–904.

Johnson, R. N. & Libecap, G. D. (1994). ***The federal civil service system and the problem of bureaucracy: The economics and politics of institutional change.*** Chicago, IL: University of Chicago Press.
Jones v. New York City Human Resource Administration, 528 F. 2d 696 (1975).
Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: A failure to disagree. ***American Psychologist***, 64(6), 515-526.
Kirkland v. New York State Department of Correctional Services, 520 F.2d 420 (2nd Cir. 1975).
Kruskall, J.B. (1964). Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. *Psychometrika, 29,* 1-27.
Landis, J.R. & Koch, G.G. (1977). The measurement of observer agreement for categorical data. ***Biometrics***, 33(1), 159-74.
Lawrence, J. E. S. (1988). Occupational information: Status and sources. In S. Gael (Ed.), ***The job analysis handbook for business, industry and government*** (Vol. I) (pp. 369-388). New York: John Wiley and Sons, Inc.
Levine, E. L., Ash, R. A., Hall, H., & Sistrunk, F. (1983). Evaluation of job analysis methods by

experienced job analysts. ***Academy of Management Journal***, 26(2), 339-348.

Levine, E. L, Thomas, J. N. & Sistrunck, F. (1988) Selecting a job analysis approach. In S. Gael (Ed.), ***The job analysis handbook for business, industry and government*** (Vol. I) (pp. 339-352). New York: John Wiley and Sons, Inc.

Lipshitz, R., Klein, G., & Carroll, J. S. (2006). Introduction to the special issue. naturalistic decision making and organizational decision making: Exploring the intersections. ***Organization Studies***, 27(7), 917-923.

Martin, R. (2007). How successful leaders think. ***Harvard Business Review***, 85(6), 60-67.

McCormick, E. J. (1979). ***Job analysis: Methods and applications***. New York, NY: AMACOM.

McCormick, E. J., Jeanneret, P. R. & Mecham, R. C. (1972). A study of job characteristics and job dimensions as based on the position analysis questionnaire (PAW). ***Journal of Applied Psychology***, 56, 347-368.

McCormick, E.J. & Jeanneret, P. R. (1988). Position analysis questionnaire (PAQ). In S. Gael (Ed.), ***The job analysis handbook for business, industry and government*** (Vol. II) (pp. 825-842). New York: John Wiley and Sons, Inc.

McEntire, L. E., Dailey, L. R., Osburn, H. K., & Mumford, M. D. (2006). Innovations in job analysis: Development and application of metrics to analyze job data. ***Human Resource Management Review***, 16(3), 310-323.

McKelvey, B. (1978). Taxonomic lessons from biology. ***Management Science***, 24(13), 1428-1440.

Mohrman, S. A., Finegold, D., & Klein, J. A. (2002). Designing the knowledge enterprise: Beyond programs and tools. ***Organizational Dynamics***, 31(2), 134-150.

Needham, R. (1975). Polythetic classification: Convergence and consequences. ***Man, new series***, 10(3), 349-369.

Osterman, P. (1997). Work organization. In P. E. Capelli (Ed.), ***Change at work***, 89-121. New York: Oxford University Press.

Occupational Information Network. (2006). Photius Coutsoukis and Information Technology Associates. [online], available: http://www.occupationalinfo.org/ [accessed 2 June 2010].

Parker, S. K., Wall, T. D., & Cordery, J. L. (2001). Future work design research and practice: Towards an elaborated model of work design. ***Journal of Occupational & Organizational Psychology***, 74(4), 413.

Pearlman, K. (1987). Job families: A review and discussion of their implications for personnel selection. ***Psychological Bulletin***, 87(1), 1-28.

Penrose, E.T. (1959). The theory of the Growth of the Firm. Oxford: Basil Blackwell.

Peterson, R. A. (1994). A meta-analysis of cronbach's coefficient alpha. ***Journal of Consumer Research,*** *21*(2), 381-391.

Porat, M. U. (1998). The information economy: Definition and measurement. In J. W. Cortada (Ed.), ***Rise of the knowledge worker*** (pp.101-132). Boston, MA: Butterworth-Heinemann.

Prien, E.P., Goodstein, L. D., Goodstein, J. & Gamble Jr., L.G. (2009). ***A practical guide to job analysis***. San Fransisco, CA: John Wiley & Sons, Inc.

Prien, E. P., Prien, K. O. & Gamble, L. G. (2004). Perspectives on nonconventional job analysis methods. ***Journal of Business and Psychology***, 18(3), 337-348.

Primoff, E. S. (1957). The j-coefficient approach to jobs and tests. ***Personnel Administration***, 20, 34-40.

Primoff, E. S. & Fine, S. A. (1988). Job element analysis. In S. Gael (Ed.), ***The job analysis handbook for business, industry and government*** (Vol. I) (pp. 14-29). New York: John Wiley and Sons, Inc.

Reskin, B. (1993). Sex segregation in the workplace. ***Annual Review of Sociology,*** 19, 241-270.

Sanchez, J. I. & Levine, E. L. (2000). Accuracy or consequential validity: Which is the better standard for job analysis data? ***Journal of Organizational Behavior***, 21(7), 809-818.

Singh, P. (2008). Job analysis for a changing workplace. ***Human Resource Management Review***, 18(2), 87-99.

Sokal, R. R. (1974). Classification: Purposes, principles, progress, prospects. ***Science***, 185(4157), 1115-1123.

Sonnentag, S., & Kruel, U. (2006). Psychological detachment from work during off-job time: The role of job stressors, job involvement, and recovery-related self-efficacy. ***European Journal of Work and Organizational Psychology,*** 15(2), 197-217.

Sparks, C. P. (1988) Selecting a job analysis approach. In S. Gael (Ed.), ***The job analysis handbook for business, industry and government*** (Vol. I) (pp. 37-47). New York: John Wiley and Sons, Inc.

Strang, D. and Baron, J. N. (1990). Categorical imperatives: The structure of job titles in California state agencies. ***American Sociological Review,*** 55(4), 479-495.

Stutzman, T. M. (1983). Within classification job differences. ***Personnel Psychology***, 36, 503-516.

Theologus, G. C. (1969). ***Development of a taxonomy of human performance: A review of biologic taxonomy and classification.*** Washington, DC: American Institutes for Research, Technical Report 3.

Thompson, D. E., & Thompson, T. A. (1982). Court standards for job analysis in test validation. ***Personnel Psychology***, 35(4), 865-874.

Turing, A. M. (1950). I-computing machinery and intelligence. ***Mind***, 59, 433-460.

Uhrbrock, R. S. (1922). The history of job analysis. ***Administration***, 3, 164-168.

United States Department of Commerce Bureau of the Census. (1976). ***Historical statistics of the United States: Colonial times to 1970*** (Part 1). Washington, D.C.: U.S. Dept. of Commerce, Bureau of the Census.

United States Department of Labor: Bureau of Statistics (2010a) ***Employment situation summary***, Table B-1. Employees on nonfarm payrolls by industry sector and selected industry detail. [online], available: http://www.bls.gov/news.release/empsit.t17.htm [accessed 30 July 2010].

United States Department of Labor: Bureau of Statistics (2010b) ***Employment situation summary***, Table A-13. Employed and unemployed persons by occupation, not seasonally adjusted. [online], available: http://www.bls.gov/news.release/empsit.t13.htm [accessed 30 July 2010].

United States Department of Labor, Employment and Training Administration. (1977). ***Dictionary of occupational titles*** (4th ed.). Washington, DC: The Administration.

Unites States Equal Employment Opportunities Commission. (1996). ***Job classification guide***. Washington, DC: US Equal Employment Opportunities Commission.

Van Wart, M. (2000). The return to simpler strategies in job analysis. ***Review of Public Personnel Administration***, 20(3), 4-27.

von Eye, A., Mun, E. Y. & Indurkhya, A. (2004). Typifying developmental trajectories: A

decision making perspective. ***Psychology Science***, 46(1), 65-98.
Washington v. Davis, 426 U.S. 229 (1976).
Wilson, M. A. (2007). A history of job analysis. In, L. L. Koppes (Ed.), ***Historical perspectives in industrial and organizational psychology*** (pp. 219-241). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Appendices

TABLE 1 Job Titles

Study I

Actor/Actress	Defense Lawyer	Professional Coach
Artist	Education Financial Analyst	Professor
Automotive Technician	Electrical Engineer	Public Elementary School Teacher
Building Design Architect	Fashion Designer	Real Estate Agent
Building Maintenance Laborer	FedEx Delivery Agent	Registered Nurse
Career Transitions Specialist	Hair Stylist/Barber	Retail Cashier
Certified Public Accountant	Hotel Bell Hop	Retail Sales Floor Clerk
Chief Executive Officers	Library Assistant	Security Guard
Commercial Airlines Pilot	Municipal Fire Fighter	Sports News Anchor
Computer Software Programmer	Office Secretary/Administrator	Statistical Research Analyst
Creative Writer	Parking Valet	Taxi Driver
Crime Scene Investigator	Pharmacist	Veterinarian
Customer Service Representative	Political Scientist	Waiter

Study II

Actor	Lawyer	Professional Coach
Artist	Education Financial Analyst	Professor
Automotive Technician	Electrical Engineer	Teacher
Architect	Fashion Designer	Real Estate Agent
Building Maintenance Laborer	Delivery Agent	Registered Nurse
Career Transitions Specialist	Hair Stylist	Retail Cashier
Accountant	Hotel Bell Hop	Retail Sales Floor Clerk
Chief Executive Officer	Librarian	Security Guard
Commercial Airlines Pilot	Fire Fighter	News Anchor
Computer Software Programmer	Office Secretary	Statistician
Writer	Parking Valet	Taxi Driver
Crime Scene Investigator	Pharmacist	Veterinarian
Customer Service Representative	Political Scientist	Waiter

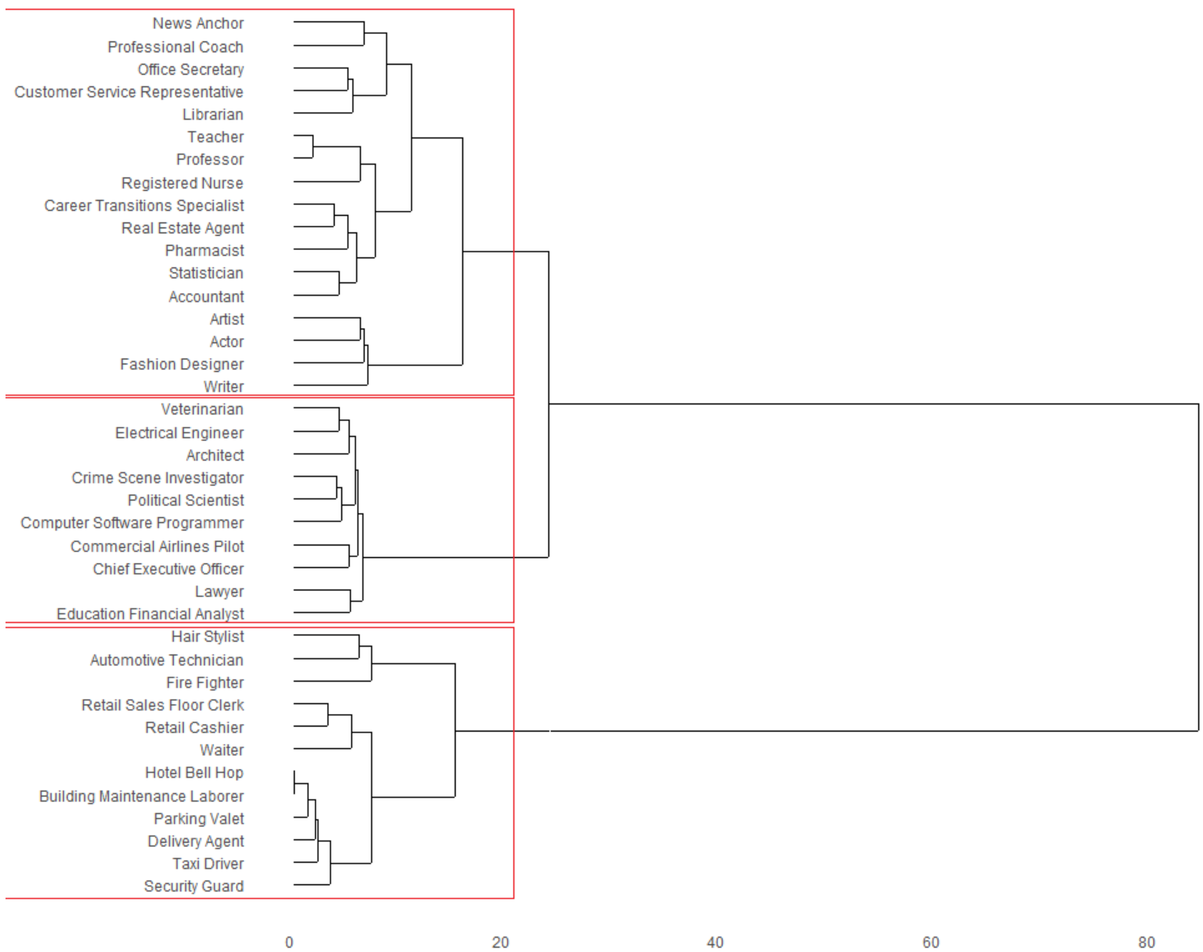
TABLE 2
Section I results- Coder Agreement by Job Title

Job Title	Alpha	Beta	Gamma	Level of Agreement
Building Maintenance Laborer	30 (100%)	0 (0%)	0 (0%)	1
FedEx Delivery	30 (100%)	0 (0%)	0 (0%)	1
Hotel Bell Hop	30 (100%)	0 (0%)	0 (0%)	1
Parking Valet	30 (100%)	0 (0%)	0 (0%)	1
Taxi Driver	30 (100%)	0 (0%)	0 (0%)	1
Waiter	30 (100%)	0 (0%)	0 (0%)	1
Retail Cashier	28 (93.3%)	2 (6.7%)	0 (0%)	0.871
Retail Sales Clerk	28 (93.3%)	2 (6.7%)	0 (0%)	0.871
CPA	0 (0%)	27 (90%)	3 (10%)	0.814
CEO	0 (0%)	3 (10%)	27 (90%)	0.814
Education Financial Analyst	0 (0%)	27 (90%)	3 (10%)	0.814
Commercial Airlines Pilot	0 (0%)	25 (83.3%)	5 (16.7%)	0.713
Computer Programmer	0 (0%)	25 (83.3%)	5 (16.7%)	0.713
Library Assistant	25 (83.3%)	5 (16.7%)	0 (0%)	0.713
RN	0 (0%)	25	5 (16.7%)	0.713
Career Transitions Specialist	0 (0%)	24 (80%)	6 (20%)	0.669
Security Guard	24 (80%)	6 (20%)	0 (0%)	0.669
Public Elementary Teacher	1(3.3%)	24 (80%)	5 (16.7%)	0.657
Customer Service Rep	23 (76.7%)	7 (23.3%)	0 (0%)	0.63
Political Scientist	0 (0%)	7 (23.3%)	23 (76.7%)	0.63
Creative Writer	2 (6.7%)	5 (16.7%)	23 (76.7%)	0.607
Statistical Analyst	0 (0%)	22 (73.3%)	8 (26.7%)	0.595
Sports News Anchor	3 (10%)	22 (73.3%)	5 (16.7%)	0.561
Real Estate Agent	8 (26.7%)	21 (70%)	1(3.3%)	0.547
Defense Lawyer	0 (0%)	10 (33.3%)	20 (66.7%)	0.54
Crime Scene Investigator	0 (0%)	19 (63.3%)	11 (36.7%)	0.52
Pharmacist	1 (3.3%)	20 (66.7%)	9 (30%)	0.52
Professor	0 (0%)	11 (36.7%)	19 (63.3%)	0.52
Building Design Architect	0 (0%)	12 (40%)	18 (60%)	0.503
Office Secretary/Administrator	18 (60%)	12 (40%)	0 (0%)	0.503
Automotive Technician	19 (63.3%)	10 (33.3%)	1 (3.3%)	0.497
Electrical Engineer	4 (13.3%)	20 (66.7%)	6 (20%)	0.485
Veterinarian	0 (0%)	15 (50%)	15 (50%)	0.483
Fashion Designer	2 (6.7%)	10 (33.3%)	18 (60%)	0.457
Professional Coach	1 (3.3%)	15 (50%)	14 (46.7%)	0.451
Actor/Actress	2 (6.7%)	11 (36.7%)	17 (56.7%)	0.441
Artist	3 (10%)	9 (30%)	18 (60%)	0.441
Municipal Firefighter	9 (30%)	18 (60%)	3 (10%)	0.441
Hair Stylist/Barber	16 (53.3%)	9 (30%)	5 (16.7%)	0.382

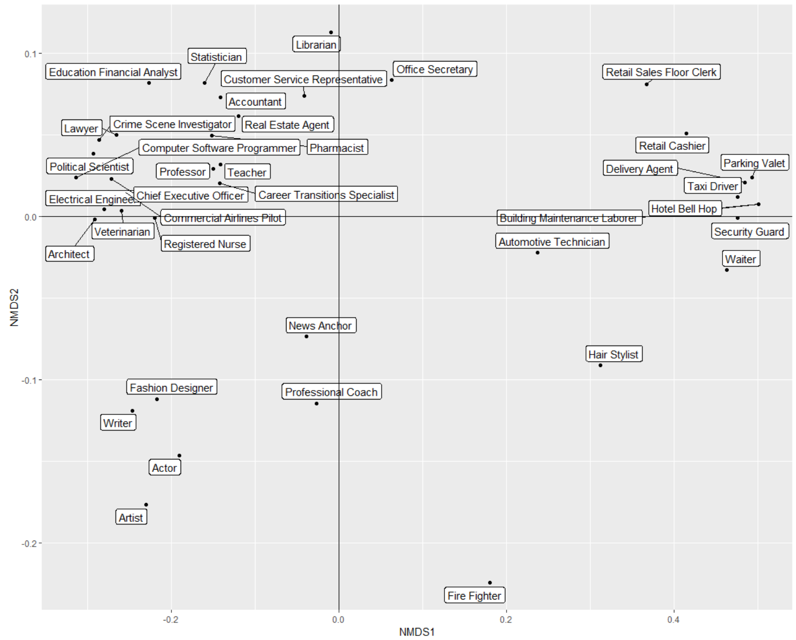
Table 3 Section II Coder Agreement by Job Title

		A Frequency (%)	B Frequency (%)	C Frequency (%)	Level of Agreement
1	Building Maintenance Laborer	60 (100%)	0 (0%)	0 (0%)	1,00
2	Hotel Bell Hop	60 (100%)	0 (0%)	0 (0%)	1,00
3	Parking Valet	59 (98,3%)	1 (1,7%)	0 (0%)	0,94
4	Delivery Agent	58 (96,7%)	2 (3,3%)	0 (0%)	0,92
5	Security Guard	57 (95%)	2 (3,3%)	1 (1,7%)	0,91
6	Taxi Driver	57 (95%)	3 (5%)	0 (0%)	0,89
7	Waiter	56 (93,3%)	1 (1,7%)	3 (5%)	0,84
8	Retail Cashier	50 (83,3%)	10 (16,7%)	0 (0%)	0,68
9	Retail Sales Floor Clerk	47 (78,3%)	10 (16,7%)	3 (5%)	0,61
10	Hair Stylist	43 (71,7%)	10 (16,7%)	7 (11,7%)	0,48
11	Automotive Technician	37 (61,7%)	17 (28,3%)	6 (10%)	0,53
12	Fire Fighter	36 (60%)	9 (15%)	15 (25%)	0,39
13	Teacher	0 (0%)	50 (83,3%)	1 (16,7%)	0,72
14	Accountant	1 (1,7%)	47 (78,3%)	12 (20%)	0,69
15	Professor	0 (0%)	49 (81,7%)	11 (18,3%)	0,69
16	Customer Service Representative	12 (20%)	46 (76,7%)	2 (3,3%)	0,64
17	Career Transitions Specialist	0 (0%)	47 (78,3%)	13 (21,7%)	0,64
18	Real Estate Agent	4 (6,7%)	43 (71,7%)	13 (21,7%)	0,59
19	Statistician	2 (3,3%)	43 (71,7%)	15 (25%)	0,54
20	Librarian	17 (28,3%)	38 (63,3%)	5 (8,3%)	0,53
21	Pharmacist	4 (6,7%)	40 (66,7%)	16 (26,7%)	0,53
22	Office Secretary	22 (36,7%)	35 (58,3%)	3 (5%)	0,48
23	Registered Nurse	1 (1,4%)	31 (51,7%)	28 (46,7%)	0,49
24	Education Financial Analyst	0 (0%)	35 (58,3%)	25 (41,7%)	0,50
25	Computer Software Programmer	0 (0%)	15 (25%)	45 (75%)	0,61
26	Architect	0 (0%)	19 (31,7%)	41 (68,3%)	0,59
27	Crime Scene Investigator	0 (0%)	20 (33,3%)	40 (66,7%)	0,57
28	Political Scientist	0 (0%)	2 (33,3%)	40 (66,7%)	0,57
29	Chief Executive Officer	0 (0%)	24 (40%)	36 (60%)	0,53
30	Writer	11 (18,3%)	11 (18,3%)	38 (63,3%)	0,48
31	Electrical Engineer	0 (0%)	24 (40%)	36 (60%)	0,53
32	Veterinarian	1 (1,7%)	24 (40%)	35 (58,3%)	0,49
33	Lawyer	0 (0%)	25 (41,7%)	35 (58,3%)	0,51
34	Commercial Airlines Pilot	1 (1,7%)	24 (40%)	35 (58,3%)	0,49
35	Artist	17 (28,3%)	11 (18,3%)	32 (53,3%)	0,40
36	Fashion Designer	8 (13,3%)	22 (36,7%)	30 (50%)	0,40
37	Actor	15 (25%)	17 (28,3%)	28 (46,7%)	0,36
38	Professional Coach	20 (33,3%)	25 (41,7%)	15 (25%)	0,34
39	News Anchor	19 (31,7%)	28 (46,7%)	13 (21,7%)	0,38

Picture 1. Dendogram of cluster analysis



Picture 2. Multidimensional mapping of job titles



Picture 3 Multidimensional mapping of job titles according to clusters