

GHOSTS IN THE SHELL: AN INVESTIGATION OF THE RELATIONSHIP BETWEEN
AUTOMATION AND THE NATURE OF WORK

By

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By David Charles Touve

For Laura, who has given so much to me while also giving up so much for me.

For Alena, may your desire to learn equal your desire to dance.

For my parents, who first encouraged in me the desire to know, not only for the sake of knowing, but also for the sake of doing something worth doing.

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CHAPTER I

INTRODUCTION

Early in the history of AT&T, switchboard operators—like my grandmother—manually connected each call with its terminus by way of patch cables (AT&T, 2008). At that time, upon picking up a telephone receiver a caller was immediately connected to a human operator, who personally and physically “patched” the connection to the desired destination according to the caller’s request. In time, artificial operators—electronic relay switches—autonomously connected callers with their intended destination. Presently, we dial the number we want to reach, a machine “hears” these numbers as formatted tones, and a computerized relay switch converts these numbers into action and connects us with our numbered destination. As a result, an automated network of information processing machines now performs a primary service provided by AT&T, a service that was once fulfilled by friendly (in most cases) human operators—connecting each caller with their desired destination.

By the middle decades of the 20th century, automation was a novel phenomenon introduced more commonly by way of large, electro-mechanical apparatus within mass production factories and utility infrastructure. The arrival of this apparatus was met with both wonder and concern. In 1959, a story in the *Denver Post* warned, “*Electronic ghosts are ready to step into American factories*” (Denver Post 1959, emphasis added). “What is automation?” was a question, the answer to which was often taken for granted. “What are consequences of automation for the nature of work?” was a puzzling concern

for which a great many conflicting predictions were made. In many ways, the answers to these questions continue to go unsettled.

The automation of work has expanded from the factory floor to the floors of global financial exchange, from the back office to the executive suite. In 1955, Alan Newell, Herbert Simon and J.C Shaw wrote a computer program called “Logic Theorist” (Newell & Simon, 1956). The application, using symbolic logic rather than mathematical computation, independently constructed logical proofs for the majority of theorems developed by Whitehead and Russell in their cornerstone work of mathematical philosophy, the *Principia Mathematica* (1913). By way of Logic Theorist, a system of proofs that took Whitehead and Russell more than a decade to produce were produced again—not copied, but logically derived—in a matter of hours by a computer comparable in information processing power to a modern financial calculator.

During the 1970’s, the “electronic ghosts” of information work would take on less philosophically foundational challenges than the *Principia Mathematica*, focusing instead upon the tasks of basic data processing. At the time, my uncle was one of a new breed of computer programmers, who by way of punch cards programmed monolith-like computing mainframes to manage information within payroll, pension, and data storage applications at the Standard Oil Company. Similar yet dustier mainframe computers are still in use today.

By the 1980’s, more complex computer programs began matching and executing trades on the major global financial exchanges (Gastineau, 1991; Stoll, 2006). I was one of those floor traders who early in the 1990’s, in a scene straight out of Vonnegut’s *Piano Player* (1952), found himself training his electro-mechanical replacement—in this case, the GLOBEX electronic exchange platform. During the years between 1980 and 2007, automation was artificially replicating not only the physical activities of floor traders, but

also the decision-making processes of these traders. According to *The Economist*, major exchange trading volume attributed to “algo” funds—firms that use computers not only to execute trades on electronic exchanges, but also to make trading decisions autonomously based upon programmed algorithms—was estimated to be 30% of total volume in 2007, likely to expand to 50% of volume by 2010 (*The Economist*, 2007). In fact, during the 30-days prior to December 17, 2009, 48% of shares traded on the NYSE exchanges were the results of trades initiated by computers (NYSE Euronext Inc, 2009).

The intent of this project is to return to this longstanding concern for the impact of automation upon the nature of work. Within this dissertation, automation will be considered quite broadly as the performance of a task, physical or mental, in whole or in part, by a machine. Davis (1963, p. 179), drawing upon the perspective of cybernetics (Wiener, 1948), defined automation quite precisely as “a work process which includes (1) computer information processing for decision-making and (2) information feedback and control systems for automatic self-regulation of production.” In a more general sense however, automation has been defined as “the process of having a machine or machines accomplish tasks hitherto performed wholly or partly by humans” (Hess, 2005, “Automation,” para. 1).

The debate over the consequences of automation for the nature of work is bounded by extremes. At the one extreme within this debate is concern that automation leads to increasingly routine work, if not the end of work altogether for a large proportion of those otherwise employed. Essentially, autonomous machines are seen as a clear substitute for the biological machines that constitute human labor. As Stafford Beer argued (1972), “History has painfully demonstrated that once mankind knows how to perform a function by machine, the machine is in and the man is out.” Nearly forty years later, Nicholas Carr—previous editor of *Harvard Business Review*—would write in an

article for *The Atlantic* (2008), “As we come to rely on computers to mediate our understanding of the world, it is our own intelligence that flattens.”

At the other extreme of this debate is the expectation that automation in the workplace leads to a very different sort of worker—a “bionic man,” who can be better, stronger, and faster than workers past. Furthermore, it is believed that automation leads not only to better workers, but also very different and altogether positive sorts of work. As Davis (1963, p. 282) argued in one of the earliest publications of the *Academy of Management Review*, “Automation releases man to perform work of a higher order—more intellectual, creative, and idealistic.”

Importantly, the phenomenon of automation is firmly staked within one of the more foundational concerns for organization theory—the relationship between the technology and the social structure of organizations. The hope for this dissertation is that the research might not only further inform, and perhaps settle certain outstanding conflicts regarding the impacts of automation upon the general nature of work, but also contribute to our understanding of technology and its relationships with work and organizations. At the very least, an empirical inquiry may be able to refine the questions themselves, given these “electronic ghosts” have now been a part of our work environments for more than a half-century.

The first article clearly focused upon automation to appear in the *Academy of Management Journal* was titled, “Organizational Implications of Automation” (Lipstreu, 1960). Executives from 210 of the “largest industrial firms in the United States” estimated the highest level of automation that existed in their firms and indicated “their experience and opinion relative to the effects of increasing automation on various aspects of manpower management” (Lipstreu, 1960, p. 119). In subsequent decades, the majority of inquiries relating automation to the nature of work would involve relatively

small samples—either in terms of the number of working individuals or the number of work settings examined within the research.

The conclusions drawn within this dissertation, while returning to the theme of the implications of automation for the nature of work, will be based upon data generated in a survey of nearly 100,000 employed individuals across nearly 750 occupations. Each individual was randomly selected from a sample of organizations, each of which was randomly selected from a population of firms operating across a range of industries within the United States. These data were collected as part of the O*NET project, a partnership involving the U.S. Department of Labor, the Research Triangle Institute (RTI) International, and a consortium of universities. The individuals surveyed span the range of occupations included within Standard Occupational Classification System (SOC), and the organizations within which the surveys were conducted span the top-level classifications of the North American Industry Classification System (NAICS). This dissertation will focus upon changes in the nature of work (e.g., routinization, skill requirements) associated with changes in the degree to which automation is a factor in work, as reported by the individuals surveyed as part of the O*NET project.

Structure of Manuscript

This manuscript is organized as follows. In Chapter II, I will provide a critical summary of the longstanding definitions of and approaches to the phenomena that are technology, work, and social structure. I will also summarize the broad theoretical debate that exists regarding the causal nature of the relationships linking technology with work and social structure. Teasing apart the various perspectives within these debates is no simple matter, as technology, work, and social structure have been conceived in

myriad ways, leading to theories that are in some ways incommensurable, and findings that are often weak, if not contradictory.

In Chapter III, I will present conflicting propositions that emerge from the scholarly debates that have formed around the central question for this research, “What are the consequences of automation for the nature of work?” Each of these debates rests upon a common theme—the nature of routines. Pentland & Rueter (1994, p. 484) argued, “routines occupy the crucial nexus between structure and action, between the organization as an object and organizing as a process.” Not only has a concern for the routinization of work persisted throughout the history of sociological inquiry (Burris, 1998; Durkheim, 1997; Weber, 1947), but also the relationship between the nature of routines and the social structure of organizations has provided a backbone for the domain that is organization theory (Burns & Stalker, 1961; Feldman & Pentland, 2003; March & Simon, 1958; Perrow, 1967; Thompson, 1967). In short, the question of the consequences of automation for the nature of work is not only a question of significant social concern, but also a question with important theoretical ramifications.

The methods employed for this empirical inquiry will be described in Chapter IV. I will describe the construction of the surveys employed by O*NET, as well as the means through which these surveys were administered and the data collected. I will also describe the constructs of interest to this research and the items from the O*NET survey that were believed to provide reasonable and reliable measures of these constructs. Finally, I will outline the means through which the scales measuring these constructs were confirmed and the hypotheses described in Chapter III were tested.

In Chapter V, I will present the results of the first phase of the analyses that were involved for this research, which involved a three-pronged method to determine whether and how the relationships among items I had drawn from the O*NET questionnaires

converged upon underlying factors similar to those proposed in Chapter IV. This triangulation of evidence involved a combination of the findings from an exploratory factor analyses with those from an investigation of face validity involving both working individuals from the general public as well as research experts.

In Chapter VI, I will describe the results of the second phase of these analyses, which involved formal tests of the hypotheses presented in Chapter III. I will preview the findings from these analyses here by saying that greater levels of automation are associated with greater levels of routinization of work, whether measured as the repetitiveness of or the lack of innovativeness in work tasks. Furthermore, greater levels of automation are associated with lesser skill requirements for work, when those requirements are measured as the level of formal education necessary for work. There are exceptions to and interactions beyond these mean effects however, the nuances of which will be described in the final chapter.

In the final chapter, Chapter VII, I will discuss: (a) the implications of this research for the domains of both organizational theory and practice, (b) the limitations of this research, and (c) the future direction for research at this intersection of automation, work, and organizations. If there were any broad-stroke inference that might be drawn from this dissertation, it would be that automation leads to something other than what we generally expect. If there were any direction in which I would hope this line of research might take us it would be a few steps closer to understanding how it could be that automation has led not only to the end of work as we knew it, but also to the beginning of work we never knew before.

CHAPTER II

LITERATURE REVIEW

In this chapter I will provide a broad, yet critical review of the literature related to the question, “What is the relationship between technology, work and the social structure of organizations?” Any inquiry into the consequences of automation for work is ultimately nested within the much broader question of the technology-structure relationship. Divining some singular conclusion from the vast literature investigating the relationship between technology and social structure is complicated by the diversity of ways in which the phenomena that are technology and social structure have been defined and the levels of analysis at which they have been researched (Fry, 1982). As such, I will first review the diverse ways in which these phenomena—technology, work, and social structure—have been defined and distinguished, along with the some key findings from these approaches.

Unfortunately, regardless of the conception of technology and structure, research has often yielded weak and unsettled findings (Barley, 1990; Burris, 1998; Markus & Robey, 1988; Scott, 2003). The ongoing debate over the nature of the relationship between technology and social structure has mirrored the overarching, and at times contentious, debate within the social sciences questioning whether and how the causal arrow goes this way, that way, or every which way among that variables that matter (Burris, 1998; Liker, Haddad & Karlin, 1999; Markus & Robey, 1988; Scott, 2003). As such, in closing this chapter I will highlight key frustrations and plausible directions for

future research in the wake of the unsettled findings that emerge when researchers try to reliably link technology and social structure.

The Nature of Technology

Child (1972, p. 14) argued, “The term technology is employed in almost as many different senses as there are writers on the subject.” Technology can refer to a wide set of factors within organizations, spanning processes, raw materials, knowledge and apparatus. For example, Perrow defined technology as “the actions that an individual performs on an object... in order to make some change in that object” (1967, p. 195), while Goodhue defined technology as “the tools used by individuals in carrying out their tasks” (1995, p. 216). So as the technology of interest shifts from the ways in which we get things done to the apparatus in our hands while getting things done, these different conceptions of just what technology *is* undoubtedly result in not only different issues of interest to researchers, but also different theoretical explanations for what these researchers observe.

Fry (1982) distinguished the approaches to technology within organizations research according to the “operational type”—objective or perceptual—of the technology variable. I will characterize the various approaches to the nature of technology as follows: those perspectives that approach technology as **technique**, those that approach technology as **tool**, and those that pursue technology as **transformation**. These categories for definitions of technology are the result of bringing together distinctions made by Barley (1986), Winner (1977), as well as Hickson, Pugh, and Pheysey (1969), as these authors surveyed the use of the word technology in the organizations literature.

In an attempt to disentangle the various conceptions of technology, Hickson et al. (1969) distinguished among knowledge, materials, and operations technologies.

Knowledge technologies referred not only to what knowledge was used in the work process, but also to how that knowledge was used. Materials technologies referred to the nature of the materials used in workflow, placing boundaries upon that workflow. Operations technologies involved a sequencing of activities, or the techniques used, in some work process.

Winner (1977) wanted to avoid using the term “technology” altogether, instead selecting three terms he felt captured the more prevalent meanings of technology within the sciences: apparatus, technique and organization. Citing a desire to avoid the “analytical abstraction” of the word organization, Barley (1986) proposed a tangible limit to the technology construct, restricting his interest to apparatus (or tools) and work (techniques). Beyond a general desire to avoid abstractions, the inclusion of “organization”—by which was meant “technical social arrangements” (Winner, 1977, p. 12)—within the technology construct could be altogether problematic for research involving the relationship between technology and social structure. Essentially, some version of technology—as tools and as social relations, for example—would reside on each and all sides of the causal equation.

Winner (1977) however, also highlighted a more longstanding conception of technology, popular among scholars writing prior to the latter part of the 20th century. Among these scholars, technology referred quite broadly to “the practical arts,” or as defined in Webster’s Second International Dictionary (1909), “the science or the systematic knowledge of the industrial arts.” This conception of technology is similar to the “knowledge” technologies of Hickson et.al. (1969) and the transformation technologies of interest to researchers such as Rousseau (1979). I will characterize this broad approach to organizational technology as that of some transformation converting

the underlying elements in production—materials, ideas, or even people—from one form to another.

Technology as Technique

Organizational research conducted during the middle decades of the 20th century tended to view technology as technique, essentially the method for getting things done: “The mechanisms or processes by which an organization turns out its product or service” (Harvey, 1968, p. 247), “The work performed by an organization” (Scott & Davis, 2007, p. 125), “The nature of work activities” (Daft & MacIntosh, 1978). Perhaps most prominent in this line of research has been the work of Charles Perrow, who clearly placed technology within the domain of technique (Perrow, 1967, p. 195):

By technology is meant the actions that an individual performs upon an object, with or without the aid of tools or mechanical devices, in order to make some change in that object. The object, or “raw material,” may be a living being, human or otherwise, a symbol or an inanimate object.

Perrow (1967) identified four types of technology, which are presented in

Figure II.1—craft, engineering, routine and nonroutine. Organizational adoption of each of these types of technology was argued to be contingent upon the perceived analyzability of the underlying raw materials and the number of exceptions encountered when analyzing these materials. The concept of exceptions captures the extent to which stimuli are perceived as familiar, or unfamiliar. Analyzability refers to nature of the search process in response to exceptions, distinguishing between some formal, rational and logical process, as opposed to a process based upon intuition, chance or guesswork. Importantly, Perrow’s two dimensions for the technology variable are not defined as wholly independent. Analyzability was in fact a function of, or at least a measured response to exceptions and this lack of strict independence appears to have

been widely overlooked by subsequent researchers. As such, it may be problematic to treat these constructs as truly independent variables for analysis.

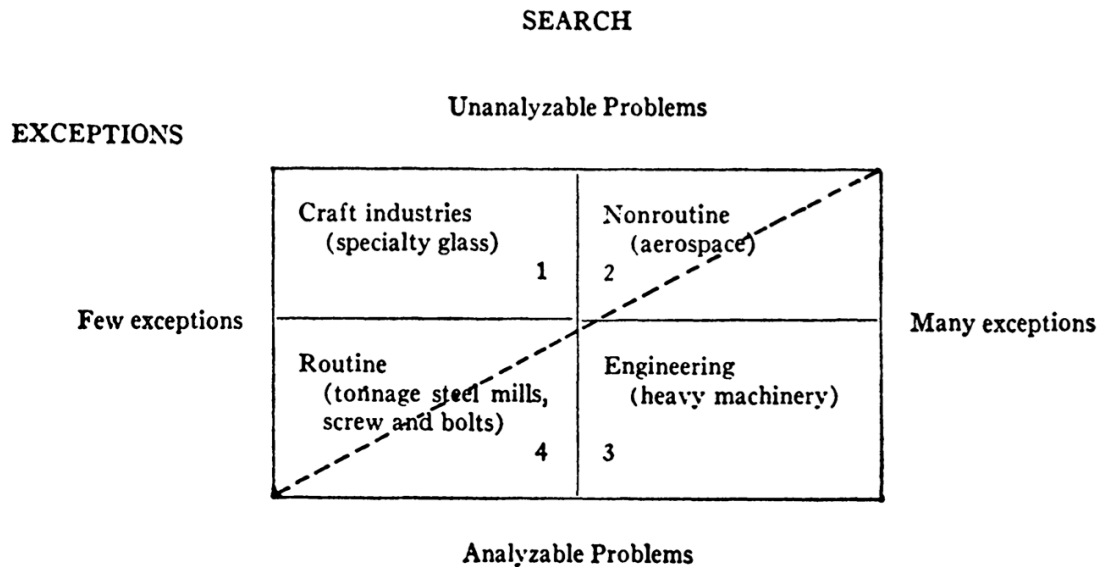


Figure II.1: Technology Variable, Industrial Example (Perrow, 1967, p. 196).

Subsequent researchers similarly classify organizational techniques in similar terms to those proposed by Perrow (Dewar & Hage, 1978; Hunt, 1970; Lynch, 1974; Pentland & Rueter, 1994; Singh, 1997; Withey, Daft & Cooper, 1983). Daft and Macintosh (1978) describe a framework, presented in Figure 2, for organizational information systems in terms based upon those of Perrow. According to the typology of Daft and Macintosh, craft, research (i.e., nonroutine), technical professional (i.e. engineering), and programmable (i.e. routine) technologies within organizations are best matched with cursory, diffuse, elaborate and concise information systems, respectively. Cursorsy systems make use of small amounts of imprecise information, used in a casual yet decisive manner. Diffuse systems make use of moderately large amounts of information across a range of information types, albeit in an imprecise, deliberate

manner. Large amounts of very detailed and precise information are used slowly and deliberately with elaborate information systems. Concise information systems entail quick decision-making by way of moderately small amounts of precise information.

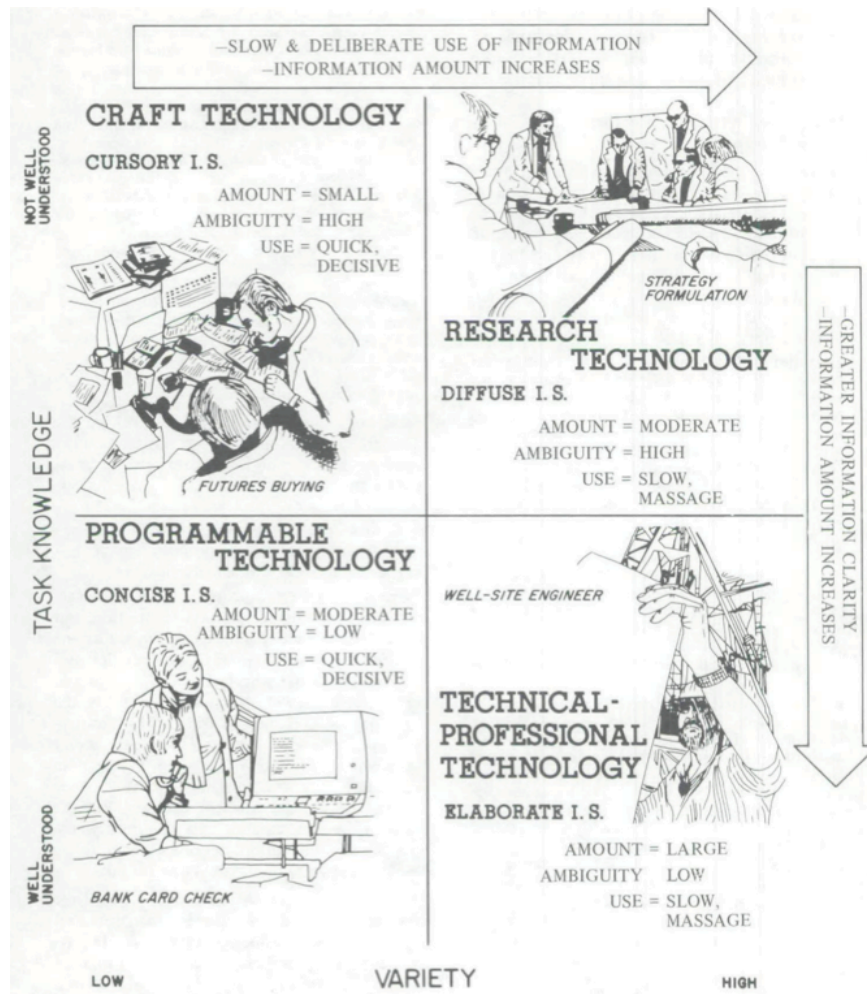


Figure II.2: Classification of Work Unit Technologies (Daft & Macintosh, 1978, p.75).

While the contingency of “fit” persists through the technique-interested research, a real advantage to the technique approach to technology has been the avoidance of a desire to classify any entire firm according to any single technique. Whether or not the desire to classify entire organizations according to singular classifications of technique

has indeed dominated, researchers within this domain admitted early on that the technology-as-technique approach was most capable of predicting things at the level of the individual or the work unit (Fry, 1982; Hickson et al., 1969).

Technology as Tool

Investigations of technology within organizations during the last quarter of the 20th century favored a conception of technology as tool, by which I mean the apparatus, artifacts, and applications with which work gets done, and through which social systems operate. What matters about these apparatus can range from qualities objectively inherent in these tools (e.g., the presence of four buttons) to qualities infused into these tools by way of social meaning (e.g. the social control interpreted by end uses by limiting these users to only those choices available through four buttons). The tools of technology have characteristics variously described as features (Griffith, 1999), functions or properties (Huber, 1990; Orlikowski, 2000). Furthermore, these tools are argued to be indwelled with capabilities (Huber, 1990), affordances (Norman, 1988; Norman, 1999; Zammuto, Griffith, Majchrzak, Dougherty & Faraj, 2007), constituting structures (Orlikowski, 2000), identity (Faulkner & Runde, 2009), or spirit (DeSanctis & Poole, 1994).

Certain discussions are quite explicit in their conceptualization of technology as tool. Goodhue referred directly to technology as the “tools used by individuals in carrying out their tasks” (1995, p. 216). Burton and Obel (2003) suggest information technologies are “a means for an organization to process information,” (p. 262), but then clarify these means as databases, expert systems, voice mail, email and computers in general. Hunt (1970) draws attention to the technical system, which involved the “collective instruments” with which operators conducted their work. In fact, for some researchers, it

is by being distinct from technique that these apparatus and applications might become occasions for structuring (Barley, 1986) and triggering for sensemaking (Griffith, 1999).

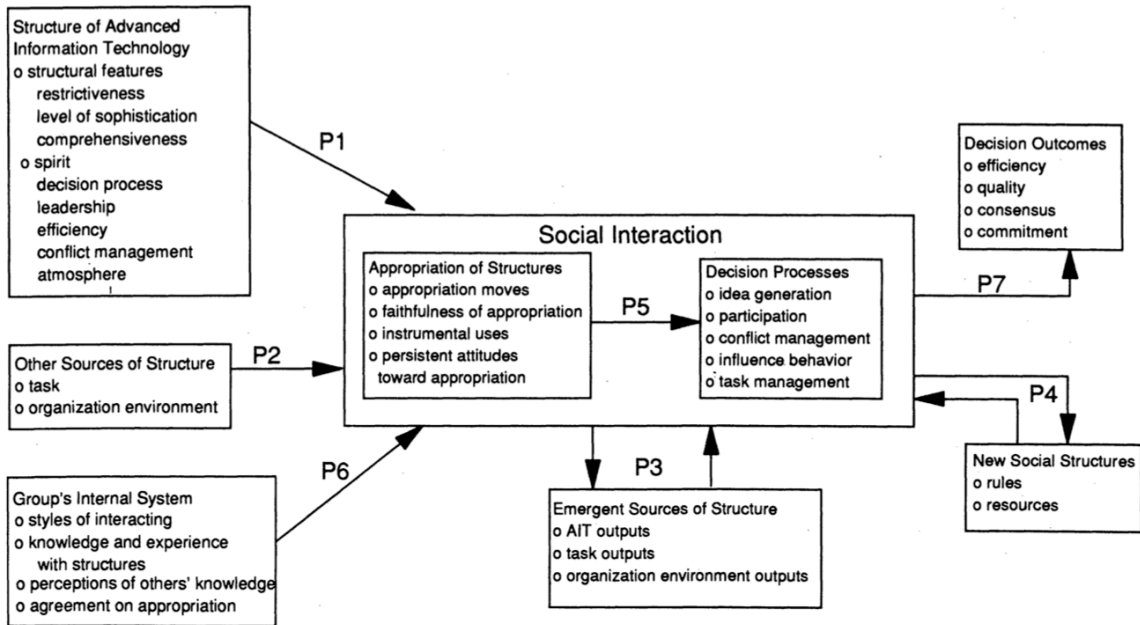


Figure II.3: Summary of Major Constructs and Propositions of Adaptive Structuration Theory (Desanctis & Poole, 1994, p.132).

Orlikowski limited technology to material artifacts, yet considered these artifacts to include “various configurations of hardware and software” (1992, p. 403), thereby including virtual, or informational tools within the classification. This distinction of technology as material was complicated further through Orlikowski’s assertion of a duality within which technology exists. Any tool is “physically constructed by actors working in a given social context,” and “socially constructed by actors through the different meanings they attach to it and the various features they emphasize and use” (Orlikowski, 1992, p. 406). From this interpretive perspective, users and developers constitute meaning (Latour, 1991), or embody structures, into these tools. Desanctis

and Poole characterized this inscription and appropriation of meaning as “spirit” (DeSanctis & Poole, 1994) within their model for the adaptive structuration of technologies, which is presented in Figure II.3. Technologies embody “structures (built in by designers during technology development), which are then appropriated by users during their use of the technology” (Orlikowski, 2000, p. 405). By way of appropriation, users bring their own meanings and models to these artifacts, such that the fate of any artifact is in the hands of the holder and out of the hands of the designer (Latour, 1991).

When technology is imagined as a tool, the qualities of information technologies (IT) studied within research on organizations tend to be limited to those related to communication and data storage, with lesser attention paid to the potential for information manipulation (e.g., numeric computation and modeling) or autonomous action in information environments (e.g., automated financial trading applications). In a very recent study, Kane and Alavu (2007) described IT that contributes to organizational learning in terms of three domains of tools: “communication technology (e-mail), knowledge repositories (KRPs) of best practices, and groupware” (p. 796). Other researchers have directed interest at decision support technologies (DeSanctis & Gallupe, 1987), media technologies (Bordetsky & Mark, 2000; Majchrzak, Malhotra & John, 2005; Rice, 1992) electronic data interchange (Dedrick & Kraemer, 2005; Zaheer & Venkatraman, 1994), and virtual environments (Castronova, 2005; Hemp, 2006). Of less but now increasing interest are the data processing, or “thinking” capabilities of these technologies. However, these tools are often not described as automation, but rather are presented as different concepts such as decision aiding applications (Huber, 1990), enterprise resource planning systems (Davenport & Brooks, 2004; Hill & Scudder, 2002), and even the more general “business intelligence” (Zammuto et al., 2007). In

essence, the automated nature of many of the tools adopted by organizations may be taken for granted, or simply ignored.

Technology as Transformation

Transformation, perhaps the broadest conception of technology within organizations, focuses empirical and theoretical attention upon “the organizational process of transforming inputs into outputs” (Fry, 1982, p. 533). From this perspective, research interest shifts from some characterization, or even average of the work individuals enact within the organization, to a general classification of the transformation process of the entire firm, with comparisons made across firms in regards to this transformation mode. Implicit in this approach is the assumption that technology within any organization is a somewhat unitary phenomenon—each organization can be classified according to a single technology. Law (1987) suggested technology “is a method, one method... for the construction of a relatively stable system of related bits and pieces” (p. 115). Berniker (1983) defined technology even more abstractly, as “a body of knowledge about the means by which we work on the world, our crafts and our methods. Essentially, it is knowledge about the cause and effect relations of our actions” (p. 10).

A focus upon transformations made through the production process has been common within strategy (Garud & Nayyar, 1994; Grant, 1996; MacIntosh & MacLean, 1999) and organizations research (Blauner, 1964, Woodward, 1965; Thompson, 1967; Billings 1977; Hodson 1996), with attention often paid to the “value added” through some organizational or inter-organizational process. Rousseau (1979, p. 531) conceptualized technology as the broad process of transforming inputs into outputs:

A sequencing of events involving admission of input (raw materials, people, knowledge) into the organizations, conversion of this input into output through the application of skill and energy, and disposal of output into the environment.

Rousseau (1979, p. 532) further described this conversion through which techniques and tools changed the value of inputs. By way of this conversion:

Value is added by transforming inputs... or by maintaining inputs. The transformation of inputs such as raw materials or people adds value by altering their form or structure (physical or mental) in some desired way.

Woodward (1965) characterized the technology in use within an organization as a firm-level process through which output was produced. Subsequent research would follow in Woodward's wake (Glisson, 1978; Hickson et al., 1969; Hull & Collins, 1987; Vázquez, 2004). Furthermore, as argued by Hull and Collins (1987), Woodward suggested that "production technologies generally follow an evolutionary pattern of development in which volume, specialization, standardization of work flow, predictability and control increase" (Hull & Collins, 1987, p. 787). Based upon observations of 100 manufacturing organizations, she placed organizational technologies into three categories: mass, batch, and continuous process. Mass production was essentially an assembly line operation, with standardized outputs and procedures. Batch production involved low levels of automation, little control over production, small lots, and general-purpose machinery. Continuous process production engaged high levels of automation, specific machinery and rather constant output.

Thompson's "technical rationality" (1967), being a unitary characterization of an organization's entire production process (or ethos), would fit within the classification of technology as transformation. The form of this firm-level transformation was contingent upon the nature of the tools, materials, and techniques required "to get the job done effectively" (p. 10). Thompson identified three classes of organizational technologies—

long-linked, mediating, and intensive—each of which appears to be a mingling of those aspects found in the works of Woodward and Perrow. Long-linked technologies were comprised of inputs and outputs, standardized for efficiency, operated upon by way of a sequential process (e.g., mass production assembly). Within mediating technologies, the conversion process was standardized, while the inputs and outputs were largely unstandardized and left in their raw form (e.g., insurance companies and commercial banks). Intensive technologies involved unstandardized inputs and outputs combined with a similarly unstandardized conversion process (e.g., “therapeutic” service providers, such as psychologists). Mahoney (1972), Goodhue (1995), Singh (1997), and other researchers (Lemak & Reed, 2000; Stabell & Fjeldstad, 1998) would later characterize firms according to the typology presented by Thompson.

A real question for the transformation approach to technology would be where and how automation might fit within or have any impact upon these unitary classifications of organizational technologies. In fact, there is reason to wonder whether automation would matter at all to the predictions and approaches of the transformation school. For example, it would seem that automation exists as a artifact representing Thompson’s technical rationality—a material manifestation of an organization’s production ethos. Are only long-linked organizational technologies fully automated, while mediating and intensive technologies are only partially automated if automated at all?

The Nature of Work

Work is often dealt with as an abstraction, if not altogether taken for granted in our theories of organizations. In essence, in order to speak about this notional entity that is an “organization” we have had to take three steps back from the similarly abstract entity that is “work.” Yet the latent aspects of organizations with which theories are

constructed (e.g., power, uncertainty, legitimacy, etc.) undeniably interact with and impact perhaps the most visceral aspect of human experience within these organizations—the work we actually do.

In *Organizations* (1958), March and Simon criticized what they considered to be the classical theories of organizations by arguing, “the grand theories of organizational structure have largely ignored factors associated with individual behavior” (p. 29). In fact, it was this focus upon the characteristics of the individuals within organizations that led March and Simon to center their influential treatise upon the implications for organization structure of social and psychological factors such as motivation, conflict and limits to rationality.

Barley (1996) more recently questioned the nominal discussion of work within organization theory by writing:

Despite the field's burgeoning interest in organizational transformation, researchers have paid almost no attention to how organizational developments might either reflect or affect the changing nature of work... Discussions of what people do and how they do it are rare (p. 405).

Barley attributed this distancing of work from the domain of organization theory to a fracture that occurred in organizations research during the 1960's, through which “organization theory” became distinguished from the “sociology of work.” The focus within organization theory upon the development of general principles of organizing seemed to require conceiving of work as an abstraction.

When researchers have broken through the abstractions by setting their attention on work itself, three predominant levels of analysis emerge—**task**, **job**, and **occupation**. Switching between these layers of analysis is akin to the experience of falling upwards during Charles and Ray Eames short film, *Powers of Ten* (Eames & Eames, 1977). A quick scan of published research article titles hints at how adept a researcher needs to

be at transversing these layers of work: e.g., “Work values and job rewards: A theory of job satisfaction” (Kalleberg, 1977), “The relationship between work experience and job performance: A conceptual and meta-analytic review” (Quinones, Ford & Teachout, 1995); “A social information processing approach to job attitudes and task design” (Salancik & Pfeffer, 1978); “Effect of occupation on task related, contextual, and job involvement orientation: a cross-cultural perspective” (Gomez-Mejia, 1984).

Work as Task

A longstanding approach to the study of work has involved work as task, which I define as a piece or element of work undertaken or to be performed. This approach takes the meaning of work for granted to the point that researchers within this domain rarely stop to define what they mean by “task.” Across this literature, a partial list of aspects of tasks considered significant for work and organizations includes: difficulty, routinization, autonomy, variety, identity, feedback, significance, and complexity (Campbell, 1988; Campbell & Ilgen, 1976; Daft & Macintosh, 1981; Grant, 2008; Hackman & Oldham 1975; Huber, 1985; Ilgen, Fisher & Taylor, 1979; Klein, 1989; Langfred & Moye, 2004; Pierce & Dunham; 1976, Shaw & Blum, 1965; Sims, Szilagyi & Keller; 1976, Skinner, 1979; Steers, 1977; Tuchman, 1973; Van de Ven & Delbecq, 1974; Turner & Lawrence, 1965; Wood, Mento & Locke, 1987). From a broad, organizational-level perspective, a task can be understood as the basic element of organizational routines. March and Simon (1958) saw organizational processes as “made up by aggregating very large numbers of elements, each element, taken by itself, being exceedingly simple” (p. 178) An organization is, essentially, a system of tasks linked together in important ways—temporally, hierarchically, conceptually.

Seeing work as a particular task is at the very heart of Taylorism, the predominant approach to management practice in the early 20th century. According to Winslow Taylor (1911), the objective for a scientific approach to management is “the development of each man to his state of maximum efficiency, so that he may be able to do, generally speaking, the highest grade of work for which his natural abilities fit him” (p. 1). More often than not, “maximum efficiency” meant performing the same task, repeatedly. Towards this end, Taylor and Taylorism were known for their focus up each moment and movement of each work task, looking for ways to refine or re-order these processes so as to make as efficient as humanly possible the production of whatever would be the final output.

Task complexity is the aspect of tasks that has been considered most significantly and repeatedly within management research (Campbell, 1988; Hackman & Oldham, 1975; Latham & Yukl, 1975; March & Simon, 1958; Pierce & Dunham, 1976). Task routinization is one component among the many involved in the conceptualization and measurement of task complexity. Across the breadth of task-related research, task complexity has emerged as a multi-dimensional counterpart to routinization, measuring (a) the multitude of methods (or pathways) for accomplishing a task, (b) the outcomes of a task, (c) the level of interdependence among tasks, and/or (d) the level of uncertainty regarding the link between methods and their anticipated outcomes (Campbell, 1988). While the goal here is not an exhaustive review of the task characteristics and complexity literature, it is worth noting that researchers have applied task complexity to a broad range of concerns: decision-making (Shepard, 1964; Taylor, 1984; Wood, 1986), job design (Beer, 1968; Hackman, 1969; Roberts & Glick, 1981), technology (Cooper & Zmud, 1990; Zigurs & Buckland, 1998; Zmud, 1984), and even goal setting (Earley,

1985; Frost & Mahoney, 1976; Locke & Latham, 2002; Locke, Latham, Smith & Wood, 1990; Wood, Mento & Locke, 1987).

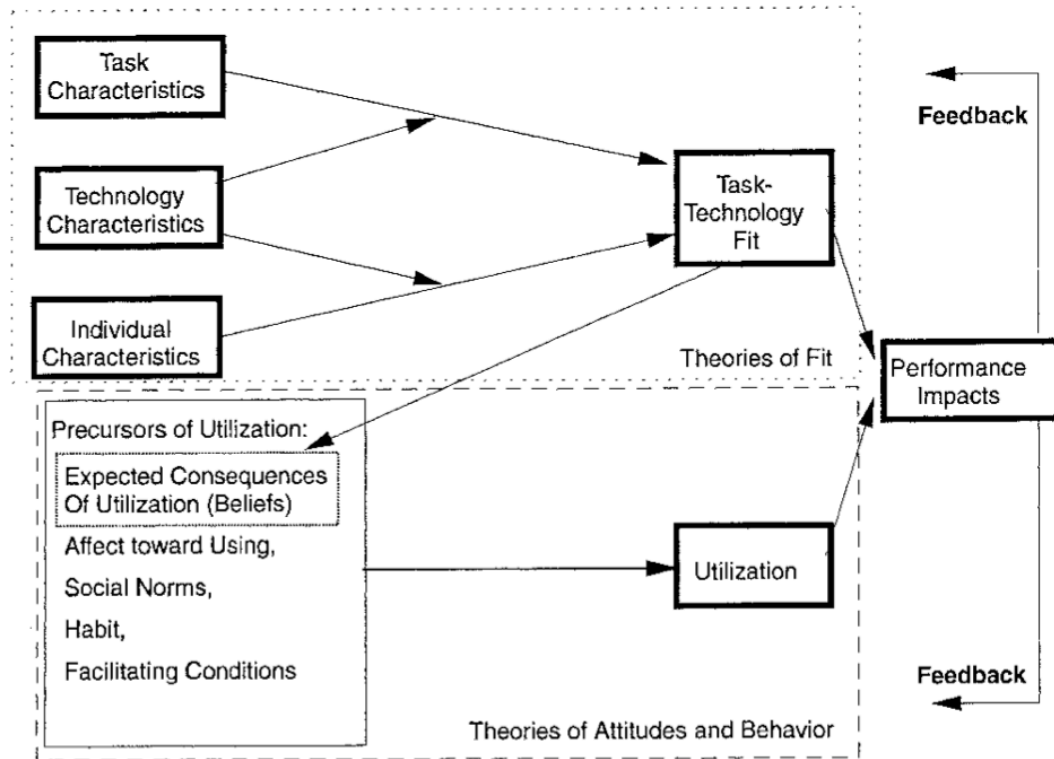


Figure II.4: The Technology-to-Performance Chain (Goodhue, 1995, p.217).

Importantly, three approaches to task complexity highlighted by Campbell (1988) could be applied to assumptions (implicit and explicit) made about the nature of tasks in general: (1) objective characteristics of the task (Campbell & Gingrich, 1986; Latham & Yukl, 1975; Schwab & Cummings, 1976), (2) psychological (i.e., perceived) aspects of tasks (Hackman & Oldham, 1975; Hackman & Oldham, 1976; Haerem & Rau, 2007; O'Reilly, 1979; Pierce & Dunham, 1976; Taylor, 1981), and (3) interactions between individual and task characteristics (Frost & Mahoney, 1976; Goodhue & Thompson, 1995; March & Simon, 1958; Shaw, 1976; Wegge, Roth, Neubach, Schmidt & Kanfer,

2008). In fact, Goodhue expanded the scope of task-technology fit through a model (presented in Figure 4) that incorporated aspects of task, technology, social context and the individual to predict overall individual performance alongside support tools. While Campbell (1988) classified a perceptions-based approach to task complexity, he also remarked, “No studies were found that treated task complexity exclusively as a subjective, psychological experience of the task-doer” (p. 41). This paucity of perceptions-exclusive research left a gap for future research—particularly at the nexus of task complexity and constructivist approaches to the technology-work relationship.

Work as Job

Moving up a layer of abstraction in regards to the nature of work, I turn next to researchers who define work as a job—a set or bundle of tasks performed (more often than not) within an organizational context. Research pursuing the relationship between job characteristics and any number of causes and consequences is vast in its scope and volume, and cannot be adequately summarized here. However, across this broad domain of research two important issues have emerged.

First, numerous work-related research studies treat the task and the job as somehow intrinsically distinct yet methodologically inseparable. For example, Hackman & Oldman (Hackman & Oldham, 1975, p. 161), in their seminal development of the Job Diagnostics Survey (JDS), defined task identity as, “The degree to which the *job* requires completion of a "whole" and identifiable piece of work” (emphasis added).” This undeniable overlap of task and job research could be seen as a subtle reflection of the Taylorist and Fordist approaches to production that informed the nature of work within industrial settings—the goal therein being to reduce any job to a single, highly efficient task nested within a larger production process.

Second, and similar to criticisms made of task research, the job characteristics approach to work has been challenged on phenomenological grounds. Some work and organizations researchers question whether job characteristics are important as objective phenomena (reliably measurable by instruments such as the JDS), suggesting instead that these characteristics are socially-constructed realities (Rousseau, 1978; Salancik & Pfeffer, 1977; Salancik & Pfeffer, 1978). Viewed through the lens of social construction, what might matter more about the job is its position within some larger constellation of meanings and work relationships.

Work as Occupation

During the latter part of the twentieth century, researchers began to focus on the nature of work as an occupation. A focus upon occupations made it feasible to place what were otherwise simply independent jobs within broad networks of interdependent, social meaning. Abbott (1993) argued that this attention to occupations became prominent through the publication of *The American Occupation Structure* (Blau, Duncan & Tyree, 1967). Fine (1996, p. 90) suggested that occupations comprise “a collection of tasks, and assignments, set in an organizational environment.” The study of occupations relies not only on observation of tasks, but also the assumption that certain collections of tasks and assignments (i.e., jobs) were so bundled together as to appear consistent and persistent across individuals operating within different organizations and industries. Simply put, jobs exist within an organization, while occupations exist not only within but also across organizations.

Researchers have conceptualized and explored occupations across the objective-subjective divide, as sources of social status and stratification, specialization, and division of labor. Johns (2006) suggested that, “knowing someone’s occupation

often permits reasonable inferences about his or her task, social, and physical environment at work” (p. 393). Clair (2005) classified occupations as “non-visible” characteristics of demographic diversity in organizations. Blau (1974), citing studies that found the specialization of occupations to coincide with the routinization/standardization of work (Blau, 1971; Pugh, Hickson, Hinings & Turner, 1968), considered the division of labor and occupational differentiation to be largely synonymous. He suggested that “an organization's division of labor takes predominately the form of routinization, and that the routinization of many jobs is accompanied by greater specialization of others, manifesting a bifurcation of skills” (Blau, 1974, p. 627). Beyond the specialization of skills, Duncan (1961) ranked occupations according to their education and income.

Occupational distinctions have proven sufficiently visible to provide a useful window for research into various conceptions of the social structure of organizations. Occupations have been seen variously as: a set of role resources (Baker & Faulkner, 1991); evidence for professionalization (Freidson, 1973; Wilensky, 1964), membership (Aydin, 1989; Kimberly & Evanisko, 1981) and occupational segregation (Joshi, Liao & Jackson, 2006); social constructions of concepts like “dirty work” (Ashforth & Kreiner, 1999); structures for knowledge (Lave & Wenger, 1991; Orr, 1996; Wenger, 1999) and sensemaking (Hughes, 1958; Salaman, 1974; Van Maanen, 1984); occupational personalities (Becker & Carper, 1956); and sources for work orientation and affiliation (Gomez-Mejia, 1984).

When organizations are imagined by researchers to be more complex than some unitary method of production, representing this muddle of interdependent techniques proves to be a difficult challenge (Orlikowski, 2007; Pickering, 1995). Occupations, representing an ongoing specialization of skills, tasks and organizational positions, may

nonetheless present meaningful bases for understanding the complex production facilities that are modern organizations (Scott & Davis, 2007).

The Nature of Structure

A central challenge for organization theory, while searching for relations between technology, work, and social structure, involves distinguishing the apparent structure of any organization. Simply put, What do organizations “look” like and how will we see them? The general contours of organization structure have been distinguished in myriad ways, such as: rational, natural, or open (Scott, 2003); formal or functional (Mintzberg, 1979); and static or process (Scott & Davis, 2007).

I argue that approaches to the social structure of organizations can be usefully distinguished in terms of whether they imagine the organization, or the organizing therein, to occur in thought, word, or deed. **Structure-as-thought** implies structure exists in how we think, or process information, and often involves inquiries into shared understandings, interpretations, or frames of mind. **Structure-as-word** imagines structure as evident in how we represent the organization, and often involves a query into the stated design of the organization or the latent constructs underlying the design we observe. **Structure-as-deed** suggests that structure exists in what we do, both independently and in relation to each other, and often results in directly observed or indirectly inferred actions of organization members.

Structure as Thought

A difficult to access, yet sought after aspect of social structure in organizations research resides within that hard to reach place—the brain—that would disclose how individuals think within organizations. By way of this approach, the real organization—or

the organizing—occurs within mental phenomena, such as collective and shared interpretations (Cohen, March & Olsen, 1972; Weick, 1979), knowledge structures (Walsh & Ungson, 1991), theories of action (Argyris, 1976; Argyris, 1977; Hedberg, 1981), and cognitive structures (Cohen & Levinthal, 1990).

The neo-institutional approach to understanding organizations (DiMaggio & Powell, 1983) emerged as a means for pursuing the thought underlying social structure. Barley and Tolbert (1997, p. 93) encapsulated this thought-bounded, institutional context in the following way:

Organizations, and the individuals who populate them, are suspended in a web of values, norms, rules, beliefs, and taken-for-granted assumptions, that are at least partially of their own making (p. 93).

Scott (2007) traces the institutional school of organizations to roots in economics, political science and sociology. Scott's cultural-cognitive pillar is comprised of "the shared conceptions that constitute the nature of social reality and the frames through which meaning is made" (2007, p. 57). Veblen (1909) considered institutions to be the "settled habits of thought common to the generality of man." Selznick highlighted the force of culture within organizations "to infuse [work] with value beyond the technical requirements of the task at hand" (1957, p. 17).

Inquiries into the relationship between technology and social structure-in-thought often see technology as socially constructed (Bijker, Hughes & Pinch, 1987; Fulk, 1993; Klein & Kleinman, 2002). Work in this domain considers not only the more specific and expressed attitudes of individuals towards new technologies (Goodhue & Thompson, 1995; Goodhue, Klein & March, 2000; Hodson, 1996; Rice & Aydin, 1991), but also the more abstract structure of expectations underlying "frames" (Bostrom & Heinen, 1977; Ginzberg, 1981; Goodman, Griffith & Fenner, 1990; Orlikowski & Yates, 1994), "fields" (Dodgson, Gann & Salter, 2007) and "spirit" (DeSanctis & Poole, 1994). For example,

Bostrom and Heinen (1977) highlighted seven “frames of reference” held by system designers (e.g., a static view of the systems development process, and implicit theories regarding human nature) that were believed to result in unsuccessful designs of MIS systems. These “implicit theories” of human nature, held by systems designers, were compared directly to the Theory X and Theory Y assumptions McGregor had uncovered in his research into the beliefs held by managers regarding the most effective methods for managing people.

Structure-in-thought, in the context of technology, can be abstracted towards the construction of what have been called institutional “fields.” These institutional fields were defined by Hargadon and Douglas (2001) to include the “network of actors and physical objects whose relationships are given meaning by a set of surrounding understandings and actors” (p. 479). Dodgson (2007) observed the variety of means through which a set of fire-fighting engineers endeavored to enact the construction of a clearly defined, technical profession. Membership within this field would require an ability to use particular simulation technologies in approved ways, while the presentation of the field was enacted publicly through the creation of a conferences and websites. Essentially, the “fire-fighting engineer” was a concept being redefined by way of an ongoing and intentional social construction of various technologies.

Future research could pursue automation as an artifact comprising explicit expressions of organizational thought. The routines built into these artifacts could be investigated as evidence of some underlying logic through which decisions are made, or previously were made within an organization. Alternatively, automation might be investigated as artifacts given meaning through the norms and values that support or constrain individual and collective thought within organizations. Being a function of social

standards, automation could be subject to inquiries into the normative principles that suggest what sort of work should or should not be programmed into machines.

Structure as Word

The “word” of social structure involves what is said about organizations, particularly by researchers. The word of structure entails our representation of these social systems—the ideal types (Weber, 1947), espoused actions (Argyris, 1976), or latent variables—in search of the underlying and oftentimes unspoken causal elements leading to the outcomes we observe within social organizations. In essence, the word of structure is a function of our theories and beliefs regarding what the explicit goes on within these systems implicitly represent.

Examples of such characterizations of structure include the more abstract conceptualizations of strategic posture (Miles, Snow, Meyer & Coleman, 1978), or “structure in fives” (Mintzberg, 1983), along with the simple measures such as the ratio of managers to supervisors (Harvey, 1968). By way of strategic posture, Miles et al., (1978) classified the strategy of firms according to attributes termed to be those of the defender, prospector and reactor. Any particular’s firm’s strategy was inferred from its chosen configuration of technology (considered to be the input-transformation-output process), process (i.e., the apparent stage of the firms within the “adaptive cycle” [Miles et al., 1978], from entrepreneurial to engineering to administrative) and structure (a function of managerial beliefs). In the case of the manager/supervisor ratio, what mattered for research was not explicit in that ratio but rather implied by that ratio—span of control, as a cause and consequences of other features of the organization).

Importantly, those things we measure and characterize within organizations are believed to be only manifestations of underlying forces and parameters that ultimately

constitute what we mean by “social structure.” Blau (1974) suggested that “a social structure is delineated by its parameters,” with a parameter being “any criterion implicit in the social distinction people make in their social interaction” that structures “the social interaction in which these relations find expression” (pp. 616-617)—such as the myriad forms of social power. These underlying forces, or what Pentland and Feldman considered the “ostensive” aspects of organizational routines (Feldman & Pentland, 2003; Pentland & Feldman, 2005; Latour, 1991), are believed to function as abstract principles that shape individual actions, perhaps even unknowingly. Within the context of engineering, Grabher (2004) referred to these fundamental yet not-directly-observed forces as the “project ecology.” However, we must be clear and accept that these principals and forces are essentially latent variables—constructs that are not measured directly, but rather are argued and methodologically confirmed to exist by way of directly observed aspects of organizations and individuals.

Numerous researchers have pursued technology in the context of structure as word (Heracleous & Barrett, 2001; Karahanna, Straub & Chervany, 1999; Venkatesh & Davis, 2000). Barley’s work in radiology labs (Barley, 1986) stands out as offering a useful example of the difference between what is being said within organizations by those individuals involved, and what is being said about organizations, by a researcher. Barley (1986) recorded the interactions of hospital radiologists and technicians while both professions were undergoing a transition from traditional X-Ray based equipment to new computer-based CT scanners. The following is an example of a conversation recorded and used for analysis (Barley, 1986, p. 89):

[radiologist]: (Incredulously) These are 256's?

[technician]: (Matter of factly) No, these are 512's.

[radiologist]: (Surprised) They're 512's?

[technician]: Yes. We reconstructed them at 512.

[radiologist]: Oh! That's good! I was wondering on the way over here if you could reconstruct a 512 and do quicklooks too. Well, that's great! It's real important.

This exchange between organization members seems like the sort of innocuous conversation that could have occurred within any radiology lab at the time. Barley's interest was in *how* things were said, providing evidence for and measures of some underlying social parameter that could be classified as renegotiation of power structures in the wake of a technological change.

This perspective—social structure as word—offers a host of approaches to explaining the role and adoption of automation within organizations. If the artifacts and applications that comprise automation do indeed have meaning, then this meaning may be influenced by underlying parameters of social organizations that are difficult to directly observe. Are there latent causes for the standardization of work processes programmed into these apparatus in addition to the more openly expressed aspirations for organizational efficiency and inter-group collaboration? Why are some jobs automated while others are not, even after taking into account the general level of routinization or standardization across these tasks, jobs, or occupations? Are organizational actors having influence over the assignment of scarce resources treated to a different sort of automation, if any automation at all, as compared to those actors having little or no control over resources?

Structure as Deed

The social structure of deed involves observed behaviors within organizations, with organizational structure seen to exist in the explicit patterns that emerge from what

organization members actually do. Fry (1982) referred to organizational structure as “the pattern of events in social systems,” with evidence for this pattern to be seen in “the arrangement of people, departments, and other subsystems of the organizations” (p. 539; see also Hunt, 1970; James & Jones, 1976; Pfeffer & Salancik, 1978). Research relating technology with the structure of behaviors has included inquiries into the patterns of advice networks (Leonardi, 2007), the centrality of interactions (Burkhardt & Brass, 1990; Hage & Aiken, 1969), the emergence of divisional forms (Chandler, 1962), the general volume of interactions (Form, 1972), and the loose, or tight coupling of organizations (Sahaym, Steensma & Schilling, 2007).

Akin to an interest in the interaction order of social relations (Goffman, 1959), graphing these networks of behaviors has its roots in social graphs and event structure models (Abell, 1987; Abell, 2004; Corsaro & Heise, 1990; Heise, 1989; Mohr, 1982). For Pentland and Feldman (2007), people using tools to complete tasks results in the “set of actions or events that embodies coherence or unity of purpose [that may be] interconnected in many different ways” (p. 781). These interconnected actions constitute the social structure that these authors described, perhaps somewhat confusingly, as the “narrative network.” Most specifically, Pentland and Feldman (2007) distinguished the structural narrative that is some series of events—the performative aspect of organizational structure—from the more literal inquiry into narrative that exists in the textual content of social interactions.

In the context of individual behaviors, changes in technology have been understood to potentially trigger events that, according to Barley (1996), instigate “reverberations that spread across levels of analysis much like ripples on the surface of a pond.” As such, changes in organizational structure begin at the level of individual work—what people actually do—spreading thereafter to the network of surrounding,

inter-dependent work relationships. Conversely, technological change has also been imagined to only succeed when it fits the organizational context, in particular the distinct task(s) that some technology supports (Goodhue & Thompson, 1995; Maruping & Agarwal, 2004).

From this perspective of social structure as evidenced by the things people actually do, automation has offered perhaps its most significant set of observations and expectations (Choi, Leiter & Tomaskovic-Devey, 2008; Faunce, 1965; Leontief & Duchin, 1986; Lipstreu, 1960; Shepard, 1971). In chapter 3, I will highlight three competing propositions that represent the most significant threads of expectations regarding the nature of work alongside increasing levels of automation. Furthermore, the sudden inclusion of automation within an organization could be easily imagined as a significant trigger for the sorts of reverberations throughout the organization to which Barley and others have alluded.

Technology, Work, and Structure

Regardless of what is understood to be technology and what is considered to be social structure, there exists an ongoing debate regarding the causal relationship between technology and social structure—a debate that mirrors a larger, ongoing discussion within sociology-at-large questioning the nature of causation within social systems (Burris, 1998; Liker, 1999; Markus, 1988; Scott, 2003). Markus and Robey (1988), drawing upon Pfeffer (1982) distinguished three approaches to the causal “impact,” or imperative, that exists between technology and social structure. One approach, which Markus and Robey dubbed the technological imperative, sees **technology as structurer**, a stable force causally constraining and conditioning social systems according to certain objective and predictable relationships (Burns, 1961;

Huber, 1990; Thompson, 1967; Woodward, 1965; Zammuto, 2007). Barley (1990) characterized this approach similarly, arguing that by treating social structure as a non-social entity, researchers could in turn “treat technology solely as a material cause, more readily assume that relations between technology and social organization are orderly, and more convincingly propose that such relations hold regardless of context” (p. 66).

A second approach imagines **technology as structured** rather predictably by ecological or organizational context, however complicated (Aldrich & Pfeffer, 1976). The organizational imperative characterized by Markus and Robey (1988) who highlighted the rational choices of managers in their selection of technologies, fits within this structured perspective. Additionally, those approaches that see implementations of technology as contingent upon wider, ecological attributes and constraints would also be placed within this domain of technology as structured.

A third approach, classified by Markus and Robey (1988) as the emergent perspective, envisions **technology as structuring**, the relationship between social structure and technology made unpredictable by ongoing, interdependent, and complex social interactions (Barley, 1986; Griffith, 1999; Orlikowski, 2000; Latour, 1991; Orr, 1996; Weick, 1990). As Weick put it, “Technology is both an a posteriori product of lessons learned while implementing a specific technical system and an a priori source of options that can be realized in specific technical terms” (2001).

Technology as Structurer

Researchers adopting an approach known as the technological imperative (Fry, 1982; Khandwalla, 1974; Markus & Robey, 1988; Orlikowski, 1992) believe that technology “exerts unidirectional causal influences over humans and organizations” (Orlikowski, 1992, p. 400). From this perspective, technology is a sort of irrevocable

structure, the attributes of which have a predictable impact upon social structure. In short, “the technology of an organization exists a priori and ... the structure of the organization is then designed for the specific technological requirements” (Glisson, 1978, p. 383). Research within what has been called the structural contingency school (Donaldson, 2001; Fry, 1982; Gerwin, 1981) sees technology itself as an instrumental variable predicting organizational structure alongside features such as size and age of the organization.

While technology is often conceived in abstract terms from this perspective as structurer, reliable predictions rely on assumedly stable attributes of these abstract conceptions. Research in this domain has argued that particular modes for manufacturing—mass, batch and continuous process—were each best suited to particular types of social structure (Woodward, 1965). Amber and Amber (1962) argued that the “automaticity” of adopted technologies, which they characterized according to ten classifications, was “adequate for discriminating all present and future self-acting devices” (p. 3). A persistent theme within subsequent interest in the automation of organizational technologies has been the structuring of work and social structure by technology apparatus (Billings et al., 1977; Blau, Falbe, McKinley & Tracy, 1976).

Galbraith (1973) attributed the influence of organizational technologies on social structure to the amount of information processing these technologies required, by way of the uncertain, complex, and interdependent nature of tasks. Pugh, Hickson, and Hinings (1969) focused upon the integration of work groups, while Thompson (1967), years before scholars would speak of the modular nature of both technical designs (Fuerst & Martin, 1984; Slaughter, Levine, Balasubramaniam & Pries-Heje, 2006) and organization structure (Galunic & Eisenhardt, 2001; Sanchez, 1995; Schilling & Steensma, 2001; Schilling, 2000), investigated the “interchangeability” of various components within a

technical system. Parthasarthy and Sethi (1992), as well as Adler (1988), have investigated and found benefits from “flexible automation.”

The study of technology as a phenomenon that structures social systems is not limited to the understanding of technology in its more abstract sense. Information technologies are often studied as tools, apparatus, and applications having characteristics variously described as features, functions, and properties, offering particular capabilities (Huber, 1990) and affordances (Gibson, 1986; Norman, 1988; Norman, 1999). These characteristics are then believed to constrain individuals to particular uses of these tools, or largely encourage users, without fixed restraints, towards particular uses of these tools. Burkhardt and Brass (1990) investigated the impact of a newly adopted computer processing system on the social network structure of a federal agency. The nature of this information processing system was quite broad, offering “distributed processing capabilities, including file editing, data-base management, statistical analysis, spreadsheet analysis, and word processing to all employees” (Burkhardt & Brass, 1990, p. 112). The consequence of the introduction of this technology was that employees using the system, particularly early adopters, shifted to more central and powerful positions within the organizational network.

While a number of researchers expected information technologies to exert some particular impact upon the structure of organizations, the nature of this impact has been highly disputed. On one hand, there was an expectation for, and a discovery of a resulting “hourglass” shape for organizational structure (Child, 1984; Crowston, Malone & Lin, 1987; Drucker, 1988; Whistler, 1970). Within this hourglass structure of organizations, “the top half would contain some high-level managers and very few middle managers, and the bottom half would contain many clerical workers, first-line supervisors, and few middle managers” (Pinsonneault & Kraemer, 1993, p. 272). On the

other hand, there was the expectation for and the discovery of an expansion in the number and role of middle managers within organizations (Blau et al., 1976; George & King, 1991; Klatzky, 1970; Meyer, 1968) as a consequence of information technology adoption.

Recently, Leonardi (2007) encouraged researchers of information technology within organizations to consider technology's potential "for creating, modifying, transmitting, and storing information in new ways" (p. 813). Changes in these moments in the transformation process—the mobilization of "information in the tool" in new and different ways—was found to lead to changes in the social structure, by way of shifts in the structure of advice networks within the organization. As such, while technology may be some causal trigger, the effect would be in fact be mediated by more local causes. Information technologies (as tools) change the way information might be stored, this new structure of information storage ultimately being the cause of changes within organizations.

When social structure is imagined more abstractly, as in strategic postures or modes, the findings relating technology with this structure prove equally as disputed. Kane and Alavi (2007) recently considered the social structure of interest to be one of two organizational learning modes—exploration or exploitation (March, 1991). These authors found that knowledge repositories and virtual team rooms differed in the extent to which each supported or hindered an organization's ability to adopt explorative or exploitative modes. While interesting in its assertions and extensions to the work of March (1991), the findings from this study were the result of a computer simulation—actual data from organizations were not employed. As such, there is reason to still wonder whether these findings would extend to individuals, organizations and technologies found "in the wild."

Technology as Structured

A second stream of research pursues technology, in its various forms, as a phenomenon reliably structured by environmental or organizational contingencies (Aldrich & Pfeffer, 1976). By way of this structured approach to technology, either the technology adopted by organizations is largely a function of features exogenous or endogenous to the organization, or there exists a predictable best “fit” between the technologies of the organization and some contingency in the environment. Galbraith (1973) characterized this equifinal approach by stating, “there is no one best way to organize; however any way of organizing is not equally effective” (p. 96). Alternatively, technology is a function, by way of fit or fate, of important features internal to the organization, such as raw materials (Perrow, 1967), information attributes (Daft & Lengel, 1986), power relationships (Thomas, 1994), or strategic choice (Child, 1997; Milgrom & Roberts, 1990).

Burns and Stalker (1961) found that organic social structure and flexible technologies were best suited for uncertain environments, while mechanistic social structures and similarly routine technologies were suited for more certain environments. However, a general disagreement emerged over what constituted uncertainty in the environment. Duncan (1972) considered the environment very broadly as “the totality of physical and social factors that are taken directly into consideration in the decision-making behavior of individuals and organizations” (p. 314). By way of this broad conception, Duncan found that the static-dynamic dimensions of the environment were more powerful predictors of organization member perspectives of uncertainty than the more commonplace simple-complex dimensions.

Turning inside the organization, Perrow (1967) suggested that the ideal technology of a firm was contingent upon the analyzability and variety of the underlying

raw material. Daft and Macintosh (1978) similarly argued that certain types of information systems within organizations—cursory, concise, elaborate, and diffuse—were best matched with variations in the knowledge possessed regarding and variety exhibited by the underlying material or process. Litwak (1961) focused upon the uniformity of inputs, while Dornbusch and Scott (1975) investigated what they considered the predictability of these inputs upon the best fit for technology.

Child (1972; 1997) wished to address what he believed to be an imbalance within organization theory, ignoring the choices of individuals. This approach echoed the critiques directed by Merton at those who spoke of “social order [as] solely a device for ‘impulse management’ and the ‘social processing’ of tensions” (Merton, 1938, p. 672). The predominant approaches “stress environmental selection rather than selection of the environment” (Child, 1997, p. 45), and thereby largely ignore the intentions and choices of members of organizations, particularly managers. As a result, perceived environmental complexity replaced some otherwise objective measure of complexity in the environment, as an explanatory term for just how and why managers adopted particular technologies within organizations.

Similarly, power-aware researchers such as Braverman (1974) and Thomas (1994) argued and observed how the resolution or production of power dynamics within organizations resulted in the adoption and design of particular machinery, or production methods. This tension among organizational agents over adopted technologies was described by Vallas (2006) as an uncertain conflict determining, “which occupational groups would gain control over the programming tasks on which the production process now depends” (p. 1701). As such, technology—whether seen in the tools put to use within an organizations, the techniques through which work was accomplished, or the

broad transformations through which organizational inputs are converted to outputs— was structured by causal agents located within the boundaries of the organization.

Technology as Structuring

A more recent stream of research, informed by structuration (Giddens, 1986) and negotiated order (Strauss, Ehrlich, Bucher & Sabshin, 1998) theories, sees the relationship between technology and social structure to be emergent, discreetly unpredictable, and best described as structuring (Barley, 1986; Orlikowski & Baroudi, 1991; Orlikowski, 1992). The structuring approach is based upon a critique similar to that of Child (1972), later summarized by Orlikowski & Barley (2001) who said that the bulk of organizations research “largely ignored the role of human agency in shaping either the design or the use of technology” (p. 147). Furthermore, similar to the earlier critique of Stanfield (1976), this school suggests that technology has been imagined abstractly and yet somehow treated deterministically. Instead, argues Latour (1987, p. 140), “understanding what... machines are is the same as understanding what people are,” a complicated mixture of social forces and individual choices.

Structuring approaches in research are beset with themes of dialectics or dualities, and based deeply in (at times) contradictory interpretations and actions of organization members (Volkoff, Strong & Elmes, 2007). By way of these dual-modes, it is not only possible that social structure is in effect an ongoing iterative process, but also it is plausible for technology to exist as both the cause and the consequent, both constituted of and constituted by social structure (Giddens, 1979). This “constitutive entanglement” (Orlikowski, 2007) of the relationship between technology and social structure mirrors the larger perspective of emergent action within organizations, highlighted by Pfeffer (1982, p. 9):

Because participation in organizational decisions is both segmented and discontinuous, because preferences develop and change over time, and because the interpretation of the results of actions—the meaning of history—is often problematic; behavior cannot be predicted a priori either by the intention of individual actors or by the conditions of the environment.

Essentially, the causal arrow between a certain technology and organizational outcomes can go both ways (Barley, 1986; Boudreau & Robey, 2005). Or alternatively, the otherwise static relationship between technology and social structure has been set in motion, permitting researchers to observe the interdependencies that emerge. Pickering (1995) somewhat humorously described this recursive technology-structure relationship as “the mangle of practice” (p. 567).

From this structuring lens, technologies may still have attributes—affordances, frames, features, properties—but the nature of these attributes emerges from enacted qualities as well as objective characteristics. While physical, these apparatus become social objects whose meaning is defined within a particular context (Barley, 1986; Griffith, 1999). And this meaning, or “spirit,” is not destined, but rather is constructed adaptively (DeSanctis & Poole, 1994)—being defined by, as well as defining context.

The structuring perspective has resulted in a constructivist version of contingency theory for the ideal fit between technology and social structure. Orlikowski (1994) found that the adoption of a Lotus Notes system (a “groupware” application supporting electronic mail, calendaring, database and file sharing) seemed to rest within “technological frames;” the ways in which actors conceived of the nature of technology, the underlying technology strategy, and the intentions for these technologies in use. Incongruities that might exist among the frames held by managers, technicians and users of the system could lead to difficulties in the initial implementation and ongoing success of these systems. Zammuto et al. (2007) argued that information technologies

offered “affordances in organizing,” and suggested a set of five such affordances (not intended as exhaustive) as a starting point for subsequent research: (1) visualizing entire work processes, (2) real-time/flexible product and service innovation, (3) collaborating virtually, (4) mass collaboration, and (5) simulation/synthetic representation. In the view of Zammuto et al. (2007), “these technology features need to be coupled with important organizational features to enact the affordance,” (p. 753). Aral and Weill (2007), in their explanation of how some firms more successfully exploited investments in IT than others, invoked strategic intent as a trigger for such affordances.

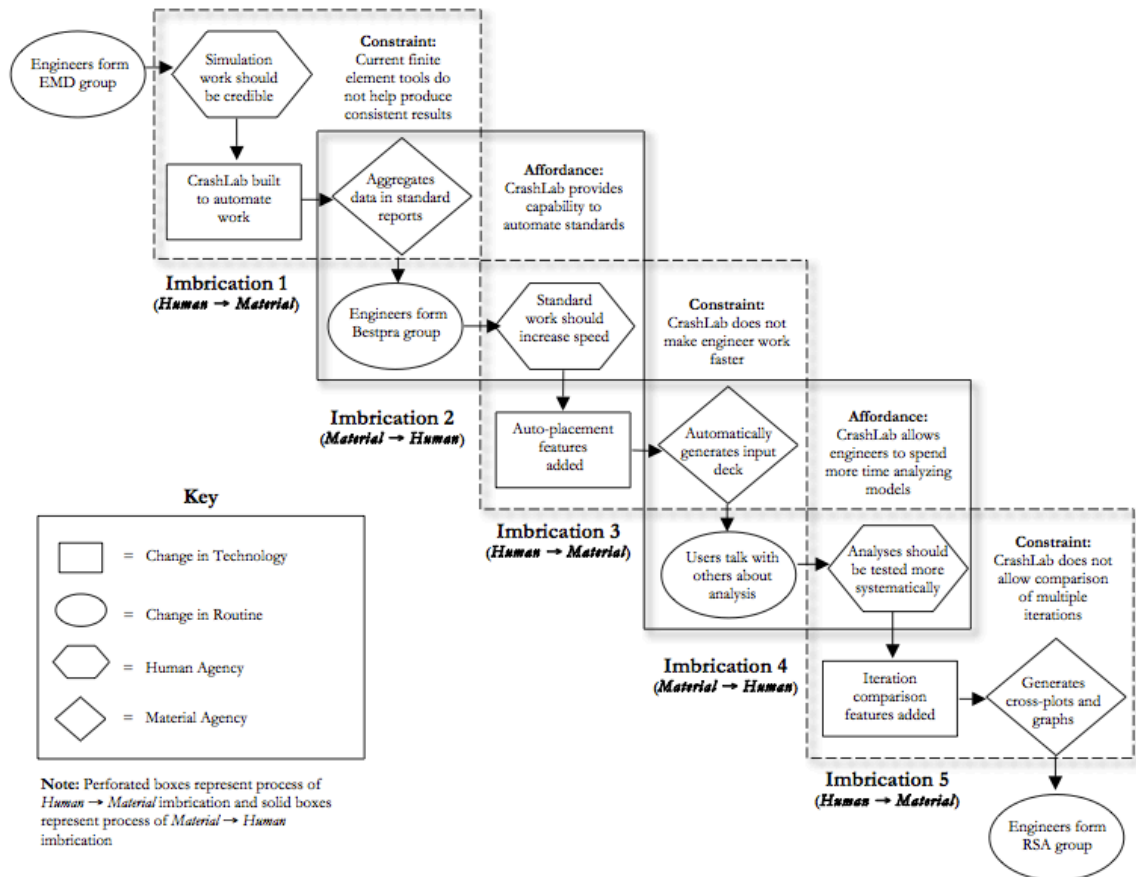


Figure II.5: Imbrications of Human and Material Agencies (Leonardi, 2010, p.48)

Importantly, while the structuring perspective tends to see technology as largely interpreted, these interpretations of technology are real enough to become triggers for unanticipated moments that afford an occasion for the renegotiation of meaning and social order (Griffith, 1999). However, technology is also re-constructed within these moments, leading to unanticipated outcomes. Recently, scholars have begun to describe this interweaving of human and material agencies as imbrication (Taylor, 2001; Ciborra, 2006; and Sassen, 2006), which Leonardi (2010, p.8) recently described as, the act of arranging “distinct elements in overlapping patterns so that they function interdependently.” Figure II.5 provides a visual representation of this sort of interwoven and iterative process, as presented by Leonardi (2010) to describe the steps through which engineers passed while employing CAD (computer assisted design) software to design automobile parts.

Perhaps the most extreme expectation of the structuring school would be that of multi-final relationships between technology and social structure—similar causes have multiple, distinct, and dynamic outcomes (Nickerson & Zenger, 2002). Barley (1986, p. 105-107) observed, “identical technologies can occasion similar dynamics and yet lead to different structural outcomes,” suggesting that “technologies do influence organizational structures in orderly ways, but their influence depends on the specific historical process in which they are embedded.” Two radiology departments, when adopting recently introduced CT scanners, came to reorganize in different ways around this equipment (one in a far more decentralized manner than the other), even though both the process through which these groups transitioned, and the change in work roles adopted by technologists and radiologists were largely identical.

Crossed Wires

Researchers have approached the relationships among technology, work, and social structure a number of ways. Unfortunately, regardless of the conception of technology, work, or structure, research has often resulted in weak or unsettled findings (Barley, 1990; Markus & Robey, 1988; Scott & Davis, 2007). The struggles researchers have had when trying to reliably relate the phenomenon of technology with other aspects of social systems can be sorted into three domains: **theories of everything**, **theories of which thing**, and perhaps most concerning, **theories of nothing** at all.

In the first case, technology and social structure have been so broadly, or abstractly defined, that researchers seem to be producing the impossibility that is a theory for everything. At the opposite extreme, across this bulk of research so many distinct aspects of technology and social structure have been considered, under very particular circumstances, that we have a large set of theories of very particular things, lacking generalizability. Finally, given the state of contradictory findings, researchers face the real prospect of having theories of nothing in particular. Conceptually, theoretically, and logically our approaches to technology and social structure seem sound. Unfortunately, once the data collected to test these theories are subjected to empirical analysis, we find weak if any support for our theoretical arguments.

Theories of Every Thing

Technology has been defined in such a wide variety of ways that Winner (1977) noted, “Technology is everything and everything is technology... the word has come to mean everything and anything; it therefore threatens to mean nothing” (pp. 9-10).

Throughout the literature pursuing the technology-structure relationship, one variable of interest—technology—has been variously defined as: “The process of transforming

inputs into outputs” (Fry, 1982, p. 533), “The mechanisms or processes by which an organization turns out its product or service” (Harvey, 1968, p. 247), “The work performed by an organization” (Scott & Davis, 2007, p. 125), “The tools used by individuals in carrying out their tasks” (Goodhue & Thompson, 1995, p. 216), as well as “The knowledge about the cause and effect relations of our actions” (Berniker, 1983, p. 10). Hickson et al. (1969) considered technology to include not only the activities of production, and the characteristics of the raw material, but also the knowledge used by the organization.

If we agree that the aggregate of research pursuing the technology-structure relationship has treated technology as, in effect, nearly everything, it should come as less of a surprise and disappointment to learn that a community of well-intentioned scholars finds it quite difficult to construct a theory to describe and explain the complete array of phenomena. Given the scope of these definitions, the entirety of any text dedicated to the phenomena that are organizations might necessarily involve, explicitly or implicitly, a discussion of technology. The chairs, walls, reporting structure, raw materials, control processes, robots that assemble the cars, hand movements of the operators, computers on the desks, software running on these computers, and even the knowledge contained within the minds of human members of the organization, have all been placed within the domain of “technology.” In fact, Hunt (1970) warned, “The concept of technology is too broad for useful research” (p. 105).

For example, Nadler and Tushman (1988) distinguish structure according to groupings of staff (activity, output, user, or some mixture of these foci), while Ouchi (1977) defined organizational control as “the process for monitoring and evaluating performance” (p. 96). Problematically, technicians like Rousseau (1979) might classify

these structural groupings and control processes as technologies within the wider project that is the organizational transformation of inputs into outputs.

Perhaps most challenging across the conceptions of technology and social structure is the overlap that occurs between technology—when imagined as technique—and structure—when conceived as deed. As a technique, technology resides in the actions of individuals. As a deed, social structure would reside in the actions of individuals. Admitting that his distinction between technology and social structure “has its grey areas,” Perrow (1967) clarified further the distinction between the two as, “the difference between an individual acting directly upon a material that is to be changed and an individual interacting with other individuals in the course of trying to change that material” (p. 195). However, Perrow’s distinction between action upon and action with does little to aid a researcher interested in understanding automation. Do we interact with automation in order to enact changes upon some underlying material? If so, do we then include automation within the social structure of organizations?

Theories of Which Thing

In many regards, navigating the history of research relating technology with social structure requires close attention to the specific things being studied. In the wake of the large supply of technology-related research on organizations produced during the 1960’s and early 1970’s, Stanfield (1976) criticized this research for a general failure to set real boundaries between categories for classification. Stanfield warned the researchers had been inferring results by drawing conclusions based upon unmeasured variables, and treating the technology applied or the structure evidenced by some organization as some aggregate, uni-dimensional classification. Conversely, Volkoff, Strong and Elmes (2007) criticized recent, more interpretive approaches to information

technology for treating these technologies as not only overly-dimensional, but also seemingly less than real—existing only in the actions and interpretations of organization members. Orlikowski and Iacono (2001) called this quandry, “Desperately seeking the ‘IT’ in IT research” (. 121). Beyond the definition of terms, Gregor argued (2006), “many [information systems] researchers who use the word theory repeatedly in their work fail to give any explicit definition of their own view of theory” (p. 612).

There is also the confusion regarding the relationship between technology and social structure resulting from research that varies widely as to the level of analysis. Essentially, the relationship between technology and social structure has been both theorized and researched at the individual, work group, organization and even industry level. This diversity in levels of analysis has been a source of contention and confusion for a number of decades (Comstock & Scott, 1977; Fry, 1982; Orlikowski & Iacono, 2001; Rousseau, 1979; Udy, 1965).

Related to the confusion over the level of analyses is uncertainty resulting from the substance for analysis—just which view of technology is of interest and to which view of structure is this technology supposed to relate. In fact, many discussions of technology within organizations are insufficiently clear about either term—technology or structure. Stanfield (1976) called this unspoken agreement over terms “consensual validity.” As a result of this consensual validity, just what is technological and what is organizational can be taken for granted.

For example, Cohen and Levinthal (1991), in their discussion of absorptive capacity, do not stop to define the nature of “technological opportunity” other than to note that this opportunity might be better realized through technical knowledge. Garud and Nayyar (1994) neglect to define the real nature of the technologies upon which these opportunities rest in their discussion of organizational transformative capacity and the

impact of this capacity upon technological opportunities. While offering a complex economic proof for why manufacturing firms might adopt new technologies, Milgrom and Roberts (1990) seem to seamlessly toggle between conceptions of technology as machinery and as methods, without clearly explaining how technology might be contained within both phenomena. Kogut and Zander (1992), in their presentation of a knowledge-based theory of the firm, while seeming to distinguish “a given technology” from “a method of organization,” never openly disclose just whether and how these are distinguished from each other, nor from the know-how and information that provide the base for the organization.

Theories of No Thing

As stated earlier, regardless of how technology and structure have been conceived, research relating technology, work, and structure has resulted in unreliable findings (Barley, 1990; Markus & Robey, 1988; Scott & Davis, 2007; Scott, 2003).

Summarizing the wide range of literature pursuing some reliable technology-structure relationship, Scott and Davis (2007, p. 137) observe:

The evidence for these associations is often relatively weak or conflicting, in part because of the wide variety of measures employed, differences in the levels of units studied (individuals, teams, departments, organizations), and vagueness over the form of the predicted relation.

Problematically, most theories imagining some objective and reliable relationship between technology and social structure have found weak statistical evidence for support. Whether this lack of reliable findings is a function of the variety of measures employed, the differences in the level of analysis, or the lack of clarity regarding the form of the predicted relations is still a matter for debate. What holds a theory together, however, is its capacity to explain, which entails some identification of correlation among

variables in a manner that is reasonably causal, logically plausible, and statistically significant. As Weick commented (1989), “Proof, in other words, consists of verification of a probabilistic statement.” Scholars have reason to question whether we possess meaningful theories of the technology-structure relationship at all without the existence of explanatory models, which by way of empirical tests offer the ability to predict outcomes in a manner that is both methodologically replicable and statistically significant.

Barley (1986) suggested, however, that researchers should simply “embrace the contradictory evidence as a replicated finding,” and “accept the inconsistent findings as a matter of course” (pp. 78-79). As such, in recent years, the formal relationship between technology and social structure has come to be understood as something far less than formalized. While largely a critical challenge of the assumptions held by positive theorists, the interpretive and reflexive approach underlying what I described as the structuring perspective has undoubtedly contributed to a more nuanced understanding of technologies within complex organizations (Baron & Kenny, 1986; DeSanctis & Poole, 1994; Tushman & O'Reilly, 1996), how ever those technologies are defined.

A criticism of more interpretive research relating technology with social structures is that abstract conceptions of technology, whether tending to coincide with more concrete and causal theories of the technology-structure relationships or messy constructivist versions of these these theories, lead organization scholars to altogether ignore materiality as a factor. Essentially, the argument goes, there is no “thing” upon which these theoretical understandings depend. Conceptions of technology as a technique, or as a transformation, treat materials—perhaps the most objective object in an organization—as largely incidental. Barad (2003) summed up this line of thinking:

“Language matters. Discourse matters. Culture matters. But there is an important sense in which the only thing that does not seem to matter anymore is matter.”

Notwithstanding their influence and significance, the findings from this interpretive school also present a certain disappointment for many organization scholars. If the relationships between technology and social structure are unpredictable, then as scholars we are better positioned to offer situated understandings rather than generalizable explanations. We can describe compelling situations under study and may even understand these situations deeply, but by finding only loose similarities across a variety of contexts and predicting nothing in particular we can reliably say very little about the consequences of technology—however conceived—for organizations, or society-at-large.

It should be noted, however, that much of the dismantling of what was called the technological imperative came by way of small sample studies, even samples as small as one. Billings’ study of a single food service facility found that as an organization shifted from a batch to a mass production method, the social structure did not shift according to the expectations of classical contingency theory (1977). Barley (1986) found that radiology labs within a sample of two hospitals did not respond identically to the introduction of the same radiological equipment, even though prior to introduction these labs were quite similar. Perhaps contingency theory embodied an unstated expectation that the assertions of the technological imperative would hold for each and every research setting, rather than for research settings “in general.” As a result, exceptions found in research to the assumed rules of contingency theory, even exceptions of one, have been treated as findings sufficient to weaken the strength of contingency as a theoretical force.

As Siggelkow (2007) argued, “Theories and models are always simplifications... Thus, we almost always will be able to find instances in which a theory does not hold precisely” (p. 21). The findings of contingency theorists may still hold true across large samples of organizations. These broad claims however, may only explain a small portion of the variety we observe across organizations. As we increase the precision through which we try to understand organizations, in the context of these truthfully complex systems (Anderson, 1999; Lewin, Parker & Regine, 1998), per Zadeh’s principle of incompatibility (1973), “precise statements lose meaning and meaningful statements lose precision” (McNeill & Freiburger, 1993, p. 43).

Conclusion

In this chapter, I have provided a rather broad, yet critical review of the literature that has pursued the question, “What is the relationship between technology, work, and the social structure of organizations?” This literature as a whole is elaborate and extensive; this review admittedly risks conceptual injustice by summarizing and classifying the major definitions and debates within this literature in somewhat simplified terms. Unavoidably, attempts to classify and therefore simplify truly complex social and technological phenomena face the very real limitation that each instance does not always fit neatly into only one cell (Liker et al., 1999).

In the next chapter I turn to the particular manifestation of technology within organizations that is the focus of the dissertation—automation. The consequences of automation for the nature of work have been debated for many decades, if not for more than a century. As such, it is not without a significant degree of apprehension that I step into this debate, headfirst.

CHAPTER III

WORK AND AUTOMATION

Within scholarly circles, the at-times tenuous relationship between automation and the nature of work has been a recurring subject of interest (a substantially limited list of this research would include: Adler, 1992; Burris, 1998; Durkheim, 1997; Lee 2004; Meyer 1968; Simon, 1973; Toffler, 1970; Winner, 1977; Olson 1982; Zuboff, 1988). Furthermore, a general concern that automation might lead to a predominance of repetitive and meaningless work, or to a scarcity of work altogether, has informed our understanding of these technologies for nearly a century (Diebold, 1952; Falconer, 1914; Faunce, 1965; Noble, 1984; Rifkin, 2004).

Outside scholarly circles, popular works of fiction and film—*Modern Times* (Chaplin, 1936), 1984 (Orwell, 1949), *2001: A Space Odyssey* (Clarke & Kubrick, 1968a; Clarke & Kubrick, 1968b), *Brazil* (Gilliam, Stoppard & McKeown, 1985), *Ghost in the Shell* (Oshii, 1996; Shirow, 1995), and *The Matrix* (Wachowski & Wachowski, 1999), to name a few—reflect dystopian concerns about the nature of work, and even the nature of human identity, alongside advances in technology. Jeremy Rifkin articulated such dystopian concerns in *The End of Work* (Rifkin, 2004, p. xxii):

Intelligent machines, in the form of computer software, robotics, nanotechnology, and biotechnology, increasingly [replace] human labor... More and more physical and mental labor, from menial repetitive tasks to highly conceptual professional work, will be done by cheaper and more efficient thinking machines in the twenty-first century. The cheapest workers in the world likely will not be as cheap as the technology coming online to replace them.

Rifkin (2004, p. xxii) continues by suggesting:

By the middle decades of the twenty-first century, the commercial sphere will have the technological wherewithal and organizational capacity to provide goods and basic services for an expanding human population using a fraction of the workforce presently employed.

In this chapter, I will present a series of conflicting propositions based upon general patterns and positions that emerge from the scholarly debate that has formed around the central question for this research: What are the consequences of automation for the nature of work? First, however, after slicing and dicing the major concepts and findings of the vast literature relating technology, work, and social structure, I will describe and define the key concepts of interest for this project.

Definitions

In this section I introduce the primary concepts of interest as they will be applied for this research. The hypotheses presented will focus upon changes in the nature of work (i.e., routinization, skill requirements), associated with changes in the degree to which automation is a factor in work, given asymmetric distributions of power (i.e., resources, discretion). A few cautionary words, however, before these introductions. For those prone to a classical approach to organization theory, or those who read the previous chapter, it will seem that technology is to play two versions of its own self—as both technique and tool. This dual version for technology is intended. In its more abstract role, technology will be treated as technique, but in this case I will call the broad class of techniques by their more common term, “work.” In its more artifactual role, technology will be treated as a class of tools believed to constitute “automation.”

Automation as Technology

The *McGraw-Hill AccessScience Encyclopedia of Science & Technology* defines automation as, “The process of having a machine or machines accomplish tasks hitherto performed wholly or partly by humans” (Hess, 2005, “Automation,” para. 1). The *Columbia Encyclopedia* (2008) defines automation as: “automatic operation and control of machinery or processes by devices, such as robots that can make and execute decisions without human intervention” (“Automation,” para.1). The automation of work, particularly factory work, was a topic of early interest and debate. This focus upon automation in the context of material production however, soon gave rise to a wider interest in the impact of the less material form of automation that existed within computer systems. Davis (1963) defined automation as “a work process which includes (1) computer information processing for decision-making and (2) information feedback and control systems for automatic self-regulation of production” (p. 179).

Within this research, automation will be broadly defined as *the performance of a task, physical or mental, in whole or in part by a machine*. For clarity, by “machine” I mean a non-human apparatus having several parts that function together to perform a task (Oxford English Dictionary, 1989). I will not consider it necessary for a human being to have previously performed some task, for automation to occur. Furthermore, the degree to which any machine involved is “self-regulating,” according to a strict definition of that term as intended by Davis (1963), will not be formally considered.

Work and Occupations

Simply put, work can be thought of as any activity involving mental or physical effort (Autor, Katz & Krueger, 1998; Autor, Levy & Murnane, 2003; Bright, 1958; Glisson, 1978; Hage & Aiken, 1969; McKean, 2005; Ohly, Sonnentag & Pluntke, 2006;

Parasuraman & Alutto, 1981; Tuchman, 1973). As noted in Chapter 2, the tasks involved in work have been characterized in myriad ways. Of particular interest herein will be the routinization of work (Hage, 1969; Tuchman, 1973; Glisson, 1978; Parasuraman, 1981; Ohly 2006) and the general level skill requirements for work (Bright, 1958; Autor, 1998; 2003).

For the purposes of the hypotheses developed here, work will be pursued across a wide range of occupations, as reported by individuals spanning a broad range of locations, organizations and industries. Occupations—whether conceived as loci for social power, bundles of organizational roles, or shared frames of mind—have been considered by many researchers to inform our understanding of structure within organizations, and even society-at-large (Barley, 1990; Blau, 1974; Scott & Davis, 2007). Scott (2007) argued that occupations provide a worthwhile unit for understanding work across the specializations of labor that describe the human factors of production in modern organizations.

Barley argued (1996), “Without a substantive knowledge of work, organizational theorists risk building theories of change around terms with shallow content.” As such, in the same spirit through which Granovetter (1985) hoped to find some middle ground between the over-socialized and the under-socialized conceptions of human action within social systems, I consider it worthwhile to try to occupy some middle space between what we might call the over-worked and the under-worked conception of organizations within organizations research. By understanding the associations between automation and the nature of work, I believe we can develop more substantive theories of the more general relationships that exist between the technology and the social structure of organizations.

For some researchers, the abstraction called work was known as “technology.” Perrow (1967) was quite upfront about this overlap, defining the broad domain that is technology as “the work done in organizations” (p. 194). As a result, organization theorists now run into a conceptual dilemma: one theorist’s work is another theorist’s technology. For those researchers who know work as technology, a broad inquiry into the relationship between automation and the nature of work can feel like an investigation of technology and the various incarnations of itself. However, organizations researchers have by and large combined this technology-as-work approach with either the general avoidance of automation as a subject for research, or the general assumption that automation is de facto routine (i.e., repetitive). By avoiding automation when investigating organizations, researchers see only the actions of individuals and risk misclassifying the routine or nonroutine nature of the technology (a.k.a., work) employed by those organizations making extensive use of automation. By assuming automation only operates as a repetitive sort of technology, researchers lose sight of the extent to which automated systems might enact explicit yet non-repetitive routines—potentially supporting nonstandard forms of production such as mass customization.

Social structure as Power

Organizations are compelling entities that blend socially constructed abstractions with concrete reality. At one level, organizations are collective delusions in which most everyone involved is somehow willing or coerced to believe. A new VP of Marketing is hired, and that individual by virtue of their position is granted any number of organizational affordances—to borrow a word from the study of technology and apply it to social systems. At another level, organizations are very real places, wherein

individuals struggle to work individually and together amidst an asymmetric distribution of influence over materials, people and information.

In the following chapter, organizational structure will be considered in word and that word will be power. I will focus specifically on two different faces of power. One form emphasizes power as a source of control over necessary and even scarce resources—whether human, material, or informational (Blau, 1964; Emerson, 1962; Etzioni, 1964). Importantly, different occupations are afforded different levels of influence over the resources within an organization. In the second form, I will focus upon power as a source of individual agency, or discretion (Montanari, 1978), supported by what French and Raven (1959) categorized as legitimate power. Individuals are afforded differing degrees of discretion as they perform their work, a condition of autonomy stemming from occupational position.

Theory and Propositions

In the following section I present two sets of conflicting propositions that emerge from the scholarly debate that has formed around the central question for this research, “What are the consequences of automation for the nature of work?” Each of these debates rests upon a common theme—the existence and nature of routines. A general concern for the routinization of work has persisted throughout the history of sociological inquiry (Durkheim, 1997; Kohn, 1976; Smith, 1997; Weber, 1947). Furthermore, the relationship between the nature of routines and the social structure of organizations has continually provided a backbone for organization theory (Burns & Stalker, 1961; Feldman & Pentland, 2003; March & Simon, 1958; Perrow, 1967; Scott & Davis, 2007; Thompson, 1967; Tuchman, 1973).

Three contradictory expectations emerge in terms of the consequences of automation for the routinization of work and the skill requirements for work. Figure II.6 (regarding the routinization of work) and Figure II.7 (regarding the skill requirements for work) visually present these conflicting expectations. First, there is the expectation—known as the *deskilling* hypothesis—that alongside increasing levels of automation, work will become increasingly routinized and repetitive, requiring decreasing levels of experience and skill (Braverman, 1974; Glenn & Feldberg, 1979; Greenbaum, 1979; Kraft, 1979; Kraft, 1984; Noble, 1984; Wood, 1982). Second, there is the prediction—characterized as the *reskilling* hypothesis—that work becomes increasingly non-routine and abstract, alongside automation, requiring greater levels of experience and skill (Adler, 1992; Autor et al., 2003; Keefe & Potosky, 1997; Levy & Murnane, 2004; Nelson & Phelps, 1966; Shaiken, 1984; Zuboff, 1988). By way of automation, the portfolio of routine and standardized work has been programmed into machines, leaving only non-routine, unprogrammable work remaining. Finally, there is the expectation that the relationship between automation and the nature of work is non-linear, in particular convex (Blauner, 1964; Hodson, 1996; Woodward, 1965). I will extend this latter perspective by proposing that a *cyclical* relationship exists between automation and the nature of work, resulting in an S-shaped link; increasing levels of automation first lessen, then increase, and then lessen again the repetitive nature of work, while conversely first increasing, then lowering, and then increasing again the specialized skill requirements for work.

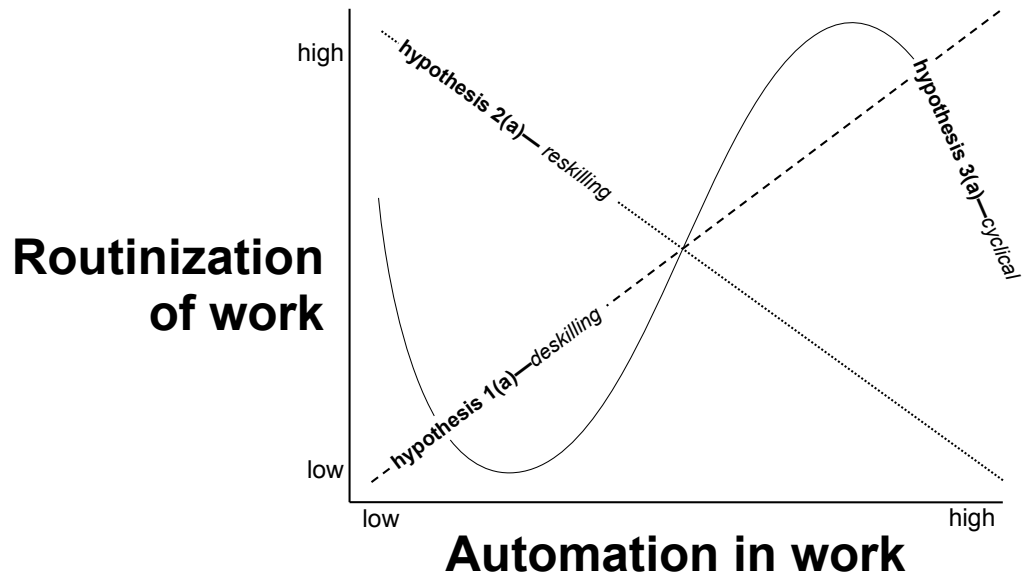


Figure II.6: Proposed Relationship Between the Degree of Automation Alongside Work and the Routinization of Work

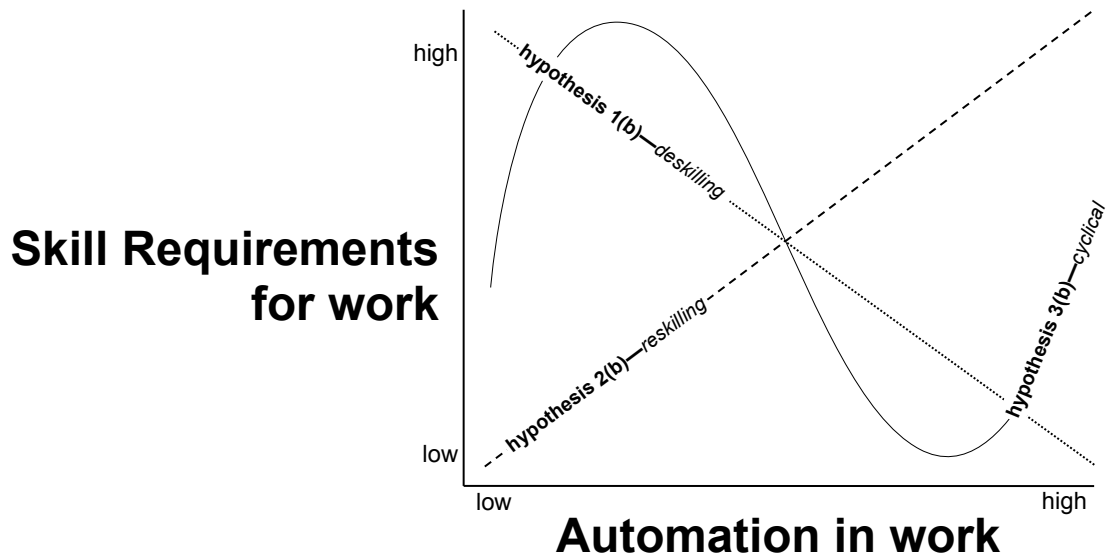


Figure II.7: Proposed Relationship Between the Degree of Automation Alongside Work and the Skill Requirements for Work

Regarding the nature of social structure alongside automation, I will focus on the relationship between power, the nature of work and the level of automation. Underlying the hypothesis for work alongside automation known as the deskilling hypothesis is the assertion that power is the arbiter of decisions regarding which tasks will or will not be automated. I will investigate the extent to which variations across occupations in perceived dimensions of power—namely, control over resources and discretion in work—might be associated with variation in the level of routinization of work, or moderate the relationship between the level of automation alongside work and the routinization of that work. These relationships are presented in Figure II.8.

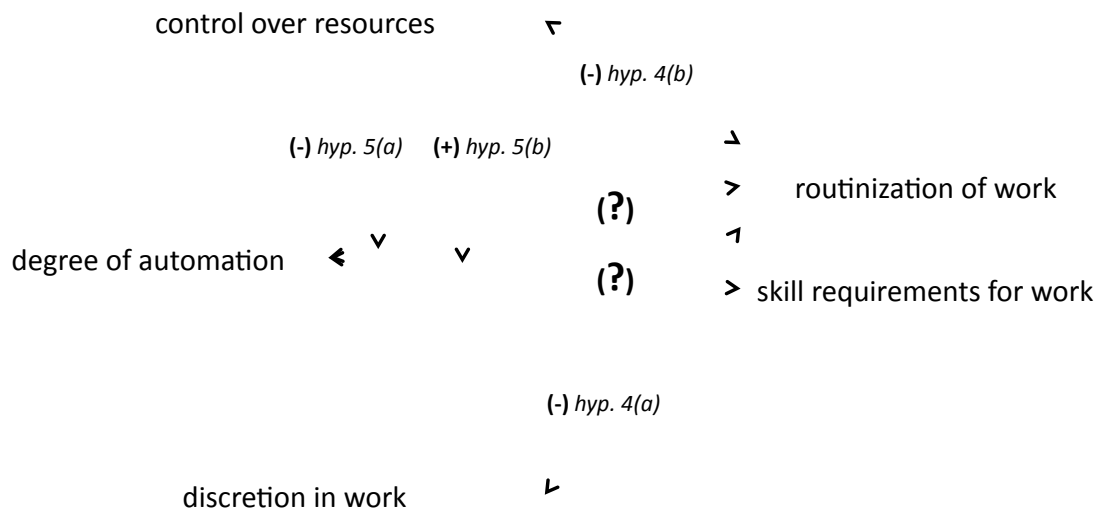


Figure II.8: Proposed Relationships Between the Dimensions of Power, the Degree of Automation and the Routinization of Work

There has also existed an expectation that work routines in organizations are guided by “matched pairs” of means and ends (March & Simon, 1958)—clearly defined routines for conducting work (means) are matched with clearly defined standards for the

outcomes of that work (ends), while poorly defined routines for conducting work are matched with vaguely defined standard for the outcomes of that work. I will suggest that automation “augments” the structure of work routines, by which I mean the means-ends pairs can be “unmatched” through the assignment of one dimension of this pair (the means or the ends) to a machine. Figure 8 presents these two predictions. As an example of this augmentation of means-ends pairs, in some genetics labs the means of work are programmed into robots that scan and classify hundreds (if not thousands) of DNA samples, while computer programs later run statistical tests on these samples. Geneticists in these labs operate under loosely defined ends, refining these ends by determining the DNA samples to be collected, the outcomes of interest and the level of significance from these results that warrants further attention. By way of this augmentation of work, defined routines for work (the means) are enacted by automation while the open-ended context and outcomes for work are managed by individuals. Alternatively, automation is introduced to support clearly defined outcomes of work (the ends), setting a context for or constraint upon loosely defined routines in work as performed by individuals.

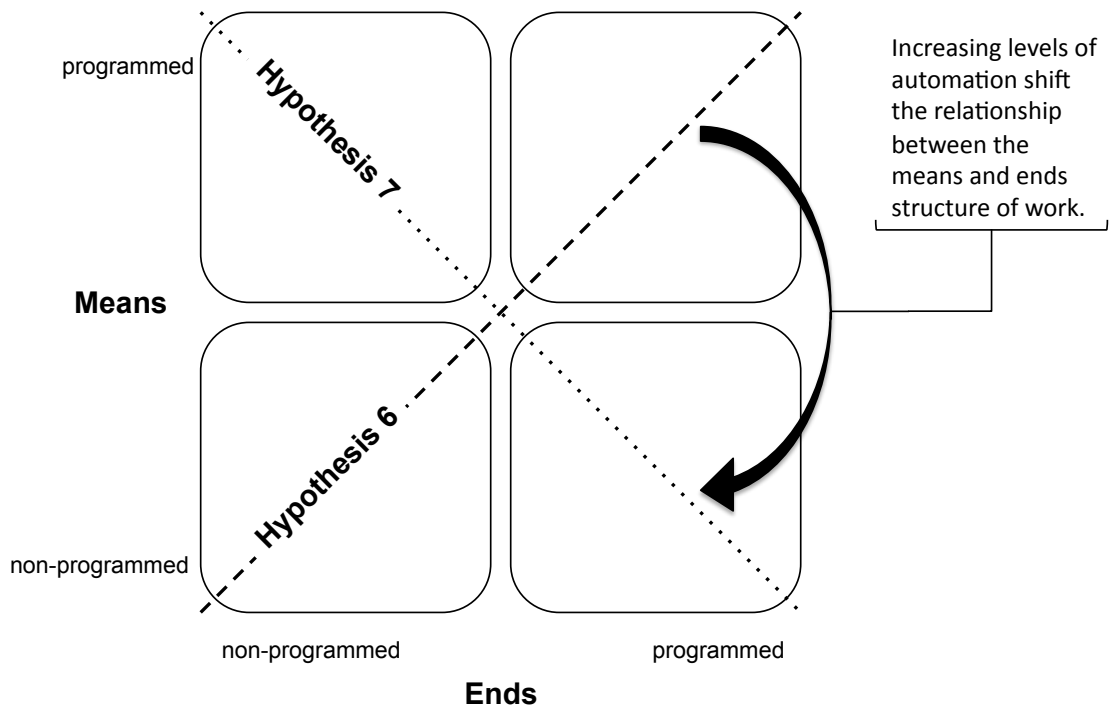


Figure II.9: Proposed relationships Between the Programmed Nature of the Means for Work and the Ends of Work, as Moderated by the Degree of Automation

Automation and the Nature of Work

There is an ongoing disagreement among scholars regarding the consequences of automation for the nature of work (Dean, Yoon & Susman, 1992; Harvey, 1968; Lewis, 1998; Liker et al., 1999). Aummarizing an edited volume of research investigating the impact of technology upon the nature of work, Adler (1992) suggested, “The dominant image of the future of work in this research is that of a kaleidoscope of complex patterns, constantly shifting and forming no over-all tendency” (p.8).

On one hand in this debate, automation is believed to be both a function and a facilitator of standardized and structured work processes, thereby leaving work alongside automation increasingly routine and highly structured in nature. On the other hand, it is assumed that routine work is far more likely than non-routine work to be automated.

Furthermore, the absorption of routine work by machines through automation complements certain abstract skills. As a result, primarily non-routine, increasingly unstructured work would remain alongside greater levels of automation. On some third hand, a convex function is believed to best describe the relationship between automation and the nature of work. As the level of automation first increases alongside work, that work becomes increasingly routine and structured. At some point however, a tipping point occurs, after which work becomes increasingly non-routine and unstructured alongside greater levels of automation. In the following section, I will present hypotheses and support for each of these three conflicting positions.

More routinization

Perrow (1967) argued, in line with March and Simon (1958), that coordination within organizations can be imagined as a function of either planning, or feedback. Coordination by planning “refers to the programmed interaction of tasks, which interaction is clearly defined by rules or by the very tools and machinery of the logic of the transformation process.” Coordination by feedback referred to, “negotiated alterations in the nature or sequence of tasks performed” (Perrow, 1967, p. 199). These two classes of coordination were largely consistent with or embedded within the theoretical assertions of a number of other early scholars of organizations: programmed versus nonprogrammed routines (March & Simon, 1958), long-linked versus intensive technologies (Thompson, 1967), mechanistic versus organic structures (Burns & Stalker, 1961).

Automation, being a well-programmed production process, would seem to be coincident with the rules and routines associated with coordination by planning. Routine work involves the application of rules, whether simple or sophisticated, to the challenge of the production process. According to Levy and Murnane (2004), “For a human task to

be programmed, we must be able to construct a representation of the required information that is suitable for a [machine], and we must be able to express the processing in deductive or inductive rules” (p. 10). Non-routine work is quite the opposite, being accomplished by feedback, by way of conditional rules that cannot be articulated, “pure pattern recognition,” or no rules whatsoever. There remain tasks that cannot be characterized by articulated rules, tasks residing within the domains considered tacit knowledge, or intuition (Nonaka, 1994; Polanyi, 1997; Wenger & Snyder, 2000).

For researchers critical of the adoption of technology within organizations, these apparatus can be instruments used for the exploitation of those classes of workers holding lesser influence over the distribution of resources, or the nature of work activities. The general concern has been that, “the question for management is... not simply one of saving money through reducing the payroll, but clearly one of the maximum control over the labour process in pursuit of maximum profitability” (Downing, 1981, p. 286). Vallas and Beck (1996) noted that programmable control systems not only reinforced routines, but also supported the hierarchical structure of the organization.

Perhaps the most vocal argument regarding the future of work amidst automation asserts that automation is associated with the “deskilling” of work, a proposition central to the critical concerns of a number of scholars (Braverman, 1974; Glenn & Feldberg, 1979; Greenbaum, 1979; Kraft, 1979; Noble, 1984; Wood, 1982). Underlying the deskilling hypothesis is a belief that certain incentives exists within organization for those in more influential positions to support the adoption of machines that reduce any task to its most basic components, such that any available worker could perform the task in the most efficient, high quality manner. By way of this deskilling, affected laborers no longer control exclusive skills but rather become part of a homogenized labor force, with no

distinctive skills leading to nominal negotiating influence. As noted by Smith (1997, p. 323), citing Taplin (1995):

Computerized systems can deskill jobs; they more subtly control their work force, as management uses it to monitor the location of products, provide detailed information about work performance, and build in quality control mechanisms.

Accordingly, automation may be associated with not only more routine work, but also lesser levels of experience and specialized skills being required to enact these work routines.

Hypothesis 1(a): Greater levels of routinization in work are associated with greater levels of automation.

Hypothesis 1(b): Lesser levels of skill requirements for work are associated with greater levels of automation.

Less routinization

Perhaps the deskilling hypothesis did not go far enough in its predictions. What if the machinery of automation can be so well designed as to replace and displace almost completely the performers of routinized tasks? As an example of such task displacement: Employees of the Federal Reserve Banks of the United States once hand sorted and counted money and bank checks. Now, such tasks are performed almost exclusively by automated machinery, at speeds and error-free rates unattainable by bank employees. Noble (1998, p. 14) described this sort dystopia of displacement as follows:

In Kurt Vonnegut's classic novel *Player Piano* the ace machinist Rudy Hertz is flattered by the automation engineers who tell him his genius will be immortalized. They buy him a beer. They capture his skills on tape. Then they fire him.

As such, the expectations of the deskilling hypothesis were perhaps not critical enough. So effective has been the deskilling, that it has become an ex-skilling—with the more

routine, low-skill tasks largely programmed into machines. The remaining tasks are composed of those kinds of routines that cannot be programmed into machine terms.

There are those who assert that alongside automation, work is essentially stripped of routines, and the remaining tasks require even greater levels of skill (Autor et al., 2003; Bright, 1958). Davis (1963) argued, “With automation, the person performs fewer routine operations because these activities have been transferred to automated systems... Rather than decreasing available work, automation releases man to perform work of a higher order —more intellectual, creative, and idealistic.” (p. 279). Automation, while a substitute for routine labor, proves to be a complement for more abstract skills, raising the level of demand for these skills within the labor force (Autor et al., 2003).

The re-skilling position can be understood as a sort of two-handed, or ambidextrous version of Perrow’s (1967) typology of organizational technologies—one hand being made of steel (i.e., mechanization) or silicon (i.e., computerization), the other made of flesh (i.e., human labor). Routine technologies are applied for that part of any organizational challenge that is analyzable and relatively exceptionless—a description of the sort of circumstance befitting automation. Non-routine technologies are adopted for largely unanalyzable problems, fraught with exceptions to any rule—the circumstances considered by most to be unsuitable for autonomous machines (unless one considers human beings to be machines).

In fact, critics of the deskilling hypothesis argue that its expectations fail to explain recent data, collected over the last decades of the twentieth century. These data suggest a general skill bias—a reskilling—within rather than a deskilling of the labor force (Autor et al., 2003; Levy & Murnane, 2004; Spitz-Oener, 2006). Across a number of occupational domains, work alongside automation appears to have become more abstract, and less routine (Keefe, 1992; Nelson & Phelps, 1966; Shaiken, 1984; Zuboff,

1988). Were the deskilling hypothesis true, general labor demand would steadily shift towards routine, unskilled labor as evidence of the increasing proportions of tasks that could be performed by any laborer, regardless of skill. Instead, according to the expectations of the re-skilling hypothesis, there has been decreasing demand for routine labor, and increasing demand for labor capable of handling so-called non-routine and complex cognitive tasks.

Accordingly, there is reason to believe automation is associated with work offering lesser degrees of routinization, requiring greater levels of skill:

Hypothesis 2(a): Lesser levels of routinization in work are associated with greater levels of automation.

Hypothesis 2(b): Greater levels of skill requirements for work are associated with greater levels of automation.

More and less routinization

While it may seem reassuring to assert that there remain some jobs machines cannot do, important unanswered questions remain. First, conceptions of the kinds of work that can be automated are continually updated. There is steady progress in our capacity to program machines to address what were previously considered non-routine challenges (Brooks, 2008; Brooks, Myopoulos & Reiter, 1991; Maes, 1991; Maes, 1994; McCorduck, 2004; Minsky, 1986, 2007; Mitchell, 1997; Newell & Simon, 1972; Russell & Norvig, 2010; Simon, 1973). Technologists are continually learning how to program “fuzzy” routines that are sufficiently general and interdependent in nature to qualify as nonroutine programming structures.

Second, if we imagine automation to be a carrier of organizational routines alongside the routines observed within the wider organizational system, there is reason to believe that the rate of routinization slows with the density of routines (Jennings, Schulz, Patient, Gravel & Yuan, 2005; Schulz, 1998). Schulz (1998) found that birth

rates for rules and routines decline with the density of these rules and routines. While more radical theories of bureaucracy suggest an unlimited capacity for rules to beget rules, rules may instead beget rules at a decreasing rate as the organization learns more about the range of contingencies within the environment. Eventually, rules are consolidated and the level of routinization, in fact, may fall back.

At the initial stages of technology adoption, practitioners and scholars speak of a phenomenon called “low hanging fruit”—gains that can be had from early, simple implementations of a technology. King and Lenox (2000) spoke of “the easy, inexpensive improvements in environmental performance” (p. 709) that can be earned from initial investments in industrial pollution reduction technologies (Hart, 1994; Hart, 1995; Rooney, 1993). Subsequent improvements in performance however, prove to be increasingly difficult (Bansal, 2003; Frosch & Gallopoulos, 1989; Walley & Whitehead, 1994). Sterman and Wittenberg (1999) suggested that the availability of easy, initial gains often provide success that leads to word-of-mouth encouraging the subsequent adoption of the ideas of management gurus. Schulz (1998) even suggested that recurring problems within organizations might be considered such low hanging fruit—visible and “easy to pick” by decision makers within the organization.

Importantly, certain core findings of organizational researchers suggest that the relationship between automation and the routines of work would be better described as non-linear—in particular, concave. Woodward (1965), in her study of organizational technology and social structure found that a mass production system’s level of mechanization was associated with the rules and routines of a bureaucratic social system, while the more extreme form of mechanization that existed under a system of continuous production was associated with a more ad-hoc and organic social order. Mintzberg (1979), drawing upon the findings of Woodward (1965), Udy (1959), Hunt

(1970), and Khandwalla (1974), suggested automation of the operating core could transform an administrative structure from bureaucratic to organic:

One apparent solution to the problem of impersonal bureaucracy is not less regulation of operating tasks, but more, to the point of automating them. Automation seems to humanize the traditional bureaucratic structure, something that democratization proves unable to do (p. 266).

Blauner (1964), in his classic study spanning a variety of production systems, found a similar transition from the less, to the more, and back to the less routine nature of work as his research context transitioned from the craft, to the assembly-line and finally to the more extreme automation of continuous production. “The chemical worker’s freedom is the result of an automated continuous process technology and constant technical change” (Blauner, 1964, p. 165). Hodson (1996) would later disagree with Blauner, attributing the convex change in the nature of work to organizational and environmental variables, particularly that of participatory management—“formal organizational structures that actively incorporate workers in operating decisions” (Hodson, 1996, p. 726)—as opposed to the underlying technology. As such there is reason to question whether automation affects the nature of work after taking into account other attributes of the work context.

Accordingly, there is reason to suggest that the levels of routinization in work, and the skills required for work, would be related to the degree of automation in a non-linear fashion:

Hypothesis 3(a): The relationship between the routinization in work and the level of automation is non-linear. Specifically, the plotted relationship between automation and routinization is S-shaped.

Initial increases in the level of automation result in decreases in the level of routinization. After this initial decrease, however, subsequently greater levels of automation result in increasing levels of routinization. At some point however, this relationship reverses, with the highest levels of automation resulting in decreasing levels of routinization.

Hypothesis 3(b): The relationship between the level of skill requirements for work and the level of automation is non-linear. Specifically, the plotted relationship between automation and skill requirements is in the shape of an inverted S.

Initial increases in the level of automation result in increases in the level of skill requirements. After this initial increase, however, subsequently greater levels of automation result in decreasing skill requirements. At some point however, this relationship reverses, with the highest levels of automation resulting in increasing skill requirements.

Power and Automation

A number of researchers have formulated research questions around issues of power in social organizations (Blau, 1964; Emerson, 1962; Krackhardt, 1990; Mintzberg, 1983; Pfeffer, 1981; Zald, 1970). Broadly conceived, power involves “the capacity of an individual, or group of individuals, to modify the conduct of other individuals or groups in the manner which he desires, and to prevent his own conduct being modified in the manner in which he does not [desire]” (Tawney, 1931, p. 229). This broad definition captures a number of perspectives. Weber (1947) defined power as “the probability that one actor within a social relationship will be in position to carry out his own will despite resistance,” while Emerson suggested “power resides implicitly in the other’s dependence” (Emerson, 1962, p. 32). Salancik and Pfeffer stated that while a clear definition of power may be elusive, within organizations “power is simply the ability to get things done the way one wants them to be done” (1977). Pfeffer argued, “power has a bad name in social science research and is most often conspicuous by its absence from the literature” (Pfeffer, 1997, p. 137). While not altogether absent, discussions of power are often cloaked by what Salancik and Pfeffer (1977) called the “cleaner” forms of power—authority, legitimization, influence, resource dependence, decision rights and control.

Issues of power within and among social organizations have been studied at various levels of analysis, spanning the superior-subordinate dyad (Cartwright, 1959; French & Raven, 1959; Tannenbaum, 1968), sub-unit relations (Perrow, 1970; Pfeffer & Moore, 1980; Pfeffer & Salancik, 1974; Salancik & Pfeffer, 1974), interior networks (Krackhardt 1990), and relations between and amongst organizations (Burt, 1983; Casciaro & Piskorski, 2005; Pfeffer & Salancik, 1978).

The assignment of control, and therefore the formal distribution of power, has been understood to impact decision making within organizations. Research has found that relative position within an organizational hierarchy matters (Lucas, 1981; Rice & Aydin, 1991; Rice, Grant, Schmitz & Torobin, 1990), with higher positions tending to predict the level of influence an individual holds within the organization (Tannenbaum, 1968). Stagner (1969) found that considerations of power, rather than optimal fulfillment of organizational objectives, better explain executive decisions. The enactment of power in decision-making can overwhelm more rational, bureaucratic means for allocating scarce resources (Baldrige, 1971; Salancik & Pfeffer, 1974). The apparent concentration of power within top management teams, whether formal or informally based, can be associated with decisions relating to strategic change and diversification (Greve & Mitsunashi, 2007). Furthermore, the centralization of decision rights can result in opportunistic behaviors in the case of both managers and their employees (Vázquez, 2004).

Importantly, the technologies employed by organizations have been seen to be both a function of internal power struggles (Orlikowski & Yates, 1994; Thomas, 1994), as well as a vehicle for restructuring the distribution of power (Burkhardt & Brass, 1990). More critical assertions suggest that the ongoing conflict between the powered and the powerless within social organizations leads to some jobs and not others being more

likely to be impacted by technologies such as automation (Braverman, 1974; Glenn & Feldberg, 1979; Greenbaum, 1979; Kraft, 1979; Noble, 1984; Wood, 1982). New technologies are possible sources of social uncertainty (Barley, 1986; Tushman & Anderson, 1986). In fact, Crozier, Friedberg and Goldhammer (1980) argued, “Those who get the upper hand in the game are those who control most of the crucial uncertainties” (p. 8).

Perrow (1967) characterized control within organizations according to two components – power and discretion: “Power affects outcomes directly because it involves choices regarding basic goals and strategies. Discretion relates to choices among means and judgments of the critical and interdependent nature of tasks... within the framework of accepted goals and strategies” (p. 198). With automation seemingly consistent with a routine production process highlighted by Perrow, discretion would be expected to be low alongside such automation, while power would as well be (in general) low. “This is a well-programmed production process and there is no need to allow much discretion. Indeed, there is a danger in doing so” (Perrow, 1967, p. 200).

Research on organizations suggests that the various manifestations of power— control, authority, discretion, and decision rights— affect decision making within organizations. These decisions may include those that relate to the assignment of work throughout the organization. Given scholars have found that individual satisfaction with a job or occupation increases with decreasing levels of routinization in work (Baba & Jamal, 1991; Blau & Lunz, 1999; Grant & Parker, 2009) or increasing levels of skill variety required for that work (Glisson & Durick, 1988; Loher, Noe, & Moeller, 1985), it is reasonable to assume that individuals, given a choice, prefer to not operate under highly routinized and skill-bounded work constraints. Accordingly, occupations that afford individuals greater influence over the assignment of work within the organization, or

discretion over work processes, would be associated with lesser levels of routinization in work.

Hypothesis 4(a): Routinization of work is inversely related to occupational task discretion and autonomy.

Hypothesis 4(b): Routinization of work is inversely related to occupational control over resources.

Even if the general effects of automation upon the nature of work routines (as described in the previous sections) were consistent across occupations, those occupations offering a more influential position within organizations would be able to select technologies that afford a greater reduction in the routinization of work. Additionally, these occupations would prefer to specialize and distinguish the non-programmable skills required for work (i.e., more tacit skills such as intuition, judgement, social connections), thereby distinguishing the position of the occupation and developing a comparative advantage as compared to automation (Simon, 1985). Furthermore, inherent to the expectations of the deskilling hypothesis is the assumption that individuals with power are able to influence the nature of their own work and the work of others by way of the tools employed in the work setting (Braverman, 1974; Glenn & Feldberg, 1979; Greenbaum, 1979; Kraft, 1979; Kraft, 1984; Noble, 1984; Wood, 1982).

Therefore:

Hypothesis 5(a): Control over resources negatively moderates the relationship between the degree of automation and the level of routinization in work.

Hypothesis 5(b): Control over resources positively moderates the relationship between the degree of automation and the skill requirements for work.

Automation and Organizational Routines

While social structure is often imagined to be a set of generally stable and unitary classifications of the organization as a whole (Perrow, 1967), there has also been research that imagines and observes these structures as iterative states, ongoing processes, or variable throughout an organization. These dual-modes of organizing are described in various terms: "parallel learning structures" (Bushe & Shani, 1991), "parallel hybrid organizations" (Lillrank & Kano, 1989), and "simultaneous" structures (McDonough & Leifer, 1983). Thus, when sampling a group of organizations, there is a somewhat equal chance of finding the system in a state of structure, or the lack thereof. Only at the far extremes of technologies would we find a general tendency towards one state, or the other. As a result, Child (2001) imagined that, "Paradox is likely to be a core theme of postmodern organizational design" (p. 1144).

March and Simon suggested that work processes within organizations alternate between the extremes of standardized production and innovation work—matched pairs of programmed, or unprogrammed means and ends. In the former process, work routines are exact and structured. In the latter process, work routines were inexact, unestablished, and unstructured. Other researchers have suggested that work processes, particularly alongside modern production technologies, occupy the off-diagonals of the March and Simon framework (Duncan, 1973; Rohlen, 1989; Victor, Boynton & Stephens-Jahng, 2000). At one extreme, the means for production are defined and programmed, while the ends are left open-ended. At the other extreme, the ends for production are defined, while the means are left unstructured. As such, there is reason to wonder whether increasing levels of automation somehow alternate, from positive to negative, that relationship between the programmed nature of the means and ends proposed by March and Simon.

It bears mentioning here that March and Simon were not silent on the issue of automation within organizations: “The extent to which many human activities, both manual and clerical, can be programmed is shown by the continuing spread of automation to encompass a wider and wider range of tasks” (March & Simon, 1958, p. 144). Organizational routines were programs that could be developed within people or machines. Determining which actor would perform the role more effectively was a question of minimizing the “investment cost per unit of program execution” (p. 158).

Well- or ill-structured problems

Two types of work structures were highlighted by March and Simon (1958)—standardized production and innovation work. These modes of work resided at the extremes of two dimensions of production, defined according to the programmed nature of the means and ends of organizational routines. In many ways, these two extremes for production identified by March and Simon—standardized and innovation—mirror the extremes supporting various other conceptions of organizational configurations: mechanistic versus organic structures (Burns & Stalker, 1961); routine and nonroutine technologies (Perrow, 1967); exploitation and exploration or opportunities (March, 1991); stable and adaptive systems (Nelson & Winter, 1982).

The means of production involve the tasks, operations, and processing capacities of the organization. These means are considered programmed “to the degree that choice has been simplified by the development of fixed response to defined stimuli” (March & Simon, 1958, p. 142), such that “the greater the repetitiveness of individual activities, the greater the programming” (March & Simon, 1958, p. 143). In short, programmed means are comprised of highly routinized routines. The ends of production are simply the output, outcomes or goals of organizational activities. Programmed or specified ends are output, outcomes, or goals that had been clearly prescribed and

defined. For programmed means to be most effective, according to March and Simon, these means must be linked to outcomes that can be observed and measured. Thus, the programmed nature of the means and the ends of production are assumed to be positively related, and only in the pairing of clearly defined means with clearly prescribed ends could these routines and their criteria be considered operational.

Just how programmed these means and ends might be is a function of uncertainty—procedural or environmental. Standardized production occurs when both the means and the ends for work processes are programmed—routines for production are established and standards for assessing the consequences of that production are defined. Any organization “has available a repertory of programs, so that once the event has been classified the appropriate program can be executed without further ado” (March & Simon, 1958, p. 163). Innovation work, triggered by exceptions or errors, occurs when both the means and the ends for production are unprogrammed—routines for production are not clearly described and the standard for qualifying the consequences of production has not been clearly defined. Importantly, innovation work in this conception involves a bounded, but seemingly rational means-end analysis. This analysis continues “until it reaches a level of concreteness where known, existing programs . . . can be employed to carry out the remaining detail” (p. 191).

As conceived by March and Simon, the non-programmed nature of innovation work is largely an outlying phenomenon within social organizations. They regarded a pairing of programmed means with programmed ends as quite ordinary within organizations, accounting for “a very large part of the behavior of all persons” (p. 142), if not all of the behaviors of individuals believed to function within relatively routine positions. Organizations are conceived, essentially, as hierarchical structures of individual-level programmed means-ends procedures, wherein procedures “of higher

levels of the organization have as their main output the modification or initiation of programs for individuals at lower levels” (p. 150). Understanding an organization involves investigating this large network of nested procedures, or elements, with “each element, taken by itself, being exceedingly simple” (p. 178). To be an organization is essentially to be composed of a set of routines, most of which once reduced to their basic elements are explicitly defined or understood. Uncertainty triggers a means-ends analysis, the consequences of which would be a redefinition or reconfiguration of programmed means and ends.

In sum, a March-and-Simon view of the structure of routines within organizations locates those routines along a continuum of matched pairs, the extremes of which involve programmed means with programmed ends, or alternatively unprogrammed means with unprogrammed ends:

Hypothesis 6: The programmed nature of the means for work processes is positively related to the programmed nature of the ends for work processes.

Oddly structured problems

Some scholars have argued that the odd structures of equivocality and complexity, rather than the ill structure of uncertainty, best describe the context faced by individuals in organizations (Anderson, 1999; Boulding, 1956; Daft & Wiginton, 1979; Lewin et al., 1998; Mintzberg, 1976; Weick, 1979). In many ways, action and interpretation cannot be so easily separated, as we “make sense of equivocal inputs and enact this sense back into the world to make that world more orderly” (Weick, Sutcliffe & Obstfeld, 2005, p. 410). From this perspective, it would seem that organizations walk sideways through this complex experience, mixing the programmed nature of means and ends in a manner befitting the off-diagonals of the March and Simon framework (1958).

In a study designed to test the March and Simon framework, specifically in the context of performance, Bourgeois (1980) found that “consensus on both ends and means did not yield the highest performance. Instead, the highest performing group exhibited consensus on means but not on ends” (p. 239). Unfortunately, the sample for this inquiry was quite small, involving 67 top executives from 12 corporations. Given Bourgeois’ study may be the only example of an empirical test directed at the March and Simon mean-ends framework there is reason to test the March and Simon premise in a broad, large sample context.

Furthermore, researchers have noticed that the structures of certain work processes seem to fit a mixed-pair of means and ends. Duncan (1973), Rohlen (1989), Victor, Boynton and Stephen-Jahng (2000), and other researchers have observed “switching” structures within organizations, even mass production factories. At times, known routines are applied to unfamiliar contexts—the means are programmed while the ends are left open-ended. At other times, pre-determined constraints guide a largely unstructured search for solutions—the ends are programmed, while the means through which to achieve these ends are left open ended. For Drucker (1985), the former, mixed pair of programmed means with unprogrammed ends was termed “systematic innovation.” The latter configuration, programmed ends with unprogrammed means, has been called “continuous improvement” (Imai, 1986; Tushman, 1979; Victor & Boynton, 1998).

Alongside programmable technologies, “standardized” work has the potential to be largely automated. Once the means and ends of some task can be clearly defined, the stage is set for automation, thereby eliminating these highly programmed tasks from the work roles of organization members. March and Simon (1958) would seem to agree:

In order to substitute automatic processes for human operatives, it is necessary to describe the task in minute detail, and to provide for the performance of each step of it. The decomposition of tasks into their elementary program steps is most spectacularly illustrated in modern computing machines which may carry out programs involving thousands of such steps (p. 144).

Alternatively, alongside automation, the unprogrammed means and ends of “innovation work” have the potential to be augmented—assisted by means or ends that have been programmed into machines. In particular, researchers are beginning to note the extent to which simulation technologies—enabling what Zammuto et al. termed “synthetic representation”—empower organization members to “temporarily decouple the metrics from the actual performance of the process and observe the possible impact of alternative actions later in the process” (Zammuto et al., 2007, p. 757).

Therefore, as the level of automation increases, the relationship between the programmed means and ends of organizational routines may shift from the kind of matched pairs expected by March and Simon (1958), to mixed pairs—programmed means with unprogrammed ends, or unprogrammed means with programmed ends.

Hypothesis 7: Level of automation will moderate the matched pairs relationship between the means-ends of organizational work processes.

Specifically, alongside low levels of automation, the programmed nature of the means for work will be positively related to the programmed nature of the ends for work. Alongside high levels of automation, the programmed nature of the means for work will be negatively related to the programmed nature of the ends for work.

Conclusion

In this chapter, I transitioned from the broad question of the relationship between the technology and the structure of social organizations to the more specific question addressing consequences of automation for the nature of work. The impact automation may have on the nature of work is a subject of great debate within scholarly circles and

society at large. Widespread interest exists regarding the plausible and possible consequences of automation—displaced labor, routinized work, changing work structures, etc. I presented two sets of conflicting hypotheses regarding the nature of work and the structure of organizational routines, alongside automation. A long history of theoretical imagination around and empirical inquiry of organizations involves the nature of routines. Accordingly, the existence and nature of routines provides the consistent theme across these conflicting predictions. I turn next to my empirical test of these hypotheses.

CHAPTER IV

METHOD

In this chapter, I will outline a method for testing hypotheses presented and supported in Chapter III. First, I will describe the source of the data underlying this empirical analysis—the Occupational Information Network (O*NET). In particular, I will highlight the research approach and methods employed by O*NET to construct the questionnaires developed and collection methods enacted to result in these data I will employ. Second, I will describe the empirical methods for this research project, including a presentation of the constructs and their proposed measures, as well as an explanation of the validation and hypothesis testing phases of the analysis.

O*Net Project Background

The U.S. Department of Labor’s Employment and Training Administration (USDOL/ETA) has provided funding for the development of the Occupational Information Network (O*NET), an ongoing project managed by the National Center of O*NET Development. In this section I provide a brief overview of the purpose and history of O*NET, the instruments developed therein, and the methods for data collection. A comprehensive presentation of the O*NET project, covering such issues as the bases for the content model and empirical validations of the questionnaires, is found in Peterson, Mumford, Borman, Jeanneret, and Fleishman (1999).

Purpose and History

The purpose of the O*NET project is to gather detailed data on the nature of work and occupations within the U.S. economy. The project was designed to replace the *Dictionary of Occupational Titles* (DOT) as “a comprehensive system of occupational description” (Peterson, Mumford, Borman, Jeanneret, Fleishman, Levin, Campion, Mayfield, Morgenson, Pearlman, Gowing, Lancaster, Silver, & Dye, 2001) across the range of occupations within the *Standard Occupational Classification* (SOC). The DOT was first developed during the 1930s as an effort of the Department of Labor to enact and understand the linkages between skill supply and demand in the wake of the great depression. As the U.S. government expanded the scope of public employment, the DOT was put to use as a research, training, and accreditation tool for both public and private employment. The DOT data came to be used in academic research, most significantly within labor economics and education (Autor, et al., 2003; Cain & Green, 1983; Cain & Trelman, 1981; England, Farkas, Kilbourne, & Dou, 1988; Fine, 1968; Gerhart, 1987; Schaubroeck & Merritt, 1997; Spenner, 1980; Xie & Johns, 1995).

In constructing the first version of the DOT, released in 1939, occupational analysts observed workers at one or more sites and developed narrative descriptors of job tasks. This qualitative process yielded more than 17,500 task definitions through which 550 occupational groups were characterized and categorized. In the most general classification, jobs were placed within one of three types: skilled, semi-skilled and unskilled. Three major revisions to the DOT were released in subsequent years—1949, 1965, 1977—with three supplements also released—1982, 1986, and 1991. For the 1965 version of the DOT, job requirements and characteristics were expanded to consider training time, temperaments, physical demands, working conditions, aptitudes, interests, work performed, and industry classifications. By the 1991 supplement, the

DOT included more than 12,000 occupations, with some occupational descriptions being identical except for the types of equipment used (e.g., various designs of sewing machines) (Dye & Silver, 1999).

After five decades of the DOT, a general consensus had emerged among researchers and policy-makers that the DOT data were based upon an outdated approach to work—a somewhat Taylorist perspective, through which work was seen primarily as repetitive, routinized, and organized hierarchically (Berryman & Bailey, 1992). In 1990, the U.S. Secretary of Labor chartered an Advisory Panel for the Dictionary of Occupational Titles (APDOT). As part of APDOT, the development and confirmation of a new classification system for occupations, as well as a revised set of models for characterizing work within these occupations began. In January 1995, the O*NET project was officially designated and funded by the U.S. Department of Labor to replace the DOT.

Questionnaires and Validation

In the *Comprehensive Handbook of Psychological Assessment*, Jeanneret, D'Egidio, and Hanson (2004) describe the Occupational Information Network project as follows:

The O*NET system consists of (1) the O*NET Content Model—the conceptual framework for the O*NET, (2) a relational electronic database of occupational information, and (3) data collection instruments for each component of the Content Model (i.e., surveys). The O*NET developers used a taxonomic approach to occupational classification to create a system that identifies, defines, and describes work according to a set of characteristics (i.e. subdomains) of work performance that is much more comprehensive than either a detailed listing of task-level information or a summary of important duties and responsibilities (pp. 192-193).

The data that have been collected as part of the O*NET project comprise expert analyst ratings of occupational ability requirements, as well as job incumbent ratings as collected

by way of four standardized questionnaires (Donsbach, Tsacoumis, Sager & Updegraff, 2003): (1) Generalized Work Activities, (2) Work Context, (3) Skills and (4) Knowledge. An additional questionnaire, which focuses on occupation-specific task requirements that are not standardized for all respondents, was not considered for this research.

The survey items incorporated within the O*NET questionnaires were informed by items included within related work-research questionnaires that have been not only used for a number of decades, but also found reliable (as measures) over the decades. The set of questionnaires to which the O*NET team most often refer in the development of the project include: the Position Analysis Questionnaire or PAQ (McCormick, Jeanneret & Mecham, 1969; 1972), the Occupational Analysis Inventory or OAI (Boese & Cunningham, 1975; Cunningham, 1988; Cunningham, Boese, Neeb & Pass, 1983); the General Work Inventory or GWI (Cunningham & Ballentine, 1982), and the Job Element Inventory or JEI (Cornelius, Hakel & Sackett, 1979).

The connection between O*NET and prior job analysis questionnaires goes beyond the items on these surveys to include the individuals involved in developing these instruments. For example, McCormick, Jeanneret, and Mecham (1972) developed the original and more recent versions of the Position Analysis Questionnaire (PAQ), while Jeanneret is one of the lead developers of O*NET and editor of the volume that describes the project's approach and methods. Additionally, Fleishman (1972; Buffardi, Fleishman, Morath, & McCarthy, 2000; Fleishman, & Hempel Jr., 1956), whose work on perceptual-motor performance has played a role in work research for more than a half-century, contributed to the development of the project and edited the O*NET volume (Peterson, et al., 1999) as released by the American Psychological Association.

Developers of the O*NET questionnaires were forced to make a compromise between the breadth of variables to be measured and the number of items included on

the questionnaire to measure each of these variables. While employing multiple items to measure each variable of interest (e.g., repetitive work, automation) would have been an ideal measurement tactic, this choice would have resulted in an impractical outcome—hundreds of items on the questionnaire. Prior research suggested that many of the variables pursued by the questions on work activities, context, skills, and knowledge surveys could be measured reliably with single items (McPhail, Blakley, Stron, Collins, Jeaneret, & Galarza, 1995; McCormick, Mecham, & Jeanneret, 1989; Cunningham, et al., 1983; Boese, & Cunningham, 1975; Cain, & Green, 1983; Geyer, Hice, Hawk, Boese, & Brannon, 1989; Dierdorff, & Wilson, 2003). Therefore, single-item measures of a wide range of variables dominate the O*NET questionnaires.

Generalized work activities

The Generalized Work Activities (GWA) survey, informed by Outerbridge's (1981) work on generalized work behaviors, is based upon "an aggregation of similar job activities/behaviors that underlie the accomplishment of major work functions" (Jeanneret, Borman, Kubisiak & Hanson, 1999, p. 106). The survey is composed of 41 questions designed to capture both the importance and level of information input, mental processes, and interaction with others required for an occupation. The three major dimensions work requirements, as pursued in the GWA survey, are based upon the stimuli (S), organism (O), and response (R) model (S-O-R) developed by Miller (1953), and derived from the work of classical behaviorist psychologists (Hull, 1943; Skinner, 1938; Watson, 1913).

Before completing the GWA questionnaire, respondents are introduced to the GWA survey with the following text:

These questions are about work activities. A work activity is a set of similar actions that are performed together in many different jobs. You will be asked about a series of different work activities and how they relate to

your current job - that is, the job you hold now (*Generalized Work Activities Questionnaire*, p. 1).

Respondents are then asked to rate each work activity tapped by the questionnaire according to both the importance and the level of that activity in the performance of their current job. During pre-testing of the GWA questionnaire, inter-rater reliability within occupations resulted in a median k-rater reliability¹ of .82 for level ratings, and .78 for importance ratings.

Work context

The Work Context (WC) survey is composed of 57 questions and was designed to investigate conditions under which work is performed across the range of occupations for which data is collected (Strong, Jeanneret, McPhail, Blakley, & D'Egidio, 1999). The variables pursued and items included within the WC survey originate within academic research that investigated impact of organizational and occupational factors upon individual job requirements and performance (McCormick, 1979; McGrath, 1976; Peterson et al., 2001). The WC survey pursues three dimensions of work characteristics, based upon the approach of prior research: (1) social interaction processes of a job (e.g., coordinating the work of others), (2) the interactions between the worker and the physical work environment (e.g., working under a pace set by machinery), and (3) the structure of the job itself (e.g., the freedom to set tasks, goals, and priorities).

Respondents receive the following instructions before taking the WC survey:

In this questionnaire you will be asked about your working conditions. These questions are about your work setting and its possible hazards, the

¹ ICC (1,k) = [BMS - WMS]/BMS, where *k* is the harmonic mean of the number of ratings provided for each occupation (Shrout & Fleiss, 1979). This is the method through which ICC was calculated during pre-testing for each of the O*NET questionnaires discussed in this section.

pace of your work, and your dealings with other people (*Work Context Survey*, p. 1).

The questionnaire includes items particularly relevant to this research, such as: “How automated is your current job?” and “How much freedom do you have to determine the tasks, priorities, or goals of your current job?” The median k-rater reliability, within occupations, of the instruments on the Work Context survey was .83 (Strong, et al., 1999).

Work skills

The 35 questions that comprise the Skills questionnaire were informed by socio-technical systems theory (Katz & Kahn, 1978) and its approach to social organizations performing complex tasks through the division of labor as well as the use of various tools (Mumford, Peterson & Childs, 1999). Five higher-order categories of workplace skills were pursued via the questionnaire: content (e.g. writing, speaking), process, service orientation, technical, and systems.

Respondents taking the Skills questionnaire received the following introduction:

These questions are about work-related skills. A skill is the ability to perform a task well. It is usually developed over time through training or experience. A skill can be used to do work in many jobs or it can be used in learning. You will be asked about a series of different skills and how they relate to your current job—that is, the job you hold now (*Skills Questionnaire*, p. 1).

During pre-tests of the O*NET questionnaires, the k-rater reliabilities of items from the Skills survey within occupations were .85 (Level) and .83 (Importance) (Mumford, et al., 1999). When these reliabilities were tested in 2006, from a sample of 10,017 O*NET respondents, the k-rater estimate of inter-rater reliability for incumbent ratings was 0.96 (Tsacoumis & Van Iddekinge, 2006).

Knowledge

For the development of the Knowledge survey, 'knowledge' was broadly defined by Costanza, Fleshman, and Marshall-Miess (1999) as "a collection of discrete but related facts and information about a particular domain" (p. 77). A taxonomic structure for knowledge requirements was developed and adopted, based upon a review of the job analysis, training, vocational, and cognition literatures. Furthermore, the knowledge domains adopted by O*NET were compared to those employed by the National Occupational Information Coordinating Committee (NOICC), as well as the Occupational Employment Statistics (OES). A final set of knowledge requirement domains and corresponding question items were adopted, with the resulting questionnaire then pre-tested with a set of job incumbents and a set of occupational analysts provided by the Occupational Analysis Field Center (O AFC). The final Knowledge questionnaire included 33 items pursuing both the level and importance of various domains of knowledge supporting work (e.g. clerical, computers and electronics, biology). Within occupations, the median k-rater reliabilities for the Knowledge survey were .85 (level) and .86 (importance).

The Knowledge survey as administered also incorporates 16 questions developed to investigate work styles—factors that affect performance in an occupation—and 5 questions related to education and training. The work style items are informed by the Five Factor Model (Barrick & Mount, 1991), the Hogan Personality Inventory (Hogan, 1982), the Assessment of Background and Life Experience (Hough, 1997), the Occupational Personality Questionnaire (Saville & Holdsworth, 1990), and the work of Guion and colleagues (Guion & Gibson, 1988; Raymark, Schmit & Guion, 1997) investigating the personality requirements for jobs (Boorman, Kubisiak, & Schneider, 1999). The education and experience items were included based upon prior research

that found these factors provided necessary skills and knowledge required for occupational preparation (Snow & Swanson, 1992; Ward, Byrnes & Overton, 1990).

Respondents were introduced to the questionnaire as follows:

These questions are about work-related areas of knowledge. Knowledge areas are sets of facts and principles needed to address problems and issues that are part of a job. You will be asked about a series of different areas of knowledge and how they relate to your current job—that is, the job you hold now. (*Knowledge Questionnaire*, p. 1).

During pre-testing, the k-rater reliabilities of the knowledge survey items within occupations were consistently in the .90s or .80s (Constanza, et al., 1999). For the work styles items, the median k-rater reliabilities were 0.66 and 0.64, for Level and Importance respectively (Borman, et al., 1999). The median k-rater reliabilities for the general level of education and related work experience items were 0.97 and 0.86, respectively (Anderson, 1999).

Data Collection and Distribution

Data collection for the O*NET project is managed and conducted by Research Triangle Institute International (RTI), a not-for-profit research organization affiliated with Duke University, the University of North Carolina at Chapel Hill, and North Carolina State University. Additional partners involved in the O*NET project include Human Resources Research Organization (HumRRO), Maher and Maher, and MCNC (a technology services provider).

Data is collected for the O*NET project by way of a multi-staged design, which will be briefly described here. For a more detailed description of the O*NET sampling methods see the Supporting Statement of the Office of Management and Budget Clearance (sub-titled, *O*NET Data Collection Program*) as released by the US

DOL/ETA.² In the first stage of data collection, a population of organizations is identified from a list of 12 million business establishments in the United States as compiled by Dunn & Bradstreet. These data are combined with those from the Occupational Employment Statistics (OES) as conducted by the Bureau of Labor Statistics (BLS) in order to identify the industries most likely to employ occupations targeted during each wave of the O*NET collection program. Next, a stratified random sample of business establishments is developed based upon this occupation-weighted target. Organizations selected from this stratified sample then receive a mailed package containing an introduction to and explanation of O*NET. Importantly, the organization is informed that they are not required to participate in the survey. In the next stage of the collection program, a random sample of workers within those responding establishment is contacted and invited to participate in the survey. Finally, if a contacted individual is willing to take a survey, he or she is randomly assigned one of the four subject area questionnaires.

The O*NET data collection project began in June 2001, after pre-test data were used to confirm and update original versions of the survey instruments. In April 2003, results from a set of 54 occupations were released. Subsequent updates to the O*NET database include not only the responses of new respondents in newly sampled occupations, but also additional results from respondents in occupations for which data have already been collected. Importantly, no significant differences have been reported between the ratings offered by more recent respondents and those offered by earlier respondents, within occupations. Furthermore, inter-rater reliability coefficients resulting

² This Supporting Statement, *O*NET Data Collection Program*, can be obtained online from the following address: <http://www.onetcenter.org/ombclearance.html>

from the ongoing O*NET data collection effort continue to meet the standards established in the initial testing of the survey instruments.

The version of the O*NET database used for this research—version 13—was released in June 2008. By the date upon which version 13 of the O*NET data was released, 153,981 establishments and 200,942 individuals had been contacted for the survey. The response rate for establishments was 75%, while that for individuals was 64%. As a result, the responses of 128,604 individuals across 809 occupations constitute the full set of responses available for this research. On average, 144 questionnaires have been collected within each occupation, resulting in an average of 36 complete sets of questionnaires (including GWA, WC, Skills and Knowledge) per occupation (Berzofsky, Welch, Williams & Biemer, 2008). O*NET provides the mean response of job incumbents within each occupation for each survey question, as well as a count of the number of respondents who selected each value of any item (i.e., on a question offering rating values from 1 through 5, O*NET releases the number of respondents who selected each value—1, 2, 3, 4 and 5). Additionally, the standard error in response values within each occupation, as well as minimum and maximum values of responses, are available for each of the survey items. In the interest of guaranteeing respondent anonymity, O*NET does not release individual-level responses within the dataset that is released to the public via the O*NET Resource Center website.³ As a result, and to be clear, the unit of analysis within these data is the occupation. For an example of the breadth of occupations available within the O*NET dataset, please see Table III.1 for a listing of the Major (top level) occupational groups within the 2000 SOC.

³ O*NET Resource Center, available from <http://www.onetcenter.org/>

Table III.1: 2000 Standard Occupational Classification System, Major Groupings

11-0000	Management Occupations
13-0000	Business and Financial Operations Occupations
15-0000	Computer and Mathematical Occupations
17-0000	Architecture and Engineering Occupations
19-0000	Life, Physical, and Social Science Occupations
21-0000	Community and Social Services Occupations
23-0000	Legal Occupations
25-0000	Education, Training, and Library Occupations
27-0000	Arts, Design, Entertainment, Sports, and Media Occupations
29-0000	Healthcare Practitioners and Technical Occupations
31-0000	Healthcare Support Occupations
33-0000	Protective Service Occupations
35-0000	Food Preparation and Serving Related Occupations
37-0000	Building and Grounds Cleaning and Maintenance Occupations
39-0000	Personal Care and Service Occupations
41-0000	Sales and Related Occupations
43-0000	Office and Administrative Support Occupations
45-0000	Farming, Fishing, and Forestry Occupations
47-0000	Construction and Extraction Occupations
49-0000	Installation, Maintenance, and Repair Occupations
51-0000	Production Occupations
53-0000	Transportation and Material Moving Occupations
55-0000	Military Specific Occupations

Measures

In this section, I will present the constructs of interest to this research (both primary variables and control variables) along with the associated items available in the

O*NET database that were expected to provide valid and reliable measures of these primary constructs.

Constructs

The Work Context and Generalized Work Activities questionnaires developed for the O*NET project provide a number of items previous research has found to provide reliable measures of the constructs of interest to this research. I will describe each of the constructs underlying this research and introduce the items intended to provide reasonable and reliable measures of these constructs. I will also briefly describe the control variables and their associated items as these variables and items have been organized and tested by O*NET.

Items were selected from the O*NET questionnaires based upon a clear overlap between the definition of constructs pursued for this research and the definition of variables measured by way of their associated items on the O*NET questionnaires. As a result, each construct of interest to this research has at least one associated variable (e.g., repetitive work, automation) that was chosen for and measured by the O*NET project. In fact, I believe that each construct mentioned below is anchored upon at least one variable from O*NET with a strong matching definition.

Automation

I have defined automation as the performance of a task, physical or mental, in whole or in part, by a machine. Measuring the level of automation alongside work is a therefore a challenge of identifying the extent to which some number, variety, or proportion of tasks involved with a job or occupation are being performed by a machine. Within O*NET, the degree of automation was defined as the “degree to which significant job functions are automated and require little input from the worker beyond monitoring”

(Strong, et al., 1999, p. 132). The question employed within O*NET to directly measure the degree of automation was, "How automated is your current job?" (*Work Context Questionnaire*, p. 14). The scale for this item spanned from "not automated at all," to "completely automated." In a pre-test of the O*NET questionnaires, there was no significant difference found between how individuals in jobs rated the level of automation in their work (mean=3.13, S.D.=0.90), as compared to that rating determined by occupational experts who observed these occupations (mean=3.19, S.D.=0.85). Furthermore, in terms of inter-rater reliability amongst job incumbents the degree of automation item offered a k-rater reliability of 0.72, while amongst expert analysts the item's k-rater reliability was 0.86.

Table III.2: Items Considered as Measures of the Level of Automation Alongside Work

Survey item				
(1) How automated is your current job?				
Not at all automated	Slightly automated	Moderately automated	Highly automated	Completely automated
1	2	3	4	5
(2) How important to your current job is keeping a pace set by machines?				
Not important at all	Fairly important	Important	Very important	Extremely important
1	2	3	4	5
(3) How important is controlling machines and processes to the performance of your current job?				
Not important	Somewhat important	Important	Very important	Extremely important
1	2	3	4	5
(4) How important is working with computers to your current job?				
Not important	Somewhat important	Important	Very important	Extremely important
1	2	3	4	5

Table III.2 presents the set of items considered as measures for the level of Automation alongside work. In addition to the above-mentioned item measuring the general degree of automation, those items believed to comprise a single scale for measuring the level of automation alongside work include: How important to your current job is keeping a pace set by machines?; How important is controlling machines and processes to the performance of your current job?; and How important is working with computers to your current job? Respondents rated each of these items on a 5-point scale, spanning from not important at all, to extremely important. The proposed scale of

the level of automation alongside work was the average response to these five items by respondents within each occupation.

Routinization / Programmed means

The nature of work routines is a central issue of this research. Similarities between the way in which routinization of work has been conceptualized and the way in which March and Simon conceptualized programmed means for work led me not only to connect these schools of thought for this research, but also to adopt the same proposed measures of these constructs. Routinization of work involves two related characteristics—repetitiveness and explicitness. March and Simon considered means to be programmed “to the degree that choice has been simplified by the development of fixed response to defined stimuli” (March & Simon, 1958, p. 142), such that “the greater the repetitiveness of individual activities, the greater the programming” (March & Simon, 1958, p. 143). Autor et al. (2003) characterized routine tasks as those comprised of a “limited and well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules.”

Within O*NET, the monotonous or repetitive level of work activities was defined in rather detailed terms as the “extent to which the worker is required to perform the same physical and/or mental activities repeatedly, in a relatively short period of time, usually less than one hour” (Strong, et al., 1999, p. 132). The exact wording of the item selected to measure the general level of repetitive work activities was, “How important to your current job are continuous, repetitious physical activities (like key entry) or mental activities (like checking entries in a ledger)?” (*Work Context Questionnaire*, p. 14). Dierdorff & Morgeson (2007) recently used this item assessing repetitive work tasks as a measure of work routinization. An item focused more precisely upon repetitive, physical activities was worded, “How much time in your current job do you spend making

repetitive motions?” (p. 12). An additional item included to measure the repetitive nature of work targeted the nature of work schedules and was worded, “How regular is your work schedule on your current job?” (p. 15). This item was measured on a 3-point scale, including Regular (established routine, set schedule), Irregular (changes with weather conditions, product demands, or contract duration), and Seasonal (only during certain times of the year).

At the opposite end of the March & Simon spectrum of the routinization of work programs was what the authors dubbed innovation work (March & Simon, 1958; Victor, et al., 2000). Within O*NET, a number of included items targeted the level of creativity, innovation or adaptability required in work: “How important is thinking creatively to the performance of your current job?” (*Generalized Work Activities Questionnaire*, p. 7), defined as “originating, inventing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions” (Jeanneret, et al., p. 114); “How important is adaptability/flexibility to the performance of your current job?,” defined within the questionnaire as the “job requires being open to change (positive or negative) and to considerable variety in the workplace. (*Work Styles Questionnaire*, p. 4); “How important is innovation to the performance of your current job?,” defined within the questionnaire as “job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems” (p. 5).

Table III.3 presents the items selected for consideration as measures of the routinization or work (the programmed means for work). Respondents rated five of the above-mentioned items on a 5-point scale, with the sixth item (work schedules) being rated on a 3-point scale. The 3-point scale item was converted to a 5-point scale by simply multiplying the value within each occupation by 5/3. The proposed measure of the level of routinization/programmed means of work was the average response to these

six items by respondents within each occupation. Importantly, being the result of averaging responses within each occupation, each of the survey items described above offers continuous treatment of the rating scales—up to two decimal places. As a result, converting an item measured in a 3-point scale to a 5-point scale by multiplying values by $5/3$ will not result in new values that could not exist in the source data. For each survey item, responses from multiple respondents have been averaged within occupations resulting in the full continuous range of values that might exist in any scale (i.e., non-integer values such 2.54, 4.38). As such, conversion of any item's values can be done in such a way that the resulting fractional values could exist in the range to which the item was converted.

Table III.3: Items Proposed as Measures of the Routinization of work / Programmed Means for Work

Survey item				
(1) How much time in your current job do you spend making repetitive motions?				
Never	Less than half the time	About half the time	More than half the time	Continually or almost continually
1	2	3	4	5
(2) How important to your current job are continuous, repetitive physical activities (like key entry), or mental activities (like checking entries in a ledger)?				
Not at all important	Fairly important	Important	Very important	Extremely important
1	2	3	4	5
(3) How regular is your work schedule on your current job?				
<i>Regular</i> (established routine, set schedule)	<i>Irregular</i> (changes in weather conditions, production demands, or contract duration)	<i>Seasonal</i> (only during certain times of the year)		
1	2	3		
(4) How important is thinking creatively to the performance of your current job? (inverse)				
Not important	Somewhat important	Important	Very important	Extremely important
1	2	3	4	5
(5) Adaptability/Flexibility: Job requires being open to change (positive or negative) and to considerable variety in the workplace. (inverse)				
Not important	Somewhat important	Important	Very important	Extremely important
1	2	3	4	5
(6) Innovation: Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems. (inverse)				
Not important	Somewhat important	Important	Very important	Extremely important
1	2	3	4	5

Skill / Experience

Prior research pursuing the skills requirements for work has focused upon the level of experience and education that would be required to perform that work (Autor, et al., 2003; Bailey, 1991; Baron & Newman, 1990; Cohen & Pfeffer, 1986; Collins, 1971; Dierdorff & Morgeson, 2007; Hartog, 2000; Scoville, 1966; Spitz-Oener, 2006). Items designed to measure the level of related work experience and education (measured at 12 levels) required for each occupation were included with the O*NET Knowledge questionnaire. The level of education required for an occupation was measured at 12 levels, and pursued with the question, "If someone were being hired to perform this job, indicate the level of education that would be required " (*Education and Training Questionnaire*, p. 1). The level of work experience required for an occupation/job was pursued with the question, "If someone were being hired to perform this job, how much related work experience would be required? (p. 2) and was measured across 11 levels in months/years (from zero to greater than ten years). Furthermore, occupational analysts from the OAFc have rated many of the occupations along a 5-stage work zones scale for level of preparation needed for an occupation (i.e., specialized skills, experience and education).

Table III.4: Items Proposed as Measures of the Skill Requirements for Work

Survey item	
(1)	<p>If someone were being hired to perform this job, indicate the level of education that would be required.</p> <hr/> <p>Less than a high school diploma</p> <hr/> <p>High school diploma</p> <hr/> <p>Post-secondary certificate</p> <hr/> <p>Some college courses</p> <hr/> <p>Associate's degree</p> <hr/> <p>Bachelor's degree</p> <hr/> <p>Post-baccalaureate certificate</p> <hr/> <p>Master's degree</p> <hr/> <p>Post-master's certificate</p> <hr/> <p>First professional degree</p> <hr/> <p>Doctoral degree</p> <hr/> <p>Post-doctoral training</p>
(2)	<p>If someone were being hired to perform this job, how much related work experience would be required? (That is, having other jobs that prepare the worker for this job)</p> <hr/> <p>None</p> <hr/> <p>Up to and including 1 month</p> <hr/> <p>Over 1 month, up to and including 3 months</p> <hr/> <p>Over 3 months, up to and including 6 months</p> <hr/> <p>Over 6 months, up to and including 1 year</p> <hr/> <p>Over 1 year, up to and including 2 years</p> <hr/> <p>Over 2 years, up to and including 4 years</p> <hr/> <p>Over 4 years, up to and including 6 years</p> <hr/> <p>Over 6 years, up to and including 8 years</p> <hr/> <p>Over 8 years, up to and including 10 years</p> <hr/> <p>Over 10 years</p>
(3)	<p>Generalized skill and education assessment (1-5 rating)</p> <hr/> <p><i>Job Zone 1: Little or No Preparation Needed</i></p> <p>No previous work-related skill, knowledge, or experience is needed for these occupations. For example, a person can become a cashier even if he/she has never worked before</p> <hr/> <p><i>Job Zone 2: Some Preparation Needed</i></p> <p>Some previous work-related skill, knowledge, or experience may be helpful in these occupations, but usually is not needed. For example, a teller might benefit from experience working directly with the public, but an inexperienced person could still learn to be a teller with little difficulty.</p> <hr/> <p><i>Job Zone 3: Medium Preparation Needed</i></p> <p>Previous work-related skill, knowledge, or experience is required for these occupations. For example, an electrician must have completed three or four years of apprenticeship or several years of vocational training, and often must have passed a licensing exam, in order to perform the job.</p> <hr/> <p><i>Job Zone 4: Considerable Preparation Needed</i></p> <p>A minimum of two to four years of work-related skill, knowledge, or experience is needed for these occupations. For example, an accountant must complete four years of college and work for several years in accounting to be considered qualified.</p> <hr/> <p><i>Job Zone 5: Extensive Preparation Needed</i></p> <p>Extensive skill, knowledge, and experience are needed for these occupations. Many require more than five years of experience. For example, surgeons must complete four years of college and an additional five to seven years of specialized medical training to be able to do their job.</p>

These three above-mentioned items—minimum level of experience, minimum level of education, and general level of preparation—were expected to comprise a scale for measuring the general level of skill requirements required for each of the occupations. With individual responses averaged within occupations, each of the items expected to measure skill requirements is treated on a continuous scale as released as part of the O*NET dataset. Rather than formulate an average of these three items that have been measured with scales of different ranges (12, 10 and 5), the items (if they prove to comprise a single factor) were added together to form a single scale measuring the skill requirements for work. The list of items proposed as measures of the Skill Requirements for work can be found in Table III.4.

Programmed ends

March and Simon (1958) considered the ends of production to be the goal-driven output or outcomes of organizational activities. Programmed or specified ends were output, outcomes, or goals that had been clearly prescribed and defined “to the extent that they have to be preceded by program-developing activities of a problem-solving kind” (p. 142). Therefore, the proposed measures for the programmed nature the ends of organizational routines are intended to capture the extent to which work operates under or involves the development of clear, specific and persistent goals, objectives, output or outcomes (e.g., standards) of work.

The item included within the O*NET questionnaires to measure goal development activities was, “How important is developing objectives and strategies to the performance of your current job? (*Generalized Work Activities Questionnaire*, p. 8). The definition of this goal-related variable as presented to survey respondents was, “Establishing long-range objectives and specifying the strategies and actions to achieve them” (p. 8). An additional item the definition of which appeared to match the conception

of programmed ends was “How important is organizing, planning and prioritizing work to the performance of your current job?” (p. 9). This planning-related item was defined within O*NET and presented to respondents as, “developing specific goals and plans to prioritize, organize, and accomplish your work” (p. 13). An Item proposed to measure jobs that operated within the bounds of given programmed ends of some sort included: “How important is evaluating information to determine compliance with standards to the performance of your current job?,” defined as “using relevant information and individual judgment to determine whether events or processes comply with laws, regulations, or standards” (p. 5).

Table III.5: Items Proposed as Measures of the Programmed Ends of Work

Survey item					
(1)	How important is developing objectives and strategies to the performance of the occupation? (reverse)				
	Not important 1	Somewhat important 2	Important 3	Very important 4	Extremely important 5
(2)	How important is organizing, planning, and prioritizing work to the performance of your current job? (reverse)				
	Not important 1	Somewhat important 2	Important 3	Very important 4	Extremely important 5
(3)	How important is evaluating information to determine compliance with standards to the performance of your current job?				
	Not at all important 1	Somewhat important 2	Important 3	Very important 4	Extremely important 5
(4)	How important is judging the qualities of objects, services, or people to the performance of your current job?				
	Not at all important 1	Fairly important 2	Important 3	Very important 4	Extremely important 5

Those items proposed as measures of the programmed ends of work are list in Table III.5. Each of these items was rated on a 5-point scale, which in the case of four of these five items spanned from not important to extremely important. One of these items—“How much freedom do you have to determine the tasks, priorities and goals of your current job?”—was rated on a 5-point scale spanning no freedom to a lot of freedom. The average of responses to these items within each occupation was used to measure the extent of the programmed nature of the ends of work.

Discretion

For Perrow (1967), discretion related to “choices among means and judgments of the critical and interdependent nature of tasks... within the framework of accepted goals and strategies” (p. 198). More specifically, “Discretion involves judgments about whether close supervision is required on one task or another, about changing programs, and about the interdependence of one's task with other tasks” (p. 198). Accordingly, items considered for inclusion within a scale that might reasonably measure discretion in work were selected given their definitions entailed some aspect of supervision, freedom, judgment, and/or task-level independence.

The five items from the O*NET questionnaires, listed in whose definitions best matched that of the discretion construct for this research were as follows: “In your current job, how much freedom do you have to make decisions without supervision?” (*Work Context Questionnaire*, p. 13); “How much freedom do you have to determine the tasks, priorities, or goals of your current job?” (p. 14); “How important is making decisions and solving problems to the performance of your current job?,” defined as “analyzing information and evaluating results to chose the best solution and solve problems” (*Generalized Work Activities Questionnaire*, p. 6); “How important is judging the qualities of objects, services, or people to the performance of your current job?,”

defined as “assessing the value, importance, or quality of things or people” (p. 4). “How important is independence to the performance of your current job?,” which was clarified for the respondent as the “job requires developing one's own ways of doing things, guiding oneself with little or no supervision, and depending on oneself to get things done” (*Work Styles Questionnaire*, p. 5). These questions gave rise to the possibility that items related to decision-making and judgment might overlap with dimensions of those items believed to measure the programmed ends for work. This risk of conceptual overlap motivated the use of exploratory factor analyses, the methods of which will be described later in this chapter.

Table III.6: Items Proposed as Measures of the Level of Discretion in Work

Survey item	Proportion selected by eLab sample	Proportion selected by Expert sample	Supported or Not Supported by EFA	Retained or Dropped for final analyses
(1) In your current job, how much freedom do you have to make decisions without supervision? <hr/> No freedom Very little freedom Limited freedom Some freedom A lot of freedom 1 2 3 4 5	79%	100%	Supported	Retained
	84% <i>adjusted</i>			
(2) How much freedom do you have to determine the tasks, priorities, or goals of your current job? <hr/> No freedom Very little freedom Limited freedom Some freedom A lot of freedom 1 2 3 4 5	69%	100%	Supported	Retained
	80% <i>adjusted</i>			
(3) Independence: Job requires developing one's own ways of doing things, guiding oneself with little or no supervision, and depending on oneself to get things done. <hr/> Not important Somewhat important Important Very Important Extremely important 1 2 3 4 5	54%	90%	Not Supported	Dropped
	62% <i>adjusted</i>			
(4) How important is making decisions and solving problems to the performance of you current job? <hr/> Not at all important Fairly important Important Very important Extremely important 1 2 3 4 5	52%	80%	Not Supported	Dropped
	58% <i>adjusted</i>			
(5) Self control: Job requires maintaining composure, keeping emotions in check, controlling anger, and avoiding aggressive behavior, even in very difficult situations. <hr/> Not at all important Fairly important Important Very important Extremely important 1 2 3 4 5		60%	Not Supported	Dropped
			added to EFA via expert sample	

Respondents rated all of the items highlighted in the previous paragraph using a 5-point scale. The two items focused upon how much freedom respondents had were rated on a scale ranging from no freedom, to a lot of freedom. The remaining items were measured on a scale of importance, spanning not important, to extremely important. Responses within occupations to these five items were averaged to create a measure of the level of discretion in work.

Resource control

Control over resources has often been considered a source of power, whether those resources deemed influential were financial, material, human, or informational in nature (Grant, 1999; Pettigrew, 1972; Pfeffer & Salancik, 1978; Stinchcombe, 1990). Perrow (1967) considered power to be the capacity to “mobilize scarce resources and to control definitions of various situations, such as the definition of the nature of the raw material” (p. 198). Accordingly, measuring resource control for this research would require estimating the level to which respondents control the distribution of resources (material, financial, human, or informational), the determination of the structure of work relations, or the definition of the nature of materials and resources.

The item included within the O*NET survey to measure control over material/financial resources was worded, “How important is monitoring and controlling resources to the performance of your current job?” (*Generalized Work Activities Questionnaire*, p. 22). This resource-related variable was defined for the respondent as “monitoring and controlling resources and overseeing the spending of money” (p. 22). The questionnaire items selected to measure control or coordination of human resources were as follows: “How important is staffing organizational units to the performance of your current job?,” which was clarified for respondents as “recruiting, interviewing, selecting, hiring, and promoting employees in an organization” (p. 21); “How important is

coordinating the work and activities of others to the performance of your current job?,” defined for respondents as “getting members of a group to work together to accomplish tasks” (p. 18); “In your current job, how important are interactions that require you to coordinate or lead others in accomplishing work activities (not as a supervisor or team leader)?” (*Work Context Questionnaire*, p. 4).

Table III.7: Items Proposed as Measures of Control Over Resources

Survey item				
(1)	How important is monitoring and controlling resources to the performance of your current job?			
	Not important	Somewhat important	Important	Very important
	1	2	3	4
(2)	How important is staffing organizational units to the performance of your current job?			
	Not important	Somewhat important	Important	Very important
	1	2	3	4
(3)	In your current job, how important are interactions that require you to coordinate or lead others in accomplishing work activities? (not as a supervisor or team leader)			
	Not important	Somewhat important	Important	Very important
	1	2	3	4
(4)	How important is coordinating the work and activities of others to the performance of your current job?			
	Not important	Somewhat important	Important	Very important
	1	2	3	4

Table III.7 lists the four items considered as measures of the level of control of resources. Each of the above-mentioned items from the O*NET questionnaires expected to comprise a reliable scale for measuring resource control were rated by

respondents on a 5-level scale of importance spanning not important to extremely important. The proposed scale for the level of resource control was created by averaging responses to these four items within each occupation.

Controls

With occupation as the unit of analysis for this research, an important consideration when testing relationships that might cut across these units is the impact of other factors that might provide alternative explanations for hypothesized effects. The Knowledge and Skills questionnaires that are part of the O*NET project provide useful and validated measures of two important dimensions of work that distinguish occupations—occupational tasks and knowledge domains—thereby offering a range of control variables capable of measuring the significance of these alternative explanations.

Occupational skill domains

Occupational skill domains capture the range of skills that are applied within an occupation. A listing of these skill domains, along with the items that reflect each domain, appears in Table III.8. As noted earlier in this chapter, the Skills questionnaire considered occupational challenges generally and within two major classes: basic and cross-functional. The distinct domains within which skills were organized were developed by Mumford & Peterson (1995) based upon their review of the literature relating skills with job performance. Basic skills included the domains of content (e.g., reading comprehension, mathematics) and process (e.g. learning strategies, critical thinking). Cross-functional workplace skills were placed within five domains: problem-solving (e.g., information gathering), technical (e.g. equipment design), social (e.g. persuasion, instruction), systems (e.g., judgment and decision making), and resource management (e.g., time, financial expenditure). In terms of inter-rater reliability within

occupations, during pre-testing the median k-rater reliability scores for the items on the Skills questionnaire were 0.83 (Important) and 0.84 (Level).

Table III.8: List of O*NET Skill Domains

Skill Category	Item	O*NET factor
Content	Reading comprehension	
	Active listening	Cognitive
	Writing	Cognitive
	Speaking	Cognitive
	Mathematics	
	Science	
Process	Critical thinking	Cognitive
	Active learning	
	Learning strategies	
	Monitoring	
Complex problem solving	Complex problem solving	Cognitive
Social	Social perceptiveness	
	Coordination	
	Persuasion	Organizational
	Negotiation	Organizational
	Instructing	
	Service orientation	
Technical	Operations analysis	
	Technology design	
	Equipment selection	
	Installation	Technical
	Programming	
	Quality control analysis	
	Operations monitoring	
	Operation and control	
	Equipment maintenance	
	Troubleshooting	Technical
	Repairing	Technical
Systems	Systems analysis	
	Systems evaluation	
	Judgement and decision making	
Resource management	Time management	
	Management of financial resources	Organizational
	Management of material resources	Organizational
	Management of personnel resources	Organizational

Each item within this questionnaire takes the form: “How important is [item] to the performance of the occupation?”—where [item] designates the inclusion of each task element of interest (e.g., active learning, persuasion, operation and control). The definition of each of these skill variables was presented within the questionnaire for respondents. For example, a definition for programming—“writing computer programs for various purposes” (*Skills Questionnaire*, p. 12)—was placed in the text of the survey before respondents were asked to rate the importance of programming to the performance of their current job.

The scales measuring each of these skill domains were formed by averaging the values of all items within each domain (as defined by O*NET) within each occupation. Given the prospect of disagreement over whether the skill domains (i.e., taxonomies) employed by O*NET truly amount to what might be considered factors underlying the measured items, I also employed an exploratory factor analysis of these task-related items, the methods for which are described in the Analyses section of this chapter and the results of which are presented in the next chapter.

Occupational knowledge domains

O*NET developers considered knowledge broadly as “a collection of discrete but related facts and information about a particular domain” (Costanza et al., 1999, p. 71). The Knowledge questionnaire, the underlying constructs of which are based upon a review of the job analysis, training, vocational, and cognition literatures, provides a useful and tested means for considering the knowledge domains that distinguish occupations. Table III.9 lists the 10 knowledge domains that underlie the O*NET dataset, along with the 33 items that were placed within these domains.

Table III.9: List of O*NET Knowledge Domains

Knowledge Category	Item	O*NET factor
Business and Management	Administration and management	Business Administration
	Clerical	Support & Clerical
	Economics and accounting	Business Administration
	Sales and marketing	Business Administration
	Customer and personal services	Business Administration
	Personnel and human resources	Business Administration
Manufacturing and Production	Production and processing	
	Food production	
Engineering and Technology	Computers and electronics	Support & Clerical
	Engineering and technology	Science & Technology
	Design	Science & Technology
	Building and construction	Science & Technology
	Mechanical	Science & Technology
Mathematics and Science	Physics	Science & Technology
	Chemistry	Medical
	Biology	Medical
	Psychology	Law Enforcement & Security
	Sociology and anthropology	Law Enforcement & Security
	Geography	Arts & Humanities
Health services	Medicine and dentistry	Medical
	Therapy and counseling	Law Enforcement & Security
Education and Training	Education and training	
Arts and Humanities	English language	Arts & Humanities
	Foreign language	Arts & Humanities
	Fine arts	Arts & Humanities
	History and archeology	Arts & Humanities
	Philosophy and theology	
Law and Public safety	Public safety and security	Law Enforcement & Security
	Law and government	Law Enforcement & Security
Communications	Telecommunications	
	Communications and media	
Transportation	Transportation	

Each survey question was either of the form, “How important is [item] knowledge to the performance of your current job,” or “How important is knowledge of [item] to the performance of your current job?”—where [item] designates the inclusion of each item of interest (e.g., customer and personal service, physics, public safety and security). Furthermore, similar to the previous questionnaire, the definition for each of the variables measured within the Knowledge questionnaire was printed just above the question items (measuring Importance and Level) associated with that variable. For example, Engineering and Technology was defined for the respondent as, “knowledge of the practical application of engineering science and technology. This includes applying principles, techniques, procedures, and equipment to the design and production of various goods and services” (*Knowledge Questionnaire*, p. 6).

The scale for measuring each of the knowledge domains was formed by averaging the values of all items within each domain for each occupation. I was concerned whether these taxonomic domains as prescribed by O*NET existed as factors underlying the measured items. Therefore, an exploratory factor analysis (EFA) of these task-related items was employed to pursue the existence (if any) of some underlying factor structure. The methods for this EFA are described in the Analyses sections within this chapter, with EFA results presented in the next chapter.

Analyses

In this section, I will first describe the three-pronged method employed to determine whether and how the relationships among items I had drawn from the O*NET questionnaires suggest underlying factors in a manner similar to those proposed in this research. This triangulation of evidence involved a combination of the findings from an

exploratory factor analyses with those from an investigation of face validity involving both working individuals from the general public as well as research experts. I will then describe the statistical methods employed for testing the hypotheses laid out in the chapter III.

Validity

I employed a three-point process in order to assess by triangulation the evidence for validity of the items I had proposed for measuring the variables in this research. The first point in this process involved an exploratory factor analysis. The second point involved a simple test of validity based upon the opinions of a small sample of working individuals collected via an online survey. The third point of the process involved the judgments of a small group of experts—researchers within occupations included within O*NET who also had experience measuring variables with multiple items, sourced from surveys or otherwise.

Exploratory factor analysis

Although I developed a priori judgments regarding which items from the O*NET questionnaires might provide suitable measures of the variables of interest, these items and their underlying factor structure had not been prescribed by or confirmed in prior research. Therefore, given that my objective was, in the words of Fabrigar, Wegener, MacCallum & Strahan (1999), to “identify a set of latent constructs underlying a battery of measured variables” (p. 275) an exploratory factor analysis (EFA) was undertaken as opposed to a confirmatory factor analysis (CFA). Conway & Huffcutt (2003), Fabrigar et al. (1999), and Ford, MacCallum, & Tait (1986) in the aggregate highlight four important considerations and associated high-quality decisions when conducting an EFA: the factor model, the factor-extraction (model fitting) procedure, the number of factors to

retain, and the factor rotation method. In this section, I justify the methodological and analytical choices I made for this EFA.

Researchers face a somewhat daunting task when selecting specific methods for each of these four EFA decision stages. First, an approach preferred by researchers during one decade often faces criticism and loses favor in later decades. In fact, the evolution of these factor analysis methods is in part a function of the ever-increasing computing power and statistical software available to support academic research—the sort of automation that I find interesting. Second, yet related to the first, as methods evolve over time a researcher loses the ability to easily communicate results in a common language. As a result, there is a degree of uncertainty regarding the extent to which a more recent method must be explained so as to be understood and believed, before the results of this method can even be presented. Finally, and perhaps most frustrating, the most popular methods employed for (or at least described in) research published in prestigious field journals are often not the methods preferred by research methods journals. Effectively, learning by example can steer anyone looking for some guidance down a road cluttered with mixed signals. In the end, exploratory factor analysis, while portrayed as a science, clearly involves a bit of art or at least the application of judgment able to bind the statistical output within the reasonable confines of just making sense.

Given the objective for this factor analysis was to reveal the latent structure underlying a set of measured items, a common factor (CFA) rather than principal components analysis (PCA) was adopted for exploratory factor analysis. Importantly, common factor analysis differentiates between unique factor variance (a factor that influences only one item) and common factor variance (a factor that influences more than one item). Furthermore, common factor analysis assumes the factors are

imperfectly reflected in the measured items. PCA makes no such assumptions, leading to factors that contain both unique and common variance (Conway & Huffcutt, 2003; Fabrigar et al., 1999). I should note that according to Fabrigar, et al. (1999), around half of all articles published in the *Journal of Applied Psychology* and the *Journal of Personality and Social Psychology* between 1991 and 1995 that reported pursuing an EFA employed PCA analysis (as opposed to CFA) even though the goal of the analysis was to identify underlying, latent factors.

Debates over appropriate factor extraction methods have continued for decades. I selected a maximum likelihood (ML) procedure as the primary common factor-extraction method because ML supports a number of goodness-of-fit indices, backed by tests for statistical significance, that can guide selection of the number of factors to retain (Cudeck & O'Dell, 1994). ML can produce problematic results, however, if the method's assumptions of multivariate normality are violated severely, yet the border of "severely" is not clear and strict. Therefore, I chose principal factors (PF) as the secondary factor-extraction method. PF offered the advantages of (a) having no assumptions regarding multivariate normality and (b) being less likely than ML to fail to produce a solution (converging on a single mix of parameters) or produce a solution with a Heywood case (i.e., the uniqueness of any parameter falls to 0, preventing a meaningful solution).

As a method, maximum-likelihood is somewhat of a brute force computing technique as compared to the more computationally efficient methods historically employed in statistics. Traditional statistics involve the discovery or definition of a formula, and the calculation of a value for that formula based upon the data. These methods are computationally minimal for the most part, developed before mainframes, desktop computers, and even calculators existed. ML, on the other hand, involves the prescription of some desired outcome value (i.e., the likelihood estimator), while a

computer program iteratively “guesses” the combinations of input parameters (i.e., the formula) that result in the maximization of that outcome. The guessing is not random, however. Instead, the program looks for patterns that signal the approach of or departure from a maximization of the likelihood function. The experience is akin to walking a surface in a deep fog, searching for the highest point on that surface. You might begin walking in one direction to see if you are going uphill. If so, you proceed. If, however, it appears you are walking downhill you then stop and turn around—up is in the other direction. Given the surface may have multiple dip and peaks, you would need to begin at multiple starting points and develop a few rules outlining how far and in how many directions you are willing to walk before calling off the search (signaling a failure of the ML method to converge upon a single solution).

When selecting the number of factors to retain, a number of tests and rules of thumb have been applied over the decades: Kaiser’s criterion (Guttman, 1954; Kaiser, 1958; 1960), scree tests (Cattell, 1966; 1978; Cattell & Jaspars, 1967), parallel analysis (Horn, 1965; Humphreys & Montanelli, 1975; Montanelli & Humphreys, 1976), and minimum desired proportion of variance explained. Each of these factor retention methods, with the exception of the fit indices from ML, has been criticized for either introducing the risk of both over- and under-factoring (Zwick & Velicer, 1982; 1986), or ultimately being arbitrary in their selection criteria (Fabrigar, et al., 1999). For example, there is no clear reasoning or test to conclude that an Eigenvalue of 1.04 would be truly and statistically superior to a value of 0.97. Notwithstanding the apparent weaknesses of these various methods, more than 30% of articles published in the JPSP and JAP from 1991-1995 employed either the Kaiser criterion or scree test to select the number of factors. These two factor retention methods may persist in their predominance simply because of their widespread availability within and default output of the more popular

statistical packages. Surprisingly, Fabrigar, et al. (1999) found that roughly 40% of articles in their sample within which EFA was described as part of the research failed to even mention the method employed in selecting the number of factors to retain.

When selecting the number of factors to retain, I employed a combination of the two techniques considered by methods researchers to be the most reliable—parallel analysis (with a principal factor-extraction method) and goodness-of-fit indices (with a ML factor-extraction method). While the application of multiple methods for factor retention decisions is suggested by methods journals, it is not a common practice “in the wild.” Conway & Huffcut (2003) found that 3.8% of articles published in JAP, PP and OBHDP from 1985 to 1999 made use of multiple factor retention methods. The fit indices made possible by the ML method (a likelihood ratio, BIC) were employed as the primary means for determining the number of factors to retain. As a factor analysis procedure, however, ML is not immune from limitations. Therefore, and as prescribed by Ford, et al. (1986), Fabrigar, et al. (1999) and Conway & Huffcutt (2003), I considered the results of a secondary technique—parallel analysis, with a principal factor-extraction method—alongside those from the ML procedures.

As a factor rotation method, I employed an oblique rather than orthogonal rotation. Simply stated, the goal of any rotation method is to uncover what Thurston (1947) called the “simple structure” underlying the observed items. Conway & Huffcut, agreeing with Ford, et al. (1986), Fabrigar, et al. (1999) and Gorsuch (1997), offered two reasons for a preference of oblique over orthogonal rotation in EFA. First, an orthogonal rotation, by assuming factors are uncorrelated, forces an unrealistic solution upon the reality that most factor are in fact correlated to some extent. An orthogonal rotation enforces an expectation of completely uncorrelated factors upon the data, an expectation that while ideal is not likely to be true. As a result, researchers often get

interpretable results—factors are effectively forced to emerge and be distinct. Perhaps this is why more than 40% of articles published in JAP, PP and OBHDP during the period 1985-1999 employed an orthogonal rotation (Conway & Huffcut, 2003). On the other hand, oblique rotation accounts for some degree of correlation among factors—a more realistic approach to the nature of most social science data wherein many variables have a least a little bit in common with other variables. Second, even if factors were indeed uncorrelated then oblique and orthogonal rotations will offer quite similar results (Floyd & Widaman, 1995).

An additional reason for preferring oblique over orthogonal rotations, one not mentioned by Conway & Huffcut (2003), is that by accounting for correlations among factors oblique rotations offer insights into the variables of interest beyond simply the loadings of items on factors. In particular, oblique rotations permit an understanding of the correlations among factors leading to further investigations into the presence of higher order factors.

Face validity

In addition to the above-described exploratory factor analysis, I also conducted two tests to assess the general face validity for the O*NET items as reasonable measures of the constructs of interest. The first test involved an online survey given to a sample of working individuals (the “eLab sample”). The second test involved paper surveys given to a small-but-targeted sample of experts—researchers who were familiar with the methods for measuring constructs by way of survey items or other means (the “expert sample”).

eLab sample: A random sample of 259 employed individuals—stratified by age, gender, and ethnicity—was drawn from a panel of roughly 127,000 individuals who have registered with eLab at Vanderbilt University as willing to participate online as subjects in

academic social science research.⁴ The goal for the stratified sample, given an anticipated low response rate, was a final set of approximately 50 respondents who were presently employed and offered as a group a distribution in gender, age, and ethnicity that matched (as nearly as possible) that of the 2008 American Community Survey conducted by the US Census Bureau.⁵ Each of these individuals received an email inviting them to participate in a brief survey (this email as well as the survey text are presented in their entirety as Exhibit B within the appendix), informing them of the general characteristics of the survey, and providing them with a link URL to take the survey online. Sixty-seven individuals responded to the survey request, resulting in a response rate of 26%. While low, this response rate is in-line with that experienced by researchers employing online surveys within large sampled populations. For example, Kaplowitz, Hadlock & Levine (2004) found that the response rates for the same public-opinion survey differed significantly based upon the method for delivery—mail versus email/online. While a mailed survey resulted in a response rate of 31.5%, an email/online version received a response rate of 21%.

Within this online survey, after completing three introductory questions, respondents were presented with a series of web pages. At the top of each page, one construct of interest to this research was presented along with a definition of this construct, followed in the lower sections of the page by a list of twenty survey items from the O*NET questionnaires. Each page offered a different construct of interest, along with its definition as well as a list of 20 questions. Any given list of 20 items comprised (a) the specific items pre-identified (as enumerated in Chapter 4) as potential measures

⁴ More information on Vanderbilt's eLab can be found online at <http://elab.vanderbilt.edu/>. Research based upon the responses of subjects within the eLab panel has been published in the *Journal of Consumer Research* and *MIT Sloan Management Review*

⁵ More information about the American Community Survey can be found online—<http://www.census.gov/acs/www/>

of their associated construct of interest, and (b) a set of additional items randomly selected (independently for each construct page) from the remaining pool of 160 total questions available from Generalized Work Activities, Work Context, Skills and Knowledge surveys. The test for face validity was a simple one—which items would a majority (i.e., greater than 50%) of respondents select as those best able to measure the construct of interest.

Figure III.1 presents a screenshot of a sample page within the online survey offered to respondents through eLab, while Appendix B presents this survey in its entirety. The respondent's task, for each list of questions, was to select as many of these items that seemed to assess or measure the construct listed and defined at the top of the web page. The selection of question-construct matches was made by way of a "checkbox"—a standard HTML object for selecting items from a list. Respondents were instructed in text above the list of items to: "Please select **as many** of those questions listed below that you think are a good way to assess or measure [*construct*], as defined above **in red**, or a *lack of [construct]*", where [*construct*] was replaced with the construct for the page (e.g., Automation, or Routinization) and text in **bold** or *italics* were employed as presented here. There was no limit to the number of items respondents could check within any list of items. By not setting a limit to the number of items any respondent could check, I was essentially placing a higher bar for validity (particularly, in terms of convergence). It was completely plausible that respondents could select a smaller or larger group of items as measures than I had proposed.

Figure III.1: Screenshot of Sample Page from the eLab Online Survey

eLab eLab Experiment

Help

Concept: AUTOMATION

Definition: The performance of some task, manual or physical, in whole or in part, by a machine.

Instructions: Please select **as many** of those questions listed below that you think are a good way to assess or measure *Automation*, as defined above **in red**, or a *lack of Automation*.

(REMEMBER: You can select more than one question listed below)

- In your current job, how often are you exposed to whole body vibration (like operating a jack hammer or earth moving equipment)?
- In your current job, how often are you exposed to extremely bright or inadequate lighting conditions?
- How important is knowledge of biology to the performance of your current job?
- How important is working with computers to your current job?
- How important is a service orientation to the performance of the occupation?
- How important is controlling machines and processes to the performance of your current job?
- How important is monitoring processes, materials, or surroundings to the performance of your current job?
- How important is quality control analysis to the performance of the occupation?
- How important is equipment maintenance to the performance of the occupation?
- How important is economics and accounting knowledge to the performance of your current job?
- How important is knowledge of personnel and human resources to the performance of your current job?
- How important to your current job is keeping a pace set by machines?
- How much contact with others (by telephone, face-to-face, or otherwise) is required to perform your current job?
- How important is knowledge of medicine and dentistry to the performance of your current job?
- How automated is your current job?
- How important is mechanical knowledge to the performance of your current job?
- In your current job, how often do your decisions affect other people or the image or reputation or financial resources of your employer?
- How much time in your current job do you spend making repetitive motions?
- How often does your current job require that you become exposed to diseases or infection? This can happen in patient care, some laboratory work, sanitation control, etc.
- How important is operations analysis to the performance of the occupation?

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Manipulation: N / A

Change Factors

Screen 2 of 8 Proceed

Expert sample: As with the eLab sample, the pursuit of face validity based upon the opinions of a sample of experts was undeniably simple—which items would a majority (i.e., greater than 50%) of these experts select as those best able to measure the constructs of interest. For this test, “expert” was defined as a researcher who (1) had experience selecting and confirming multiple measures for variables included within academic research, (2) worked within a research field that fell within an occupation included within the O*NET sampling frame (directly based upon the Standard Occupational Classification System), and (3) ideally had a previously held an occupation different from that describing their research field. The expert sample comprised nine individuals who met all three criteria. For example, two individuals I targeted were a management faculty who had previously been a lawyer and an accounting faculty who had previously been a CFO. In aggregate, this expert sample consisted of two economists, three management professors, one professor of Politics, one accounting professor, and two professors of psychology. Prior occupations of these faculty included management consultant, lawyer, accountant, human resources executive, landscape designer, marketing analyst and athlete.

Respondents within the expert sample were asked to fill out a paper survey, rather than an online survey. The content of the paper survey was constructed identically to that of the survey placed online via eLab. Each page of this handout offered a different construct, with the definition of this construct along with 20 questions from which respondents were asked to select those questions presented on the page. Respondent were asked to “Please select **as many** of those questions listed below that you think are a good way to assess or measure [*construct*], as defined above **in red**, or a *lack of [construct]*”, where [*construct*] was replaced with the construct for the page (e.g., Automation, or Routinization) and text in **bold** or *italics* were employed as presented

here. Respondents marked their selections by placing a check mark within or filling in a box located next to each of the 20 questions.

Hypotheses Testing

In this section I briefly describe the statistical methods—multiple regression involving a non-linear transformation of key variables—employed to test the hypotheses developed in chapter III.

Multiple regression

Multiple regression was employed as the method for testing each of the hypotheses presented in chapter III. For each hypothesis, a model was developed comprising the theorized and controlled variables. In the case of those models involving interaction effects, primary variables were centered about their means before being interacted within regressions so as to avoid multi-collinearity between these primary variables and their interactions terms (Aguinis, 2004; Aiken & West, 1991; Baron & Kenny, 1986). A likelihood-ratio test was employed to test whether the more complex models added significantly to the amount of collective variance (R^2) that could be explained as compared to that explained by the more parsimonious, nested models (Clogg, 1995; Gouieroux, Holly & Monfort, 1982).

Non-linear transformation

Since the relationship between the automation and the routinization of work was hypothesized to be non-linear (Chapter III, hyp. 3(a) and (b)), a transformation of the automation variable was applied within the regression models. While linear regression is a method believed to be relatively robust to minor deviations from the assumption of normality (Hoffmann, 2004), when the relationships between the independent predictors and the dependent variable are believed to be something other than directly linear,

various nonlinear transformations of either the independent or dependent variables are appropriate and necessary (Agresti & Finlay, 1997; Breiman & Friedman, 1985; Seber & Wild, 2005). Breiman and Friedman (1985) noted that nonlinear transformations of variables within otherwise linear regression models accomplishes three objectives: (1) stabilization of error variances, (2) normalization/symmetrization of error distributions, and (3) production of the best-fitting, additive model by way of this transformation. Importantly, “knowledge of such transformation aids in the interpretation and understanding of the relationship between the response and predictors” (Breiman & Friedman, 1985, p. 580).

In the case of this research, the transformations involved not only squaring, but also cubing the variable representing automation. Squaring a term captures flexion around the mean of the variable, while cubing captures any curvature towards upper and lower bounds of the variable’s values. In the case of a squared term, a positive squared term would imply a similar weighting at the extremes of the predicting variable—both the lower and the higher values require greater weighting in order to for the prediction to conform to a linear relationship with the predicted/dependent variable. In the case of a cubed term, a negatively weighted cubed term implies a reversal of weightings along the range of the predicting variables—lower values require lesser weighting than the middle values, while the higher values require greater weighting than these middle values. Importantly, a likelihood-ratio test was performed to test the null hypothesis that the added non-linear transformations do indeed result in a statistically significant contribution to the overall fit of the regression model (Hoffmann, 2004).

Conclusion

In this chapter I described the research approach and methods employed by O*NET to construct the questionnaires developed and collection methods enacted to result in the data used for this project. I also outlined the empirical methods I employed within this project, presenting the constructs and measures involved, and explaining the validation and hypothesis testing phases of the analysis. In the next chapter, I will present, in detail, the results of these analyses.

CHAPTER V

RESULTS: VALIDITY TESTING AND SCALE CONSTRUCTION

In this chapter I will describe the results from the various analyses employed to test the validity of measures presented in Chapter IV. First, I will summarize the characteristics of the O*NET sample employed for this research. Second, I will describe the validity test results, including those that are a function of the online and expert sample inquiries into face validity as well as those resulting from the exploratory factor analyses investigating convergent/divergent validity.

O*NET Sample Summary

As noted in Chapter IV, the purpose of the O*NET project is to gather detailed data on the nature of work and occupations within the United States. The ongoing development of O*NET is funded by the U.S. Department of Labor's Employment and Training Administration (USDOL/ETA). The project is managed by the National Center of O*NET Development. The data that have been collected as part of the O*NET project comprise expert analyst and job incumbent ratings, which are collected by way of four standardized questionnaires.

A summary of the general characteristics of the O*NET sample resulting in version 13 of the dataset can be found in Table IV.1 below. The O*NET project does not publish demographic data (such as race, age, or gender) collected from job incumbents and analysts, even in aggregate. These data are gathered and held privately under the program's data collection agreement with establishments and individuals. However, the

O*NET development team uses the demographic data to support response bias analyses, in order to ensure that no particular group of incumbents within the relevant population are systematically excluded from the data collection.⁶

Table IV.1: General Characteristics of the O*NET Sample

Total Number of Individual Respondents:	99,886
Proportion responding by:	
<i>Paper</i>	86.2%
<i>Web</i>	13.8%
Average number of respondents per occupation:	
<i>Minimum</i>	20
<i>Maximum</i>	791
Average response rate for establishments:	
<i>Minimum</i>	37.9%
<i>Maximum</i>	97.6%
Average response rate for employees:	
<i>Minimum</i>	33.1%
<i>Maximum</i>	100.0%
Average case response rate (completions):	
<i>Minimum</i>	63.5%
<i>Maximum</i>	100.0%
SIC Classification of respondent industry:	
<i>Construction</i>	4.5%
<i>Ag</i>	2.8%
<i>Mining</i>	2.0%
<i>Manufacturing</i>	18.7%
<i>Transport</i>	9.5%
<i>Wholesale</i>	1.3%
<i>Retail</i>	5.0%
<i>Financial</i>	3.5%
<i>General Services</i>	27.1%
<i>Public Admin</i>	8.5%
<i>Non Classifiable</i>	15.2%
Total number of occupations:	
<i>with only analyst responses</i>	70
<i>with incumbent responses</i>	737
Number of incumbent respondents	96,899
Total number of occupations included for analyses:	737

⁶ Confirmed through email correspondence with a representative from the National Center for O*NET Development.

O*NET data collection is carried out through a multi-staged design. As a result, there are two relevant response rates for the survey, one at the level of establishment and the other at the level of employee. The project reports occupation-level response rates for both establishments and individuals, along with a final case completion rate (the proportion of respondents within each occupation who return a completed survey). Furthermore, an industry-level breakdown (by SIC and NAIC codes) of establishments from which respondents were sourced is reported.

Individual-level responses are aggregated within each occupation and only occupation-level data are released by the project. Given the random assignment of one-of-four surveys (Work Context, Work Activities, Skill, or Knowledge survey) to each respondent, at least four respondents are needed within any occupation before a complete set of responses may have been gathered for that occupation. For each question in the O*NET survey the available dataset includes for each occupation (a) the number of respondents, (b) the average and standard deviation of responses, and (c) the counts of individuals selecting each level of a response scale (e.g., how many respondents selected scale level 1, 2, 3, 4, or 5).

The version of the O*NET dataset considered for my analyses (version 13) is comprised of responses from 99,886 individuals, including both expert analysts and job incumbents, spanning 807 occupations. On average there were 124 respondents per occupation, with 86% responding via paper surveys and the remainder responding via an online version of the surveys. The average response rate for establishments was 68.2%, while that for employees within these establishments was 67.3%. 89.8% of respondents who agreed to fill out a questionnaire returned a completed questionnaire.

A breakdown of the Standard Industrial Classification (SIC) for the organizations employing survey respondents can also be found in Table X. Seventy occupations had responses from only expert analysts as opposed to job incumbents. My preference was for responses from incumbents over analysts. This set of occupations lacking data from incumbents did not appear to fit some systematic pattern. As a result, these seventy occupations were withheld from the analyses.

In total, O*NET data for 737 occupations—the result of survey responses from 96,899 individuals—were used for the analyses described in this chapter.

Validity

I employed a three-point, triangulation method to validate the items I had proposed in chapter IV for measuring the independent and dependent variables. I will first describe the results from a simple test of face validity based upon the opinions of a small sample of working individuals collected via an online survey. Next, I will describe the results from the second point of the triangulation process, which involved the face-value judgments of my proposed measures gathered from a small group of experts. The final point in this process involved an exploratory factor analysis, the results of which will be described last in this section.

Online Survey

General characteristics

As mentioned in Chapter IV, a random sample of 259 individuals employed within the United States was drawn from a panel of roughly 127,000 individuals who have registered with eLab at Vanderbilt University. Sixty-seven individuals responded to the survey request, resulting in a response rate of 26%. Fifteen respondents did not

complete the entire survey online, leaving the results from 52 respondents remaining. While the goal for the sample was one stratified by age, race and gender, what I received from eLab was a random sample. The general characteristics of this eLab sample as compared to those of the US workforce can be found in Table IV.2.

Table IV.2: General Characteristics of the eLab sample

Number of individuals invited to complete eLab survey:			259		
Number of respondents			67		
Response rate:			25.9%		
Number with incomplete surveys:			15		
Number of completed surveys used for analysis:			52		
Completion rate:			77.6%		
<hr/>					
Proportion of respondents, by gender			Proportion of US workforce, by gender ¹		
<i>Male</i>	59.6%	53.4%	Male		
<i>Female</i>	40.4%	46.6%	Female		
<hr/>					
Average age of respondents, in years	43.4				
Proportion of respondents, by age group			Proportion of US workforce, by age group ¹		
<i>18 to 24</i>	3.8%	12.0%	<i>18 to 24</i>		
<i>25 to 34</i>	23.1%	21.9%	<i>25 to 34</i>		
<i>35 to 44</i>	25.0%	23.3%	<i>35 to 44</i>		
<i>45 to 54</i>	32.7%	24.1%	<i>45 to 54</i>		
<i>55 to 64</i>	11.5%	14.5%	<i>55 to 64</i>		
<i>over 65</i>	3.8%	4.2%	<i>over 65</i>		
<hr/>					
Proportion of respondents, by race/ethnicity			Proportion of US workforce, by race/ethnicity ²		
<i>African American</i>	3.8%	10.3%	<i>African American</i>		
<i>Asian</i>	1.9%	4.4%	<i>Asian</i>		
<i>Hispanic</i>	1.9%	5.7%	<i>Hispanic</i>		
<i>Caucasian</i>	92.3%	73.6%	<i>Caucasian</i>		
<i>Other</i>	0.0%	6.0%	<i>Other</i>		

Notes:

¹ As estimated using US Bureau of Labor statistics, <http://www.bls.gov/cps/demographics.htm>

² As estimated using America Community Survey statistics, available from http://www.census.gov/acs/www/Products/users_guide/2006-2008/index.htm

While it was not clear how gender, age, or race would impact responses to this test for simple face validity, it was clear that the eLab sample did not tightly match the demographic characteristics of the US workforce. Demographically, the eLab sample is likely over-represented by males as compared to females. The Bureau of Labor Statistics (BLS) reports a coefficient of variation in their estimates of the US Employment

of +/- 8% (90% likelihood), centered upon 53.4% male and 46.6% female. The proportion of males in the eLab sample (59.6%) is greater than that of the BLS estimate, while the proportion of females (40.4%) is below the BLS estimate. Both proportions are outside the margin of error for the BLS estimates. Furthermore, in comparison to BLS estimates the eLab sample was under-represented by individuals younger than 25 or older than 54 (15.3% combined in eLab versus 26.5% in the BLS), while over-represented by those between the ages of 25 and 54 (80.8% combined in eLab versus 69.3 in the BLS). Finally, the sample was racially over-represented by those claiming to be Caucasian (92.3% versus 73.6%), while under-represented by individuals claiming to be described by any of the remaining races considered in the American Community Survey (ACS).

I found other aspects of the eLab sample characteristics more concerning than the demographic distributions. A number of respondents, while completing the entire survey—in the sense of hitting “Proceed” at the bottom of each page of the survey online—either did not select any items at all as measures of constructs or did not select at least a single item for some constructs. While I could not rule out the case of individuals not finding items on any page as plausible measures for some or all of the constructs, this set of respondents also tended to finish the entire survey in noticeably less time than respondents on average. On average, the survey took respondents 14.2 minutes to complete with a median completion time of 12.1 minutes. The individuals selecting only one item per construct, or fewer, tended to complete the entire survey in less than 3 minutes. One such individual completed the entire survey in 80 seconds. In fact, the completion time of most individual respondents who selected such a small numbers of items was significantly different (p -value < 0.05) from the completion time for the remaining sample.

Therefore, I included two numbers within the column labeled “proportion selected by eLab” for each of the tables found later in this chapter summarizing the results of validity tests for each construct (i.e., Table IV.45,

Table IV.48, Table IV.50, Table IV.51, Table IV.53, and Table IV.55). I listed not only the proportion of the 52 individuals who responded to and completed the survey, but also that adjusted proportion resulting from the removal of nine individuals from the sample whose behavior within the online survey reasonably suggested their selections may be less than reliable. I felt it appropriate to offer both proportions within the Tables given I lacked complete knowledge of unreliable responses since the behaviors of these individuals whose responses were discarded could not be directly observed.

Results

The results for the test of face validity using the online (eLab) sample were mixed. A majority of eLab respondents selected only one of the items proposed as measures of automation, “How important is working with computers to your current job.” By way of adjusted proportions however, one of the four items would be clearly supported, while two received just under the majority support, at 49%. All of the measures proposed for discretion were confirmed by a majority of eLab users. Two of the four proposed measures for programmed ends did not receive support from the 52 respondents: “How important is evaluating information to determine compliance with standards to the performance of your current job?” and “How important is judging the qualities of objects, services, or people to the performance of your current job?” The latter was supported, however, by the adjusted sample. Only a single measure for resource control, “How important is monitoring and controlling resources to the performance of your current job,” was supported by the 52 respondents, while all four measures received a majority of confirmations in the adjusted sample.

The results from the validation of the dependent variables are as follows. Three of the six items believed to measure routinization of work received a confirmation from a majority of eLab respondents: “How much time in your current job do you spend making repetitive motions,” “How important to your current job are continuous, repetitious physical activities (like key entry), or mental activities (like checking entries in a ledger),” and “Adaptability/Flexibility: Job requires being open to change (positive or negative) and to considerable variety in the workplace” (reverse coded). All of the measures proposed for skill requirements were confirmed by a majority of eLab respondents.

Expert Sample

General characteristics

In addition to the eLab sample I identified a sample of experts to investigate face validity of the items proposed as measures. The test for validity within the expert sample was also simple—which items would a majority (i.e., greater than 50%) of these experts select as reasonable measures? Potential respondents to this expert sample had three desirable characteristics: (1) experience selecting and confirming multiple measures for variables included within academic research; (2) a present occupation within a research field that resided within the O*NET sampling frame, and (3) a prior occupation that also was included within the O*NET sampling frame. I identified and secured the participation of ten experts who met these three requirements.

In the aggregate, the expert sample consisted of three professors of economics, three management professors, one professor of politics, one accounting professor, and two professors of psychology. Prior occupations of these faculty included management consultant, lawyer, accountant, human resources executive, economist, landscape designer, marketing analyst and athlete. Fifty percent of the respondents were female.

A 50/50 split of respondents by gender resides within the range of BLS estimates of the US labor force given the margin of error. Racially, the expert sample was completely Caucasian, quite different in composition from the BLS estimates of the US workforce. However, as noted earlier, I had no clear reason to believe race would impact responses to this test for face validity and was concerned more with measurement experience and occupational variety among the experts.

Results

Results from the expert sample matched my selection of measures, with few exceptions. All proposed measures for the independent variables automation, discretion, and resource control received confirmation from at least 50% of the expert sample. One measure for automation received only 70% confirmation (“How important is working with computers to the job?”), two received 90% and one measure was selected by all of the experts in the sample. Two measures for discretion were selected by 100% of experts, one measure by 90%, and the fourth and final measure by 70% (“How important is making decisions and solving problems to the performance of your current job?”). Two measures of resource control received 100% of experts’ selections, while two received weak support with only 50% of selections (“How important is staffing organizational units to the performance of your current job” and “In your current job, how important are interactions that require you to coordinate or lead others in accomplishing work activities, not as a supervisor or team leader”). All items proposed to measure the programmed ends of work were supported, except, “How important is judging the qualities of objects, services, or people to the performance of your current job?,” which received only 40% of the selections of experts.

In terms of the dependent variables, four out of the six proposed measures for routinization of work received at least 70% of experts’ selections, while “How important is

thinking creatively to the performance of your current job” received only 60% of selections and “How important to your current job are continuous, repetitious physical activities (like key entry), or mental activities (like checking entries in a ledger)” received only 50%. All proposed measures of the skill requirements for work received support from the entirety (100%) of the expert sample.

Overall, I found it surprising and a bit disappointing that the most general question developed by O*NET to measure repetitious work (How important to your current job are continuous, repetitious physical activities... or mental activities...?) received such weak support (50%) from the expert sample, while the most general question developed for automation (How automated is your job?) received such strong support (90%).

For most of the constructs, a majority of the expert sample selected at least one item I had not. For skill requirements, 50% of experts selected “How important is systems evaluation to the performance of the occupation,” while 60% selected “How important is knowledge of medicine and dentistry to the performance of your current job” and “How important is knowledge of personnel and human resources to the performance of your current job.” All of these items seemed to be better measures of jobs that required particular skills rather than an overall assessment of skill requirements for jobs in general. Therefore, in these cases, I felt the expert sample had construed connections into the analysis beyond those directly linking a construct with a measure, and chose not to consider these items for the EFA.

For automation, 80% of experts selected “How important is equipment maintenance to the performance of the occupation” as a reasonable measure, while 60% selected “How important is mechanical knowledge to the performance of your current job?” For programmed ends, 60% of experts selected “How important to your current job

is being very accurate or highly accurate” and “How much freedom do you have to determine the tasks, priorities, or goals of your current job” as plausible measures. Interestingly, 100% of experts selected the latter of these two measures as plausible for discretion as well, setting up a useful challenge within the EFA for distinctiveness of this item. 60% of experts selected “How important is self-control to the performance of your current job” as a reasonable measure for discretion in work, adding a dimension I felt did not truly correspond to the definition of discretion. 70% of experts felt “How important is scheduling work and activities to the performance of your current job” would measure resource control, introducing a dimension of time management for consideration within this construct.

For constructs associated with items selected by experts but not proposed by myself, I concluded that if I add any new items to the EFA for methodological or exploratory reasons, then I must also include those above-mentioned items selected by experts. To foreshadow the eventual outcome of this if/then condition: I did encounter methodological/exploratory reasons to add additional items to the EFA and, therefore, also added these expert-selected items for consideration within the factor structure of the proposed measures.

Exploratory Factor Analysis, Initial Items

Although I developed a priori judgments regarding which items from the O*NET questionnaires might provide suitable measures of the variables for this research, these items and their underlying factor structure had not been prescribed by or confirmed in prior research. Therefore, an exploratory factor analysis (EFA) was undertaken to pursue the set of latent constructs possibly underlying the variables as measured. I conducted separate analyses for those items selected as measures for dependent

variables and those selected for independent variables. The control variables, Task and Knowledge domains, were used in the structure prescribed by O*NET, and therefore I did not conduct an EFA involving these control variable items.

As described in the chapter IV, I selected a maximum likelihood (ML) procedure as the primary common factor-extraction method and principal factors (PF) as the secondary factor-extraction method. Fit indices—primarily the Bayesian Information Criterion (BIC) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy—provided guidance when selecting the number of factors to retain during the ML procedures, while parallel analysis (PA) guided my choice of the number of factors under the PF method. I will report the results from the combination of these methods given the strongest support for the EFA findings occur when different methods converge upon the same factor structure (Conway & Huffcutt, 2003; Fabrigar, et al., 1999; Ford, et al., 1986). I employed an oblique (promax) rotation of items, permitting a degree of correlation among factors, when investigating the loadings of items within and the correlations among factors. Finally, given this was an exploration into factor structure—essentially, an attempt to understand if and how certain perceptions were nested within larger concepts—I tried to combine these empirical methods with reasonable judgments in the event of conflicting or surprising findings along the way.

Factor Structure of Independent Variables

The hypothesized independent variables for this research were automation, discretion, programmed ends, and resource control. I began the EFA in search of reliable measures of these variables with an estimate of the Kaiser-Meyer-Olkin (KMO) measure including all of the items comprising the proposed measures of the independent variables. The KMO results for each of the items, as well as the overall measure for all of

the items combined, can be found in Table IV.3. The overall adequacy of the items as being represented by some factor structure appeared reasonably strong, with an overall KMO of 0.85. Individually, the item most likely to be independent of other items was that directed at the general level of automation (“How automated is your current job”) with an individual KMO of only 0.4. These results suggested while most the items had a good chance of residing within some over-arching factor structure (individual KMOs at or above 0.70), the item directed at measuring the general level of automation was likely to operate independent of other items (perhaps comprising its own factor).

Table IV.3: KMO of Independent Variable Items

Variable	kmo
evaluating information to determine compliance with standards	0.89
developing objectives and strategies	0.93
judging the qualities of objects, services, or people	0.93
making decisions and solving problems	0.92
organizing, planning, and prioritizing work	0.91
coordinating others, not as supervisor/leader	0.91
monitoring and controlling resources	0.88
staffing organizational units	0.87
coordinating the work of others	0.87
freedom to determine the tasks, priorities, or goals	0.80
Independence	0.93
freedom to make decisions without supervision	0.79
keeping a pace set by machines	0.73
controlling machines and processes	0.67
working with computers	0.81
how automated is your current job	0.40
Overall	0.85

An ML-based investigation of the factor structure suggested the independent variable items composed no greater than eight factors. Table IV.4 reports the fit indices associated with an unrestricted ML-based analysis (meaning the number of factors were not pre-defined) of the number of factors underlying the independent variable items. The

unrestricted analysis ceases after 10 factors, just prior to the log-likelihood becoming positive. The BIC minimizes at eight factors, suggesting the eight-factor solution best captures the factor structure. However, the models with 7, 9, and 10 factors offered Heywood cases⁷, limiting a truly reliable ML-based rotation of the factor structure to eight, six, or fewer factors. As such, a rotation of items based upon a principal factors solution would have to be considered more robust in the case of seven or ten factor solutions.

Table IV.4: Maximum-Likelihood Analysis Considering the Number of Factors Underlying the Proposed Measures of the Independent Variables

Number of Factors	log-likelihood	df-m	df-r	AIC	BIC
1	-1376.94	16	104	2785.87	2859.51
2	-898.19	31	89	1858.37	2001.05
3	-576.93	45	75	1243.85	1450.97
4	-314.69	58	62	745.39	1012.34
5	-168.89	70	50	477.79	799.97
6	-116.04	81	39	394.08	766.89
7	-48.67	91	29	279.34	698.18
8	-15.36	100	20	230.72	690.98
9	-10.03	108	12	236.07	733.15
10	-2.17	115	5	234.34	763.63

NOTE: The models with 7, 9, and 10 factors are Heywood cases

A parallel analysis of the independent variable items also suggested no more than eight factors underlie the items proposed to measure the independent variables. The results of this parallel analysis can be seen in Table IV.5 and Figure IV.1. The estimated difference between the eigenvalues that result from a PF-based factor analysis (FA in the table) and those resulting from a parallel analysis (PA in the table)

⁷ Heywood cases occur during factor rotation when the uniqueness of any parameter is estimated to be 0 (or conversely, communality is estimated to be 1), preventing a meaningful solution.

becomes negative at nine factors. When this difference becomes negative, the solution as determined by the FA of observed data is no longer better than (i.e., eigenvalue greater than) that resulting from the FA of random data given the same number of observations and variables.

Table IV.5: Parallel Analysis Considering the Number of Factors Underlying the Proposed Measures of the Independent Variables

Number of factors	FA	PA	Difference
1	5.84	0.27	5.57
2	1.70	0.22	1.49
3	0.95	0.18	0.78
4	0.73	0.14	0.59
5	0.42	0.11	0.31
6	0.24	0.08	0.16
7	0.11	0.05	0.06
8	0.06	0.02	0.03
9	-0.03	0.00	-0.03
10	-0.09	-0.03	-0.06
11	-0.11	-0.06	-0.05
12	-0.12	-0.08	-0.04
13	-0.13	-0.11	-0.02
14	-0.16	-0.13	-0.02
15	-0.17	-0.16	0.00
16	-0.22	-0.20	-0.01

Note: Eigenvalues Averaged Over 100 Replications
 FA = Eigen value from Factor Analysis
 PA = Eigen Value from Parallel Analysis

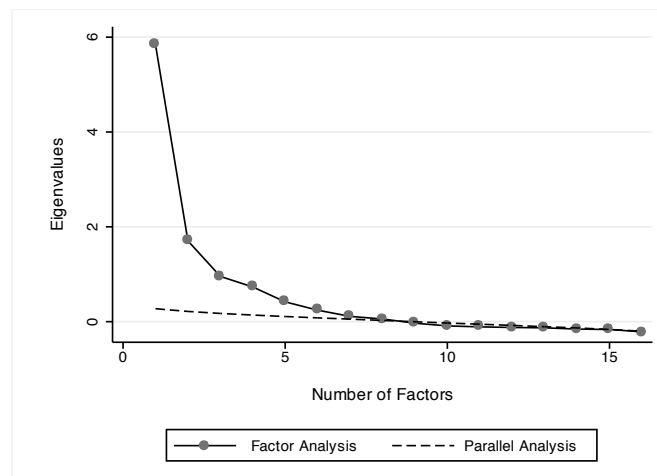


Figure IV.1: Parallel Analysis versus Factors Analysis for Number of Factors Underlying

Proposed Measures of Independent Variables

At this point it is worth highlighting any differences between BIC-based and Kaiser criterion-based investigations of the number of factors. Table IV.6 presents the Eigenvalues, proportion of and cumulative variance accounted given the assumption of 1 through 10 factors underlying the proposed items by way of an ML-based estimated of these values. A Kaiser-criterion approach, criticized for often under-estimating the number of factors underlying some set of items, indeed suggests a smaller number of factors—no greater than five—as compared the number suggested by ML-based fit indices or a PA. At the assumption of six factors, the Eigenvalue drops below 1.00, while the cumulative variance is 0.87. Seven factors offer a cumulative variance of 0.93, but the Eigenvalue, still below the 1.0 Kaiser criterion, has now increased from 0.56 to 0.79 suggesting a non-linear eigenvalue distribution. Were I to have employed a Kaiser criterion approach, I risked beginning the investigation into the factor structure with too few factors.

Table IV.6: Maximum Likelihood Factor Analysis with Eigenvalues, Proportion of and Cumulative Variance, Including Items Proposed to Measure Independent Variables

Factor	Eigenvalue	Difference	Proportion	Cumulative
1	2.26	-1.64	0.18	0.18
2	3.90	2.65	0.32	0.50
3	1.26	0.10	0.10	0.60
4	1.16	-0.43	0.09	0.70
5	1.59	1.03	0.13	0.83
6	0.56	-0.23	0.05	0.87
7	0.79	0.38	0.06	0.93
8	0.41	0.22	0.03	0.97
9	0.19	-0.01	0.02	0.98
10	0.20	.	0.02	1.00

LR test: independent vs. saturated: $\chi^2(120) = 6556.18$ Prob > $\chi^2 = 0.0000$

LR test: 10 factors vs. saturated: $\chi^2(5) = 4.26$ Prob > $\chi^2 = 0.5126$

(tests formally not valid because a Heywood case was encountered)

Similarly, the results of a PF-based estimation of Eigenvalues, proportion of and cumulative variance (presented in Table IV.7) would suggest that I begin the factor exploration at what would likely be too few factors, in this case no more than two or three. The point of this comparison of the results from various factoring methods was not to confuse the reader. Instead, I wanted to highlight the inherent challenges to and even contradictions within factor analysis, adding weight to my choice to compare these methods in an effort to “zero in” on a factor structure that might find the support of more than one single method.

Table IV.7: Principal Factors Factor Analysis with Eigenvalues, Considering the Number of Factors Underlying the Proposed Measures of the Independent Variables

Factor	Eigenvalue	Difference	Proportion	Cumulative
1	5.84	4.14	0.65	0.65
2	1.70	0.75	0.19	0.84
3	0.95	0.22	0.11	0.94
4	0.73	0.31	0.08	1.02
5	0.42	0.18	0.05	1.07
6	0.24	0.13	0.03	1.09
7	0.11	0.05	0.01	1.11
8	0.06	0.09	0.01	1.11
9	-0.03	0.06	0.00	1.11
10	-0.09	0.02	-0.01	1.10
11	-0.11	0.01	-0.01	1.09
12	-0.12	0.01	-0.01	1.07
13	-0.13	0.03	-0.01	1.06
14	-0.16	0.01	-0.02	1.04
15	-0.17	0.05	-0.02	1.02
16	-0.22		-0.02	1.00

LR test: independent vs. saturated: $\chi^2(120) = 6556.18$ Prob > $\chi^2 = 0.0000$

With both the ML-based fit indices, as well as the PA-based results suggesting a factor structure involving no greater than eight factors, I began my investigation into the more discreet factor structure (i.e., the question of whether and which items comprise

specific factors) via rotating these factors with the assumption of eight underlying factors. My expectation for the coefficient of correlation between items and factors was a minimum loading of 0.5 and preferably 0.7 or higher—an expectation more stringent than that drawn by many researchers for exploratory factor analysis. In essence, I employed EFA but placed expectations upon factor loadings akin to those expected during CFA. Frankly, I wanted to err on the side of caution by exclusion rather than inclusion—a coefficient of 0.7 would suggest the factor could explain roughly half or more of the item variance. I felt factors comprised of as few as two items offering substantial correlations within factors would be more reliable and interpretable in the final analysis.

Initial results, from both the ML-based (found in Table IV.8 and Table IV.9) and PF-based (Table IV.10 and Table IV.11) oblique rotation of the factors suggested that in fact fewer than eight factors were operating. No more than six factors emerged, comprised of at least one item offering greater than a moderate loading of 0.5. Furthermore, the correlation matrix of factors (Table IV.11, factors 4 and 5) suggested that at least one of these weak factors was more than moderately correlated (loading > 0.70) with one of the stronger factors. And so I continued the exploration of the factor structure by reducing the number of assumed factors to seven and then six.

Table IV.8: ML-based Rotated (Oblique) Factor Loadings and Unique Variances, Eight-Factor Solution

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Uniqueness
evaluating information to determine compliance with standards	0.67	0.04	-0.01	-0.07	0.08	0.01	0.13	0.08	0.53
developing objectives and strategies	0.37	0.27	0.22	-0.02	-0.07	<i>0.27</i>	-0.09	0.01	0.27
judging the qualities of objects, services, or people	0.43	-0.05	0.21	-0.02	0.04	<i>0.49</i>	-0.01	-0.05	0.41
making decisions and solving problems	0.76	0.01	0.06	0.10	-0.01	0.13	-0.04	0.03	0.22
organizing, planning, and prioritizing work	0.09	0.84	0.13	0.00	0.07	-0.03	-0.06	0.08	0.17
coordinating others, not as supervisor/leader	0.16	-0.02	0.21	0.22	-0.10	-0.05	0.06	<i>0.43</i>	0.57
monitoring and controlling resources	0.04	-0.02	0.81	0.13	0.08	-0.03	0.01	-0.14	0.26
staffing organizational units	-0.06	-0.06	0.83	-0.04	-0.12	0.12	0.08	0.08	0.31
coordinating the work of others	0.05	0.19	0.66	-0.07	0.05	-0.04	-0.07	<i>0.45</i>	0.18
freedom to determine the tasks, priorities, or goals	-0.11	0.11	0.05	0.91	-0.02	-0.05	0.04	0.01	0.11
Independence	-0.02	0.31	-0.09	0.28	-0.08	0.17	0.01	-0.11	0.64
freedom to make decisions without supervision	0.13	-0.14	-0.05	0.92	0.02	0.04	-0.04	0.06	0.19
keeping a pace set by machines	-0.14	0.02	-0.02	-0.04	0.83	0.12	0.30	0.05	0.13
controlling machines and processes	0.15	0.06	0.01	0.04	0.96	-0.10	-0.12	-0.09	0.19
working with computers	0.25	0.31	-0.02	0.01	-0.33	-0.09	0.37	-0.09	0.29
how automated is your current job	-0.01	-0.07	0.01	0.00	0.10	0.00	0.85	0.01	0.27

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.9: Correlation Matrix of the Rotated (Oblique) Common Factors, Eight Factor Solution

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Factor 1	1							
Factor 2	0.60	1						
Factor 3	0.57	0.43	1					
Factor 4	0.45	0.51	0.41	1				
Factor 5	-0.26	-0.59	-0.15	-0.46	1			
Factor 6	0.13	0.31	0.28	0.25	-0.12	1		
Factor 7	0.10	0.14	-0.09	-0.07	0.03	-0.23	1	
Factor 8	0.11	0.01	0.08	-0.08	0.09	0.21	-0.01	1

Table IV.10: PF-based Rotated (Oblique) Factor Loadings and Unique Variances, Eight Factor Solution

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Uniqueness
evaluating information to determine compliance with standards	0.65	-0.01	-0.05	-0.06	0.05	0.17	-0.01	0.06	0.56
developing objectives and strategies	0.53	0.25	-0.04	0.18	-0.08	-0.09	0.14	0.00	0.28
judging the qualities of objects, services, or people	<i>0.47</i>	0.24	-0.01	-0.02	0.05	-0.04	0.27	-0.03	0.49
making decisions and solving problems	0.73	0.07	0.12	-0.03	-0.04	-0.01	0.04	0.02	0.27
organizing, planning, and prioritizing work	<i>0.43</i>	0.17	-0.01	<i>0.47</i>	0.02	0.01	-0.02	0.03	0.30
coordinating others, not as supervisor/leader	0.13	0.22	0.19	-0.03	-0.08	0.03	-0.03	0.38	0.59
monitoring and controlling resources	0.06	0.71	0.16	-0.02	0.06	0.03	-0.04	-0.12	0.38
staffing organizational units	-0.04	0.82	-0.04	-0.06	-0.11	0.07	0.06	0.02	0.35
coordinating the work of others	0.15	0.65	-0.07	0.10	0.08	-0.09	-0.02	0.27	0.29
freedom to determine the tasks, priorities, or goals	-0.07	0.05	0.84	0.10	-0.04	0.05	-0.02	0.03	0.19
Independence	0.12	-0.07	0.26	0.27	-0.05	0.04	0.16	-0.09	0.64
freedom to make decisions without supervision	0.07	-0.05	0.89	-0.06	0.02	-0.05	0.03	0.07	0.23
keeping a pace set by machines	-0.12	0.00	-0.06	0.03	0.83	0.20	0.06	0.04	0.22
controlling machines and processes	0.14	0.00	0.04	0.03	0.87	-0.12	-0.06	-0.09	0.33
working with computers	0.30	-0.01	0.02	0.15	-0.34	<i>0.46</i>	-0.04	-0.05	0.33
how automated is your current job	-0.06	0.00	-0.01	-0.05	0.15	0.69	0.01	0.02	0.49

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.11: Correlation Matrix of Common Factors, Eight Factor Solution

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Factor 1	1							
Factor 2	0.62	1						
Factor 3	0.48	0.43	1					
Factor 4	0.38	0.27	0.46	1				
Factor 5	-0.27	-0.15	-0.46	-0.73	1			
Factor 6	0.14	-0.06	0.00	0.21	-0.01	1		
Factor 7	0.11	0.23	0.23	0.30	-0.13	-0.31	1	
Factor 8	0.27	0.20	-0.01	0.04	-0.02	0.12	-0.07	1

A reduction in the number of assumed factors—from seven factors and then six factors—resulted in two observations that led me to reconsider the items included for the factor analysis. The results from the ML-based oblique rotations assuming seven and six factors can be found in Table IV.12 and Table IV.13, respectively. The results from the PF-based oblique rotations of the factor matrix assuming seven and six factors can be found in Table IV.14 and Table IV.15, respectively.

First, the items believed to comprise a single factor measuring resource control “fall apart” into separate factors and then “fall together” into a single factor dependent upon the number of assumed factors being seven or six. These resource control items reside within different factors in the seven-factor solution (as seen in Table IV.12), and then within a single factor in the six-factor solution (as seen in Table IV.13). It is worth nothing that this divergence of item loadings in the seven-factor solution could be the result of this solution involving a Heywood case, whereby the uniqueness of the “monitoring and controlling resources” item was estimated at zero in both the non-rotated and rotated factor matrices. Furthermore, this divergence of factor loadings occurs only within the ML-based seven-factor oblique rotation and does not occur within the PF-based rotation, further suggesting the former is a function of the Heywood case. That said, my goal being to err on the side of caution, this “falling apart” led me to re-consider the reliability of these items believed to measure resource control.

Second, evidence appeared suggesting the items proposed to comprise a single measure for automation instead comprised more than a single measure. The items “keeping a pace [of work] set by machines” and “controlling machines and processes” appeared to reside within a factor distinct from general automation, one that immediately reminded me of the “mechanized” forms of technology discussed by Blauner (1964),

Woodward (1965), and others (Hunt, 1970; Ford & Slocum, 1977; Jelinek, 1977; Hirschorn, 1986; Swanson, McComb, Smith, & McCubbrey, 1991). The item “working with computers,” which I had also proposed would reside within broad factor measuring general automation of work, appeared to be only weakly associated with the more general measure of automation, “How automated is your job.” In this case, I felt there was reason to consider additional items directed at measuring working with computers. These additional measures would enable me to investigate whether a distinct factor would emerge measuring “Informed” work, akin to that sort of work described by Zuboff (1988), Barley (1996), Barley & Kunda (2001), among others (Davenport & Beers, 1995; Kholi & Kettinger, 2004; Leonardi & Barley, 2010).

Table IV.12: ML-based Rotated (Oblique) Factor Loadings and Unique Variances, Seven-Factor Solution

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Uniqueness
evaluating information to determine compliance with standards	0.67	0.04	-0.05	-0.16	-0.02	-0.03	0.21	0.52
developing objectives and strategies	0.54	0.10	-0.04	<i>0.46</i>	0.03	0.01	-0.06	0.24
judging the qualities of objects, services, or people	0.51	0.07	0.00	0.32	0.05	0.17	-0.15	0.50
making decisions and solving problems	0.78	0.01	0.11	0.01	0.03	-0.07	0.03	0.22
organizing, planning, and prioritizing work	0.36	0.18	-0.02	<i>0.44</i>	-0.02	-0.04	0.17	0.31
coordinating others, not as supervisor/leader	0.11	0.50	0.22	-0.08	-0.10	-0.05	0.07	0.62
monitoring and controlling resources	0.02	0.01	0.06	-0.06	0.98	-0.04	0.06	0.00
staffing organizational units	0.00	<i>0.46</i>	-0.03	0.12	0.36	0.00	-0.01	0.41
coordinating the work of others	0.07	0.91	-0.05	-0.01	0.03	0.01	-0.08	0.11
freedom to determine the tasks, priorities, or goals	-0.07	-0.01	0.83	0.15	0.07	-0.03	0.07	0.14
Independence	0.10	-0.12	0.25	<i>0.45</i>	-0.06	0.01	0.07	0.64
freedom to make decisions without supervision	0.09	-0.02	0.91	-0.03	0.00	0.00	-0.10	0.16
keeping a pace set by machines	-0.08	0.04	-0.02	0.08	-0.08	1.03	0.11	0.00
controlling machines and processes	0.18	-0.08	0.01	-0.17	0.11	0.66	-0.16	0.37
working with computers	0.24	-0.10	-0.02	0.18	0.05	-0.26	0.65	0.23
how automated is your current job	-0.11	0.00	0.00	-0.10	0.03	0.32	0.71	0.44

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.13: ML-based Rotated (Oblique) Factor Loadings and Unique Variances, Six-Factor Solution

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Uniqueness
evaluating information to determine compliance with standards	0.72	-0.06	-0.08	0.15	0.13	0.10	0.56
developing objectives and strategies	0.64	0.24	-0.02	-0.09	-0.13	-0.01	0.29
judging the qualities of objects, services, or people	0.53	0.25	0.00	0.15	-0.13	-0.02	0.53
making decisions and solving problems	0.81	0.02	0.10	0.09	-0.07	0.06	0.26
organizing, planning, and prioritizing work	0.59	0.17	0.00	-0.20	0.05	0.01	0.35
coordinating others, not as supervisor/leader	0.16	0.17	0.20	-0.13	0.06	<i>0.49</i>	0.52
monitoring and controlling resources	0.07	0.71	0.16	0.14	0.04	-0.11	0.36
staffing organizational units	-0.08	0.90	-0.04	-0.08	0.06	0.04	0.28
coordinating the work of others	0.21	0.64	-0.09	-0.01	-0.04	0.34	0.25
freedom to determine the tasks, priorities, or goals	-0.06	0.05	0.91	-0.08	0.07	0.02	0.13
Independence	0.21	-0.03	0.29	-0.17	0.00	-0.14	0.69
freedom to make decisions without supervision	0.04	-0.07	0.94	0.08	-0.06	0.10	0.19
keeping a pace set by machines	-0.10	0.02	-0.05	0.79	0.28	0.02	0.20
controlling machines and processes	0.16	-0.03	0.04	0.95	-0.04	-0.11	0.24
working with computers	<i>0.46</i>	-0.04	0.00	-0.39	<i>0.43</i>	-0.08	0.29
how automated is your current job	-0.06	0.03	0.01	0.14	0.84	0.04	0.28

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.14: PF-based Rotated (Oblique) Factor Loadings and Unique Variances, Seven-Factor Solution

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Uniqueness
evaluating information to determine compliance with standards	0.67	-0.01	-0.05	0.05	-0.13	0.18	0.06	0.56
developing objectives and strategies	0.55	0.25	-0.04	-0.06	0.22	-0.10	0.00	0.28
judging the qualities of objects, services, or people	<i>0.49</i>	0.25	0.00	0.17	0.18	-0.13	-0.05	0.51
making decisions and solving problems	0.75	0.07	0.12	-0.03	-0.07	-0.01	0.02	0.27
organizing, planning, and prioritizing work	<i>0.45</i>	0.17	-0.02	-0.09	0.32	0.09	0.05	0.32
coordinating others, not as supervisor/leader	0.13	0.23	0.19	-0.06	-0.07	0.02	0.38	0.59
monitoring and controlling resources	0.06	0.71	0.15	0.02	-0.08	0.06	-0.12	0.38
staffing organizational units	-0.04	0.83	-0.03	-0.07	-0.01	0.04	0.02	0.36
coordinating the work of others	0.16	0.65	-0.07	0.05	0.01	-0.07	0.28	0.29
freedom to determine the tasks, priorities, or goals	-0.07	0.05	0.82	-0.07	0.11	0.07	0.03	0.19
Independence	0.13	-0.07	0.25	-0.03	0.38	0.03	-0.10	0.64
freedom to make decisions without supervision	0.07	-0.05	0.87	0.04	0.01	-0.08	0.06	0.23
keeping a pace set by machines	-0.13	0.00	-0.05	0.85	0.07	0.19	0.04	0.22
controlling machines and processes	0.14	-0.01	0.03	0.79	-0.07	-0.07	-0.08	0.34
working with computers	0.31	-0.01	0.02	-0.36	0.09	0.50	-0.05	0.33
how automated is your current job	-0.07	0.00	-0.01	0.20	-0.01	0.68	0.02	0.50

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.15: PF-based, Rotated (Oblique) Factor Loadings and Unique Variances, Six-Factor Solution

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Uniqueness
evaluating information to determine compliance with standards	0.67	-0.02	-0.05	0.14	0.17	0.15	0.57
developing objectives and strategies	0.63	0.26	-0.04	-0.11	-0.10	-0.05	0.28
judging the qualities of objects, services, or people	0.55	0.25	0.00	0.16	-0.13	-0.09	0.51
making decisions and solving problems	0.77	0.06	0.13	0.06	-0.03	0.10	0.28
organizing, planning, and prioritizing work	0.56	0.19	-0.03	-0.21	0.11	-0.05	0.33
coordinating others, not as supervisor/leader	0.17	0.26	0.19	-0.15	0.04	0.39	0.60
monitoring and controlling resources	0.02	0.70	0.16	0.14	0.04	-0.05	0.40
staffing organizational units	-0.05	0.84	-0.03	-0.05	0.04	0.03	0.36
coordinating the work of others	0.22	0.69	-0.08	-0.03	-0.05	0.26	0.30
freedom to determine the tasks, priorities, or goals	-0.06	0.05	0.86	-0.09	0.07	0.00	0.19
Independence	0.21	-0.05	0.26	-0.14	0.05	-0.23	0.65
freedom to make decisions without supervision	0.06	-0.06	0.91	0.06	-0.08	0.07	0.23
keeping a pace set by machines	-0.09	0.03	-0.06	0.81	0.21	-0.03	0.24
controlling machines and processes	0.14	-0.01	0.03	0.89	-0.07	-0.06	0.34
working with computers	0.32	-0.02	0.02	-0.36	<i>0.49</i>	-0.03	0.33
how automated is your current job	-0.08	0.00	-0.01	0.21	0.69	0.03	0.50

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Exploratory Factor Analysis, Additional Items

With empirical, theoretical, and inquisitive reasons to introduce new items for consideration within factor analyses, I decided to add a specific set of items I identified as reasonable additions directed at measuring resource control and informed work. I also added to the analyses, for both the independent and dependent variables, those items experts had selected during the tests for face validity. In this section, I will describe the results of the exploratory factor analyses given the addition of new items.

Factor Structure of Independent Variables

Regarding resource control, I selected four items the O*NET development team had already sourced from prior research and tested for reliability measuring whether and to what extent an occupation required resource management skills. I had previously chosen to not use these items from the Skills questionnaire given I would use other items from this questionnaire exclusively as measures of control variables. I discarded the resource control items I had proposed—those items that encountered discrepancies in factor loadings during the EFA—and replaced them with the four resource management items from the Skills questionnaire. These four items measuring resource management skills were: How important is managing one's own time and the time of others to the performance of your current job; How important is determining how money will be spent to get the work done, and accounting for these expenditures to the performance of your current job; How important is obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work; How important is motivating, developing, and directing people as they work, or identifying the best people for the job to the performance of your current job.

As plausible measures of informed work I selected two items in addition to the “working with computers” item previously selected: “How important is writing computer programs for various purposes to the performance of your current job,” and “How important is knowledge of computers and electronics (knowledge of circuit boards, processors, chips, electronic equipment, and computer hardware and software, including applications and programming) to the performance of your current job.” Each of these additional items were measured according to the same, five-level scale of importance by which previously included items had been measured.

As mentioned earlier, I also added items selected by experts (but not proposed by myself) during the face validity phase to this now expanded EFA. The two items selected by experts to measure automation appeared conceptually and empirically compatible with items previously described as measuring the mechanized nature of work: “How important is equipment maintenance to the performance of the occupation” and “How important is mechanical knowledge to the performance of your current job.” Sixty percent of experts selected “How important to your current job is being very accurate or highly accurate” as a measure of programmed ends, and so this item was added. “How important is self-control to the performance of your current job” was added as a possible measure for discretion in work. Finally, the item “If someone were being hired to perform this job, how much on-the-job training would be required” was added a potential measure of the skill requirements for work. All of these items were measured on a five-level scale of importance except for the item measuring on-the-job training, which was measured according to a nine-level scale, spanning no training at all to over ten years of training.

The initial investigation of the factors structure underlying this now expanded set of items measuring the various independent variables included, as with the prior

analysis, an assessment of individual item and overall Kaiser-Meyer-Olkin measures. The results of this KMO assessment can be found in Table IV.16. Overall, the items offered a KMO of 0.86. Individually, and as previously noticed, the item measuring a general level of automation alongside work (“How automated is your job?”) appeared to very likely operate as a distinct measure, unaffiliated within any other items forming a factor.

Table IV.16: KMO, Items Proposed as Measures of Independent Variables

Variable	kmo
evaluating information to determine compliance with standards	0.87
developing objectives and strategies	0.91
judging the qualities of objects, services, or people	0.90
making decisions and solving problems	0.90
organizing, planning, and prioritizing work	0.92
importance of being exact or accurate	0.73
importance of time management	0.94
importance of management of financial resources	0.85
importance of management of material resources	0.78
importance of management of personnel resources	0.89
freedom to determine the tasks, priorities, or goals	0.84
Independence	0.89
freedom to make decisions without supervision	0.81
self control	0.82
keeping a pace set by machines	0.87
controlling machines and processes	0.87
importance of equipment maintenance	0.84
importance of mechanical knowledge	0.84
working with computers	0.85
programming	0.77
importance of knowledge of computers/electronics	0.82
how automated is your current job	0.58
Overall	0.86

The ML-based fit indices (found in Table IV.17) and results from a parallel analysis (found in Figure IV.2 and Table IV.18) both suggest an underlying factor structure of no greater than nine factors. The BIC estimate (Table IV.17) minimized at eight or nine factors, the difference between these two estimates being negligible (0.02).

The nine-factor solution introduced a Heywood case, however, as would a seven-factor solution. The difference in eigenvalues as calculated by PF and PA became negative after nine factors (Table IV.18).

Table IV.17: Maximum-Likelihood Analysis Considering the Number of Factors Underlying the Proposed Measures of the Independent Variables

Number of Factors	log-likelihood	df-m	df-r	AIC	BIC
1	-2999.68	22	209	6043.35	6144.61
2	-1856.07	43	188	3798.14	3996.05
3	-1245.61	63	168	2617.21	2907.17
4	-831.04	82	149	1826.08	2203.49
5	-483.70	100	131	1167.39	1627.65
6	-289.24	117	114	812.47	1350.97
7	-225.13	133	98	716.26	1328.40
8	-158.84	148	83	613.68	1294.87
9	-112.62	162	69	549.23	1294.85
10	-70.18	175	56	490.36	1295.81
11	-43.20	187	44	460.40	1321.08
12	-26.17	198	33	448.34	1359.65
13	-13.92	208	23	443.84	1401.18
14	-5.85	217	14	445.70	1444.46
15	-1.14	225	6	452.29	1487.87

NOTE: The models with 7, 9, 10, 11, 12, 13, 14, and 15 factors are Heywood cases

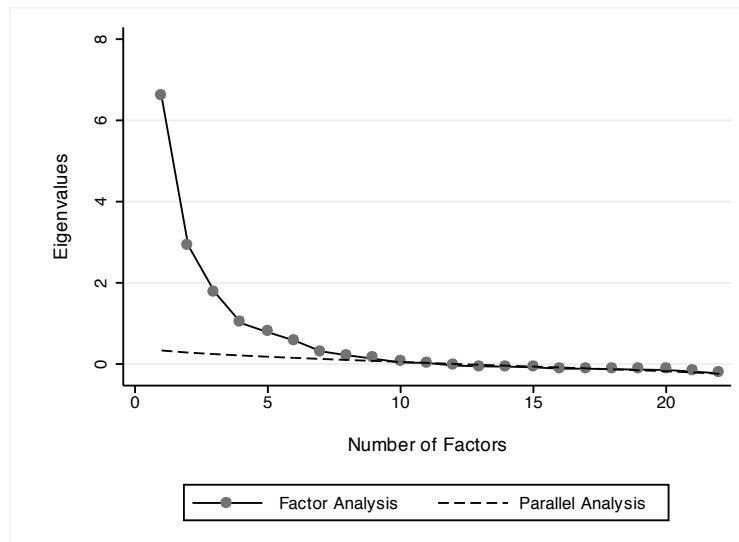


Figure IV.2: Factor Analysis vs Parallel Analysis, Considering the Number of Factors Underlying the Proposed Measures of the Independent Variables

Table IV.18: Parallel Analysis Considering the Number of Factors Underlying the Proposed Measures of the Independent Variables

Number of factors	FA	PA	Difference
1	6.58	0.33	6.25
2	2.92	0.28	2.64
3	1.77	0.24	1.53
4	1.01	0.21	0.80
5	0.78	0.18	0.60
6	0.58	0.15	0.43
7	0.31	0.13	0.19
8	0.21	0.10	0.12
9	0.13	0.08	0.05
10	0.04	0.05	-0.01
11	0.03	0.03	0.00
12	-0.04	0.00	-0.04
13	-0.06	-0.02	-0.04
14	-0.06	-0.04	-0.02
15	-0.08	-0.06	-0.02
16	-0.11	-0.08	-0.03
17	-0.12	-0.11	-0.01
18	-0.13	-0.13	0.00
19	-0.14	-0.15	0.02
20	-0.15	-0.18	0.03
21	-0.18	-0.21	0.02
22	-0.23	-0.24	0.01

Note: Eigenvalues Averaged Over 100 Replications
 FA = Eigen value from Factor Analysis
 PA = Eigen Value from Parallel Analysis

I restarted the investigation into the underlying factor structure with the new items added to the analysis assuming a nine-factor solution, bearing in mind that the ML-based results for this number of factors may be confounded by a Heywood case. Indeed, the factors loadings derived from an ML-based oblique rotation (found in Table IV.19 and Table IV.20) of the factors showed the shortcomings of a Heywood case, with the uniqueness estimate being zero for the item measuring self-control. Accordingly, I considered the item loadings based upon the PF-based oblique rotation (found in Table IV.21 and Table IV.22) to be the more reliable approach for this nine-factor solution. In this case, two of the factors were clearly weak, offering only single items with weak

loadings—in one case being 0.44 and the other 0.37. Therefore, it seemed reasonable to consider a seven-factor solution.

Table IV.19: ML-based Rotated (Oblique) Factor Loadings and Unique Variances, Nine-Factor Solution

ITEM	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Uniqueness
evaluating information to determine compliance with standards	0.55	0.11	-0.05	-0.06	0.01	-0.10	0.01	0.06	<i>0.42</i>	0.49
developing objectives and strategies	0.82	-0.08	-0.01	0.00	0.10	0.12	-0.04	-0.05	-0.18	0.20
judging the qualities of objects, services, or people	0.70	0.00	0.06	0.07	-0.07	0.00	0.10	0.07	-0.11	0.48
making decisions and solving problems	0.70	0.09	-0.01	0.12	0.07	-0.06	-0.11	0.03	0.21	0.24
organizing, planning, and prioritizing work	0.60	-0.07	0.03	-0.07	0.08	0.38	-0.01	-0.10	0.09	0.28
importance of being exact or accurate	-0.10	0.07	-0.04	0.07	0.08	0.08	0.15	-0.02	0.52	0.64
importance of time management	0.15	-0.06	<i>0.40</i>	-0.01	0.00	0.37	-0.07	-0.02	0.09	0.40
importance of management of financial resources	-0.05	-0.15	0.84	0.11	0.01	0.00	0.04	-0.03	-0.03	0.25
importance of management of material resources	-0.06	<i>0.44</i>	0.80	-0.03	-0.05	0.09	-0.05	0.02	-0.03	0.19
importance of management of personnel resources	0.21	-0.12	0.72	0.02	-0.03	-0.16	0.07	0.08	-0.02	0.37
freedom to determine the tasks, priorities, or goals	0.01	-0.08	0.09	0.78	0.04	0.13	0.03	-0.07	0.02	0.17
Independence	0.04	0.08	-0.07	0.19	0.14	0.50	0.01	0.19	-0.05	0.54
freedom to make decisions without supervision	0.06	0.05	0.01	0.92	-0.03	-0.02	-0.02	0.00	0.02	0.14
self control	-0.02	-0.05	0.03	-0.05	0.04	0.08	-0.01	0.97	0.01	0.00
keeping a pace set by machines	0.04	0.51	-0.05	-0.04	-0.12	0.04	0.67	-0.03	-0.08	0.08
controlling machines and processes	0.09	0.84	-0.06	-0.02	-0.08	0.02	0.17	0.00	0.04	0.21
importance of equipment maintenance	-0.09	0.90	0.17	-0.07	-0.04	0.06	-0.02	-0.01	0.06	0.18
importance of mechanical knowledge	0.01	0.85	-0.03	0.10	0.08	-0.08	-0.09	-0.02	0.04	0.28
working with computers	0.11	-0.26	-0.01	-0.05	0.67	0.11	0.09	-0.03	0.16	0.13
programming	0.03	0.21	0.13	-0.07	0.65	-0.09	0.00	-0.10	-0.09	0.56
importance of knowledge of computers/electronics	0.02	0.02	-0.08	0.07	0.91	0.03	0.00	0.09	-0.05	0.17
how automated is your current job	-0.12	-0.08	0.07	0.00	0.22	-0.07	0.63	0.01	0.24	0.43

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.20: Correlation matrix of Rotated Common Factors, Nine-Factor Solution

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
Factor 1	1								
Factor 2	-0.14	1							
Factor 3	0.48	0.00	1						
Factor 4	0.43	-0.23	0.41	1					
Factor 5	0.37	-0.23	0.28	0.33	1				
Factor 6	0.31	-0.53	0.34	0.46	0.33	1			
Factor 7	-0.27	0.18	-0.29	-0.37	-0.11	-0.27	1		
Factor 8	0.31	-0.30	0.08	0.19	-0.03	0.29	-0.16	1	
Factor 9	0.24	-0.20	0.05	0.20	0.50	0.17	0.11	0.12	1

Table IV.21: PF-based Rotated (Oblique) Factor Loadings and Unique Variances, Nine-Factor Solution

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Uniqueness
evaluating information to determine compliance with standards	0.52	-0.06	0.12	-0.04	0.07	0.02	-0.01	0.08	0.36	0.52
developing objectives and strategies	0.77	0.03	-0.07	0.00	0.09	0.15	-0.05	-0.09	-0.14	0.25
judging the qualities of objects, services, or people	0.64	<i>0.05</i>	0.03	0.08	-0.04	-0.05	0.15	0.07	-0.09	0.48
making decisions and solving problems	0.66	0.12	0.09	-0.01	0.12	0.02	-0.02	-0.09	0.21	0.26
organizing, planning, and prioritizing work	0.59	-0.01	-0.05	0.01	0.03	<i>0.44</i>	-0.04	-0.02	0.06	0.31
importance of being exact or accurate	-0.10	0.09	0.10	-0.04	0.15	0.10	0.04	0.25	0.37	0.68
importance of time management	0.12	-0.01	-0.05	0.39	<i>0.01</i>	0.35	0.12	-0.06	0.06	0.40
importance of management of financial resources	-0.05	0.14	-0.13	0.80	0.04	0.03	-0.02	0.08	-0.07	0.29
importance of management of material resources	-0.04	-0.02	<i>0.41</i>	0.76	-0.04	0.06	0.05	-0.05	-0.03	0.25
importance of management of personnel resources	0.21	-0.01	-0.13	0.72	-0.05	-0.07	-0.05	0.05	0.05	0.38
freedom to determine the tasks, priorities, or goals	0.04	0.82	-0.08	0.08	0.00	0.06	-0.03	0.04	-0.01	0.19
Independence	-0.02	0.16	0.08	-0.05	0.19	0.16	0.52	-0.01	-0.08	0.52
freedom to make decisions without supervision	0.08	0.86	0.04	0.03	-0.05	-0.08	0.02	-0.03	0.04	0.23
self control	0.07	-0.11	-0.21	0.05	-0.04	-0.10	0.53	-0.03	0.12	0.57
keeping a pace set by machines	0.02	-0.06	0.54	-0.03	<i>-0.14</i>	-0.01	0.00	<i>0.50</i>	-0.08	0.22
controlling machines and processes	0.11	-0.02	0.85	-0.07	-0.10	-0.01	0.02	0.13	0.02	0.20
importance of equipment maintenance	-0.08	-0.08	0.88	0.15	-0.04	0.06	-0.01	-0.06	0.05	0.20
importance of mechanical knowledge	0.02	0.09	0.83	-0.03	0.05	-0.08	-0.04	-0.12	0.07	0.30
working with computers	0.13	-0.03	-0.27	-0.02	0.67	0.11	-0.01	0.16	0.11	0.16
programming	0.02	-0.08	0.19	0.11	0.69	-0.07	-0.11	0.00	-0.10	0.55
importance of knowledge of computers/electronics	0.03	0.04	-0.03	-0.05	0.85	-0.06	0.11	0.02	0.01	0.26
how automated is your current job	-0.09	0.00	-0.05	0.06	0.22	-0.04	-0.03	0.66	0.13	0.48

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.22: Correlation Matrix of Rotated Common Factors, Nine-Factor Solution

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
Factor 1	1								
Factor 2	0.39	1							
Factor 3	-0.14	-0.27	1						
Factor 4	0.47	0.43	0.03	1					
Factor 5	0.32	0.42	-0.20	0.26	1				
Factor 6	0.19	0.49	-0.50	0.31	0.54	1			
Factor 7	0.44	0.43	-0.47	0.23	0.09	0.41	1		
Factor 8	-0.24	-0.35	0.14	-0.34	-0.05	-0.13	-0.24	1	
Factor 9	0.25	0.21	-0.17	0.00	0.40	0.16	0.20	0.13	1

Table IV.23: ML-based (Oblique) Rotated Factor Loadings and Unique Variances, Seven Factor Solution

ITEM	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Uniqueness
evaluating information to determine compliance with standards	0.68	0.16	-0.02	-0.13	0.15	-0.07	0.13	0.57
developing objectives and strategies	0.75	-0.06	-0.01	0.07	0.06	-0.02	-0.15	0.28
judging the qualities of objects, services, or people	0.73	0.08	0.01	0.08	-0.18	0.04	0.00	0.48
making decisions and solving problems	0.79	0.14	0.14	-0.06	0.15	-0.06	-0.08	0.27
organizing, planning, and prioritizing work	0.57	-0.15	-0.04	0.12	0.19	0.07	0.01	0.35
importance of being exact or accurate	0.00	0.05	0.12	-0.09	0.27	0.05	0.35	0.76
importance of time management	0.16	-0.19	0.03	<i>0.47</i>	0.10	0.12	-0.01	0.44
importance of management of financial resources	-0.07	-0.11	0.08	0.85	0.02	0.00	0.07	0.26
importance of management of material resources	-0.03	<i>0.42</i>	-0.02	0.84	-0.05	0.04	-0.04	0.19
importance of management of personnel resources	0.27	-0.06	0.01	0.69	-0.07	-0.14	0.07	0.39
freedom to determine the tasks, priorities, or goals	0.00	-0.10	0.75	0.12	0.06	0.05	0.03	0.21
freedom to make decisions without supervision	0.08	0.08	0.97	-0.02	-0.07	0.00	-0.02	0.09
independence	-0.05	0.07	0.03	-0.02	0.06	1.02	-0.02	0.00
self control	0.29	-0.28	-0.05	-0.03	-0.17	0.26	0.00	0.69
keeping a pace set by machines	-0.05	0.60	-0.08	0.00	-0.23	0.03	<i>0.47</i>	0.19
controlling machines and processes	0.14	0.89	-0.02	-0.05	-0.12	0.04	0.11	0.19
importance of equipment maintenance	-0.04	0.88	-0.02	0.18	-0.03	0.03	-0.03	0.21
importance of mechanical knowledge	0.05	0.91	0.09	-0.01	0.07	0.01	-0.13	0.25
working with computers	0.12	-0.30	-0.05	-0.01	0.76	0.01	0.17	0.11
programming	-0.02	0.29	-0.11	0.12	0.63	0.01	-0.05	0.60
importance of knowledge of computers/electronics	0.06	-0.02	0.04	-0.07	0.83	0.05	-0.02	0.23
how automated is your current job	-0.11	-0.03	0.00	0.07	0.18	-0.04	0.75	0.38

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.24: Correlation Matrix of Rotate Common Factors

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Factor 1	1						
Factor 2	-0.30	1					
Factor 3	0.46	-0.30	1				
Factor 4	0.47	-0.08	0.44	1			
Factor 5	0.41	-0.22	0.39	0.27	1.00		
Factor 6	0.43	-0.43	0.43	0.28	0.28	1	
Factor 7	-0.10	0.09	-0.22	-0.31	0.10	-0.12	1.00

Table IV.25: PF-based (Oblique) Rotated Factor Loadings and Unique Variances, Seven Factor Solution

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Uniqueness
evaluating information to determine compliance with standards	0.63	-0.04	0.15	0.13	-0.11	0.04	0.19	0.56
developing objectives and strategies	0.76	0.01	-0.12	0.07	0.07	-0.09	-0.17	0.27
judging the qualities of objects, services, or people	0.68	0.02	0.05	-0.17	0.09	0.06	-0.02	0.50
making decisions and solving problems	0.75	0.14	0.12	0.15	-0.05	0.00	-0.04	0.28
organizing, planning, and prioritizing work	0.52	0.00	-0.15	0.20	0.12	0.09	-0.01	0.36
importance of being exact or accurate	-0.07	0.12	0.10	0.27	-0.08	0.16	0.39	0.72
importance of time management	0.07	0.01	-0.11	0.14	<i>0.47</i>	0.27	-0.02	0.42
importance of management of financial resources	-0.05	0.13	-0.12	0.01	0.82	-0.05	0.08	0.29
importance of management of material resources	-0.04	-0.02	<i>0.42</i>	-0.04	0.78	0.07	-0.05	0.25
importance of management of personnel resources	0.28	0.00	-0.08	-0.09	0.69	-0.09	0.08	0.40
freedom to determine the tasks, priorities, or goals	0.02	0.82	-0.10	0.02	0.11	-0.02	0.04	0.19
Independence	-0.07	0.14	0.06	0.16	0.01	0.57	-0.08	0.55
freedom to make decisions without supervision	0.11	0.86	0.07	-0.08	0.01	0.00	-0.03	0.24
self control	0.16	-0.11	-0.14	-0.15	-0.02	0.55	-0.03	0.59
keeping a pace set by machines	-0.04	-0.09	0.51	-0.22	0.04	-0.07	<i>0.44</i>	0.26
controlling machines and processes	0.10	-0.03	0.85	-0.12	-0.04	0.01	0.11	0.20
importance of equipment maintenance	-0.09	-0.07	0.88	0.01	0.17	0.04	-0.05	0.20
importance of mechanical knowledge	0.05	0.10	0.86	0.06	-0.06	-0.04	-0.11	0.30
working with computers	0.12	-0.03	-0.29	0.73	-0.01	0.01	0.19	0.16
programming	0.03	-0.09	0.22	0.66	0.12	-0.20	-0.05	0.56
importance of knowledge of computers/electronics	0.06	0.02	0.00	0.83	-0.08	0.05	0.00	0.27
how automated is your current job	-0.10	-0.01	-0.05	0.20	0.07	-0.08	0.69	0.48

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.26: Correlation Matrix of (Oblique) Rotated Common Factors, Seven Factor Solution for Independent Variable Items

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Factor 1	1						
Factor 2	0.45	1					
Factor 3	-0.20	-0.28	1				
Factor 4	0.42	0.46	-0.24	1			
Factor 5	0.46	0.44	-0.04	0.29	1.00		
Factor 6	0.53	0.51	-0.54	0.32	0.28	1	
Factor 7	-0.10	-0.25	0.12	0.06	-0.34	-0.09	1

The seven-factor solutions based upon the ML-based (Table IV.23 and Table IV.24) and PF-based (Table IV.25 and Table IV.26) oblique factor rotations were markedly similar, even though the ML-based rotation suffered from a Heywood case (in this case, the uniqueness for the item measuring independence was estimated to be zero). Seven factors clearly emerged in the ML-based rotation (Table IV.23), with the item “How automated is your job” residing within its own factor, as anticipated by the KMO measures. The correlation matrix of common factors (Table IV.24) did not suggest any two factors were overly correlated with each other, which is particularly important in the case of oblique rotations whereby the assumption of uncorrelated factors is not imposed upon the calculated loadings of items onto factors during the factor rotation. Similarly, seven factors clearly emerged in the PF-based oblique factor rotation (Table IV.25). In this case, however, factor six was composed of the item measuring independence, as well as that measuring self-control

Table IV.27 offers the proportion of total item variance that might be explained by the common factors as a result of an oblique rotation of these factors (such that the resulting factors are permitted to be correlated). The concern here is whether any single factor might account for some majority of variance, which is not the case for this set of factors. Each of the factors is able to accommodate a reasonable proportion of variance, with the “weakest” factor accounting for 12% of total variance. Importantly, the cumulative variance explained by the factors can total greater than one given factors are permitted to be correlated through oblique rotations. Table IV.28 offers the proportion and cumulative variance explained by the common factors under an orthogonal rotation. Since the model in this case has been constrained to seven factors that would not be correlated, cumulative variance sums to 1. Even when constrained to account for only unique variance, each of the seven factors accounts for a reasonable proportion of total

variance, the largest proportion being 23% (factor one) while the smallest is 7% (factor seven).

Table IV.27: Proportion of Variance, Oblique Rotation, Seven-Factor Solution

Factor	Variance	Proportion
1	4.71	0.36
2	3.96	0.30
3	3.86	0.29
4	3.77	0.29
5	3.73	0.29
6	3.69	0.28
7	1.51	0.12

Note: Rotated factors are correlated

Table IV.28: Proportion of Variance, Orthogonal Rotation. Seven-Factor Solution

Factor	Variance	Difference	Proportion	Cumulative
1	3.41	0.62	0.26	0.26
2	2.80	0.51	0.21	0.47
3	2.28	0.08	0.17	0.65
4	2.21	0.24	0.17	0.81
5	1.97	1.10	0.15	0.96
6	0.87	0.39	0.07	1.03
7	0.48		0.04	1.07

Note: Rotated factors are not correlated

Worth noting at this point would be that a Kaiser-criterion assessment of Eigenvalues derived from an ML-based factor analysis suggested—albeit with caveats—the items included for this factor analysis comprised roughly seven factors, accounting for 77% of cumulative variance. While use of the Kaiser-criterion could lead to the assumption of too few factors, in this case the convergence of three different approaches

to factor analysis offered substantial assurances for the viability of the seven-factor solution. The seven-factor solution, capable of accounting for roughly 77% of cumulative variance among the items, was the last solution offering an Eigenvalue greater than one (see Table IV.29). However, the Eigenvalue distribution was confusing, with the nine-factor solution offering a value greater than that of the eight factor solution

Table IV.29: ML-based Factor Analysis Considering Different Numbers of Factors Underlying Proposed Items Measuring Independent Variables

Factor analysis/correlation	Number of obs =	737
Method: maximum likelihood	Retained factors =	15
Rotation: (unrotated)	Number of params =	225
	Schwarz's BIC =	1487.87
Log likelihood = -15.36102	(Akaike's) AIC =	452.287

Factor	Eigenvalue	Difference	Proportion	Cumulative
1	3.03	1.49	0.17	0.17
2	1.54	0.10	0.08	0.25
3	1.43	-3.26	0.08	0.33
4	4.70	3.49	0.26	0.58
5	1.21	0.03	0.07	0.65
6	1.17	0.09	0.06	0.71
7	1.08	0.29	0.06	0.77
8	0.79	-0.19	0.04	0.82
9	0.98	0.02	0.05	0.87
10	0.96	0.42	0.05	0.92
11	0.54	0.11	0.03	0.95
12	0.43	0.22	0.02	0.97
13	0.20	0.06	0.01	0.99
14	0.15	0.04	0.01	0.99
15	0.11	.	0.01	1.00

LR test: independent vs. saturated: $\chi^2(231) = 1.0e+04$, Prob > $\chi^2 = 0.0000$
 LR test: 15 factors vs. saturated: $\chi^2(6) = 2.23$, Prob > $\chi^2 = 0.8974$
 (tests formally not valid because a Heywood case was encountered)

Table IV.30: Factor structure of Item Proposed as Measures of Independent Variables

ITEM	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Uniqueness
evaluating information to determine compliance with standards	0.68	0.16	-0.02	-0.13	0.15	-0.07	0.13	0.57
developing objectives and strategies	0.75	-0.08	-0.01	0.07	0.08	-0.02	-0.15	0.28
judging the qualities of objects, services, or people	0.73	0.08	0.75	0.85	0.84	0.04	0.00	0.48
making decisions and solving problems	0.79	0.4	0.75	0.85	0.84	-0.06	-0.08	0.27
organizing, planning, and prioritizing work	0.57	-0.15	-0.04	0.12	0.19	0.07	0.01	0.35
importance of being exact or accurate	0.00	0.05	0.12	-0.09	0.27	0.05	0.35	0.76
importance of time management	0.16	-0.19	0.03	0.47				0.44
importance of management of financial resources	-0.07	-0.11	0.08	0.85				0.26
importance of management of material resources	-0.03	0.42	-0.02	0.84	-0.05	0.04	-0.04	0.19
importance of management of personnel resources	0.27	-0.06	0.01	0.69	-0.07	-0.14	0.07	0.39
freedom to determine the tasks, priorities, or goals	0.00	-0.10	0.75	0.85	0.06	0.05	0.03	0.21
freedom to make decisions without supervision	0.08	0.08	0.97	0.85	0.06	0.00	-0.02	0.09
independence	-0.05	0.07	0.03			1.02	-0.02	0.00
self control	0.29	-0.28	-0.05	-0.03	-0.17	0.26	0.00	0.69
keeping a pace set by machines	-0.05	0.60	0.08	0.08	-0.23	0.03	0.47	0.19
controlling machines and processes	0.14	0.89	0.08	0.08	-0.12	0.04	0.11	0.19
importance of equipment maintenance	-0.04	0.88	0.08	0.08	-0.03	0.03	-0.03	0.21
importance of mechanical knowledge	0.05	0.91	0.09	-0.01	0.07	0.07	0.07	0.25
working with computers	0.12	-0.30	-0.05	-0.01	0.76	0.07	0.07	0.11
programming	-0.02	0.29	-0.11	0.12	0.63	0.07	0.07	0.60
importance of knowledge of computers/electronics	0.06	-0.02	0.04	-0.07	0.83	0.05	-0.02	0.23
how automated is your current job	-0.11	-0.03	0.00	0.07	0.18	-0.04	0.75	0.38

PROGRAMMED ENDS

RESOURCE CONTROL

DISCRETION

MECHANIZED

INFORMED

AUTOMATION

?

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.30 presents the results of the ML-based oblique rotation of the factors, with visual tags overlaid to highlight the variable each emerging factor was believed to measure. I was uncertain about the nature of factor six, comprised of a single item (in the case of this ML-based rotation) whose anticipated relationship with other items measuring discretion in work was not supported. Later in this chapter I will describe in further detail the factor structure emerging from this EFA, combining these results with those from the eLab and expert sample inquiries into face validity to support my final decisions regarding measures for the independent, dependent, and control variables.

Factor Structure of the Dependent Variables

The dependent variables for this research will require valid measures for the routinization of and skill requirements for work. In Chapter IV, I described those items employed as measures of various aspects of work by the O*NET project that might prove to be viable and valid as measures of the variables proposed for this research. In fact, certain O*NET items were intended and tested as measures for routine work (e.g., the repetitiveness of work tasks) and certain skill requirements of work (e.g., the level of education, or training). And so, in the following section I will describe the results of an exploratory analysis of the factors that emerged from these proposed measures for skill requirements and routinization.

I began this inquiry into the factor structure of the items proposed as measures for the dependent variables identically to that conducted for the independent variables—employing the fit indices from an ML-based analysis, alongside the results of a parallel analysis, to assess the number of factors emerging from the included items. Table IV.31 offers the log-likelihood, AIC, and BIC for the assumption of one through six underlying factors. The model was saturated at six factors. The BIC minimized at four

factors, albeit with only a slight if not insignificant advantage over the estimate for five factors. Unfortunately, the models with three, four, and six factors were possibly confounded by Heywood cases, which required that in the case of these numbers of factors I rely more upon the PF-based rotations and results than those ML-based.

Table IV.31: Maximum-Likelihood Analysis Considering the Number of Factors Underlying the Proposed Measures of the Dependent Variables

Number of Factors	log-likelihood	df-m	df-r	AIC	BIC
1	-475.83	10	35	971.66	1017.69
2	-277.25	19	26	592.50	679.95
3	-145.33	27	18	344.66	468.93
4	-33.49	34	11	134.98	291.47
5	-14.29	40	5	108.59	292.69
6	-0.68	45	0	91.36	298.47

Note: the models with 3, 4, and 6 factors are Heywood cases

The results of a parallel analysis (Table IV.32 and Figure IV.3) suggested no more than five factors would account for the variation among the included items, this five-factor solution being the largest number of factors under which the PF-based Eigenvalue was larger than that estimated employing random rather than observed values for an identical number of observations and items.

Table IV.32: Parallel Analysis Considering the Number of Factors Underlying the Proposed Measures of the Dependent Variables

Number of Factors	FA	PA	Difference
1	4.07	0.19	3.88
2	0.76	0.13	0.62
3	0.65	0.10	0.55
4	0.33	0.06	0.28
5	0.10	0.02	0.07
6	-0.03	-0.01	-0.02
7	-0.06	-0.04	-0.02
8	-0.15	-0.07	-0.07
9	-0.16	-0.11	-0.05
10	-0.26	-0.15	-0.11

Note: Eigenvalues Averaged Over 100 Replications
 FA = Eigen value from Factor Analysis
 PA = Eigen Value from Parallel Analysis

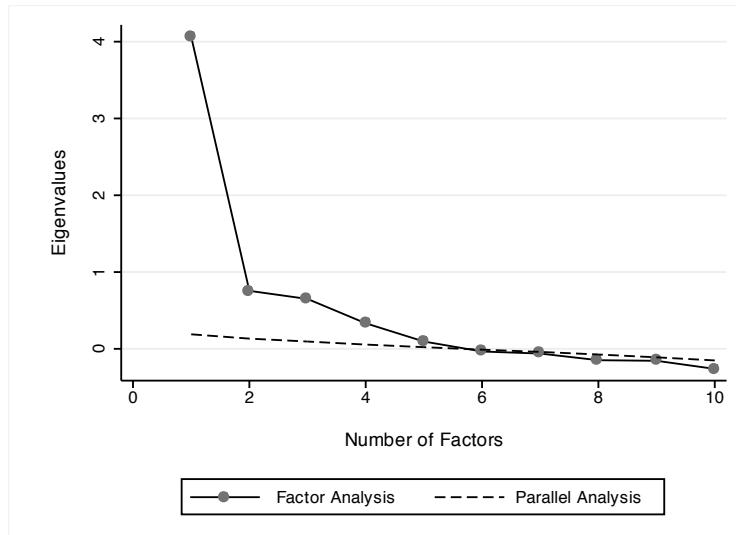


Figure IV.3: Factor versus Parallel Analysis, Considering the Number of Factors Underlying the Proposed Measures of the Dependent Variables

Therefore, with the PA suggesting no more than five underlying factors and the ML-based indices effectively indifferent between four and five factors, I continued the investigation into the factor structure with an initial assumption of five factors. Table IV.33 displays the results of an ML-based oblique rotation of the five-factor model.

Factor five, albeit emerging in its own right, was composed of a single item with only a moderate loading (0.55). Of concern was the relatively high correlation between factors one and two (see Table IV.34), suggesting factor one was perhaps a predominant factor capable of absorbing most of the variance amongst items and factors.

Table IV.33: ML-based (Oblique) Rotated Factor Loadings and Unique Variances, Five Factor Solution for Dependent Variable Items

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
spend time making repetitive motions	-0.34	-0.09	-0.10	<i>0.40</i>	0.55	0.32
repetitive physical or mental activities	0.01	0.08	0.16	0.86	0.16	0.38
work schedule regularity	-0.38	-0.04	0.27	-0.31	-0.02	0.76
thinking creatively	<i>0.41</i>	0.28	-0.02	-0.30	0.15	0.36
adaptability and flexibility	-0.02	0.85	-0.07	0.17	-0.17	0.35
requires creativity and alternative thinking	0.13	0.66	0.12	-0.09	0.08	0.28
level of education (log)	0.99	-0.01	-0.02	0.04	-0.10	0.05
job zone	0.96	-0.04	0.04	0.01	-0.05	0.11
related work experience	<i>0.50</i>	0.02	0.58	0.08	0.04	0.24
on-the-job training	-0.05	-0.01	0.85	0.13	-0.09	0.39

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.34: Correlation Matrix of Rotated Common Factors, Five Factor Solution for Dependent Variable Items

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	1				
Factor 2	0.68	1			
Factor 3	0.33	0.33	1		
Factor 4	-0.29	-0.30	-0.35	1	
Factor 5	-0.02	0.08	0.22	-0.18	1

Frankly, this sort of partial overlap between the items “spend time making repetitive motions” and “repetitive physical or mental activities” was to be expected—the former item applies to a subset of the latter. Furthermore, I believe this relationship highlights an overlooked advantage to “or” when used as an inclusive rather than a corresponding conditional in items intended to measure variables of interest. A

corresponding conditional is an “or” statement whereby the “or” defines the complete universe of outcomes that bound a logical conclusion. Example: A dissertation is either good or done. If the dissertation were done, then it would logically follow that the dissertation is not good. While my dissertation may not be any good, the corresponding conditional statement effectively rules out the event of a dissertation that might be both good and done.

With my goal being to measure the repetitiveness of tasks, regardless of task domain (manual or mental), an inclusive conditional use of “or” is more useful than a set of questions aimed at distinct task domains. Essentially, it makes sense that the item “How much time in your current job do you spend making repetitive motions” would correlate with the item “How important to your current job are continuous, repetitious physical activities (like key entry) or mental activities (like checking entries in a ledger)” for only some subset of work tasks—i.e., those involving manual tasks. In fact, given this incomplete overlap of task domains it would be problematic to use two distinct items focused upon the repetitiveness of tasks, one measuring physical tasks and the other measuring mental tasks, when the repetitiveness of tasks—in general—is of real interest. A scale composed of these two distinct items would confound the measure by modulating based upon the composition of tasks (manual versus mental) as much as it would vary according to the repetitive nature of these tasks; the value would minimize in the case of work that is low in repetitiveness for both manual and mental tasks, maximize in the case of work repetitive both mentally and manually, and earn a middle value for work highly repetitive in manual *or* mental work. The inclusion of both manual and mental task domains within the question, by way of “or,” leads to an item that varies according to repetitiveness yet does not modulate according to task domain.

A PF-based oblique rotation of the five-factor solution (see Table IV.35) produced results similar to those of the ML-based rotation, except for lack of the “repetitive motions” composing a sufficient anchor item for some fifth factor. Instead, this item only loaded moderately (albeit below a 0.5 loading, at 0.47) with the “repetitive physical or mental activities” item, as it had in the ML-based estimates. The remaining four factors were identical (in terms of composition) to those in the ML-based results. The four factors involved the level of: (1) education and job zone, (2) adaptability/flexibility and creative/alternative thinking, (3) related work experience and on-the-job-training, and (4) repetitive physical or mental activities. Of similar concern to that introduced by the ML-based results, the correlation between factor one and two as seen in these PF-based results was high—0.72 (see Table IV.36).

Table IV.35: PF-based (Oblique) Rotated Factor Loadings and Unique Variances, Five Factor Solution for Dependent Variable Items

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
spend time making repetitive motions	-0.34	-0.04	-0.06	<i>0.47</i>	0.27	0.48
repetitive physical or mental activities	-0.03	0.03	0.15	0.67	0.02	0.60
work schedule regularity	-0.35	-0.03	0.24	-0.32	0.04	0.74
thinking creatively	0.39	0.36	-0.03	-0.22	0.21	0.39
adaptability and flexibility	0.04	0.66	-0.05	0.09	-0.11	0.53
requires creativity and alternative thinking	0.13	0.66	0.11	-0.03	0.06	0.34
level of education (log)	0.94	0.00	0.01	0.00	-0.04	0.09
job zone	0.96	-0.05	0.07	0.00	0.03	0.11
related work experience	<i>0.44</i>	0.07	0.58	0.08	0.04	0.27
on-the-job training	-0.03	0.00	0.71	0.07	-0.06	0.56

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.36: Correlation Matrix of Rotated Common Factors, Five Factor Solution for Dependent Variable Items

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	1				
Factor 2	0.72	1			
Factor 3	0.29	0.34	1		
Factor 4	-0.23	-0.27	-0.33	1	
Factor 5	-0.26	-0.09	0.28	-0.30	1

In terms of cumulative variance explained, factor one could account for approximately 56% of cumulative variance when factors were assumed and permitted to be correlated though oblique rotation (see Table IV.37). Factor five, on the other hand, could account for only 5% of variance, a rather small amount considering the permitted correlation among factors. Under orthogonal rotation, which limited the factors to being uncorrelated, factor one was still the more substantial factor, accounting 45% of total variance (see Table IV.38). Similar to the results of the oblique rotation, however, under the orthogonal rotation factor five accounted for only 5% of total variance.

Table IV.37: Proportion of Variance, Oblique Rotation, Five-Factor Solution for Dependent Variable Items

Factor	Variance	Proportion
1	3.82	0.56
2	2.99	0.44
3	1.76	0.26
4	1.47	0.22
5	0.36	0.05

Note: Rotated factors are correlated

Table IV.38: Proportion of Variance, Orthogonal Rotation, Five-Factor Solution for Dependent Variable Items

Factor	Variance	Difference	Proportion	Cumulative
1	3.08	1.91	0.45	0.45
2	1.17	0.00	0.17	0.63
3	1.17	0.14	0.17	0.80
4	1.03	0.70	0.15	0.95
5	0.33	.	0.05	1.00

Note: Rotated factors are not correlated

At this point, I was content with the single item measure for repetitiveness of work (How important to your current job are continuous, repetitious physical activities... or mental activities...?), but was concerned that the item focused upon repetitive motions would effectively overweight the combined measure more heavily towards aspects associated with occupations defined by manual tasks rather than repetitiveness in general. Furthermore, I was concerned that factor one—composed of items primarily weighted towards the level of education—was a predominant factor, one that could absorb a majority of the variation among the included items. Such a predominant factor was not a substantial concern, however, given only one of these factors would be used as the dependent variable in any one model. Therefore, any co-linearity among the items/factors included in this analysis of dependent variables would not likely confound the regression results. However, with the level of education appearing to be such a substantial factor, I was concerned the item might lead to the sort of variable that would be highly correlated with any number of factors, even those selected as independent variables; The implication of such large correlation being not only the ability to explain large amounts of variance (i.e., high R-squared), but also the converse lack of ability to say anything substantial about these relationships other than stressing the importance of education.

To test these suspicions, I investigated the four-factor solution, paying explicit attention to the factor affiliation of the “repetitive motions” item. My hunch (quite plainly stated) was that the “repetitive motions” item, in the four-factor solution, would affiliate as equally with the “repetitive physical and mental activities” item as it would with the “level of education” item, given the tendency for education to distinguish manual from mental labor (regardless of proficiency). Additionally, were a further reduction in the number of factors called for, I reckoned items would more likely affiliate with the factor anchored by the level of education rather than factors anchored in experience, innovation, or repetitiveness.

Both the ML-based and PF-based oblique rotations confirmed the suspicion regarding item affiliation, with the item measuring repetitive motions mixing its affiliation between general repetitiveness and level of education. Table IV.39 presents the results of the ML-based analysis, an analysis likely confounded slightly by the Heywood case affecting the uniqueness of the repetitious physical/mental tasks item. Table IV.41 presents the results of the PF-based analysis, wherein the affiliations of the repetitive motions item appear nearly balanced between the factor anchored by the level of education (with a -0.48 correlation) and the factor anchored by general repetitiveness (with a 0.41 correlation). While I will describe later in this chapter my final conclusions regarding item-factor relationships, I will preview these conclusions by stating that the nature of this mixed affiliation of the repetitive motions item led me to discard the item rather than include it within any scale. Furthermore, while I did not doubt that the item measuring the level of education succeeded in measuring the level of education, I was concerned that regressions based upon this dependent variable might have “too much to say” in terms of prediction—an observation that will lead to a discussion in Chapter VII of different ways to measure education for research.

Table IV.39: ML-based (Oblique) Rotated Factor Loadings and Unique Variances, Four Factor Solution for Dependent Variable Items

	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
spend time making repetitive motions	-0.55	0.03	-0.04	0.30	0.56
repetitive physical or mental activities	0.03	-0.04	0.11	1.01	0.00
work schedule regularity	-0.33	-0.04	0.31	-0.23	0.78
thinking creatively	0.38	0.32	0.08	-0.18	0.47
adaptability and flexibility	0.24	<i>0.47</i>	-0.10	0.13	0.60
requires creativity and alternative thinking	-0.08	1.03	0.06	-0.04	0.00
level of education (log)	1.03	-0.06	0.00	0.04	0.04
job zone	0.95	-0.04	0.08	0.02	0.12
related work experience	<i>0.47</i>	0.06	0.63	0.09	0.21
on-the-job training	-0.04	0.06	0.72	0.10	0.48

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.40: Correlation Matrix for Rotated Common Factors, Four Factor Solution for Dependent Variable Items

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1.00			
Factor 2	0.68	1.00		
Factor 3	0.25	0.30	1.00	
Factor 4	-0.17	-0.14	-0.19	1.00

Table IV.41: PF-based (Oblique) Rotated Factor Loadings and Unique Variances, Four Factor Solution for Dependent Variable Items

Item	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
spend time making repetitive motions	<i>-0.48</i>	0.00	0.01	<i>0.41</i>	0.52
repetitive physical or mental activities	-0.02	0.01	0.14	0.66	0.60
work schedule regularity	-0.37	-0.02	0.25	-0.33	0.74
thinking creatively	0.27	<i>0.41</i>	0.04	-0.26	0.42
adaptability and flexibility	0.13	0.63	-0.09	0.13	0.55
requires creativity and alternative thinking	0.12	0.67	0.12	-0.03	0.34
level of education (log)	0.95	0.01	0.02	0.00	0.09
job zone	0.93	-0.03	0.09	-0.01	0.11
related work experience	<i>0.42</i>	0.08	0.60	0.07	0.27
on-the-job training	0.02	-0.01	0.68	0.09	0.56

NOTE: Values greater than 0.50 are in bold, and highlighted in yellow
 Values greater than 0.40, but less than 0.50 are in italics and highlighted in blue

Table IV.42: Correlation Matrix for Rotated Common Factors, Four Factor Solution for Dependent Variable Items

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1.00			
Factor 2	0.70	1.00		
Factor 3	0.26	0.35	1.00	
Factor 4	-0.22	-0.28	-0.32	1.00

Beyond the concerns for factor affiliation, both the ML-based and PF-based analyses suggested not only four emergent factors, but also these factors could account for a sufficient proportion of variance among the included items. Three of these factors (factors two through three in Table IV.41) were composed of items with moderately strong loadings, between 0.6 and 0.7, while one factor was composed of items with very strong loadings, between 0.93 and 0.95. However, factor one could account for a predominance of variance, 56% (see Table IV.43), if factors are permitted to correlate, and 46% (see Table IV.44) if factors are restrained to be uncorrelated. The weakest factor, factor four, is not truly weak however, able to account for 21% of correlated variance and 16% of uncorrelated variance.

Table IV.43: Proportion of Variance, Oblique Rotation, Four-Factor Solution for Dependent Variable Items

Factor	Variance	Proportion
1	3.80	0.56
2	3.06	0.45
3	1.56	0.23
4	1.39	0.21

Note: Rotated factors are correlated

Table IV.44: Proportion of Variance, Orthogonal Rotation, Four-Factor Solution for Dependent Variable Items

Factor	Variance	Difference	Proportion	Cumulative
1	2.88	1.34	0.43	0.43
2	1.54	0.30	0.23	0.66
3	1.24	0.16	0.18	0.84
4	1.08		0.16	1.00

Note: Rotated factors are not correlated

Furthermore, the item-factor relationships resulted in factors that made sense. Factor one, composed of the level of education and job zone, appears to measure formal education/training. Factor two, composed of the level adaptability/flexibility and innovation, appears to measure innovative and adaptive thinking. Factor three appears focused upon specific skill/training, composed of a measure of related work experience and a measure of on-the-job training. Finally, factor four is composed of a single, general item measuring the repetitiveness of work functions, whether physical or mental in nature.

Findings

In this section I will describe my conclusions regarding the selection of valid measures for the independent, dependent, and control variables to be used in hypotheses testing. For each variable, I will (a) evaluate the items that comprise the factor based upon the EFA, (b) report Cronbach's alpha as a secondary confirmation (or denial) of the item-factor relationship, and (c) identify the final composition of scales measuring the variables.

Automation

The results of the EFA, combined with those from the investigations of face validity, suggested the level of automation of work could be measured generally, but would benefit from a consideration of two theoretically important automated work contexts—mechanized and informed environments. And so, I decided to employ a measure of the general level of automation (regardless of work context) alongside measures of the more specific contexts of automation.

Table IV.45 lists all items that were proposed for measures of the automation of work. A single item, how automated is your job, emerged during the EFA comprising a single factor (factor seven in Table IV.25). While this single measure for the level of automation alongside work might be less preferred than a multi-item measure, this single measure would in fact be preferred when testing the non-linear hypotheses (by way of a squared term). The preference for employing a single-item measure as a squared term can be understood conceptually as the difference between squaring “weight in pounds” as compared to squaring some multi-item measure of the concept “heaviness.” And so, this single item was retained as the item measuring the general level of automation alongside work.

Table IV.45: Summary of Items Measuring the Level of Automation Alongside Work

Survey item	Proportion selected by eLab sample	Proportion selected by Expert sample	Supported or Not Supported by EFA	Retained or Dropped for final analyses
(1) How automated is your current job? Not at all automated 1 Slightly automated 2 Moderately automated 3 Highly automated 4 Completely automated 5	44%	90%	Supported	Retained Automation factor
	49% <i>adjusted</i>			
(2) How important to your current job is keeping a pace set by machines? Not important at all 1 Fairly important 2 Important 3 Very important 4 Extremely important 5	37%	90%	Supported	Retained Mechanized factor
	40% <i>adjusted</i>			
(3) How important is controlling machines and processes to the performance of your current job? Not important 1 Somewhat important 2 Important 3 Very important 4 Extremely important 5	44%	100%	Supported	Retained Mechanized factor
	49% <i>adjusted</i>			
(4) How important is knowledge of machines and tools, including their designs, uses, repair, and maintenance to the performance of your current job? Not important 1 Somewhat important 2 Important 3 Very important 4 Extremely important 5	N/A	60%	Supported added to EFA via expert sample	Retained Mechanized factor
(5) How important is equipment maintenance (performing routine maintenance on equipment and determining when and what kind of maintenance is needed) to the performance of your current job? Not important 1 Somewhat important 2 Important 3 Very important 4 Extremely important 5	N/A	80%	Supported added to EFA via expert sample	Retained Mechanized factor
(6) How important is working with computers to your current job? Not important 1 Somewhat important 2 Important 3 Very important 4 Extremely important 5	52%	70%	Supported	Retained Informed factor
	58% <i>adjusted</i>			
(7) How important is programming [computers] to the performance of your current job? Not important 1 Somewhat important 2 Important 3 Very important 4 Extremely important 5	N/A	N/A	Supported added via EFA	Dropped Informed factor
(8) How important is knowledge of computers and electronics to the performance of your current job? Not important 1 Somewhat important 2 Important 3 Very important 4 Extremely important 5	N/A	N/A	Supported added via EFA	Retained Informed factor

Table IV.46 lists the four items that emerged comprising factor three from the EFA involving the independent variable items (found in Table IV.25). Each of these four items, measuring various sorts of interactions with machinery (e.g., controlling, maintaining, knowledge of, and pace-setting) is associated with the mechanized nature of work. When considered as a scale, these four items together yield a Cronbach's

alpha of 0.882 with an inter-item covariance of 0.628. The scale alpha could be improved to 0.888 through the removal of the item measuring a need to keep a pace set by machines. I decided this slight increase in alpha (0.006) was not worth the removal of an item the nature of which seemed so closely aligned with that of a mechanized work environment. And so the four items (numbered 2-5 in Table IV.45) were used as a scale measuring the mechanized nature of work.

Table IV.46: Scale Reliability, Items Measuring the Mechanized Nature of Work

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average inter-item Covariance	Alpha
keeping a pace set by machines	737	+	0.792	0.640	0.711	0.888
controlling machines and processes	737	+	0.922	0.854	0.565	0.807
importance of equipment maintenance	737	+	0.898	0.794	0.600	0.837
importance of mechanical knowledge	737	+	0.849	0.722	0.637	0.858
<i>Test scale</i>					0.628	0.882

Three items comprise factor four in the results of the seven-factor EFA (found in Table IV.25), and these items match those anticipated as measures of an informed work context. Measures of reliability for a scale composed of these three items can be found in Table IV.47. While the inclusion of an item directed at the importance of computer programming to the performance of a job seemed intuitive, the scale could be significantly improved through the removal of this item—from an alpha of 0.772 to 0.859. Therefore, I removed this programming item from the final scale, which was composed of the items measuring working with computers (in general) and the importance of knowledge regarding computers and electronics to the performance of the job (items six and eight in Table IV.45). As it happens, the results of analyses testing hypotheses were not meaningfully different whether this programming item were included or withheld as part of the scale measuring the informed work context.

Table IV.47: Scale Reliability, Items Measuring the Informed Nature of Work

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average inter-item Covariance	Alpha
working with computers	737	+	0.917	0.711	0.212	0.617
programming	737	+	0.623	0.438	0.682	0.859
knowledge of computers/electronics	737	+	0.919	0.801	0.214	0.463
<i>Test scale</i>					0.369	0.772

Programmed ends

Table IV.48 lists all six items considered for measuring the programmed ends of work, including the findings from the eLab and expert inquiries into face validity, the results from the EFA, and finally my decision regarding whether to retain or drop an item within hypotheses testing phase. Four items were retained (items 1, 2, 4 and 5), while two were discarded (items 3 and 6).

The five items comprising factor one (as presented in Table IV.25) matched, with one exception, the items proposed to measure the programmed ends of work. The exception in this group was the item measuring the importance of making decisions and solving problems (defined more specifically for respondents as “analyzing information and evaluating results to choose the best solution and solving problems”), which I had anticipated would reside within a factor measuring discretion in work rather than that measuring programmed ends. The five items are listed in Table IV.49, along with measures of item-rest correlation, average inter-item covariance, and the cronbach’s alpha. The alpha for the combination of items (0.849) could be improved to 0.859 through the removal of the item measuring the importance of evaluating information to determine standards compliance. This improvement in alpha was worth the loss of a single item out of five.

Table IV.48: Summary of Items Measuring Programmed Ends of Work

Survey item	Proportion selected by eLab sample	Proportion selected by Expert sample	Supported or Not Supported by EFA	Retained or Dropped for final analyses
(1) How important is developing objectives and strategies to the performance of the occupation? (reverse) <hr/> Not important Somewhat important Important Very important Extremely important 1 2 3 4 5 52% 56% adjusted	60%	Supported	Retained	
(2) How important is organizing, planning, and prioritizing work to the performance of your current job? (reverse) <hr/> Not important Somewhat important Important Very important Extremely important 1 2 3 4 5 65% 69% adjusted	70%	Supported	Retained	
(3) How important is evaluating information to determine compliance with standards to the performance of your current job? <hr/> Not at all important Somewhat important Important Very important Extremely important 1 2 3 4 5 39% 42% adjusted	60%	Not Supported	Dropped	
(4) How important is judging the qualities of objects, services, or people to the performance of your current job? <hr/> Not at all important Fairly important Important Very important Extremely important 1 2 3 4 5 44% 51% adjusted	40%	Supported	Retained	
(5) How important is making decisions and solving problems to the performance of you current job? <hr/> Not at all important Fairly important Important Very important Extremely important 1 2 3 4 5 N/A		Supported added via EFA	Retained	
(6) How important to your current job is being very exact or highly accurate? <hr/> Not at all important Fairly important Important Very important Extremely important 1 2 3 4 5 N/A	60%	Not Supported added to EFA via expert sample	Dropped	

Table IV.49: Measures of Scale Reliability, Items Measuring Programmed Ends of Work

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average inter-item Covariance	Alpha
determining standards compliance	737	+	0.698	0.513	0.198	0.859
developing objectives and strategies	737	+	0.860	0.752	0.157	0.792
judging the qualities of things/people	737	+	0.737	0.603	0.198	0.833
making decisions and solving problems	737	+	0.861	0.772	0.168	0.789
organizing, planning and prioritizing	737	+	0.803	0.683	0.180	0.812
<i>Test scale</i>					0.180	0.849

Discretion

Table IV.50 lists the five items initially considered as measures for the level of discretion in work. Two of these items were retained for the final analyses while three

were discarded. Independence and self-control, the latter item added as a result of the face validity results, were discarded for reasons I will describe in the following paragraph. As described above, the item measuring the importance of making decisions and solving problems was employed within the programmed ends factor, rather than discretion in work. The two remaining items, measuring the freedom to make decisions without supervision and the freedom to determine tasks, priorities, and goals were retained. These two items comprise a scale offering a Cronbach's alpha of 0.90, with an average inter-item covariance of 0.22.

Table IV.50: Summary of Items Measuring Discretion in Work

Survey item	Proportion selected by eLab sample	Proportion selected by Expert sample	Supported or Not Supported by EFA	Retained or Dropped for final analyses
(1) In your current job, how much freedom do you have to make decisions without supervision? <hr/> No freedom Very little freedom Limited freedom Some freedom A lot of freedom 1 2 3 4 5	79%	100%	Supported	Retained
	<i>84% adjusted</i>			
(2) How much freedom do you have to determine the tasks, priorities, or goals of your current job? <hr/> No freedom Very little freedom Limited freedom Some freedom A lot of freedom 1 2 3 4 5	69%	100%	Supported	Retained
	<i>80% adjusted</i>			
(3) Independence: Job requires developing one's own ways of doing things, guiding oneself with little or no supervision, and depending on oneself to get things done. <hr/> Not important Somewhat important Important Very Important Extremely important 1 2 3 4 5	54%	90%	Not Supported	Dropped
	<i>62% adjusted</i>			
(4) How important is making decisions and solving problems to the performance of you current job? <hr/> Not at all important Fairly important Important Very important Extremely important 1 2 3 4 5	52%	80%	Not Supported	Dropped
	<i>58% adjusted</i>			
(5) Self control: Job requires maintaining composure, keeping emotions in check, controlling anger, and avoiding aggressive behavior, even in very difficult situations. <hr/> Not at all important Fairly important Important Very important Extremely important 1 2 3 4 5		60%	Not Supported added to EFA via expert sample	Dropped

The EFA findings suggest that the four items expected to provide measures of a single factor (discretion) in fact comprised two distinct factors. Factor two (as presented

in Table IV.25), comprised of the items measuring (a) the freedom to determine tasks priorities, and goals, as well as (b) the freedom to make decisions without supervision, matched more closely the definition of discretion as compared to the items comprising factor six, measuring independence and self-control. In fact, it seemed to me that independence and self-control were measures of personal traits (appropriate for a position offering discretion in work) rather than measures of work characteristics akin to having discretion. Furthermore, while these two factors were moderately correlated at 0.5, the items comprising factor two loaded more strongly (both greater than 0.8) upon that factor than those two items loading onto factor six (both less than 0.6). And so, I selected as the factor measuring discretion in work that factor which appeared more substantial, both empirically (in terms of item loadings) and intuitively (in terms of the “closeness” of the items to the definition of the measured construct), and discarded the less substantial factor.

Resource control

All of the items considered as possible measures for resource control are listed in Table IV.51, along with the findings from the tests for validity as well as my final decision whether to retain or drop any item from the final analyses. The four items originally posited to provide reasonable measures for resource control received mixed support in not only the tests for face validity, but also the EFA. Two of the items were selected by 100% of respondents in the expert sample, while the remaining two items received support from barely 50% of this sample. Only one of the items was selected by a majority of the eLab sample, although as noted earlier I believe there were other issues hampering the reliability of selections made by the eLab sample. During the EFA, a single factor for resource control would coalesce and then fragment, depending upon

any change in the number of assumed factors and the choice of factor rotation method (ML or PF).

Table IV.51: Summary of Items Measuring Resource Control

Survey item	Proportion selected by eLab sample	Proportion selected by Expert sample	Supported or Not Supported by EFA	Retained or Dropped for final analyses
<p>(1) How important is monitoring and controlling resources to the performance of your current job?</p> <hr/> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p>	62%	100%	Not supported	Dropped
	64% <i>adjusted</i>			
<p>(2) How important is staffing organizational units to the performance of your current job?</p> <hr/> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p>	44%	50%	Not supported	Dropped
	51% <i>adjusted</i>			
<p>(3) In your current job, how important are interactions that require you to coordinate or lead others in accomplishing work activities? (not as a supervisor or team leader)</p> <hr/> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p>	44%	50%	Not supported	Dropped
	51% <i>adjusted</i>			
<p>(4) How important is coordinating the work and activities of others to the performance of your current job?</p> <hr/> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p>	46%	100%	Not supported	Dropped
	53% <i>adjusted</i>			
<p>(5) How important is time management to the performance of your current job? [Managing one's own time and the time of others]</p> <hr/> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p>	N/A	N/A	Supported added via EFA	Retained
<p>(6) How important is management of financial resources to the performance of your current job? [Determining how money will be spent to get the work done, and accounting for these expenditures.]</p> <hr/> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p>	N/A	N/A	Supported added via EFA	Retained
<p>(7) How important is management of material resources to the performance of your current job? [Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work]</p> <hr/> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p>	N/A	N/A	Supported added via EFA	Retained
<p>(8) How important is management of personnel resources to the performance of your current job? [Motivating, developing, and directing people as they work, identifying the best people for the job]</p> <hr/> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p>	N/A	N/A	Supported added via EFA	Retained

As a result of conflicted findings regarding the original items proposed as measures of resource control, I discarded the original items and introduced four new items, items that had been chosen and tested by the O*NET development team as measures of the importance of resource management tasks to a job/occupation. These new items are numbered 5 through 8 in Table IV.51. Three of these new items received support via the EFA, with correlations from 0.69 to 0.82 supporting their convergence upon a single factor, as seen in Table IV.25. Together, these three items presented a scale offering a Cronbach's alpha of 0.815, which could not be improved via the removal of any items. As a result, items 6-8 in Table IV.52 were the three items used to compose a scale employed to measure resource control.

Table IV.52: Measures of Reliability, Items Measuring Resource Control

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average inter-item Covariance	Alpha
management of financial resources	737	+	0.894	0.721	0.206	0.691
management of material resources	737	+	0.823	0.634	0.300	0.781
management of personnel resrouces	737	+	0.847	0.658	0.268	0.755
<i>Test scale</i>					<i>0.258</i>	<i>0.815</i>

Routinization/Programmed Means

Six items were initially considered as measures of the routinization of work (or alternatively, the programmed means for work). These six items, along with the findings of the various tests for validity can be found in Table IV.53. While the tests for face validity largely treated these items as comprising a single factor, the EFA results suggested these items comprised two different factors—one measuring the repetitiveness of work, the other measuring the creativity/innovation in work. Furthermore, the EFA highlighted some challenges to measuring the repetitiveness of

work, whether that work were manual or mental in nature. Given manual work can be associated with other work requirements (such as education), a more general measure of repetitiveness (regardless of task type) offered advantages over a measure looking at repetitiveness of any specific task type.

Table IV.53: Summary of Items Measuring Routinization of work

Survey item	Proportion selected by eLab sample	Proportion selected by Expert sample	Supported or Not Supported by EFA	Retained or Dropped for final analyses
<p>(1) How much time in your current job do you spend making repetitive motions?</p> <p>Never Less than half the time About half the time More than half the time Continually or almost continually</p> <p>1 2 3 4 5</p> <p>60%</p> <p>67% adjusted</p>			Supported	Dropped
<p>(2) How important to your current job are continuous, repetitious physical activities (like key entry), or mental activities (like checking entries in a ledger)?</p> <p>Not at all important Fairly important Important Very important Extremely important</p> <p>1 2 3 4 5</p> <p>60%</p> <p>69% adjusted</p>			Supported	Retained Repetitiveness factor
<p>(3) How regular is your work schedule on your current job?</p> <p><i>Regular</i> (established routine, set schedule) <i>Irregular</i> (changes in weather conditions, production demands, or contract duration) <i>Seasonal</i> (only during certain times of the year)</p> <p>1 2 3</p> <p>44%</p> <p>49% adjusted</p>			Not supported	Dropped
<p>(4) How important is thinking creatively to the performance of your current job? (inverse)</p> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p> <p>37%</p> <p>42% adjusted</p>			Not Supported	Dropped
<p>(5) Adaptability/Flexibility: Job requires being open to change (positive or negative) and to considerable variety in the workplace. (inverse)</p> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p> <p>56%</p> <p>53% adjusted</p>			Supported	Retained Innovativeness factor
<p>(6) Innovation: Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems. (inverse)</p> <p>Not important Somewhat important Important Very important Extremely important</p> <p>1 2 3 4 5</p> <p>42%</p> <p>44% adjusted</p>			Supported	Retained Innovativeness factor

As a result of the various findings, I selected a single measure, item two in Table IV.53, as the measure for the repetitiveness of work. I selected two items to measure the creativity/innovation in work, items supported not only by the EFA but also by the

majority of respondent in the expert sample. These two items together offered an alpha of 0.708 (see Table IV.54), which could be improved to 0.741 by including the item measuring creativity that received only weak support in the EFA (see Table IV.41)—a finding I found a bit puzzling. However, in order to err on the side of caution, I retained only the two items as measures of creativity/innovation in work, numbered five and six in Table IV.53.

Table IV.54: Measures of Reliability, Creativity/Innovation in Work

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average inter-item Covariance	Alpha
thinking creatively	737	+	0.879	0.591	0.118	0.708
adaptability and flexibility	737	+	0.715	0.515	0.233	0.739
creativity and alternative thinking	737	+	0.869	0.708	0.118	0.505
<i>Test scale</i>					<i>0.156</i>	<i>0.741</i>

Skill requirements for work

Table IV.55 presents the four items proposed as measures of the skill requirements for work. Overall, the majority if not totality of respondents in the eLab and expert samples selected each of these four items as plausible measures of the skill requirements for work, as defined. While my assumption had been these items would comprise a single factor, the findings of the EFA supported the conclusion that these items in fact comprise two distinct factors—one measuring the formal preparation and education required for an occupation, the other measuring the related work experience and on-the-job training required for an occupation (the weaker of the two factors, in terms of item-factor correlations). This distinction between factors makes sense, intuitively and conceptually, the former factor capturing the more general requirements for work while the later captures something akin to the specificity of experience and

training. Both of these factors, education and specificity of skill, are relevant to the hypotheses proposed in Chapter III.

The two items measuring the general preparation and education required for an occupation, items one and three in Table IV.55, composed a satisfactorily reliable scale, offering a cronbach's alpha of 0.805 with average inter-item covariance of 0.56. The two items measuring related work experience and on-the-job training (items two and four in Table IV.56) composed a less reliable scale offering a cronbach's alpha of only 0.64 with inter-item covariance of 0.94. These reliability statistics led me to question whether these four items indeed comprised two distinct factors, as EFA findings suggest. Considered as a single factor, the four items composed a scale offering an alpha of 0.757, with inter-item covariance of 0.614 (see Table IV.56). Given my hesitations regarding the predominance of education in the composition of this measure for skill requirements, I chose to test the skill-related hypotheses using both a two factor and a single-factor approach to skill requirements.

Table IV.55: Summary of Items Measuring Skill Requirements

Survey item	Proportion selected by eLab sample	Proportion selected by Expert sample	Supported or Not Supported by EFA	Retained or Dropped for final analyses
<p>(1) If someone were being hired to perform this job, indicate the level of education that would be required.</p> <p>Less than a high school diploma</p> <p>High school diploma</p> <p>Post-secondary certificate</p> <p>Some college courses</p> <p>Associate's degree</p> <p>Bachelor's degree</p> <p>Post-baccalaureate certificate</p> <p>Master's degree</p> <p>Post-master's certificate</p> <p>First professional degree</p> <p>Doctoral degree</p> <p>Post-doctoral training</p>	52%	100%	Supported	Retained
	60% <i>adjusted</i>			
<p>(2) If someone were being hired to perform this job, how much related work experience would be required? (That is, having other jobs that prepare the worker for this job)</p> <p>None</p> <p>Up to and including 1 month</p> <p>Over 1 month, up to and including 3 months</p> <p>Over 3 months, up to and including 6 months</p> <p>Over 6 months, up to and including 1 year</p> <p>Over to 1 year, up to and including 2 years</p> <p>Over 2 years, up to and including 4 years</p> <p>Over 4 years, up to and including 6 years</p> <p>Over 6 years, up to and including 8 years</p> <p>Over 8 years, up to and including 10 years</p> <p>Over 10 years</p>	62%	100%	Supported	Retained
	69% <i>adjusted</i>			
<p>(3) Generalized skill and education assessment (1-5 rating)</p> <p><i>Job Zone 1: Little or No Preparation Needed</i></p> <p>No previous work-related skill, knowledge, or experience is needed for these occupations. For example, a person can become a cashier even if he/she has never worked before</p> <p><i>Job Zone 2: Some Preparation Needed</i></p> <p>Some previous work-related skill, knowledge, or experience may be helpful in these occupations, but usually is not needed. For example, a teller might benefit from experience working directly with the public, but an inexperienced person could still learn to be a teller with little difficulty.</p> <p><i>Job Zone 3: Medium Preparation Needed</i></p> <p>Previous work-related skill, knowledge, or experience is required for these occupations. For example, an electrician must have completed three or four years of apprenticeship or several years of vocational training, and often must have passed a licensing exam, in order to perform the job.</p> <p><i>Job Zone 4: Considerable Preparation Needed</i></p> <p>A minimum of two to four years of work-related skill, knowledge, or experience is needed for these occupations. For example, an accountant must complete four years of college and work for several years in accounting to be considered qualified.</p> <p><i>Job Zone 5: Extensive Preparation Needed</i></p> <p>Extensive skill, knowledge, and experience are needed for these occupations. Many require more than five years of experience. For example, surgeons must complete four years of college and an additional five to seven years of specialized medical training to be able to do their job.</p>	67%	100%	Supported	Retained
	78% <i>adjusted</i>			

Table IV.56: Measures of Reliability, Items Measuring Skill Requirements

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average inter-item Covariance	Alpha
level of education (log)	765	+	0.784	0.714	0.815	0.721
job zone			0.929	0.775	0.297	0.592
related work experience	765	+	0.629	0.403	0.804	0.773
on-the-job training	765	+	0.841	0.665	0.539	0.645
<i>Test scale</i>					<i>0.614</i>	<i>0.757</i>

Controlling for task characteristics

What people “do” in various occupations might explain the nature of their work as plausibly as the work context—resource control, discretion, and programmed ends. Therefore, my purpose in employing task categories as control variables was to account for any variation in the repetitiveness of or skill requirements for work that might be accounted for by the importance of various task types for each occupation. The O*NET development team developed and tested a set of items directed at measuring a variety of task types (sometimes labeled skills in older O*NET development publications) important to occupations. These categories and their associated items from the O*NET surveys are listed in Table IV.57. As described in Chapter IV, these task types were organized taxonomically by the O*NET team, based upon prior work research and theory. I employed these distinct task categories as variables, constructing each variable—content, process, complex processing, social, technical, and systems—as an aggregation of its associated items. The items measuring resource-related tasks were employed as measures of resource control, as described earlier in this chapter, and, therefore, were not used as control variables.

Table IV.57: O*NET Task Categories, with Items

Task Category	Item
Content	Reading comprehension
	Active listening
	Writing
	Speaking
	Mathematics
	Science
Process	Critical thinking
	Active learning
	Learning strategies
	Monitoring
Complex problem solving	Complex problem solving
Social	Social perceptiveness
	Coordination
	Persuasion
	Negotiation
	Instructing
	Service orientation
Technical	Operations analysis
	Technology design
	Equipment selection
	Installation
	Programming
	Quality control analysis
	Operations monitoring
	Operation and control
	Equipment maintenance
	Troubleshooting
	Repairing
Systems	Systems analysis
	Systems evaluation
	Judgement and decision making
Resource management	Time management
	Management of financial resources
	Management of material resources
	Management of personnel resources

All Task Item survey questions are of the form:

How important is [survey item] to the performance of the occupation?

Not important	Somewhat important	Important	Very important	Extremely important
1	2	3	4	5

Controlling for occupational knowledge

As described in Chapter 4, the O*NET development team had developed and tested a set of items designed to measure various categories of knowledge required for occupations. A listing of these items and their associated items from the O*NET surveys can be seen in Table IV.58.

An assessment of the item response characteristics revealed the distribution of values for each item within each knowledge category, while continuous when responses were aggregated within each occupation, was highly skewed as if measured through binary, Yes/No means. This binary distribution of the item values led me to conclude these knowledge categories were more like dummy variables for various occupations—business/management, manufacturing/production, etc. Frankly speaking, if the knowledge categories were effectively occupational domains, then I could find a more comprehensive list of occupations within the dataset itself—the Standard Occupational Code (SOC) category for each occupation. A listing of the O*NET knowledge categories as compared to the SOC categories is presented in Table IV.59.

Table IV.58: O*NET Knowledge domains and items

Knowledge Category	Item
Business and Management	Administration and management
	Clerical
	Economics and accounting
	Sales and marketing
	Customer and personal services
	Personnel and human resources
Manufacturing and Production	Production and processing
	Food production
Engineering and Technology	Computers and electronics
	Engineering and technology
	Design
	Building and construction
	Mechanical
Mathematics and Science	Physics
	Chemistry
	Biology
	Psychology
	Sociology and anthropology
	Geography
Health services	Medicine and dentistry
	Therapy and counseling
Education and Training	Education and training
Arts and Humanities	English language
	Foreign language
	Fine arts
	History and archeology
	Philosophy and theology
Law and Public safety	Public safety and security
	Law and government
Communications	Telecommunications
	Communications and media
Transportation	Transportation

Table IV.59: O*NET Knowledge Categories as Compared to Top-level SOC Categories

O*NET Knowledge Categories	SOC Categories (top level)
Business and Management	Management
	Business and Financial Operations
	Sales and Related
	Office and Administrative Support
Manufacturing and Production	Construction and Extraction
	Installation, Maintenance, and Repair
	Production
Engineering and Technology	Architecture and Engineering
Mathematics and Science	Computer and Mathematical
	Life, Physical, and Social Science
Health services	Healthcare Practitioners and Technical
	Healthcare Support
Education and Training	Education, Training, and Library
Arts and Humanities	Arts, Design, Entertainment, Sports, and Media
Law and Public safety	Legal
	Protective Service
Communications	
Transportation	Transportation and Material Moving
	Community and Social Services
	Food Preparation and Serving Related
	Building and Grounds Cleaning and Maintenance
	Personal Care and Service
	Farming, Fishing, and Forestry

Given the SOC is organized hierarchically, with increasingly specific occupations located hierarchically within more broad occupational categories, I opted for a tactical approach directed at minimizing the risk of omitted variables. I control for variation that might exist in the dependent variables across occupations by way of unmeasured variables by treating the occupations within a fixed-effects model. Employing the top-level SOC categories as dummy variables results in the equivalent of a fixed effects model, and the validity of this assumption of fixed effects could be tested via a Hausman test, which tests for any significant difference between the coefficients resulting from a fixed-effects model versus those obtained from a random-effects model. Should the Hausman test fail for any regression model, I would know that occupational categories, as proxies for bundles of unmeasured predictors, were unable to reliably account for variation in the predicted variable (i.e., variation in the dependent variable could not be distinguished by drawing distinctions between occupations as drawn by the SOC). And so, I chose to use the 22 top-level categories of the SOC as controls for any important differences—particularly those not measured—across occupations that might affect the level of repetitiveness in, innovation in, or skill requirements for work.

Conclusion

With scales constructed and confirmed, I proceeded to the next stage in the analyses whereby I would test the hypotheses presented in Chapter III. The results of these hypotheses tests are presented in the next chapter.

CHAPTER VI

RESULTS: HYPOTHESIS TESTING

In this chapter I describe the results of tests of the hypotheses presented in Chapter III. The tests of those hypotheses directed at the routinization of work (i.e. repetitiveness and lack of creativity/innovativeness in work) will be presented first, followed by the tests of hypotheses related to the skill requirements for work (i.e., education and experience/training required for work).

Each of the hypotheses was tested via models employing ordinary least squares regression. Descriptive statistics for all of the variables can be found in Table V.1. For each dependent variable, the regression results are presented in three stages. Stage one presents a model wherein only the control variables have been included. First order terms are added to construct the stage two models. Finally, the interaction terms are added to the models at stage three. Unless otherwise noted, interaction terms were constructed of continuous variables, with both variables in each interaction centered about their means. The coefficients presented for first order terms are their main effects. In the event of significant interaction effects, I include visuals and tables that present these effects, in terms of both slope and intercept, at the mean value of the interaction term as well as ± 1 and ± 2 standard deviations from that mean.

Additional methods were employed to test the reliability of the regression results. The results of a likelihood-ratio test are presented for stages two and three of each model, confirming or denying that the variables added in these stages significantly improve upon the performance of the prior model nested within (i.e., whether variables

added in stage two improve upon the results of stage one, and those added to stage three improve upon stage two). I will also present for each stage three model the results of two tests: (1) a Breusch-Pagan / Cook-Weisberg test for heteroskedasticity (wherein the null hypothesis predicts constant variance among the error terms), and (2) a Hausman test to confirm or deny whether the fixed effects model were justified as compared to a random effects model (wherein the null hypothesis predicts no difference between the coefficients from the fixed versus random effects models).

Routinization of Work

Hypotheses 1(a), 2(a), and 3(a) presented conflicting expectations regarding the relationship between the level of automation and the level of routinization of work.

Hypothesis 1(a): Greater levels of routinization in work are associated with greater levels of automation.

Hypothesis 2(a): Lesser levels of routinization in work are associated with greater levels of automation.

Hypothesis 3(a): The relationship between the routinization in work and the level of automation is non-linear. Specifically, the plotted relationship between automation and routinization is S-shaped.

Hypotheses 4(a) and (b) presented similar expectations relating the level of discretion in work and the level of resource control to the routinization of work.

Hypothesis 4(a): Routinization of work is inversely related to occupational task discretion and autonomy.

Hypothesis 4(b): Routinization of work is inversely related to occupational control over resources.

Table V.1: Descriptive Statistics and Pairwise Correlation Matrix
(First presented on a single page, and then split across two pages)

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38		
1 Resource Control	2.46	0.57	1.00																																							
2 Discretion	4.09	0.49	0.43	1.00																																						
3 Automation	2.22	0.57	-0.14	-0.12	1.00																																					
4 Mechanized	2.45	0.84	0.00	-0.31	0.11	1.00																																				
5 Informed	2.95	0.89	0.18	0.39	0.25	-0.41	1.00																																			
6 Programmed Ends	2.67	0.48	-0.48	-0.52	0.13	0.27	-0.49	1.00																																		
7 Repetitiveness	3.22	0.68	-0.16	-0.10	0.52	0.00	0.26	0.12	1.00																																	
8 Lack of Innovativeness	2.48	0.46	0.36	0.46	-0.18	-0.35	0.48	-0.61	-0.08	1.00																																
9 Education / Preparation	4.17	1.85	0.37	0.58	-0.14	-0.48	0.55	-0.67	-0.11	0.61	1.00																															
10 Experience / On Job Training	9.04	2.43	0.42	0.48	-0.03	0.01	0.45	-0.48	-0.01	0.45	0.55	1.00																														
Task Domains																																										
11 Content	3.40	0.48	0.48	0.48	-0.08	-0.33	0.57	-0.59	-0.04	0.51	0.73	0.43	1.00																													
12 Process	3.51	0.48	0.51	0.45	-0.10	-0.25	0.50	-0.68	-0.09	0.56	0.72	0.44	0.82	1.00																												
13 Complex	3.20	0.66	0.52	0.51	-0.09	-0.10	0.53	-0.59	-0.08	0.49	0.70	0.60	0.73	0.78	1.00																											
14 Social	3.17	0.48	0.57	0.46	-0.16	-0.43	0.36	-0.64	-0.13	0.56	0.61	0.28	0.69	0.80	0.59	1.00																										
15 Technical	2.48	0.61	0.33	-0.02	0.04	0.75	0.00	-0.03	-0.03	-0.06	-0.09	0.30	0.13	0.21	0.36	-0.07	1.00																									
16 Systems	2.74	0.51	0.59	-0.34	0.05	0.19	-0.38	-0.47	-0.02	0.32	0.41	0.53	0.48	0.59	0.70	0.43	0.58	1.00																								
Occupational Classifications																																										
17 Managerial	0.03	0.18	0.31	0.18	0.05	-0.13	0.10	-0.22	0.02	0.18	0.14	0.16	0.07	0.13	0.08	0.19	-0.07	0.16	1.00																							
18 Business/Financial	0.04	0.20	0.06	0.11	0.20	-0.21	-0.17	-0.11	0.14	0.06	0.11	0.10	0.07	0.05	0.08	0.09	-0.13	0.05	-0.04	1.00																						
19 Computer/Mathematics	0.02	0.13	0.00	0.05	0.05	-0.08	0.25	-0.09	0.07	0.09	0.13	0.14	0.03	0.08	0.19	0.01	0.12	0.20	-0.02	-0.03	1.00																					
20 Architecture/Engineering	0.04	0.20	0.07	0.07	0.00	-0.02	0.24	-0.03	-0.01	0.06	0.15	0.22	0.16	0.06	0.21	-0.03	0.14	0.20	-0.04	-0.04	-0.03	1.00																				
21 Life/Physical/Social Science	0.05	0.22	0.03	0.06	-0.03	-0.10	0.16	-0.07	-0.02	0.09	0.26	0.14	0.25	0.10	0.16	0.03	-0.01	0.08	-0.04	-0.05	-0.03	-0.05	1.00																			
22 Social Services	0.02	0.13	0.03	0.03	-0.07	-0.16	0.00	-0.12	-0.11	0.12	0.17	0.00	0.04	0.13	0.07	0.21	-0.14	0.03	-0.02	-0.03	-0.02	-0.03	-0.03	1.00																		
23 Legal	0.01	0.10	-0.04	0.08	0.04	-0.11	0.08	-0.01	0.02	0.01	0.11	0.04	0.04	0.03	0.07	0.02	-0.11	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02	-0.01	1.00																	
24 Education/Training	0.08	0.27	0.07	0.24	-0.19	-0.27	0.22	-0.31	-0.26	0.28	0.44	0.04	0.37	0.44	0.22	0.35	-0.15	-0.01	-0.05	0.05	-0.06	-0.04	-0.06	-0.07	-0.04	-0.03	1.00															
25 Arts/Entertainment/Media	0.05	0.22	0.04	0.04	-0.08	-0.11	-0.11	-0.11	-0.02	0.25	0.08	0.09	-0.02	0.06	0.02	-0.03	-0.04	-0.05	-0.03	-0.05	-0.05	-0.03	-0.05	-0.05	-0.03	-0.05	-0.06	1.00														
26 Healthcare Practitioner/Technical	0.06	0.23	0.05	0.14	-0.06	-0.06	0.04	-0.13	0.04	0.11	0.23	-0.03	0.16	0.13	0.15	0.16	-0.08	0.06	-0.05	-0.03	-0.05	-0.06	-0.03	-0.03	-0.03	-0.07	-0.06	1.00														
27 Healthcare Support	0.02	0.14	-0.11	-0.12	-0.06	-0.08	-0.05	0.06	0.02	0.03	0.05	-0.15	-0.04	-0.06	-0.07	-0.01	-0.12	-0.11	-0.03	-0.03	-0.02	-0.03	-0.03	-0.02	-0.01	-0.04	-0.03	-0.03	1.00													
28 Protective Services	0.03	0.18	-0.01	0.03	-0.04	-0.06	0.01	-0.08	0.08	-0.01	-0.04	-0.02	0.00	0.05	0.08	0.12	-0.07	0.02	-0.04	-0.04	-0.02	-0.04	-0.04	-0.02	-0.02	-0.05	-0.04	-0.05	-0.03	1.00												
29 Food Preparation and Serving	0.02	0.14	-0.05	-0.10	-0.02	-0.03	-0.16	0.15	-0.08	-0.13	-0.19	-0.19	-0.11	-0.16	-0.18	-0.04	-0.10	-0.10	-0.03	-0.03	-0.02	-0.03	-0.03	-0.02	-0.02	-0.04	-0.03	-0.04	-0.02	-0.03	1.00											
30 Cleaning/Maintenance	0.01	0.10	0.03	0.00	-0.07	0.07	-0.12	0.01	-0.06	-0.07	-0.09	-0.05	-0.03	-0.06	0.01	-0.03	-0.02	-0.02	-0.01	-0.01	-0.03	-0.02	-0.02	-0.01	-0.01	-0.03	-0.02	-0.03	-0.01	-0.02	-0.02	1.00										
31 Personal Care	0.04	0.20	-0.02	-0.04	-0.08	-0.12	-0.12	0.11	-0.09	-0.03	-0.12	-0.22	-0.05	-0.05	-0.12	0.08	-0.15	-0.10	-0.04	-0.04	-0.03	-0.04	-0.05	-0.03	-0.02	-0.06	-0.05	-0.05	-0.03	-0.04	-0.03	-0.02	1.00									
32 Sales Related	0.03	0.16	-0.01	0.00	0.03	-0.15	-0.02	0.06	0.03	-0.01	-0.05	-0.07	0.00	-0.10	-0.10	0.04	-0.14	-0.10	-0.03	-0.03	-0.02	-0.04	-0.04	-0.02	-0.02	-0.05	-0.04	-0.04	-0.02	-0.03	-0.02	-0.02	-0.03	1.00								
33 Farm/Fishery/Forestry	0.08	0.28	0.13	0.03	0.04	0.12	-0.13	0.06	-0.05	-0.13	-0.13	-0.01	-0.09	-0.10	-0.06	-0.08	0.06	0.00	-0.03	-0.03	-0.02	-0.03	-0.03	-0.02	-0.02	-0.04	-0.03	-0.04	-0.02	-0.03	-0.02	-0.02	-0.03	-0.02	1.00							
34 Construction/Extraction	0.02	0.15	0.08	-0.13	-0.18	0.27	-0.36	0.08	-0.15	-0.12	-0.24	0.09	-0.18	-0.14	-0.11	-0.14	0.15	-0.04	-0.05	0.01	-0.06	-0.04	-0.06	-0.04	-0.03	-0.08	-0.08	-0.07	-0.07	-0.04	-0.05	-0.04	-0.03	-0.06	-0.05	-0.04	-0.03	-0.06	-0.05	-0.04	1.00	
35 Installation/Maintenance/Repair	0.07	0.26	0.00	0.04	-0.17	0.27	-0.04	0.04	-0.10	-0.05	-0.08	0.13	-0.06	-0.03	-0.11	-0.10	0.35	0.13	-0.05	-0.06	-0.03	-0.06	-0.06	-0.03	-0.03	-0.08	-0.06	-0.06	-0.04	-0.05	-0.04	-0.03	-0.06	-0.04	-0.03	-0.06	-0.04	-0.04	-0.08	1.00		
36 Production	0.07	0.25	-0.17	-0.32	0.24	0.47	-0.24	0.24	0.04	-0.28	-0.29	-0.17	-0.27	-0.21	-0.17	-0.36	0.29	-0.04	-0.08	-0.08	-0.05	-0.09	-0.09	-0.05	-0.04	-0.12	-0.10	-0.10	-0.10	-0.06	-0.08	-0.06	-0.04	-0.08	-0.07	-0.06	-0.12	-0.11	1.00			
37 Transportation/Material Moving	0.15	0.35	-0.12	-0.07	0.04	0.21	-0.15	0.12																																		

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	
1 Resource Control	2.46	0.57	1.00																	
2 Discretion	4.09	0.49	0.43	1.00																
3 Automation	2.22	0.57	-0.14	-0.12	1.00															
4 Mechanized	2.45	0.84	0.00	-0.31	0.11	1.00														
5 Informed	2.95	0.89	0.18	0.39	0.25	-0.41	1.00													
6 Programmed Ends	2.67	0.48	-0.48	-0.52	0.13	0.27	-0.49	1.00												
7 Repetitiveness	3.22	0.68	-0.16	-0.10	0.52	0.00	0.26	0.12	1.00											
8 Lack of Innovativeness	2.48	0.46	0.36	0.46	-0.18	-0.35	0.48	-0.61	-0.08	1.00										
9 Education / Preparation	4.17	1.65	0.37	0.58	-0.14	-0.48	0.65	-0.67	-0.11	0.61	1.00									
10 Experience / On Job Training	9.04	2.43	0.42	0.48	-0.03	0.01	0.45	-0.48	-0.01	0.45	0.55	1.00								
Task Domains																				
11 Content	3.40	0.48	0.48	0.48	-0.08	-0.33	0.57	-0.59	-0.04	0.51	0.73	0.43	1.00							
12 Process	3.51	0.48	0.51	0.45	-0.10	-0.25	0.50	-0.68	-0.09	0.56	0.72	0.44	0.82	1.00						
13 Complex	3.20	0.66	0.52	0.51	-0.09	-0.10	0.53	-0.59	-0.08	0.49	0.70	0.60	0.73	0.78	1.00					
14 Social	3.17	0.48	0.57	0.46	-0.16	-0.43	0.36	-0.64	-0.13	0.56	0.61	0.28	0.69	0.80	0.59	1.00				
15 Technical	2.48	0.61	0.33	-0.02	0.04	0.75	0.00	-0.03	-0.03	-0.06	-0.09	0.30	0.13	0.21	0.36	-0.07	1.00			
16 Systems	2.74	0.51	0.59	0.34	0.05	0.19	0.38	-0.47	-0.02	0.32	0.41	0.53	0.48	0.59	0.70	0.43	0.58	1.00		
Occupational Classifications																				
17 Managerial	0.03	0.18	0.31	0.18	0.05	-0.13	0.10	-0.22	0.02	0.18	0.14	0.16	0.07	0.13	0.08	0.19	-0.07	0.16	1.00	
18 Business/Financial	0.04	0.20	0.06	0.11	0.20	-0.21	0.17	-0.11	0.14	0.06	0.11	0.10	0.07	0.05	0.08	0.09	-0.13	0.05	-0.04	
19 Computer/Mathematics	0.02	0.13	0.00	0.05	0.05	-0.08	0.25	-0.09	0.07	0.09	0.13	0.14	0.03	0.08	0.19	0.01	0.12	0.20	-0.02	
20 Architecture/Engineering	0.04	0.20	0.07	0.07	0.00	-0.02	0.24	-0.03	-0.01	0.06	0.15	0.22	0.16	0.06	0.21	-0.03	0.14	0.20	-0.04	
21 Life/Physical/Social Science	0.05	0.22	0.03	0.06	-0.03	-0.10	0.16	-0.07	-0.02	0.09	0.26	0.14	0.25	0.10	0.16	0.03	-0.01	0.08	-0.04	
22 Social Services	0.02	0.13	0.03	0.03	-0.07	-0.16	0.00	-0.12	-0.11	0.12	0.17	0.00	0.04	0.13	0.07	0.21	-0.14	0.03	-0.02	
23 Legal	0.01	0.10	-0.04	0.08	0.04	-0.11	0.08	-0.01	0.02	0.01	0.11	0.04	0.04	0.03	0.07	0.02	-0.11	-0.02	-0.02	
24 Education/Training	0.08	0.27	0.07	0.24	-0.19	-0.27	0.22	-0.31	-0.26	0.28	0.44	0.04	0.37	0.44	0.22	0.35	-0.15	-0.01	-0.05	
25 Arts/Entertainment/Media	0.05	0.22	0.04	0.04	-0.08	-0.11	0.11	-0.11	-0.02	0.26	0.08	0.09	-0.02	0.06	-0.04	0.06	-0.02	-0.03	-0.04	
26 Healthcare Practitioner/Technical	0.06	0.23	0.05	0.14	-0.06	-0.06	0.04	-0.13	0.04	0.11	0.23	-0.03	0.16	0.13	0.15	0.16	-0.06	0.06	-0.05	
27 Healthcare Support	0.02	0.14	-0.11	-0.12	-0.06	-0.08	-0.05	0.06	0.02	0.03	-0.05	-0.15	-0.04	-0.06	-0.07	-0.01	-0.12	-0.11	-0.03	
28 Protective Services	0.03	0.18	-0.01	0.03	-0.04	-0.06	0.01	-0.08	0.08	-0.01	-0.04	-0.02	0.00	0.05	0.06	0.12	-0.07	0.02	-0.04	
29 Food Preparation and Serving	0.02	0.14	-0.05	-0.10	-0.02	-0.03	-0.16	0.15	-0.08	-0.13	-0.19	-0.19	-0.11	-0.16	-0.18	-0.04	-0.10	-0.10	-0.03	
30 Cleaning/Maintenance	0.01	0.10	0.03	0.00	-0.07	0.07	-0.12	0.01	-0.06	-0.07	-0.09	-0.05	-0.03	-0.06	-0.05	-0.03	0.01	-0.03	-0.02	
31 Personal Care	0.04	0.20	-0.02	-0.04	-0.08	-0.12	-0.17	0.11	-0.09	-0.03	-0.12	-0.22	-0.05	-0.05	-0.12	0.08	-0.15	-0.17	-0.04	
32 Sales Related	0.03	0.16	-0.01	0.00	0.03	-0.15	0.02	0.06	-0.03	-0.01	-0.05	-0.07	0.00	-0.10	-0.10	0.04	-0.14	-0.10	-0.03	
33 Farm/Fishery/Forestry	0.08	0.28	0.13	0.03	0.04	0.12	-0.13	0.06	-0.05	-0.13	-0.13	-0.01	-0.09	-0.10	-0.06	-0.08	0.06	0.00	-0.03	
34 Construction/Extraction	0.02	0.15	0.08	-0.13	-0.18	0.27	-0.36	0.08	-0.15	-0.12	-0.24	0.09	-0.18	-0.14	-0.07	-0.14	0.15	-0.04	-0.05	
35 Installation/Maintenance/Repair	0.07	0.26	0.00	0.04	-0.17	0.27	-0.04	0.04	-0.10	-0.05	-0.08	0.13	-0.06	0.11	-0.10	0.35	0.13	-0.05	-0.05	
36 Production	0.07	0.25	-0.17	-0.32	0.24	0.47	-0.24	0.24	0.04	-0.28	-0.29	-0.17	-0.27	-0.21	-0.17	-0.36	0.29	-0.04	-0.08	
37 Transportation/Material Moving	0.15	0.35	-0.12	-0.07	0.04	0.21	-0.15	0.12	0.04	-0.14	-0.16	-0.04	-0.15	-0.09	-0.13	-0.11	0.07	0.03	-0.05	
38 Office Administration	0.07	0.25	-0.20	-0.07	0.24	-0.24	0.16	0.17	0.41	-0.13	-0.14	-0.15	-0.06	-0.17	-0.23	-0.11	-0.26	-0.25	-0.06	

Note: N = 737

Occupational Classification variables are coded as dummy variables with 1 = Yes and 0 = No

† p < 0.1; *p < 0.05; ** p < 0.01; ***p < 0.001

Hypothesis 5(a) focused upon how the level of resource control would be expected to moderate the relationship between automation and the routinization of work, such that greater levels of resource control should be associated with a less impactful (if not negative) link between automation and routinization.

Hypothesis 5(a): Control over resources negatively moderates the relationship between the degree of automation and the level of routinization in work.

Hypotheses 6 and 7 presented expectations regarding the relationship between the programmed means and ends of work and how that relationship would be moderated by automation. Specifically, the relationship between the programmed nature of means and ends should be positive. However, the level of automation should moderate this relationship between the means and ends of, converting a positive relationship to one that is nominal it not negative.

Hypothesis 6: The programmed nature of the means for work processes is positively related to the programmed nature of the ends for work processes.

Hypothesis 7: Level of automation will moderate the matched pairs relationship between the means-ends of organizational work processes.

The above-described hypotheses were tested in two phases, each employing one of the two variables measuring routinization of work that emerged from validity analyses described in the last chapter: (1) the repetitiveness of work and (2) the lack of creativity/innovation in work.

Routinization Measured as Repetitiveness of Work

The results of the model designed to test those hypotheses related to the repetitiveness of work are presented in Table V.2. Importantly, the addition of variables in stages two and three significantly improved upon the results of prior stages (stage

two: $\chi^2(6)=151.2$, $p < 0.001$; stage three: $\chi^2(5) = 14.33$, $p < 0.05$). The result of a Breusch-Pagan / Cook-Weisberg test for heteroskedasticity was non-significant ($\chi^2(1) = 0.31$, $p\text{-value} = 0.58$), as was the result of the Hausman test for fixed versus random effects ($\chi^2(17) = 10.35$, $p\text{-value} = 0.89$).

Hypotheses 1(a) was supported ($p < 0.001$), expecting a positive relationship between automation and the routinization of work, while hypothesis 1(b) (expecting a negative relationship) was rejected. Hypothesis 1(c), expecting a U-shaped relationship between automation and routinization, appears to be supported (given the significant squared interaction term, $p < 0.05$). An investigation of the marginal effects of automation upon repetitiveness of work, however, suggested a link characterized by diminishing returns rather a true reversal of effect (U-shaped).

Table V.3 presents the marginal effects for automation upon the repetitiveness of work across a range of levels of automation (+/- 1 standard deviation, +/- 2 s.d., and at the mean). The marginal effect is consistently positive, except for the case of the value +2 s.d. from the mean, at which the effect becomes non-significant (from zero). At best, therefore, while the level of automation does negatively moderate its own main effect, the nature of this moderation displays diminishing returns unable to convert the overall effect of automation from positive to negative (which would lead to a U-shape relationship). These changes in slope are presented visually in Figure V.1, while the shape of the underlying automation-repetitiveness relationship is presented in Figure V.2.

Table V.2: Regression Results Predicting the Repetitiveness of Work

Variable	Stage 1		Stage 2		Stage 3	
	including only control variables		with addition of primary variables		with addition of interaction terms	
	Beta	Standard error	Beta	Standard error	Beta	Standard error
Main Effects						
Resource control			-0.03	<i>0.06</i>	-0.02	<i>0.06</i>
Discretion			-0.03	<i>0.05</i>	-0.02	<i>0.05</i>
Automation			0.36 ***	<i>0.04</i>	0.38 ***	<i>0.05</i>
Mechanized			0.18 **	<i>0.06</i>	0.15 *	<i>0.06</i>
Informed			0.18 ***	<i>0.04</i>	0.17 ***	<i>0.04</i>
Programmed Ends			0.13 *	<i>0.06</i>	0.16 *	<i>0.07</i>
Interaction Effects						
Resource Control x Automation					-0.07	<i>0.07</i>
Discretion x Automation					0.00	<i>0.08</i>
Programmed Ends x Automation					0.02	<i>0.09</i>
Automation ^{squared}					-0.10 *	<i>0.05</i>
Programmed Ends ^{squared}					-0.24 **	<i>0.08</i>
Skills						
Content	0.06	<i>0.09</i>	0.08	<i>0.09</i>	0.05	<i>0.09</i>
Process	0.29 *	<i>0.12</i>	0.24 *	<i>0.11</i>	0.28 *	<i>0.11</i>
Complex processing	-0.11	<i>0.07</i>	-0.09	<i>0.06</i>	-0.11 †	<i>0.06</i>
Social	-0.28 **	<i>0.09</i>	-0.07	<i>0.09</i>	-0.08	<i>0.09</i>
Technical	0.10	<i>0.06</i>	-0.11	<i>0.08</i>	-0.11	<i>0.08</i>
Systems	0.02	<i>0.07</i>	-0.05	<i>0.07</i>	-0.04	<i>0.07</i>
Occupational Groups						
Managerial	-0.81 ***	<i>0.14</i>	-0.56 ***	<i>0.14</i>	-0.51 ***	<i>0.14</i>
Business/Financial	-0.42 ***	<i>0.13</i>	-0.39 ***	<i>0.12</i>	-0.37 **	<i>0.12</i>
Computer/Mathematics	-0.63 ***	<i>0.20</i>	-0.41 *	<i>0.18</i>	-0.41 *	<i>0.18</i>
Architecture/Engineering	-1.04 ***	<i>0.14</i>	-0.78 ***	<i>0.13</i>	-0.78 ***	<i>0.13</i>
Life/Physical/Social Science	-1.05 ***	<i>0.13</i>	-0.77 ***	<i>0.12</i>	-0.76 ***	<i>0.12</i>
Social Services	-1.36 ***	<i>0.19</i>	-1.01 ***	<i>0.18</i>	-0.99 ***	<i>0.18</i>
Legal	-0.71 ***	<i>0.22</i>	-0.63 ***	<i>0.20</i>	-0.64 ***	<i>0.20</i>
Education/Training	-1.58 ***	<i>0.12</i>	-1.23 ***	<i>0.12</i>	-1.17 ***	<i>0.12</i>
Arts/Entertainment/Media	-1.04 ***	<i>0.12</i>	-0.69 ***	<i>0.12</i>	-0.68 ***	<i>0.12</i>
Healthcare Practitioner/Technical	-0.81 ***	<i>0.12</i>	-0.50 ***	<i>0.12</i>	-0.49 ***	<i>0.12</i>
Healthcare Support	-0.78 ***	<i>0.17</i>	-0.45 **	<i>0.16</i>	-0.45 **	<i>0.16</i>
Protective Services	-0.56 ***	<i>0.14</i>	-0.27 *	<i>0.13</i>	-0.25 †	<i>0.13</i>
Food Preparation and Serving	-1.22 ***	<i>0.17</i>	-0.87 ***	<i>0.16</i>	-0.85 ***	<i>0.16</i>
Cleaning/Maintenance	-1.33 ***	<i>0.22</i>	-0.80 ***	<i>0.21</i>	-0.75 ***	<i>0.21</i>
Personal Care	-1.16 ***	<i>0.13</i>	-0.77 ***	<i>0.13</i>	-0.76 ***	<i>0.12</i>
Sales Related	-0.96 ***	<i>0.15</i>	-0.79 ***	<i>0.14</i>	-0.72 ***	<i>0.14</i>
Farm/Fishery/Forestry	-1.19 ***	<i>0.17</i>	-0.85 ***	<i>0.17</i>	-0.78 ***	<i>0.17</i>
Construction/Extraction	-1.35 ***	<i>0.12</i>	-0.78 ***	<i>0.13</i>	-0.78 ***	<i>0.13</i>
Installation/Maintenance/Repair	-1.29 ***	<i>0.13</i>	-0.79 ***	<i>0.13</i>	-0.78 ***	<i>0.13</i>
Production	-1.00 ***	<i>0.11</i>	-0.79 ***	<i>0.12</i>	-0.77 ***	<i>0.12</i>
Transportation/Material Moving	-0.89 ***	<i>0.12</i>	-0.62 ***	<i>0.12</i>	-0.60 ***	<i>0.12</i>
Constant (Office/Administrative)	3.88 ***	<i>0.22</i>	3.69 ***	<i>0.29</i>	-0.63	<i>1.27</i>
<hr/>						
R ²	33.43		45.78		46.82	
Adjusted R ²	30.90		43.23		43.93	
Δ Chi Square			151.20		14.33	
p - value Chi Square			0.00 ***		0.01 *	
Observations	737		737		737	

Notes:

Standard errors are italicized

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001

Table V.3: Marginal effect of Automation upon Repetitiveness of Work for Different Levels of Automation

	Marginal Effect	SE	z	p > z	95% confidence interval	
-2 S.D.	0.606	0.135	4.500	0.000	0.343	0.870
-1 S.D.	0.492	0.082	6.020	0.000	0.332	0.652
Mean	0.377	0.045	8.390	0.000	0.289	0.465
+1 S.D.	0.262	0.065	4.060	0.000	0.136	0.389
+2 S.D.	0.148	0.115	1.290	0.198	-0.077	0.373

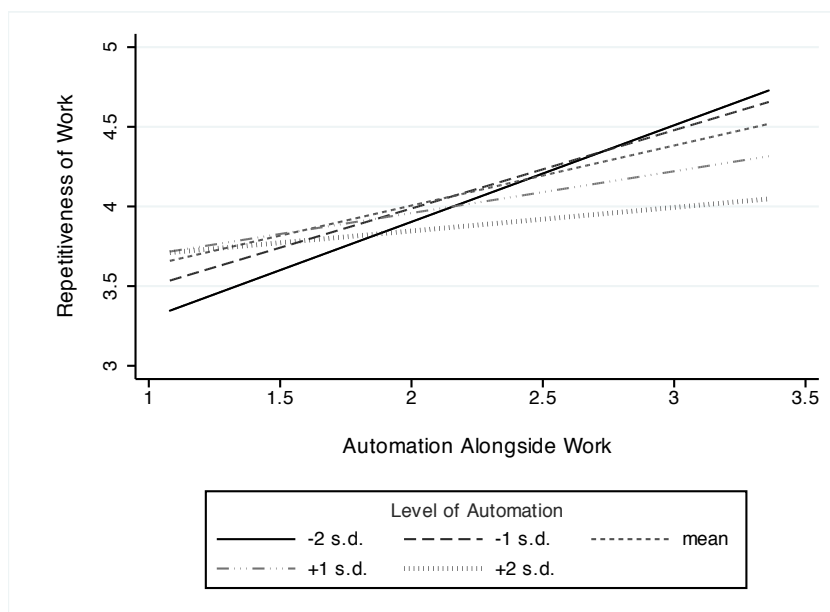


Figure V.1: Marginal effect of Automation upon Repetitiveness of Work for Different Levels of Automation

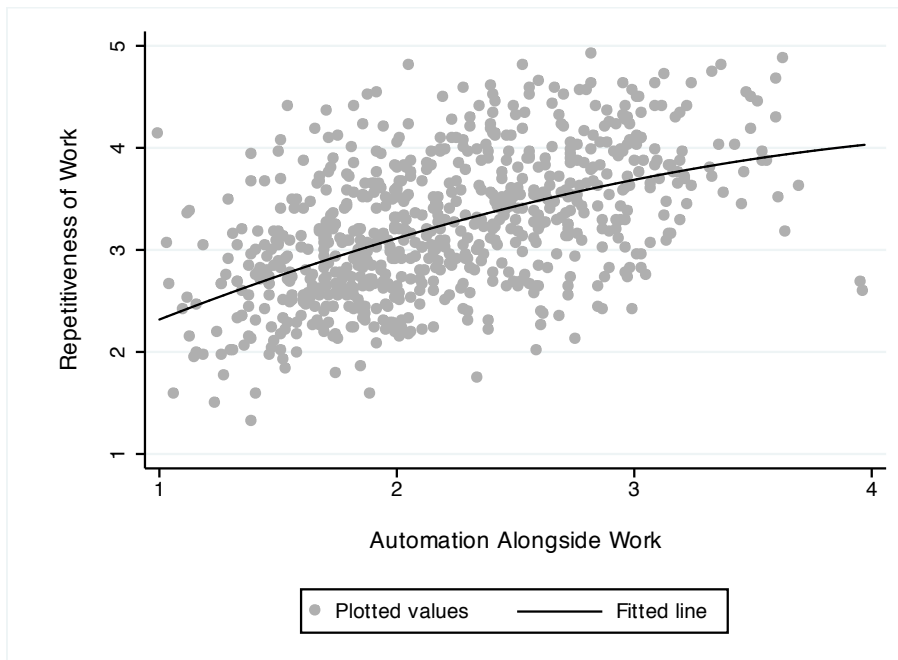


Figure V.2: Relationship Between the Level of Automation and the Level of Routinization of Work

Hypotheses 4(a) and (b), predicting a positive relationship between automation and the level of discretion as well as the level of resource control, respectively, were not supported (see Table V.2, Main Effects). Furthermore, hypotheses 5(a) was not supported, with resource control not significantly moderating the automation-repetitiveness relationship (see Table V.2, Interaction Effects). Hypothesis 6, which predicted a positive relationship between the programmed ends of work and the programmed means, was supported ($p < 0.05$, see Table V.2, Main Effects). Hypothesis 7 was not supported, however, as a significant moderation of this means-ends relationship does not appear to occur by way of automation (see Table V.2, Interaction Effects, “Programmed Ends x Automation”).

While no hypotheses were presented regarding the relationship between the mechanized or informed work environments and the repetitiveness of work, both contexts were positively associated with the repetitiveness of work—suggesting that the positive relationship found for automation persists even after controlling for the nature of these work environments. Furthermore, I included a test of a non-linear relationship between the programmed ends and programmed means of work, taking into account the possibility of diminishing marginal returns from programmed work routines as discovered by Schulz (1998). The marginal effects of programmed ends ± 2 s.d. from the mean were significantly different from each other, and opposite in effect (see Table V.4). In this case, not only is there a significant moderation by programmed ends upon its main effect, but also it appears this moderation may reverse the otherwise positive relationship between means and ends at high levels of programmed ends (see Figure V.3 and Figure V.4). That said, the negative slope associated with these high levels of programmed ends ($+2$ s.d. from the mean) is only significant at the level of $p < 0.1$.

Table V.4: Marginal Effect of Programmed Ends upon Repetitiveness of Work for Different Levels of Programmed Ends

	Marginal Effect	SE	z	p > z	95% confidence interval	
-2 S.D.	0.615	0.171	3.590	0.000	0.280	0.951
-1 S.D.	0.390	0.106	3.660	0.000	0.181	0.598
Mean	0.164	0.065	2.520	0.012	0.037	0.292
+1 S.D.	-0.062	0.090	-0.680	0.493	-0.238	0.115
+2 S.D.	-0.287	0.151	-1.900	0.057	-0.583	0.009

Table V.5: Intercept Programmed Ends

	Intercept	SE	z	p > z	95% confidence interval	
-2 S.D.	2.901	0.091	31.910	0.000	2.723	3.079
-1 S.D.	3.142	0.036	86.150	0.000	3.070	3.213
Mean	3.275	0.026	127.770	0.000	3.225	3.325
+1 S.D.	3.300	0.037	90.020	0.000	3.228	3.371
+2 S.D.	3.216	0.078	41.400	0.000	3.064	3.368

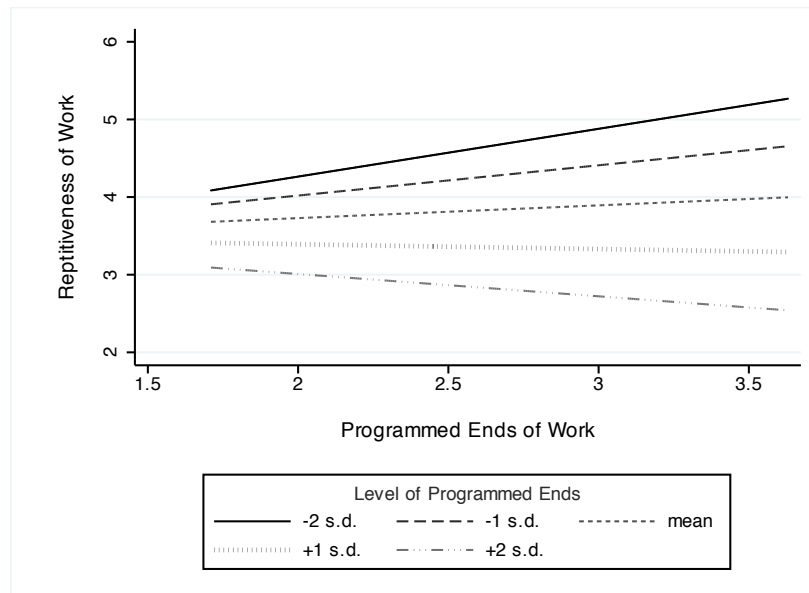


Figure V.3: Marginal Effect of Programmed Ends upon Repetitiveness of Work for Different Levels of Programmed Ends

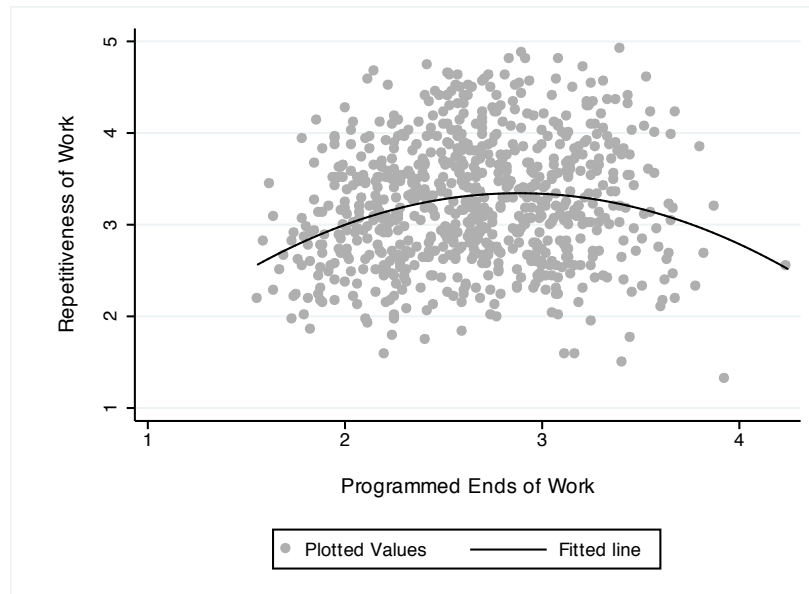


Figure V.4: Plotted values and Fitted Line Relationship Between the Programmed Ends of Work and the Repetitiveness of Work

Routinization Measured as Lack of Creativity / Innovation in Work

Table V.6 presents the results of the model designed to test those hypotheses related to the lack of creativity or innovation in work (an alternative conception of the routinization / programmed means of work). Those variables added in stage two significantly improved upon the results of stage one ($\chi^2(6)=292.71$, $p < 0.001$). The stage three results, however, which introduced the interaction effects, could not significantly improve upon those of stage two ($\chi^2(5) = 2.48$, $p = 0.78$). The result of a Breusch-Pagan / Cook-Weisberg test for heteroskedasticity was significant ($\chi^2(1) = 7.31$, $p\text{-value} = 0.007$). In response, I tested the stage three model employing ordinary least squares regression with robust errors, the results of which are presented in the fourth column (labeled “Stage 3, robust results”) in Table V.6. The result of the Hausman test for fixed versus random effects was significant at the $p < 0.1$ level, but

not at the $p < 0.05$ level ($\chi^2(17) = 26.74$, $p\text{-value} = 0.062$). Therefore I was not as confident in the assumption of fixed effects by way of the occupational domains when predicting creativity/innovation as I could be when predicting other dependent variables (i.e., repetitiveness, education/preparation, and training/experience).

With routinization of work conceived as a lack of creativity or innovation in work, hypothesis 1(a) was supported ($p < 0.001$), while hypotheses 2(a) and 3(a) were rejected (see Table V.6). A significant and positive relationship exists between automation and the lack of innovation in work. Hypothesis 4(a) was supported ($p < 0.001$), with discretion in work negatively associated with a lack of innovation in work, while hypothesis 4(b) was rejected, suggesting resource control does not impact innovativeness of work in the same manner as discretion. Hypothesis 5(a) is not supported either, there being no significant moderation of the link between automation and innovativeness by way of resource control. Hypothesis 6(a) was supported ($p < 0.001$), suggesting the programmed ends of work relate positively with the programmed means, whether these means are conceived in terms of innovativeness or repetitiveness (as in the prior section).

Of some interest is the observation that while informed work environments were negatively associated with a lack of innovativeness in work, such an association was not significant for mechanized work environments. While not hypothesized, this finding would appear to both confirm and disconfirm conventional wisdom, which associates informed work environments with more creative occupations while associating mechanized work environs with less creative occupations.

Table V.6: Regression Results Predicting the Lack of Creativity / Innovation in Work

Variable	Stage 1		Stage 2		Stage 3		Stage 3	
	including only control variables		with addition of primary variables		with addition of interaction terms		robust results	
	Beta	Standard error	Beta	Standard error	Beta	Standard error	Beta	Standard error
Main Effects								
Resource control			-0.03	<i>0.03</i>	-0.03	<i>0.03</i>	-0.03	<i>0.03</i>
Discretion			-0.11 ***	<i>0.02</i>	-0.10 ***	<i>0.02</i>	-0.10 ***	<i>0.03</i>
Automation			0.11 ***	<i>0.02</i>	0.12 ***	<i>0.02</i>	0.12 ***	<i>0.02</i>
Mechanized			-0.05	<i>0.03</i>	-0.05 †	<i>0.03</i>	-0.05	<i>0.03</i>
Informated			-0.08 ***	<i>0.02</i>	-0.08 ***	<i>0.02</i>	-0.08 ***	<i>0.02</i>
Programmed Ends			0.40 ***	<i>0.03</i>	0.39 ***	<i>0.03</i>	0.39 ***	<i>0.03</i>
Interaction Effects								
Resource Control x Automation					-0.02	<i>0.03</i>	-0.02	<i>0.03</i>
Discretion x Automation					0.01	<i>0.04</i>	0.01	<i>0.05</i>
Programmed Ends x Automation					-0.01	<i>0.04</i>	-0.03	<i>0.03</i>
Automation ^{squared}					-0.03	<i>0.02</i>	-0.01	<i>0.05</i>
Programmed Ends ^{squared}					0.03	<i>0.04</i>	0.03	<i>0.04</i>
Skills								
Content	-0.01	<i>0.05</i>	0.08 †	<i>0.04</i>	0.08 †	<i>0.04</i>	0.08 †	<i>0.04</i>
Process	-0.10	<i>0.06</i>	-0.07	<i>0.05</i>	-0.06	<i>0.05</i>	-0.06	<i>0.06</i>
Complex processing	-0.18 ***	<i>0.03</i>	-0.09 **	<i>0.03</i>	-0.09 **	<i>0.03</i>	-0.09 **	<i>0.03</i>
Social	-0.17 ***	<i>0.05</i>	-0.08 †	<i>0.04</i>	-0.09 *	<i>0.04</i>	-0.09 †	<i>0.05</i>
Technical	0.11 ***	<i>0.03</i>	0.07 †	<i>0.04</i>	0.07 †	<i>0.04</i>	0.07 †	<i>0.04</i>
Systems	-0.05	<i>0.04</i>	0.05	<i>0.03</i>	0.05	<i>0.03</i>	0.05	<i>0.03</i>
Occupational Groups								
Managerial	-0.39 ***	<i>0.07</i>	-0.17 **	<i>0.06</i>	-0.18 **	<i>0.07</i>	-0.18 **	<i>0.06</i>
Business/Financial	-0.14 *	<i>0.07</i>	-0.06	<i>0.06</i>	-0.06	<i>0.06</i>	-0.06	<i>0.06</i>
Computer/Mathematics	-0.41 ***	<i>0.10</i>	-0.25 ***	<i>0.09</i>	-0.26 **	<i>0.09</i>	-0.26 ***	<i>0.08</i>
Architecture/Engineering	-0.30 ***	<i>0.07</i>	-0.22 ***	<i>0.06</i>	-0.22 ***	<i>0.06</i>	-0.22 ***	<i>0.06</i>
Life/Physical/Social Science	-0.25 ***	<i>0.07</i>	-0.17 **	<i>0.06</i>	-0.17 **	<i>0.06</i>	-0.17 **	<i>0.06</i>
Social Services	-0.26 **	<i>0.10</i>	-0.16 *	<i>0.08</i>	-0.17 *	<i>0.08</i>	-0.17 *	<i>0.08</i>
Legal	0.01	<i>0.11</i>	0.04	<i>0.09</i>	0.03	<i>0.09</i>	0.03	<i>0.13</i>
Education/Training	-0.48 ***	<i>0.06</i>	-0.27 ***	<i>0.05</i>	-0.28 ***	<i>0.06</i>	-0.28 ***	<i>0.05</i>
Arts/Entertainment/Media	-0.83 ***	<i>0.06</i>	-0.62 ***	<i>0.05</i>	-0.62 ***	<i>0.05</i>	-0.62 ***	<i>0.05</i>
Healthcare Practitioner/Technical	-0.11 †	<i>0.06</i>	0.01	<i>0.06</i>	0.01	<i>0.06</i>	0.01	<i>0.05</i>
Healthcare Support	-0.19 *	<i>0.09</i>	-0.20 **	<i>0.07</i>	-0.19 *	<i>0.07</i>	-0.19 ***	<i>0.05</i>
Protective Services	-0.03	<i>0.07</i>	0.09	<i>0.06</i>	0.08	<i>0.06</i>	0.08	<i>0.07</i>
Food Preparation and Serving	0.08	<i>0.09</i>	0.00	<i>0.07</i>	-0.01	<i>0.07</i>	-0.01	<i>0.08</i>
Cleaning/Maintenance	-0.01	<i>0.11</i>	0.12	<i>0.10</i>	0.11	<i>0.10</i>	0.11	<i>0.08</i>
Personal Care	-0.17 *	<i>0.07</i>	-0.20 ***	<i>0.06</i>	-0.20 ***	<i>0.06</i>	-0.20 **	<i>0.07</i>
Sales Related	-0.17 *	<i>0.08</i>	-0.16 *	<i>0.06</i>	-0.16 *	<i>0.06</i>	-0.16 *	<i>0.07</i>
Farm/Fishery/Forestry	0.10	<i>0.09</i>	0.17 *	<i>0.08</i>	0.16 *	<i>0.08</i>	0.16 *	<i>0.08</i>
Construction/Extraction	-0.17 **	<i>0.06</i>	-0.07	<i>0.06</i>	-0.07	<i>0.06</i>	-0.07	<i>0.07</i>
Installation/Maintenance/Repair	-0.17 *	<i>0.07</i>	-0.03	<i>0.06</i>	-0.03	<i>0.06</i>	-0.03	<i>0.06</i>
Production	-0.10 †	<i>0.06</i>	-0.09 †	<i>0.05</i>	-0.09 †	<i>0.05</i>	-0.09 †	<i>0.06</i>
Transportation/Material Moving	-0.03	<i>0.06</i>	0.00	<i>0.06</i>	0.00	<i>0.06</i>	0.00	<i>0.05</i>
Constant (Office/Administrative)	4.03 ***	<i>0.11</i>	2.80 ***	<i>0.14</i>	2.39 ***	<i>0.60</i>	2.39 ***	<i>0.72</i>
<hr/>								
R ²	61.38		74.04		74.10			
Adjusted R ²	59.91		72.82		72.77			
Δ Chi Square			292.71		2.48			
p - value Chi Square			0.00 ***		0.78			
Observations	737		737		737			

Notes:

Standard errors are italicized

† p < 0.1; *p < 0.05; ** p < 0.01; ***p < 0.001

Skill Requirements for Work

Hypotheses 1(b), 2(b), and 3(b) presented conflicting expectations for the relationship between automation and the skill requirements for work. Specifically, hypothesis 1(b) aligned with the expectations of the “deskilling” hypothesis, while 2(b) aligned with those of the “re-skilling” hypothesis. Hypothesis 3(b) reflected the findings of scholars who observed a non-linear relationship between automation and the nature of work.

Hypothesis 1(b): Lesser levels of skill requirements for work are associated with greater levels of automation.

Hypothesis 2(b): Greater levels of skill requirements for work are associated with greater levels of automation.

Hypothesis 3(b): The relationship between the level of skill requirements for work and the level of automation is non-linear. Specifically, the plotted relationship between automation and skill requirements is in the shape of an inverted S.

Hypothesis 5(b) reflected expectations that occupations offering high levels of resource control, unlike those offering low levels of such control, were in position to select the sort of automation that operated alongside their work. Given the opportunity to select the nature of automation, there would be a preference for automation that raises the level of skill required, specializing and increasing the requirements for these positions—effectively, using technology to construct a barrier to entry into the occupation.

Hypothesis 5(b): Control over resources positively moderates the relationship between the degree of automation and the skill requirements for work.

Both variables that emerged from the tests for validity as measures of the skill requirements for work were employed to test the above-described hypotheses: (1) formal

education and preparation, and (2) related experience and on-the-job training required for work.

Skill Requirements Measured as Formal Education / Preparation for Occupation

The results presented in Table V.7 are those resulting from the model designed to test the hypotheses related to the formal education and preparation required for work. Those variables added in stage two ($\chi^2(6) = 133.35$, $p < 0.001$) and stage three ($\chi^2(5) = 16.36$, $p < 0.01$) significantly improve upon the results of their prior stages. The result of the Hausman test challenging the relevance of fixed versus random effects was not significant ($\chi^2(17) = 21.5$, $p\text{-value} = 0.20$). The assertion of constant variance among the error terms could not be rejected, with the result of a Breusch-Pagan / Cook-Weisberg test for heteroskedasticity proving non-significant ($\chi^2(1) = 0.04$, $p\text{-value} = 0.84$).

Hypothesis 1(b) was supported, but only marginally ($p < 0.1$), suggesting there would be a weakly significant and negative relationship between the level of resource control and that of automation. Hypotheses 2(b) and 3(b) were not supported. Hypothesis 5(b) was supported ($p < 0.01$), with the automation-skill requirements relationship being positively moderated by resource control. The nature of this moderation is not quite as expected, however (see Figure V.5). While the relationship between automation and skill requirements is indeed negative for those occupations having average or below average levels of resource, this relationship proves non-significant for high levels of resource control (see Table V.8).

Table V.7: Regression Results Predicting the Formal Education / Preparation Requirements for Work

Variable	Stage 1		Stage 2		Stage 3	
	including only control variables		with addition of primary variables		with addition of interaction terms	
	Beta	Standard error	Beta	Standard error	Beta	Standard error
Main Effects						
Resource control			0.11	<i>0.07</i>	0.12 †	<i>0.07</i>
Discretion			0.37 ***	<i>0.07</i>	0.36 ***	<i>0.07</i>
Automation			-0.17 **	<i>0.06</i>	-0.15 **	<i>0.06</i>
Mechanized			-0.13 †	<i>0.08</i>	-0.10	<i>0.08</i>
Informed			0.28 ***	<i>0.05</i>	0.29 ***	<i>0.05</i>
Programmed Ends			-0.40 ***	<i>0.08</i>	-0.42 ***	<i>0.08</i>
Interaction Effects						
Resource Control x Automation					0.21 *	<i>0.09</i>
Discretion x Automation					-0.26 **	<i>0.10</i>
Programmed Ends x Automation					-0.14	<i>0.11</i>
Automation ^{squared}					-0.01	<i>0.07</i>
Programmed Ends ^{squared}					0.25 *	<i>0.10</i>
Skills						
Content	0.73 ***	<i>0.12</i>	0.44 ***	<i>0.11</i>	0.44 ***	<i>0.11</i>
Process	0.42 **	<i>0.15</i>	0.48 ***	<i>0.15</i>	0.48 ***	<i>0.15</i>
Complex processing	0.79 ***	<i>0.08</i>	0.55 ***	<i>0.08</i>	0.58 ***	<i>0.08</i>
Social	-0.31 **	<i>0.12</i>	-0.45 ***	<i>0.12</i>	-0.46 ***	<i>0.12</i>
Technical	-0.71 ***	<i>0.08</i>	-0.49 ***	<i>0.11</i>	-0.49 ***	<i>0.11</i>
Systems	0.34 ***	<i>0.10</i>	0.12	<i>0.09</i>	0.09	<i>0.09</i>
Occupational Groups						
Managerial	1.06 ***	<i>0.18</i>	0.79 ***	<i>0.18</i>	0.67 ***	<i>0.18</i>
Business/Financial	0.72 ***	<i>0.17</i>	0.60 ***	<i>0.16</i>	0.55 ***	<i>0.16</i>
Computer/Mathematics	1.36 ***	<i>0.25</i>	1.00 ***	<i>0.24</i>	0.98 ***	<i>0.24</i>
Architecture/Engineering	0.89 ***	<i>0.18</i>	0.83 ***	<i>0.17</i>	0.80 ***	<i>0.17</i>
Life/Physical/Social Science	1.43 ***	<i>0.16</i>	1.47 ***	<i>0.15</i>	1.42 ***	<i>0.15</i>
Social Services	1.76 ***	<i>0.25</i>	1.78 ***	<i>0.23</i>	1.77 ***	<i>0.23</i>
Legal	1.22 ***	<i>0.28</i>	1.19 ***	<i>0.26</i>	1.19 ***	<i>0.26</i>
Education/Training	1.80 ***	<i>0.16</i>	1.55 ***	<i>0.15</i>	1.47 ***	<i>0.16</i>
Arts/Entertainment/Media	1.16 ***	<i>0.16</i>	0.87 ***	<i>0.15</i>	0.85 ***	<i>0.15</i>
Healthcare Practitioner/Technical	1.32 ***	<i>0.15</i>	1.37 ***	<i>0.15</i>	1.34 ***	<i>0.15</i>
Healthcare Support	0.06	<i>0.22</i>	0.32	<i>0.20</i>	0.29	<i>0.21</i>
Protective Services	-0.16	<i>0.18</i>	-0.12	<i>0.17</i>	-0.15	<i>0.17</i>
Food Preparation and Serving	-0.70 ***	<i>0.21</i>	-0.32	<i>0.21</i>	-0.37 †	<i>0.21</i>
Cleaning/Maintenance	-0.39	<i>0.28</i>	-0.18	<i>0.27</i>	-0.24	<i>0.27</i>
Personal Care	-0.09	<i>0.17</i>	0.14	<i>0.16</i>	0.10	<i>0.16</i>
Sales Related	0.24	<i>0.19</i>	0.27	<i>0.18</i>	0.18	<i>0.18</i>
Farm/Fishery/Forestry	-0.24	<i>0.21</i>	-0.06	<i>0.22</i>	-0.16	<i>0.22</i>
Construction/Extraction	-0.29 †	<i>0.15</i>	0.03	<i>0.17</i>	0.03	<i>0.17</i>
Installation/Maintenance/Repair	0.31 †	<i>0.17</i>	0.36 *	<i>0.17</i>	0.33 †	<i>0.17</i>
Production	0.06	<i>0.14</i>	0.43 **	<i>0.15</i>	0.38 *	<i>0.15</i>
Transportation/Material Moving	0.03	<i>0.15</i>	0.32 *	<i>0.16</i>	0.28 †	<i>0.16</i>
Constant (Office/Administrative)	-1.00 ***	<i>0.29</i>	0.93 *	<i>0.37</i>	-0.32	<i>1.65</i>
<hr/>						
R ²	81.35		84.43		84.78	
Adjusted R ²	80.64		83.70		83.95	
Δ Chi Square			133.35		16.36	
p - value Chi Square			0.00 ***		0.01 **	
Observations	737		737		737	

Notes:

Standard errors are italicized

† p < 0.1; *p < 0.05; ** p < 0.01; ***p < 0.001

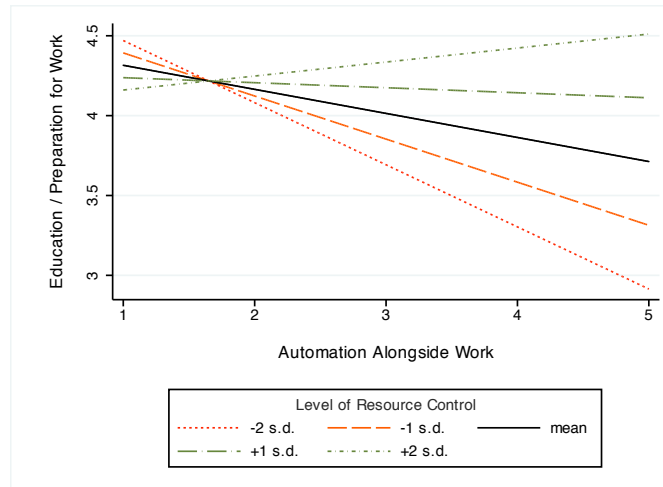


Figure V.5: Marginal Effect of Automation Upon Education / Preparation for Work, by Level of Resource Control

Table V.8: Marginal Effect of Automation Upon Education / Preparation for Work, by Level of Resource Control

	Marginal Effect	SE	z	p > z	95% confidence interval	
-2 S.D.	-0.389	0.120	-3.250	0.001	-0.624	-0.154
-1 S.D.	-0.270	0.079	-3.430	0.001	-0.424	-0.116
Mean	-0.151	0.058	-2.580	0.010	-0.265	-0.036
+1 S.D.	-0.032	0.077	-0.410	0.684	-0.183	0.120
+2 S.D.	0.088	0.118	0.740	0.458	-0.144	0.319

While no hypotheses were offered relating discretion with skill requirements for work, I did test whether discretion might also moderate the automation-skill requirements relationship even after taking into account the effect introduced by control over resources. In fact, the negative moderation of an otherwise positive relationship between discretion and skill requirements was supported ($p < 0.01$). In this case, while greater levels of discretion are associated overall with higher levels of education/preparation for work, greater levels of discretion also coincide with a more

significant and negative relationship between automation and education—a finding the implications of which will be discussed in the discussion section.

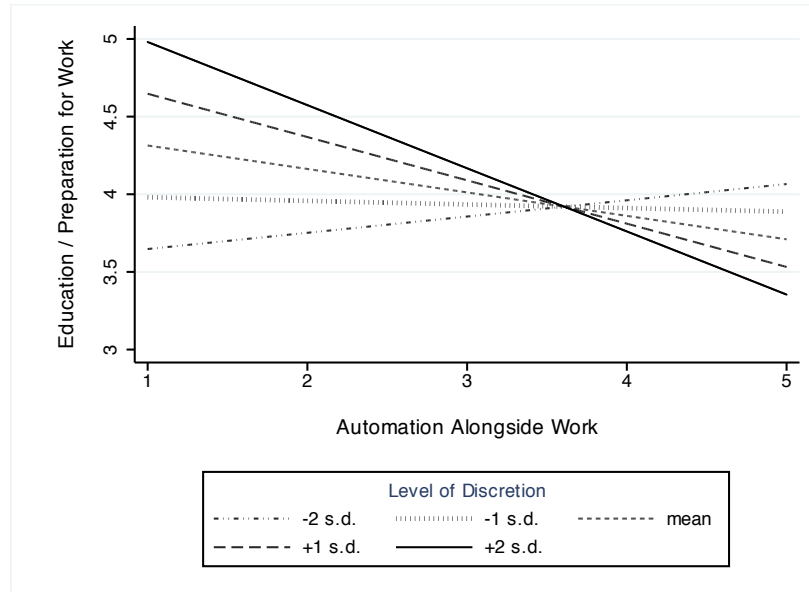


Figure V.6: Marginal Effect of Automation Upon Education / Preparation for Work, by Level of Discretion

Table V.9: Marginal Effect of Automation Upon Education / Preparation for Work, by Level of Discretion

	Marginal Effect	SE	z	p > z	95% confidence interval	
-2 S.D.	0.105	0.116	0.900	0.368	-0.123	0.332
-1 S.D.	-0.023	0.077	-0.300	0.764	-0.175	0.128
Mean	-0.151	0.058	-2.580	0.010	-0.266	-0.036
+1 S.D.	-0.279	0.076	-3.660	0.000	-0.428	-0.130
+2 S.D.	-0.407	0.115	-3.550	0.000	-0.631	-0.182

Since the main effects are positive for both automation and discretion as these variables relate to the level of education or preparation required for work, there is ample reason to questions the moderation effect from the alternative angle—that of automation

moderating discretion. Without prior research to inform this debate, a more inductive approach to these relationships seemed appropriate. In fact, with discretion being a work context that might be granted to an organization member as well as granted by that organization member, the nature of causation in the moderation seemed unclear.

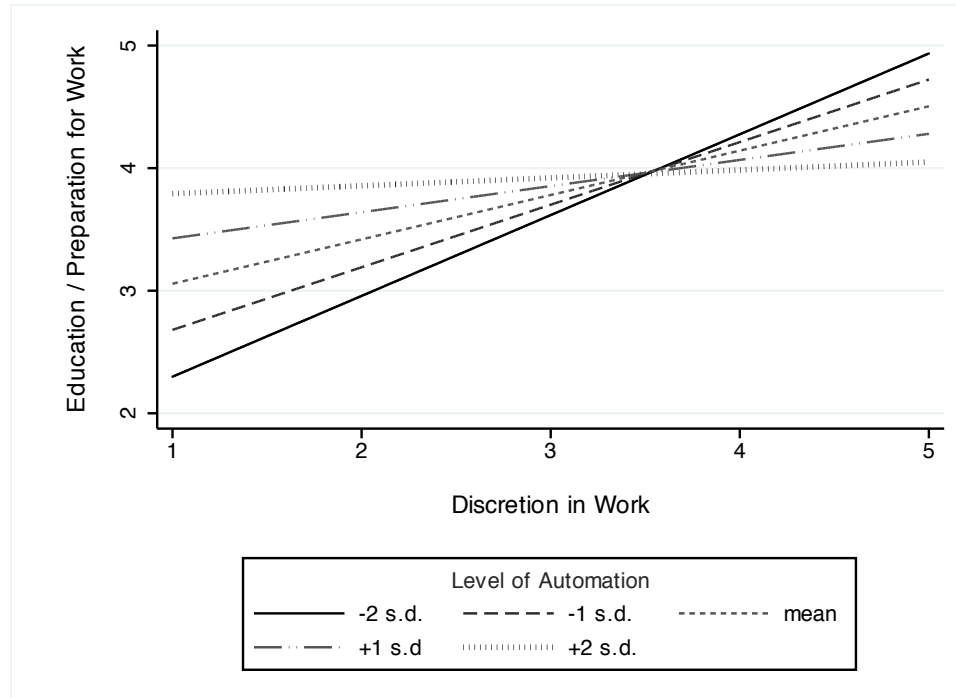


Figure V.7: Marginal Effects of Discretion Upon Education / Preparation for Work, by Level of Automation

Figure V.7 presents, visually, the marginal effect of discretion upon education/preparation for specific levels of automation. Table V.10 presents these effects by their substance (raw effect) and significance (p-value). In this case the results seem more intuitive—at low levels of automation, the relationship between discretion and education/preparation is positive and significant, while at high levels of automation this link between discretion and education/preparation becomes non-significant. In effect, automation attenuates the link between discretion and education/preparation for work.

Table V.10: Marginal Effects of Discretion Upon Education / Preparation for Work, by Level of Automation

	Marginal Effect	SE	z	p > z	95% confidence interval	
-2 S.D.	0.659	0.133	4.970	0.000	0.399	0.919
-1 S.D.	0.511	0.088	5.820	0.000	0.339	0.683
Mean	0.362	0.067	5.380	0.000	0.230	0.494
+1 S.D.	0.213	0.090	2.380	0.017	0.037	0.389
+2 S.D.	0.065	0.135	0.480	0.633	-0.200	0.330

Similarly, a different yet intuitive effect can be observed if the moderation of automation by resource control were seen in the inverse (see Figure V.8 and Table V.11). This approach seems reasonable since the main effect of resource control was only weakly significant, while that of automation was clearly significant. In this case, greater levels of automation coincide with increasingly positive and significant relationships between resource control and education/preparation.

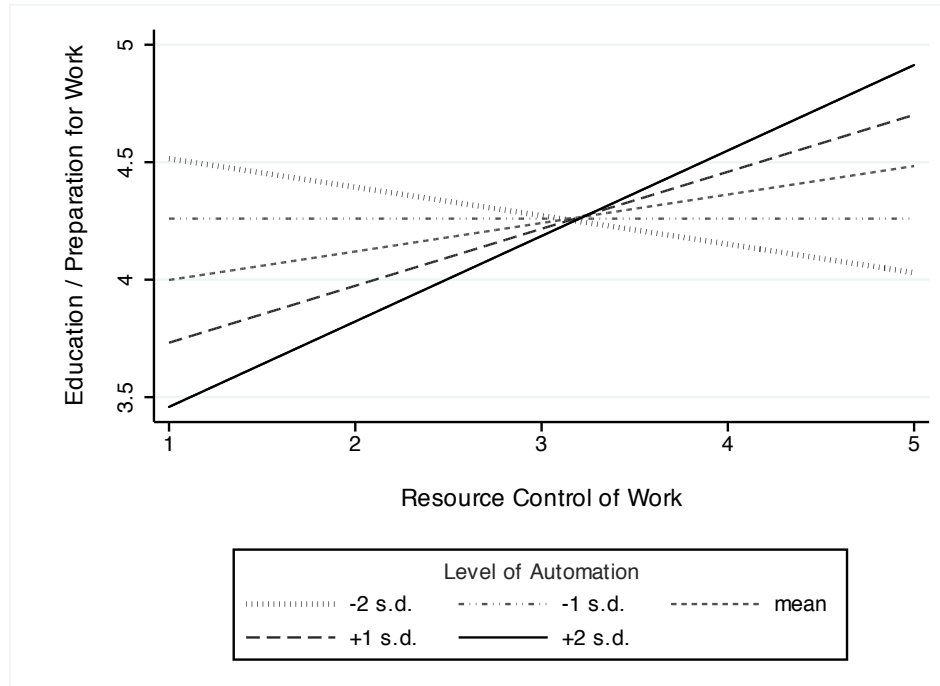


Figure V.8: Marginal Effect of Resource Control upon Education / Preparation for Work, by Level of Automation

Table V.11: Marginal Effect of Resource Control upon Education / Preparation for Work, by Level of Automation

	Marginal Effect	SE	z	p > z	95% confidence interval	
-2 S.D.	-0.121	0.123	-0.990	0.322	-0.362	0.119
-1 S.D.	0.000	0.086	0.000	0.999	-0.168	0.168
Mean	0.121	0.073	1.670	0.095	-0.021	0.264
+1 S.D.	0.242	0.094	2.590	0.010	0.059	0.426
+2 S.D.	0.364	0.133	2.730	0.006	0.102	0.625

Skill Requirements Measured as Related Experience / On-the-job Training

The results of the model developed to test those hypotheses regarding the skill requirements for work, measured as related experience and on-the-job-training, are presented in

Table V.12. The assertion of constant variance among the error terms could not be rejected ($\chi^2(1) = 0.26, p = 0.61$), and the Hausman test for any difference between the fixed and random effects coefficients proved non-significant ($\chi^2(17) = 17.31, p = 0.43$). Model two significantly improved upon the explanatory power of model one ($\chi^2(6) = 122.72, p < 0.001$), while only moderate support ($\chi^2(5) = 10.66, p < 0.1$) suggested model three improved upon model two.

Hypotheses 1(b), 2(b), and 3(b) were all rejected in this case, there being no significant link, linear or non-linear, between automation and skill requirements, when those requirements are measured as the amount of related experience / on-job training. Furthermore, hypothesis 5(b) was not supported, with the effect of the resource control-automation interaction being non-significant.

While not hypothesized, there was a moderately supported ($p < 0.1$) positive relationship between resources control and experience/training. As with the prior model, discretion positively moderated the automation/skill requirements relationship (see Table V.12), albeit with only marginal support ($p < 0.1$). The nature of this support can be seen in Table V.13, wherein only at the lowest levels of discretion (-2 s.d.) is the link between automation and experience/training significant ($p < 0.05$).

Table V.12: Regression Resulting Predicting Related Work Experience / On-Job Training

Variable	Stage 1		Stage 2		Stage 3	
	including only control variables		with addition of primary variables		with addition of interaction terms	
	Beta	Standard error	Beta	Standard error	Beta	Standard error
Main Effects						
Resource control			0.33 †	<i>0.17</i>	0.30 †	<i>0.18</i>
Discretion			1.12 ***	<i>0.16</i>	1.15 ***	<i>0.16</i>
Automation			-0.16	<i>0.14</i>	-0.11	<i>0.14</i>
Mechanized			0.47 *	<i>0.19</i>	0.49 *	<i>0.19</i>
Informed			0.67 ***	<i>0.13</i>	0.63 ***	<i>0.13</i>
Programmed Ends			-0.59 **	<i>0.20</i>	-0.59 **	<i>0.20</i>
Interaction Terms						
Resource Control x Automation					-0.11	<i>0.22</i>
Discretion x Automation					0.47 †	<i>0.25</i>
Programmed Ends x Automation					-0.32	<i>0.28</i>
Automation ^{squared}					-0.19	<i>0.16</i>
Programmed Ends ^{squared}					-0.15	<i>0.24</i>
Skills						
Content	0.06	<i>0.09</i>	0.15	<i>0.28</i>	0.16	<i>0.28</i>
Process	0.29 *	<i>0.12</i>	0.50	<i>0.35</i>	0.56	<i>0.35</i>
Complex processing	-0.11	<i>0.07</i>	1.01 ***	<i>0.20</i>	1.01 ***	<i>0.20</i>
Social	-0.28 **	<i>0.09</i>	-0.77 **	<i>0.29</i>	-0.80 **	<i>0.29</i>
Technical	0.10	<i>0.06</i>	-0.64 *	<i>0.26</i>	-0.62 *	<i>0.26</i>
Systems	0.02	<i>0.07</i>	0.28	<i>0.22</i>	0.27	<i>0.22</i>
Occupational Groups						
Managerial	1.66 ***	<i>0.44</i>	1.02 *	<i>0.43</i>	0.90 *	<i>0.43</i>
Business/Financial	0.83 *	<i>0.40</i>	0.62 †	<i>0.37</i>	0.51	<i>0.38</i>
Computer/Mathematics	0.89	<i>0.60</i>	0.77	<i>0.58</i>	0.66	<i>0.58</i>
Architecture/Engineering	1.34 **	<i>0.42</i>	1.37 ***	<i>0.40</i>	1.32 ***	<i>0.40</i>
Life/Physical/Social Science	0.58	<i>0.39</i>	0.72 †	<i>0.37</i>	0.65 †	<i>0.37</i>
Social Services	-0.21	<i>0.59</i>	0.02	<i>0.55</i>	0.00	<i>0.55</i>
Legal	0.32	<i>0.67</i>	0.16	<i>0.62</i>	0.06	<i>0.62</i>
Education/Training	-0.43	<i>0.37</i>	-0.94 **	<i>0.37</i>	-0.92 *	<i>0.37</i>
Arts/Entertainment/Media	1.54 ***	<i>0.37</i>	1.12 **	<i>0.36</i>	1.04 **	<i>0.36</i>
Healthcare Practitioner/Technical	-0.85 *	<i>0.37</i>	-0.88 *	<i>0.37</i>	-0.89 *	<i>0.37</i>
Healthcare Support	-1.50 **	<i>0.51</i>	-0.78	<i>0.49</i>	-0.79	<i>0.49</i>
Protective Services	-0.29	<i>0.43</i>	-0.22	<i>0.42</i>	-0.35	<i>0.42</i>
Food Preparation and Serving	-1.20 *	<i>0.51</i>	-0.38	<i>0.50</i>	-0.50	<i>0.50</i>
Cleaning/Maintenance	-0.04	<i>0.66</i>	0.21	<i>0.66</i>	0.07	<i>0.66</i>
Personal Care	-1.28 ***	<i>0.40</i>	-0.74 †	<i>0.39</i>	-0.76 †	<i>0.39</i>
Sales Related	0.06	<i>0.45</i>	0.19	<i>0.42</i>	0.16	<i>0.42</i>
Farm/Fishery/Forestry	0.80	<i>0.51</i>	0.84	<i>0.52</i>	0.76	<i>0.52</i>
Construction/Extraction	1.57 ***	<i>0.37</i>	2.16 ***	<i>0.42</i>	2.02 ***	<i>0.42</i>
Installation/Maintenance/Repair	1.19 **	<i>0.40</i>	1.34 ***	<i>0.42</i>	1.27 **	<i>0.42</i>
Production	-0.08	<i>0.34</i>	0.46	<i>0.36</i>	0.42	<i>0.36</i>
Transportation/Material Moving	0.53	<i>0.36</i>	0.83 *	<i>0.38</i>	0.70 †	<i>0.39</i>
Constant (Office/Administrative)	1.65 *	<i>0.68</i>	6.36 ***	<i>0.90</i>	6.33 ***	<i>0.90</i>
<hr/>						
R ²	51.07		58.57		59.05	
Adjusted R ²	49.21		56.63		56.95	
Δ Chi Square			122.72		10.66	
p - value Chi Square			0.00 ***		0.06 †	
Observations	737		737		737	

Notes:

Standard errors are italicized

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001

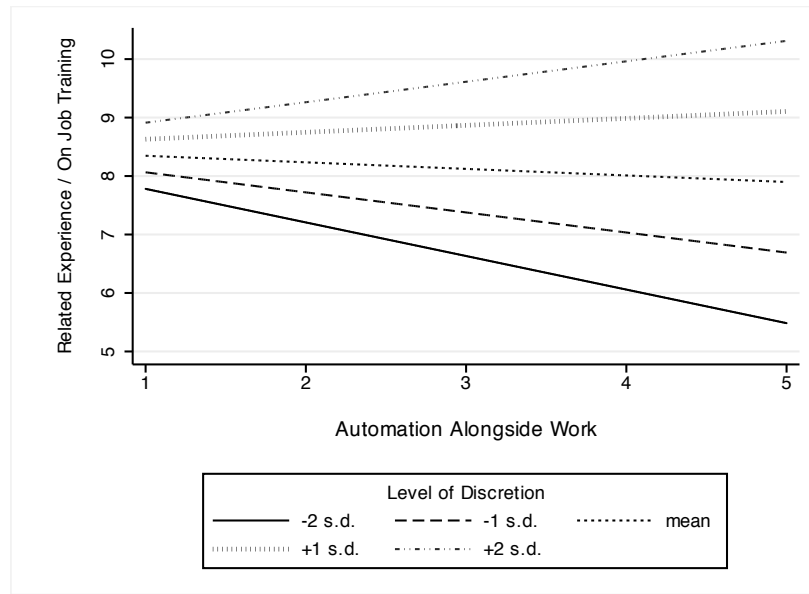


Figure V.9: Marginal Effect of Automation Upon Related Experience / On-Job Training, by Level of Discretion

Table V.13: Marginal Effect of Automation Upon Related Experience / On-Job Training, by Level of Discretion

	Marginal Effect	SE	z	p > z	95% confidence interval	
-2 S.D.	-0.574	0.281	-2.050	0.041	-1.124	-0.024
-1 S.D.	-0.343	0.187	-1.840	0.066	-0.709	0.023
Mean	-0.112	0.141	-0.800	0.427	-0.389	0.164
+1 S.D.	0.119	0.184	0.650	0.518	-0.241	0.479
+2 S.D.	0.350	0.277	1.270	0.206	-0.192	0.892

In this model, an inverse interpretation of the discretion-automation moderation proves to be inappropriate (as suggested by the significance, or lack thereof, among the underlying main effects). Across the range of levels of automation a positive and significant discretion-experience relationship persists (see Table V.14 and Figure V.10),

suggesting it is not likely the case the automation moderates this link between discretion and experience/training.

Table V.14: Marginal Effect of Discretion Upon Related Experience / On-Job Training, by Level of Automation

	Marginal Effect	SE	z	p > z	95% confidence interval	
-2 S.D.	0.912	0.203	4.500	0.000	0.515	1.310
-1 S.D.	1.139	0.162	7.010	0.000	0.820	1.457
Mean	1.365	0.198	6.880	0.000	0.976	1.754
+1 S.D.	1.591	0.283	5.620	0.000	1.037	2.146
+2 S.D.	1.817	0.385	4.720	0.000	1.062	2.573

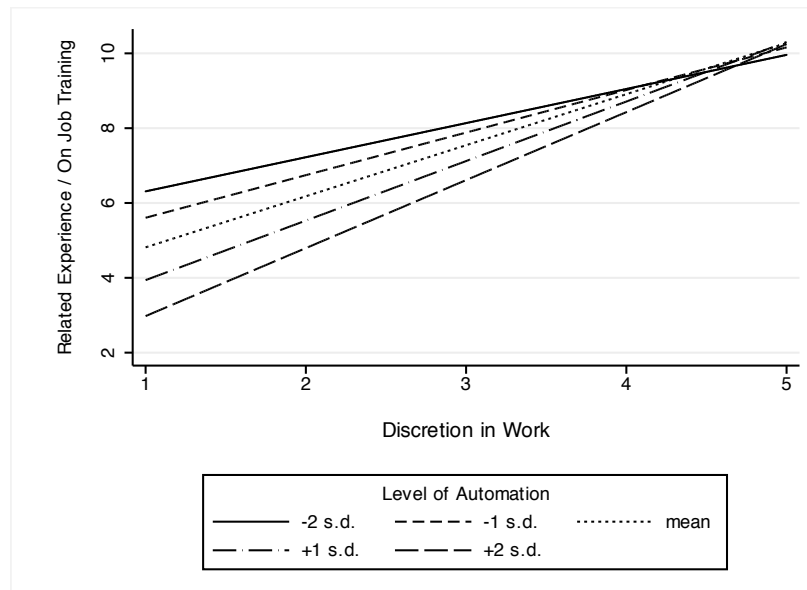


Figure V.10: Marginal Effect of Discretion Upon Related Experience / On-Job Training, by Level of Automation

Skill Requirements Measured as General Requirements

Table V.15 presents the results of the model developed to test those hypotheses regarding the skill requirements for work, measured as general skill requirements composed of both education/preparation and related experience/training. The assertion of constant variance among the error terms could not be rejected ($\chi^2(1) = 1.62$, $p = 0.20$), and the Hausman test for any difference between the fixed and random effects coefficients proved non-significant ($\chi^2(12) = 13.25$, $p = 0.35$). Model two significantly improved upon the explanatory power of model one ($\chi^2(6) = 161.53$, $p < 0.001$), while model three could not significantly improve upon model two ($\chi^2(5) = 6.95$, $p = 0.22$).

With no significant link, linear or non-linear, existing between automation and skill requirements, when those requirements are measured as the general skill requirements for work, hypotheses 1(b), 2(b), and 3(b) are all rejected. Furthermore, hypothesis 5(b) is not supported as resource control does not moderate the link between automation and skill requirements.

While not hypothesized, it is worth noting that both the informed level of work and the mechanized level of work are positively related to the general skill requirements for work. Albeit, the link between mechanization and general skill requirements is only significant at the $p < 0.1$ level ($p = 0.097$). Additionally, the level of both resource control and discretion are significantly and positively related to the skill requirements for work.

Table V.15: Regression Resulting Predicting General Skill Requirements for Work

Variable	Stage 1		Stage 2		Stage 3	
	including only control variables		with addition of primary variables		with addition of interaction terms	
	Beta	Standard error	Beta	Standard error	Beta	Standard error
Main Effects						
Resource control			0.44 *	<i>0.21</i>	0.42 *	<i>0.21</i>
Discretion			1.48 ***	<i>0.20</i>	1.51 ***	<i>0.20</i>
Automation			-0.33 *	<i>0.16</i>	-0.26	<i>0.17</i>
Mechanized			0.34	<i>0.23</i>	0.39 †	<i>0.23</i>
Informed			0.94 ***	<i>0.15</i>	0.92 ***	<i>0.16</i>
Programmed Ends			-0.99 ***	<i>0.24</i>	-1.01 ***	<i>0.25</i>
Interaction Effects						
Resource Control x Automation					0.10	<i>0.27</i>
Discretion x Automation					0.21	<i>0.30</i>
Programmed Ends x Automation					-0.46	<i>0.33</i>
Automation ^{squared}					-0.19	<i>0.19</i>
Programmed Ends ^{squared}					0.09	<i>0.29</i>
Skills						
Content	1.38 ***	<i>0.35</i>	0.58 †	<i>0.33</i>	0.60 †	<i>0.34</i>
Process	0.58	<i>0.46</i>	0.99 *	<i>0.43</i>	1.05 *	<i>0.43</i>
Complex processing	2.34 ***	<i>0.25</i>	1.56 ***	<i>0.24</i>	1.57 ***	<i>0.24</i>
Social	-0.92 **	<i>0.35</i>	-1.21 ***	<i>0.35</i>	-1.22 ***	<i>0.35</i>
Technical	-1.09 ***	<i>0.24</i>	-1.13 ***	<i>0.31</i>	-1.12 ***	<i>0.31</i>
Systems	1.15 ***	<i>0.28</i>	0.40	<i>0.27</i>	0.39	<i>0.27</i>
Occupational Groups						
Managerial	2.73 ***	<i>0.54</i>	1.80 ***	<i>0.52</i>	1.62 **	<i>0.53</i>
Business/Financial	1.55 **	<i>0.50</i>	1.23 **	<i>0.45</i>	1.05 *	<i>0.46</i>
Computer/Mathematics	2.25 **	<i>0.75</i>	1.77 *	<i>0.70</i>	1.65 *	<i>0.70</i>
Architecture/Engineering	2.23 ***	<i>0.53</i>	2.20 ***	<i>0.48</i>	2.14 ***	<i>0.49</i>
Life/Physical/Social Science	2.01 ***	<i>0.48</i>	2.19 ***	<i>0.45</i>	2.10 ***	<i>0.45</i>
Social Services	1.55 *	<i>0.73</i>	1.80 **	<i>0.67</i>	1.83 **	<i>0.67</i>
Legal	1.54 †	<i>0.83</i>	1.36 †	<i>0.75</i>	1.29 †	<i>0.75</i>
Education/Training	1.37 **	<i>0.46</i>	0.61	<i>0.44</i>	0.65	<i>0.45</i>
Arts/Entertainment/Media	2.70 ***	<i>0.46</i>	2.00 ***	<i>0.44</i>	1.93 ***	<i>0.44</i>
Healthcare Practitioner/Technical	0.47	<i>0.46</i>	0.49	<i>0.44</i>	0.49	<i>0.44</i>
Healthcare Support	-1.43 *	<i>0.64</i>	-0.46	<i>0.59</i>	-0.48	<i>0.60</i>
Protective Services	-0.45	<i>0.53</i>	-0.33	<i>0.50</i>	-0.50	<i>0.51</i>
Food Preparation and Serving	-1.90 **	<i>0.63</i>	-0.69	<i>0.60</i>	-0.87	<i>0.60</i>
Cleaning/Maintenance	-0.43	<i>0.82</i>	0.03	<i>0.79</i>	-0.15	<i>0.80</i>
Personal Care	-1.37 **	<i>0.49</i>	-0.60	<i>0.47</i>	-0.67	<i>0.47</i>
Sales Related	0.30	<i>0.56</i>	0.46	<i>0.51</i>	0.35	<i>0.52</i>
Farm/Fishery/Forestry	0.55	<i>0.63</i>	0.77	<i>0.62</i>	0.66	<i>0.63</i>
Construction/Extraction	1.28 **	<i>0.45</i>	2.19 ***	<i>0.51</i>	2.04 ***	<i>0.51</i>
Installation/Maintenance/Repair	1.50 **	<i>0.50</i>	1.70 ***	<i>0.50</i>	1.59 **	<i>0.51</i>
Production	-0.02	<i>0.42</i>	0.89 *	<i>0.43</i>	0.81 †	<i>0.44</i>
Transportation/Material Moving	0.56	<i>0.45</i>	1.14 *	<i>0.46</i>	0.97 *	<i>0.47</i>
Constant (Office/Administrative)	0.65	<i>0.85</i>	7.29 ***	<i>1.09</i>	-0.98	<i>4.83</i>
<hr/>						
R ²	65.86		72.58		72.84	
Adjusted R ²	64.56		71.29		71.36	
Δ Chi Square			161.53		6.95	
p - value Chi Square			0.00 ***		0.22	
Observations	737		737		737	

Notes:

Standard errors are italicized

† p < 0.1; *p < 0.05; ** p < 0.01; ***p < 0.001

Conclusion

So there you have it. You have reached the end of two undeniably lengthy chapters offering detailed and rather expansive coverage of the results of the analyses conducted in order to construct the scales for variables measuring the constructs described and test the hypotheses presented in Chapter III. The implications of the findings described herein for both organization theory and management practice, the limitations of these findings, as well as the future directions for research at the intersection of work, organizations, and automation shall be presented in the next (and final) chapter.

CHAPTER VII

DISCUSSION

In this chapter I will first outline the implications of the findings from this research for management theory and practice. Second, I will describe the limitations of this research when applied to theory and practice. Finally, I will outline future directions for research at this intersection of automation, work, and organizations, explaining how automation could become once again a promising subject of future research for scholars of work and organizations.

Implications for Theory

The broad question for this research has been: What are the consequences of automation for the nature of work? While pursuing this question, however, I did not treat automation as a monolithic force having a unitary impact upon work. Instead, I assumed automation is a multifarious phenomenon, taking different forms across different work environments and occupations. With each passing decade, the universe of tasks we seem capable of automating expands and, in turn, our conception of what automation “is” expands as well. During this expansion, “automation” has failed to manifest as one particular thing and instead has assumed all varieties of incarnations—for instance, robots that build automobiles, machinery that sort and process checks, server applications that provide web-based information services to millions of customers simultaneously, software that trades thousands of shares of stock in a micro-second, or

even personal mobile device “apps” that remind us where we should be and when we should be there.

Accordingly, this research asked, more specifically: Given substantial variety in automation as implemented across a wide range of occupations, do persistent patterns still emerge in the link between automation and the nature of work? I pursued this question by testing sets of competing hypotheses, each of which emerges from an influential school of thought at this intersection of work and automation. Table VI.1 presents a summary of the findings for each predicted variable (e.g., Routinization of Work, measured as both Repetitiveness and as Lack of Innovativeness), and includes results from both the intended tests of hypotheses as well as ad hoc analyses that went beyond these hypotheses.

Table VI.1 : Summary of Results, Including Tests of Hypotheses and Unexpected Findings

Hypotheses	Results by Predicted Variable				
	Routinization of Work		Skill Requirements for Work		
	Repetitiveness	Lack of Innovativeness	Formal Education and Preparation	Related Experience and Training	Education/Preparation & Experience/Training
1(a) Greater levels of routinization in work are associated with greater levels of automation	Supported	Supported			
1(b) Lesser levels of skill requirements for work are associated with greater levels of automation.			Supported	<i>Not Supported</i>	Supported
2(a) Lesser levels of routinization in work are associated with greater levels of automation.	<i>Not Supported</i>	<i>Not Supported</i>			
2(b) Greater levels of skill requirements for work are associated with greater levels of automation.			<i>Not Supported</i>	<i>Not Supported</i>	<i>Not Supported</i>
3(a) The relationship between the routinization in work and the level of automation is non-linear. Specifically, the plotted relationship between automation and routinization is S-shaped.	Mixed Support	<i>Not Supported</i>			
3(b) The relationship between the level of skill requirements for work and the level of automation is non-linear. Specifically, the plotted relationship between automation and skill requirements is in the shape of an inverted S.			<i>Not Supported</i>	<i>Not Supported</i>	<i>Not Supported</i>
4(a) Routinization of work is inversely related to occupational task discretion.	<i>Not Supported</i>	Supported			
4(b) Routinization of work is inversely related to occupational control over resources.	<i>Not Supported</i>	<i>Not Supported</i>			
5(a) Control over resources negatively moderates the relationship between the degree of automation and the level of routinization in work.	<i>Not Supported</i>	<i>Not Supported</i>			
5(b) Control over resources positively moderates the relationship between the degree of automation and the skill requirements for work.			Supported	<i>Not Supported</i>	<i>Not Supported</i>
6 The programmed nature of the means for work processes is positively related to the programmed nature of the ends for work processes.	Supported	Supported			
7 Level of automation will moderate the matched pairs relationship between the means-ends of organizational work processes.	<i>Not Supported</i>	<i>Not Supported</i>			
Ad Hoc Predictions for Unexpected Findings					
U.1 Mechanized work environments are positively related to greater levels of routinization	Supported	<i>Not Supported</i>			
U.2 Informed work environments are negatively related to greater levels of routinization	<i>Not Supported</i>	Supported			
U.3 Skill requirements for work are positively related to occupational task discretion			Supported	Supported	Supported
U.4 Skill requirements for work are positively related to occupational control over resources			Supported	Supported	Supported
U.5 The level of automation negatively moderates the relationship between discretion and the skill requirements for work			Supported	<i>Not Supported</i>	<i>Not Supported</i>
U.6 The relationship between the programmed nature of means and the end of work is positive overall but non-linear, exhibiting diminishing marginal returns	Supported	<i>Not Supported</i>			

Key Contributions

This research makes four clear contributions to our understanding of work and organizations. First, the findings from my research support not only the expectations of the deskilling hypothesis (Braverman, 1974; Glenn & Feldberg, 1979; Greenbaum, 1979; Kraft, 1979; Noble, 1984; Wood, 1982), but also a longstanding assertion within organization theory that routine technologies are associated with routine (i.e., explicit if not also repetitive) organizational challenges (March & Simon, 1958; Burns & Stalker, 1961; Perrow, 1967; Thompson, 1967; Daft & Macintosh, 1978). I find a persistently positive relationship between the level of automation and the level of routinization in work, confirming hypothesis 1(a). Whether in the form of mechanical apparatus or information processing devices, automation can be understood as a bundle of explicitly described routines programmed (by physical design or computer code) into a single machine or a set of machines. What I find is that while people and machines may be performing different kinds of routines, the nature of their work is similarly matched—routine with routine, nonroutine with nonroutine.

To be clear, however, this “routine goes with routine” link between automation and the nature of work rests in stark contrast to the expectations of the re-skilling hypothesis (Bright, 1958; Davis 1963; Shaiken, 1984; Autor et al., 2003; Levy & Murnane, 2004; Spitz-Oener, 2006), expressed as hypothesis 2(a), anticipating that increasingly automated work environments coincide with increasingly adaptive and creative work challenges. Davis (1963, p. 279) perhaps best exemplifies this re-skilling perspective, arguing that, “With automation, the person performs fewer routine operations because these activities have been transferred to automated systems... Rather than decreasing available work, automation releases man to perform work of a

higher order—more intellectual, creative, and idealistic.” Far from outdated, the reskilling hypothesis informs recent labor and education policy (Levy & Murnane, 2004).

In fact, my findings suggest that discretion and not automation (or computerization) is the more reliable predictor of less routine, more innovative/adaptive work. Hypothesis 4(a), which was supported, predicted that the routinization of work was inversely related to occupational discretion. By rejecting hypothesis 2(a) and (b) while supporting hypothesis 4(a), my findings call into question the reasoning underlying education and labor policy, which assumes that automation is the factor shifting demand for labor.

Importantly, while I rejected in most cases hypotheses 3(a) and (b), which predicted a fully non-linear relationship (i.e., either U-shaped or inverted U-shaped) between automation and routinization, I did find partial support for hypothesis 3(a), when routinization was operationalized as the repetitiveness of work. By partial support I mean that I found support for a non-linear relationship, but that relationship displayed the characteristics of diminishing marginal returns rather than a complete shift in the direction of the effect. As the level of automation increases, only at the highest levels of automation does the link between automation and routinization dampen, shifting from significantly positive to non-significant.

Both Blauner (1964) and Woodward (1965) were hard-pressed to clearly explain the convex relationship they observed between method of production and the routinization of work as the organizations under study shifted from craft to mass to continuous production. Blauner attributed the shift in work routinization to technology (i.e., automation), but he did not control for other factors. Perrow (1967), Mintzberg (1979), and Scott (2003) suggested that the control mentality that often coincides with work routinization is, in effect, a sort of ideology. According to Mintzberg (1979, p. 265),

this mentality “spills over the operating core and affects all levels of the hierarchy, from the first level of supervision to the strategic apex.” He argued, however, that automation “eliminates the source of many of the social conflicts, throughout the organization” (p. 265) and the bulk of routinized work by essentially absorbing complex interactions among routine tasks into the designs of machines and applications. Hodson (1996) used his findings to question the work of Blauner without actually controlling for any degree of automation in the context of work; only skill and autonomy (i.e., discretion) were considered as controls alongside Hodson’s measures of work organization (craft, direct supervision, assembly line, bureaucratic, and worker participation). By taking into account not only the level of automation, but also that of discretion and broad task characteristics (e.g., content, social, complex tasks), I was able to simultaneously test for alternative explanations that were tested independently in prior research.

Second, my findings add a new dimension to the literature on organizational learning (Fiol & Lyles, 1985; Levitt & March, 1988; Huber 1991, Dewett & Jones, 2001; Kane, & AlaVi, 2007) by providing evidence for the role automation can play in such learning. This evidence comes in the form of support for hypothesis 1(a), which predicted a positive link between automation and routinization (when measured as a lack of innovativeness/adaptability). While the presence of organizational routines is at times assumed to be a negative aspect of organizations, the routines of organizational bureaucracy have also been construed as evidence of adaptive and necessary organizational learning (Cohen, 1991; Langton, 1984; Levitt & March, 1988; Nelson & Winter, 1982; Walsh & Ungson, 1991; Zhou, 1993). As described by Cohen et al. (1996, p. 684), an organizational routine is an “executable capability for repeated performance in some context that has been learned by an organization in response to selective

pressures." Routines are the storehouse of organizational experience (Schulz, 1998), a function of inferences from past experiences (Levitt & March, 1988).

If increasingly explicit routines are evidence of organizational adaptation and learning, then the findings of this research take on important meaning. The increase in routinization, in the form of a general lack of innovativeness and adaptability (i.e., explicit routines), may be construed as evidence of some ongoing refinement and specificity of organizational responses to environmental uncertainty. In other words, the finding that automation begets more explicit routines supports an inference that organizations have successfully developed, by way of automation, more specific responses to contingencies in the environment. Furthermore, this finding suggests an important yet largely overlooked direction for future research, to be discussed later in this chapter: understanding the role automation might play in organizational learning.

Third, the results of this research clarify the conditions under which automation is related to the skill requirements for work. My findings support hypothesis 1(b), but do not support hypothesis 2(b), revealing a negative and direct link between automation and the skill requirements for work, when operationalized as the level of formal education or preparation for an occupation. It is important to note that this negative linkage between automation and skill requirements could also be interpreted as an "upskilling" effect— simply stated, automation enables people to do more with less (education). I find that occupations operating alongside high levels of automation are able to accomplish similar tasks (in terms of content, process, complex processing, etc) with lesser levels of formal education and preparation as compared to those occupations working alongside low levels of automation.

However, the negative moderating effect of power upon automation, supporting hypothesis 5(b), adds credence to a deskilling as opposed to an upskilling interpretation

of my findings. Additionally, the unexpected finding that automation negatively moderates the link between discretion and skill requirements further supports the reasoning underlying deskilling predictions. The logic of the deskilling hypothesis is that automation is a technology introduced by those high in power to weaken the bargaining position of those low in power (or discretion). Essentially, I find that for occupations with low levels of resource control, a significant and negative link between automation and level of education/preparation exists. For occupations with high levels of resource control, however, no significant link exists between automation and level of education/preparation. Additionally, increasing levels of automation attenuate and eventually nullify the otherwise positive link between discretion and education. In short, automation eliminates distinctions between occupations, in terms of formal education and preparation, which might otherwise exist.

The results of this research did not reveal a reliable (i.e., statistically significant) and direct (i.e., main effect) link, positive or negative, between automation and the skill requirements of work, when operationalized as the level of related work experience or on-the-job training required for an occupation. As a result, the findings, in this case, fail to confirm either hypothesis 1(b) or 2(b). Scholarly debate over the role played by automation in either decreasing or increasing specialization of labor is longstanding (Faunce, 1965; Kalleberg & Sorensen, 1979; Wood, 1982), and the level of related work experience or job training is often seen as evidence for labor specialization. However, as far as job specialization is concerned, neither the de-skilled nor the re-skilling hypothesis received direct support in my findings.

On the other hand, one of the key interaction effects inherent in the deskilling hypothesis does find support, albeit weak support, in these data: automation eliminates differences among occupations that might otherwise exist. While testing hypothesis

5(b), which focused upon the moderation of the automation-skill requirements link by resource control, I also tested automation as a moderator of the discretion-skill requirements link. I found that increasing levels of automation dampen (i.e., turn non-significant) the otherwise positive and significant relationship between discretion and experience/training. In the debate between the de-skilling and re-skilling proponents, this moderation effect is theoretically important. At low levels of automation, a positive relationship between discretion and experience/training exists. At high levels of automation, however, this link between discretion and experience/training fades to non-significance. This moderating effect, however, was significant only at the $p < 0.1$ level.

Finally, the findings from this research call into question a longstanding assertion of organizational contingency theory regarding the link between task structure and the nature of work. I found that neither discretion nor power reliably predicted the routinization of work, thereby rejecting both hypothesis 4(a) and 4(b). Perrow (1967) imagined organizational work processes existing along a continuum from the routine to the nonroutine, with the state of these work processes best matched with particular structures for control and coordination. Perrow (1967) considered the dimensions of control to be “the degree of discretion an individual or group possesses in carrying out its tasks, and the power of an individual or group to mobilize scarce resources” (p. 198). The coordinating structure of work was instrumentalized by Perrow in line with March and Simon (1958) on a continuum from coordination by planning (i.e., programmed means/ends) to coordination by feedback (i.e., nonprogrammed mean/ends).

My findings suggest that under certain conditions technology (in the form of automation, mechanization, or computerization) might substitute for the factors of organizational coordination or control otherwise introduced through aspects of task structure. Were the tested link between work processes and structure akin to that

anticipated by Perrow, I should have observed a positive link between routinization and both discretion and resource control, regardless of whether routinization was measured as repetitive work tasks or as the absence of innovativeness/flexibility in work. I find, however, that only when routinization is measured as a lack of innovativeness/flexibility is the link between discretion and routinization supported. Unexpectedly, I did find a positive link between the skill requirements for work and both resource control as well as discretion, suggesting there are conditions in addition to the raw nature of work (routine or nonroutine) that qualify individuals within organizations for the organizational affordances of discretion and power.

Implications for Practice and Policy

The relationship between automation and organizational outcomes has led to questions and prognostications from management practitioners and pundits for decades, spanning the mundane subject of operational efficiencies in the factory and the office (Attewell & Rule, 1984; Daft, 2010; Drucker, 1990; Olson & Jr, 1982), to the strategic dimensions of information advantages (Carr, 2003; Davenport & Harris, 2005; McAfee, 2006a; McAfee, 2006b; Porter & Millar, 1985; Rockart, Earl & Ross, 1996), to the possibilities for outright transformations of business processes (Ansoff, 1965; Cotteleer, Lee & Inderrieden, 2006; Hammer, 1990; Venkatraman, 1994).

In the wild, however, automation has been found to lead to both an increase in employment and a decrease, greater productivity and the lack thereof, yielding paradoxes that still perplex both scholars and managers (Anderson, Banker & Ravindran, 2003; Brynjolfsson & Hitt, 1998; Brynjolfsson, 1993; David, 1990; Santhanam & Hartono, 2003). The findings of this research contribute a new dimension to the debate over the consequences of automation for work and organizations.

The Automator's Dilemma

The results of investigatory interviews leading to this research suggest that managers typically associate automation with primarily three things: the reduction of errors, the harvesting of efficiencies, and greater operational stability if not also resiliency; in essence, greater productivity (i.e., same output from fewer people) and few if any surprises. Leonardi (2008) recently dubbed these sorts of prescribed assumptions about technology project outcomes as a discourse of inevitability. I would express these managerial aspirations for automation, colloquially, as the Bionic Man hypothesis—the implementation of automation within any system will make that system better, stronger, and faster.

Unfortunately, case studies and research into technology projects are replete with anecdotal stories and more concrete findings of over-budget, dysfunctional, and failed automation projects (Brown & Jones, 1998; Keil, Mixon, Saarinen & Tuunainen, 1994; Montealegre & Keil, 2000; Sarter, Woods & Billings, 1997). It is easy to assume that technology projects fail to meet with expectations simply because the projects themselves were poorly implemented. However, what if the automation of organizational routines has the natural and perhaps necessary capacity for unintended consequences? This emergence of work from automation may not be a function of displacement, as argued by many economist—by making work disappear into machines those people displaced are left searching around for something else to do. Neither may this emergence be a function of newfound freedom to pursue less routine types of work. But rather, it seems that automation might directly elicit new explicit and even repetitive routines.

The generally positive relationship discovered between automation and the routinization of work suggests that, by and large, managers shouldn't get what they

expect from automation. Rather than absorbing routines, automation appears to be associated with the production of more routinized work, whether we choose to see this routinization as merely more explicit (lacking flexibility or innovativeness) or truly repetitious tasks. And so, organizations program some collection of work routines into machines, only to find a set of increasingly refined work routines is required to adapt to this automation. There is perhaps no other way to characterize this result of routines breeding routines than to imagine that automation is a sort of whirligig, somehow powered by old routines while also spinning out new routines. This outcome, while seemingly paradoxical at first, makes a great deal of sense.

In essence, when we automate a task we explicitly state and rigidly program our response to some particular environmental condition (e.g., “Green means go.”). Developing these explicit statements is a learning event, akin to E.M. Forster’s (1927, p. 101) infamous phrase, “How can I tell what I think til I see what I say?” (a phrase later adapted and adopted by Weick, 1979). Once explicitly stated however, these routines built into automation become open to exceptions to the explicit rules and the cues embedded therein, fueling occasions for surprise, sensemaking, and the development of new, explicit rules required to adapt to these surprises (e.g., “Green means go, unless you see a pedestrian in the intersection.”).

Eisenhardt (2000) argued that the reformation of routines provide dynamic capabilities, the means through which “managers alter their resource base—acquire and shed resources, integrate them together, and recombine them—to generate new value” (p. 1107). I am suggesting, however, that this dynamism in response to automation results from an updated and even more explicit understanding of value previously believed to be well understood, by way of encountering exceptions to the routines that are embedded in automation. We program machines to respond to the world more

explicitly through the automation of work processes and inevitably bump into exceptions to these explicit statements. We call these exceptions “failures,” when in fact they may crucial and inevitable learning events—the sources of new work that needs to be done.

Limitations

As with any empirical inquiry, this project as outlined and undertaken was not without its limitations. However, I have attempted to reduce the impact of these limitations wherever possible. First and foremost, there may be doubts that occupations provide a sufficiently reliable a unit of analysis. For example, occupations may be so specialized within industries as to be carriers of unmeasured, industry-level effects. To allay such concerns, I remind the reader that, by and large, job incumbents who responded within each occupation studied by O*NET spanned a number of industries across the top-level of the NAICS. Furthermore, occupational domains (as defined by the SOC) were included as control variables into the tested models in order to capture any causal factors that might be specific to particular occupations but may have gone unmeasured.

A second limitation is the potential for bias given that measures employed for this research were obtained from a single method, a questionnaire. To be clear, the O*NET instruments are based upon survey items that prior research found to be reliable. Furthermore, the findings from the exploratory factor analysis suggest a significant ability to discriminate among the factors of interest, an outcome that would not be plausible were the underlying items muddled by common response bias. Essentially, response bias would have a disruptive effect upon the reliability of responses (Kline, 2005), making it difficult to distinguish factors.

Third, and as noted in Chapter 3, the hypotheses tested in this research treated automation as a broad and generalized phenomenon, spanning occupations, organizations, and industries. I admit that the generalizable relationships I uncovered in this analysis may fade under a more precise inquiry into the impacts of automation, were automation itself measured more discreetly. However, I have operated under the assumption that social systems are, in fact, complex phenomena (Boulding, 1956). In the context of this complexity, the more meaningful statements that can be made about the relationship between technology, the nature of work, and the social structure of organizations, may be those statements that are the most general.

Fourth, with its reliance on survey data, the research reported here investigates the effects of subjective perceptions rather than those of objectively measured phenomena. Depending upon the reader's perspective this matter of perceptions is either a limitation posed by, or a valuable asset of, survey-based research. Importantly, and as noted in Chapter IV, no significant differences in the measures employed for this research were found between the self-reported scores of job incumbents and the assessments of work requirements made by expert analysts during a pre-test of the O*NET methods. Furthermore, not only is the inter-rater reliability generally quite high among responses within occupations, but also these data were gathered from individuals spanning different organizations, industries, and locations throughout the United States. When a number of individuals from independent settings come to strikingly similar conclusions about the context of their work, I do believe the coincidence warrants attention as a reasonable and real phenomenon.

Even if this research is framed as a study of perceptions of work and automation, its contributions remain significant. Little research has been published pursuing the link between perceptions of automation and perceptions of other aspects of work or

organizations. Let me put this claim in context. A search within the full text and summaries of a broad range of academic journals via Google Scholar for the phrases “perceptions of work” and “perception of work” return more than 6,700 results. A similarly conducted search for the phrases “perception of automation” and “perceptions of automation,” however, return only fifty results. There appears to be some breathing room for new research pursuing the consequences of our perceptions of automation.

Finally and frankly, a significant limitation to this research (at least in my mind) would be what I was not able to discover. I am disappointed that I was not able to find a moderating role for automation within the means-ends relationship. My concern is that the rather clear link I did find between automation, the routinization of work, and the skill requirements for work might somehow provide fuel for the sort of technological determinism I find hard to accept. The view that work (routines or tasks or jobs or occupations) disappears into machines is a woefully constrained, zero-sum view of human labor. Essentially, by way of this perspective, the full domain of human work is seen as some finite entity such that the more of that domain that might be enacted by a machine, the less of that domain that would be left for the rest of us to perform. The alternative extreme to this technological determinism, the re-skilling hypothesis, still sees work as a zero sum game (albeit, a sum of two factors). From this perspective, the pool of work is divided into two categories, routine and nonroutine. While this reskilling perspective has been characterized as seeing technology as a sort of liberator from routine work, this characterization overlooks the unstated endgame: As more routine work is programmed into machines, we will all eventually find ourselves swimming in an over-crowded pool of nonroutine labor. Unfortunately, my findings are not able to highlight a clear pathway out of this dilemma.

Future Research

Any jazz performer asked to show you his or her “fake book” will most likely pull out a thick volume of musical text with tattered pages and bandaged bindings. The fake book, far from fake, offers pages of very real musical notes comprising the stylized progressions and melodic themes—the vamp—for compositions considered to be the standards of jazz performance. Decades after their introduction, these jazz standards are continually re-interpreted by musicians, providing the substance for an ongoing musical alchemy, the product of which is new performances and recordings.

While organization theory has no official fake book, there still exist a number of themes within the literature providing a “vamp” that is continually re-interpreted through new research questions and theoretic explanations. Routines have provided such a theme for understanding organizations and work for reasons Pentland and Reuter (1994, p. 484) highlighted eloquently: “Routines occupy the crucial nexus between structure and action, between the organization as an object and organizing as a process.” I believe that routines also occupy the crucial nexus between action and automation, between work as performed by apparatus or applications (i.e., machines) and as performed by people.

An important contribution I have made in this research arrives not by way of the findings but vis-à-vis the approach. I have intentionally linked automation with work and organizations through a common theme: organizational routines. This approach stands in contrast to more recent work that differentiates between routines and technologies. Leonardi (2010) supports this differentiation by way of “imbrication,” arranging truly distinct elements in overlapping patterns such that these elements might function interdependently. In his words, “Imbrication of human and material agencies creates

infrastructure in the form of routines and technologies that people use to carry out their work” (p.1). I think this discrimination between technologies and routines, while perhaps empirically convenient, is a mistake. Both people and machines enact routines. It is simply difficult for most researchers to look inside the machines (and even people) to describe the routines enacted therein. Making a distinction between routines and technologies, however, is ultimately false—the latter is simply an incarnation of the former.

By seeing automation as some manifestation of routines, we can pull together the loose ends of our otherwise disparate definitions of Technology (with a capital “T”). In effect, our conceptions of Technology—as a technique, a tool, or a transformation—converge, quite substantively, within automation. Automation is a tool that transforms through explicit techniques. Furthermore, by way of routines we have a way of bringing automation back into our understanding of organizations

This research scratched the surface of what I believe to be a large, untapped market for understanding modern organizations as truly socio-technical systems wherein people and machines work together to get things done. In the following section I will highlight directions for future research, focusing in particular upon the nature and study of organizational routines. I will characterize organizational routines in three ways: **nouns**, as explicit patterns of action; **adjectives**, as standardized and repeated actions; and **artifacts**, as designed into machines.

Routine as Noun

As a noun, the word “routine” has been used to describe the existence and performance of explicit patterns of physical or mental action (Feldman, 2000; Nelson & Winter, 1982; Pentland & Feldman, 2005). As noted in Chapter II, organization structure

has been imagined as deed, existing within routines characterized as “programmed procedures” (March & Simon, 1958), “complex patterns of action” (Pentland & Rueter, 1994), “standard operating procedures” (Cyert & March, 1963), “know-how” (Simonin, 1997; Teece, 1998), “grammars of action” (Pentland & Rueter, 1994), or “procedural memory” (Cohen & Bacdayan, 1994). A large volume of social science research suggests that individual cognition as well as social behaviors involve the application and re-combination of routines, in the form of such things as organizational processes, individual roles (Goffman, 1959), scripts for social interaction (Shank & Abelson, 1977), and decision-making heuristics (Cyert, Dill & March, 1958; Eisenhardt, 1989; March & Simon, 1958).

In fact, the history of organization theory can be read as a history of our understanding of routines themselves. For Weber (1947), the ideal type of bureaucracy holds impersonal routines and regulations, rather than the opinions of individuals or the qualifications of social rank, as the final arbiters of appropriate action. Burns and Stalker (1961) considered the ongoing refinement of organizational routines (particularly those employed in mass production) as characteristic to the ideal-typical mechanistic organization, wherein “functionaries tend to pursue the technical improvement of the means rather than the accomplishment of the ends of the concern” (Burns & Stalker, 1961, p. 120). For Katz and Kahn (1966), routines—i.e., patterns of behavior—were nearly synonymous with individual roles within organizations. Routines, supported by rules and regulations, are considered so coincidental with the mechanistic vision of bureaucracy that Schulz (1998) noted, “Bureaucratization is regarded as a rule generation process turned loose.”

Importantly, a lexicon for organizational routines might provide a common language for modeling and understanding what both people and machines do within

socio-technical organizations. The “concept, cue, and connection” approach to reasoning described by Weick (1979, 1995) would perhaps provide a usable method for modeling organizational routines. Figure VI.1 presents a basic design for this sort of modeling, with concepts (i.e., the basic elements of reasoning), cues (i.e., the triggers that signal the presence of a concept) and connections (i.e., the reasoning that links concepts). Figure VI.2 through Figure VI.5 present the evolution of a routine as possibly modeled, from the initial routine (e.g., “Green means go,” Figure VI.2), to clarifying cues (what constitutes “green” within the color spectrum, Figure VI.3) to the refinement of that routine through exceptions (green leaves in the forest don’t mean go, Figure VI.4) and ideal conditions (green really means go in the context of a stoplight, Figure VI.5).

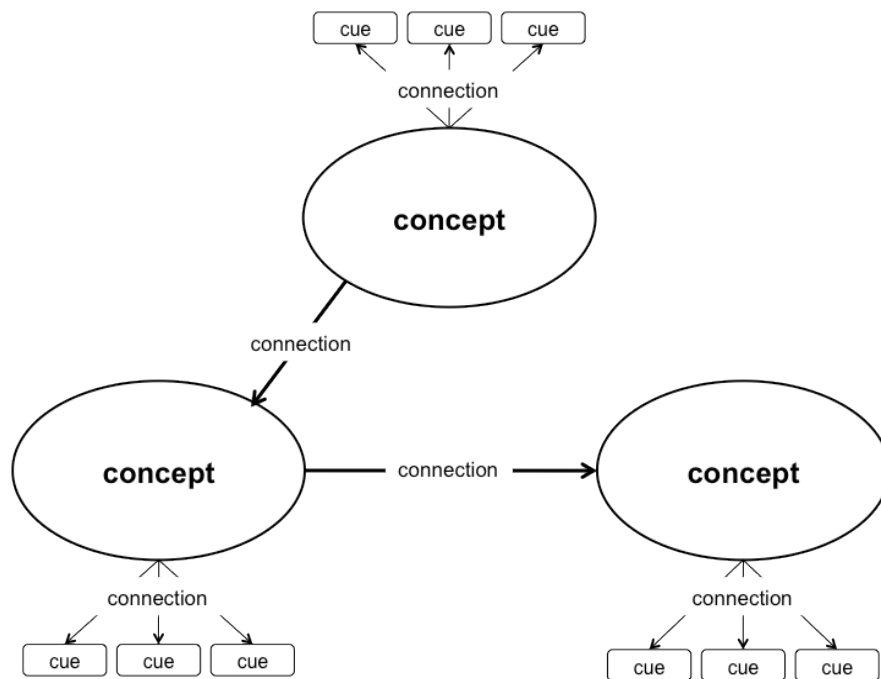


Figure VI.1: Modeling organizational routines; Concept, cue, and connection.

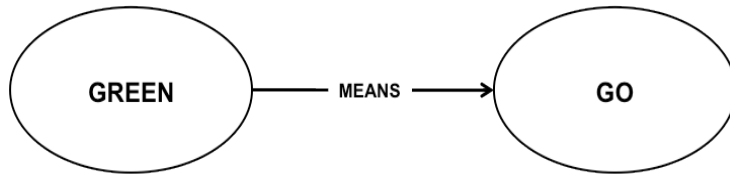


Figure VI.2: Modeling a basic routine, “Green means go.”

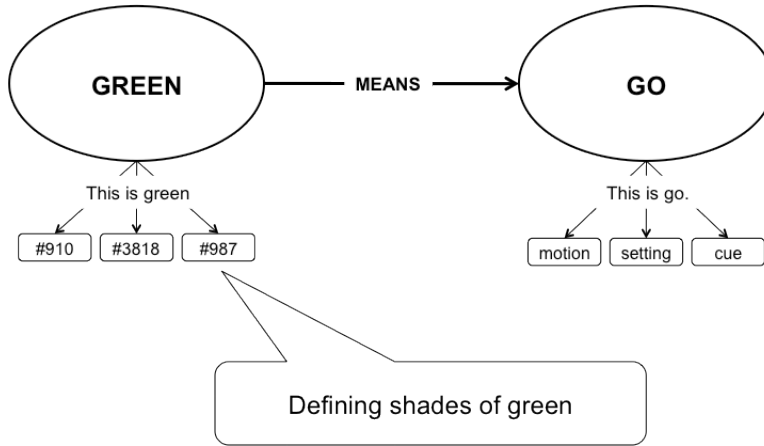


Figure VI.3: Defining cues within routines

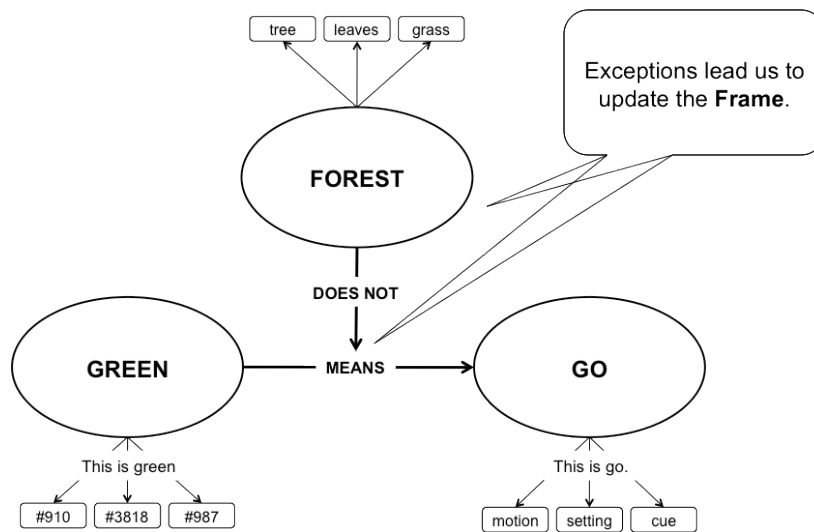


Figure VI.4: Modeling exceptions within routines.

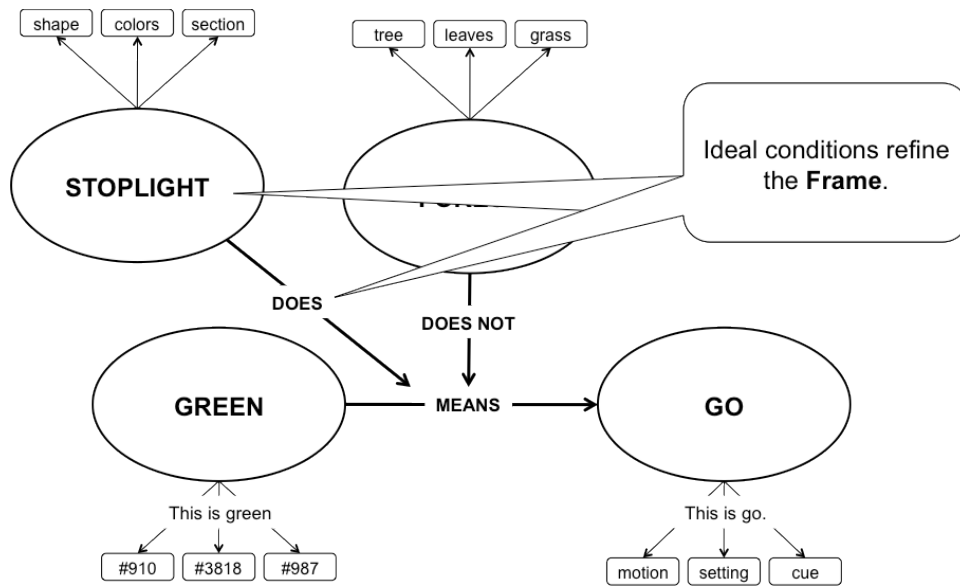


Figure VI.5: Modeling ideal conditionals within routines.

Importantly, if routines were modeled across both people and machines we could begin to investigate more fully the assumption we hold about which type of routines tend to be programmed into machines rather than enacted by people. Is it altogether true that people perform routines more likely to involve sensing the environment, while machines are involved in “crunching the numbers?” Under which conditions might these roles reverse? What are the factors that predict whose routines are more likely to be programmed into machines? Was Simon correct, —s comparative advantage, whether measured in terms of time, effort, or raw price the determining factor for the assignment of tasks across people and machines?

Furthermore, such a lexicon of routines might be used to investigate (and test) assertions made earlier in this chapter involving the role automation plays in organizational learning. Upon the introduction of automation within some process, we might be able to observe the subsequent refinement of routines as a result of unanticipated outcomes. For example, early mass email applications simply blasted the

same email to an entire list of recipients, regardless of any individual's expressed (or implied) interest in the discreet contents of the email. As recipients "unsubscribed" from these lists, organizations began to question how the interests of list members had been categorized. As a result, signup forms began to ask more detailed questions about the interests of new list members and the rules for mass email expanded to include the option of more targeted communications—only certain groups of individuals received specific mass mailings based upon the likelihood of individual interest in the content of the email. An initial routine that was quite general (send this email to everyone on the list) became more refined over time, leading to a more variegated understanding of the customer as well as more discreetly programmed routines.

Finally, as a result of a more nuanced language through which to model organizational routines, we have the opportunity to look rather closely at the role automation plays in the process of creative destruction, a phenomenon largely attributed to Shumpeter (1942), but in fact earlier highlighted by Sombart (1902) and Nietzsche (1885, 1968, p. 59) who wrote: "Whoever must be a creator always annihilates." This process has been studied at great length from a very macro perspective—the extinction of certain organizations and occupations alongside the birth of new organizations and occupations. What we lack, however, is a more thorough understanding of the underlying processes through which this transfer between creation and destruction occurs.

Routine as Adjective

Ironically, routines have been classified as either routine or non-routine. As an adjective, "routine" implies wholly repetitive actions (Gersick, 1991), or responses to stimuli that are without exception (Perrow, 1967) even to the point of being a truly mindless aspect of action (Ashforth & Fried, 1988; Langer, 1989). Stinchcombe thought

of the routineness of organizational routines as akin to a computer program for the mind, such that "once a routine is switched on in the worker's mind, it goes on [to] the end without further consultation of the higher faculties" (Stinchcombe, 1990, p. 63).

This research resulted in unexpected findings, leading to key questions for our ongoing understanding of routines as adjectives. First and foremost, my findings suggest there is more work to be done in terms of our understanding and acceptance of the relationship between the means and the ends of organizational routines. In support of hypothesis six, I find that the programmed nature of the means and ends of work are indeed positively related, as suggested by March and Simon years ago. However and unexpectedly, this link between the programmed means and ends of work is not wholly linear, but rather is non-linear (see results in Table V.2, predicting the repetitiveness of work). The means-ends framework developed by March and Simon (1958) has provided a theme upon which a number of subsequent approaches to understanding organizations have been based. Simon (1964) suggested that such means-ends chains in fact mediate actions and goals, firmly planting this framework within the behavior of organizational action. When not directly based upon the March and Simon framework, multiple foundational theories of organization structure posit some dominant continuum between the programmed and unprogrammed, the routine and the non-routine (Perrow, 1967), the mechanistic and the organic (Burns & Stalker, 1961) nature of organizational routines. Perrow (1967), while providing for firms that might occupy the off-diagonals of his framework for organizational technologies, reckoned only a few cases might actually fall into these cells.

The premise that the programmed nature of organizational routines somehow varies across a continuum of matched means-ends pairs is an elegant, simple, yet largely taken-for-granted relationship in organizations research. I believe only one

empirical test of this means-ends framework has been conducted (Bourgeois, 1980), and while the findings from that study did in fact contradict the expectations of March and Simon, the implications were limited by the small sample (67 executives 12 corporations). As such, a test of this framework, by way of a large, broad sample of individuals across a range of organizations, was long overdue.

Hypothesis 7 predicted that the level of automation alongside work would negatively moderate the otherwise positive relationship between the programmed means and ends of organizational routines, thereby explaining the convex means-ends relationship. Unfortunately, this hypothesis anticipating the augmentation of organizational routines by automation was not supported. As such, I have been able to contribute to the short list of findings that call into question the long-held assumption of a uniquely positive means-ends relationship, while unable to offer a more substantial explanation for the observed non-linear relationship. Perhaps the diminishing returns from organizational routines, as observed by Schulz (1998), simply transfer to the mean-ends relationship as a function of organizational learning. However, the root cause for these diminishing returns remains untested explicitly and, therefore, unclear.

Second, while no hypotheses were presented regarding the relationship between informed work and the routinization of work, the links I discovered challenge the reasoning underlying both the deskilling and the reskilling hypothesis. I find that increasingly informed work coincides with more repetitive yet also more innovative/adaptive work. However, central to the expectations of the reskilling hypothesis, as stated in hypothesis 2(a), is the assertion that computers are substitutes for routine labor but complements of nonroutine labor. Simply stated, increasingly informed work should be associated with less routine work, both in terms of repetitiveness and innovativeness/adaptability. Conversely, the deskilling hypothesis

would expect that technology in general, whether as automation or computerization (i.e., informed work), would be associated with more routine work, as stated in hypothesis 1(a) that requires less skill, as stated in hypothesis 2(b). Importantly, alongside the routine-yet-adaptive mixture of work characteristics I did find a positive link between informed work and skill requirements, whether operationalized as the level of educational/preparation or related experience/training.

This mixture of work characteristics and skill requirements suggested by my findings—repetitive-yet-adaptive mixture of routinization combined with increasing skill requirements—leads to a set of important questions for subsequent research. Is it the case that increasingly informed work requires the increasingly adaptive and flexible application of an expanding portfolio of repeated yet also specialized tasks? If so, then why does this not seem to be the case for mechanized work? Our understanding of the specialization of labor will need to adapt this sort of highly trained yet routinized (as in repetitive) work in the context of computerization. Are we seeing a deskilling effect in the context of computerization within some categories of occupations while seeing a re-skilling effect within other categories—thereby suggesting that both the deskilling and reskilling hypotheses ring true, but under distinct conditions? If so, then which conditions determine this difference in effect?

Routine as Artifact

As an artifact, automation entails a machine capable of performing material- and/or information-processing tasks. The performance of such tasks by machines requires, in effect, that routines be somehow imbued into artifacts. Orlikowski & Barley (2001, p. 121) describe automation as, “bundles of material and cultural properties packaged in some socially recognizable form such as hardware and / or software.”

Often in research, the meaning of the term “automation” appears taken for granted. For instance, while Parthasarthy et al (1992) outline a typology of and framework for the varieties of automation, these authors never define the term “automation” itself. Lipstreu (1960), in one of the earliest articles published in the *Academy of Management Journal*, investigates a series of hypotheses regarding the impact of automation upon various aspects of work and organizations. Unfortunately, Lipstreu does not define automation as it was considered for his research.

Quite frankly, while lacking a clear definition for automation, many approaches to automation suggest that once programmed into machines, work disappears. Blau, et al. (1976, p. 21) described technology itself quite bluntly as, “the substitution of equipment for human labor.” We can perhaps find no better expression of this premise that automation substitutes for human labor than that found in the popular press. For example, Goodman (2010) explained a recent increase in joblessness as follows:

Automation has helped manufacturing cut 5.6 million jobs since 2000—the sort of jobs that once provided lower-skilled workers with middle-class paychecks. “American business is about maximizing shareholder value,” said Allen Sinai, chief global economist at the research firm Decision Economics. “You basically don’t want workers. You hire less, and you try to find capital equipment to replace them.”⁸

What makes automation such a puzzling, at times frightening, and in my opinion altogether interesting aspect of organizations is the extent to which the phenomenon blurs the line between that which is apparatus and that which is work. In fact, by replacing the word “machine” with the word “person” in the definition of automation used in this dissertation, we likely have an acceptable definition for work (the performance of a task, manual or mental, in whole or in part by a *person*). While some readers might question a definition if it can be so easily re-positioned from one form to the next, I think

⁸ Goodman, P. S. (2010). Despite signs of recovery, chronic joblessness rises. New York Times [Web page]. Retrieved from <http://www.nytimes.com/2010/02/21/business/economy/21unemployed.html?>

this transitivity is quite important. Is it in fact true that automation is a nearly perfect substitute for human labor, flawlessly replacing human labor? Alternatively, is automation an imperfect if not quirky substitute—and this quiriness matters?

Frankly, testing for the true substitution of human labor by machines would require a simple experimental condition—assign the same task to a machine and to a human. In fact, this sort of condition would also describe a test between two controversial subjects—the automation and the raw outsourcing of work. I argued earlier in this chapter that the automation of routines leads to the emergence of exceptions to these routines and the opportunity for organizational learning. Does outsourcing tasks move these sorts of learning opportunities “offshore,” while automating tasks leaves the learning potential “in-house?”

On the question of perceptions of automation, what do people think about automation in the workplace? From this rather broad and frankly naïve question it would seem that a host of more explicit research questions emerge. How do our perceptions of automation relate to key work constructs like autonomy, efficacy, justice, and even job satisfaction? Front and center in the today’s debate over information overload (Wright, 2008; Carr, 2010; Shirky, 2010) are questions about whether and how automation (beyond information design) assists (or hinders) our ability to find and make sense of overwhelming blocks of information.

Returning to a macro-organizational level of inquiry, a number of key research questions relate to the role automation now plays in organizational forms. Are previously untenable forms of production, such as mass customization (Victor, et al, 2000; Salvador 2009), in fact tenable by way of this human-machine collaboration? If so, how and under what conditions do organizations accomplish this form of collaboration? Has a new sort of “cyborgated” organization emerged by way of automation, wherein the behaviors of a

network of machines—a silicon shell beyond the iron cage, if you will—buffer the human organization from unpredictable variations in the environment.

One further direction for future research concerns the position held by automation within the hierarchy of organizational authority. Does automation wield a sort of authority amidst organizational hierarchies akin to that decried by Parsons (1947) as professional (as if an expert), or rather that ascribed to the bureaucratic type of authority described by Weber (1947)? On this distinction between professional and bureaucratic authority, Blau (1968, p. 455) wrote:

Professional authority rests on the certified superior competence of the expert, which prompts others voluntarily to follow his directives because they consider doing so to be in their own interest. Bureaucratic authority, in contrast, rests on the legitimate power of command vested in an official position, which obligates subordinates to follow directives under the threat of sanctions.

Alternatively, has automation been granted its own distinct sort of authority, one truly technocratic in nature (i.e., based upon beliefs we hold about the fallibility or infallibility of machines) given its ability to trump the credentialed sort of authority described by Burrell (1989). Alternatively, does automation function as a sort of wormhole for responsibility, an apparatus into which we toss decision-making rights in order evade individual responsibility by blaming errors on the random glitches of machines?

Conclusion

The intent for this dissertation was to return to questions asked rather early in the history of the Academy regarding the impact of automation upon the nature of work. My hope at the outset was that this empirical inquiry might, at the very least, refine the questions themselves. “Electronic ghosts” have been aspects of organizational life for nearly a half-century, arriving within organizations in many forms, from the complex to

the seemingly incidental (e.g., robotic production equipment, autonomous trading programs, expert engineering systems, calendar management software). Prestigious management journals have been rather silent on the issue of automation, its impact upon organizations, and the challenge of managing amidst this interdependent mashup of people and machines. As such, I have attempted to make just a little bit of noise in the context of this silence.

I have firmly staked the issue that is automation within one of the more foundational concerns of organization theory—the relationship between the technology and the social structure of organizations. The critical debates and contradictory findings surrounding this technology-structure relationship have perhaps suggested only one reliable finding: the relationships among technology, work, and social structure are everything but straightforward. The results of this project however, suggest that the link between automation and the routinization of work is quite straightforward. The more automated an occupation is, the more routine is that occupation, requiring less innovation or adaptability, and less education or related experience.

Within this dissertation, automation was considered rather broadly, as the assignment of a task, physical or mental, in whole or in part, to a machine. More specifically, given the nature of the data employed for empirical analysis, automation occurs when a number of distinct individuals, in distinct work settings, similarly describe their work context as one into which some level of automation has been incorporated. Admittedly, such a broad-brush stroke is both a benefit and a curse of macro-level analysis. While some might criticize such a broad consideration of automation, I believe this breadth was appropriate. Conceiving of automation generally permitted an analysis that could take into consideration the diversity of those technologies that now constitute automation, across a wide range of organizational, industrial, and occupational contexts.

I presented contradictory hypotheses regarding the impacts of automation upon the nature of work. These competing perspectives were held together, however, by a common theme—the existence and nature of routines. Routines have provided a backbone for organization theory over a great many decades, most likely because the nature of work and the nature of organizations are undeniably connected at the hip. My hope for this dissertation is that the research herein might not only contribute to our theoretical understanding of technology and its relationship with work and organizations, but also further inform certain outstanding conflicts regarding the impacts of automation upon organizations and the individuals who (in some cases, used to) who work therein.

I shall end this dissertation by describing the moment at which the project began. During a family trip back to Chicago, while walking along the Chicago River towards Union station to catch a late night train, I found myself on the boardwalk between Madison and Monroe streets. From this particular spot I could peer across the river and through huge windows, which previously darkened for security now offer a clear view into what once was the trading floor where I worked for nearly a decade. All that remained of that exchange floor were the steel casings that previously supported the walls of multi-colored screens and the “pits” within which I shoved and screamed while doing math in my head in order to make a living. Instead of trading floors, the exchange now predominantly manages a network of computers that autonomously perform the tasks previously performed by floor traders such as myself. The substance of such a disruptive change that took decades to unfold struck me solidly in a single moment...

...I am now a ghost somewhere in that shell.

APPENDIX A: E-LAB SURVEY

OUTGOING EMAIL TO RANDOMLY SELECTED ELAB PANELISTS

EMAIL SUBJECT: You're invited to participate in Vanderbilt eLab study, developed by David Touve and conducted by Vanderbilt University.

Dear {eLab User/Nickname},

Congratulations! You were randomly chosen from the Vanderbilt University eLab Panel to participate in a brief study. This study should take about 10-15 minutes to complete.

Your participation in this study is voluntary. Should you choose to participate, you may complete this study at any time of your choice during the next 7 days. We ask that you find a quiet time and location to sign-in to the study, and to try and minimize any outside distractions.

If you complete the study, you will be entered into one of several drawings for a cash prize of \$50.

The purpose of this study is to determine which questions and phrases seem to best match a set of concepts of interest to our research. During this computer survey, we will be asking you to select those questions or phrases, from a set of alternatives that seem to best match or measure some concept of interest, or a clear lack of that concept. For all of these decisions we ask you to make during this study, there are no right or wrong answers -- only your opinions matter.


Your individual results in the study will be kept anonymous (a random code is used in place of any personal identifiers) and you will not be identified in the data that will be collected, or in the results that will be reported. Furthermore, your responses to this survey will remain confidential; Only the researchers conducting this study (David Touve and Bruce Barry), and the eLab technical team (for the purpose of conducting the study online) will have access to these data.

You must be 18 years of age or older to participate in this study. If you have any questions about this study, either before or after your choice to participate, please contact David Touve, by email (david.touve@vanderbilt.edu), or by telephone (615-322-1318). For technical problems while taking the survey, please contact the eLab technical team (email elab@owen.vanderbilt.edu)

To participate in the study, please proceed to the following URL:
<http://elab.vanderbilt.edu/experiments/foo.html>

Thanks for your participation in our research.

David Touve
PhD Candidate, Management - Organization Studies
Owen Graduate School of Management
Vanderbilt University
david.touve@vanderbilt.edu
(615) 322-1318

eLab Experiment

Help

Welcome to the eLab Research Study, eLab Admin!

Before we begin the study, we'd like to ask you a few questions about yourself and your use of the Internet.

Please answer the following questions by clicking once in the box that best describes your answer.

How much time would you estimate that you personally use the Internet?

- over 40 hours a week
- over 20 and up to 40 hours a week
- over 10 and up to 20 hours a week
- over 5 and up to 10 hours a week
- over 1 and up to 5 hours a week
- one hour a week or less
- prefer not to say

When did you start using the Internet?

- less than 6 months ago
- over 6 months and up to a year ago
- over 1 year and up to 2 years ago
- over 2 years and up to 3 years ago
- over 3 years and up to 5 years ago
- over 5 years ago
- prefer not to say


What best describes the type of connection to the Internet you are using right now?

- Dialup modem
- ISDN
- Cable, DSL, ADSL, Satellite
- T1/T3
- Other

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Manipulation:

Screen 1 of 8

 eLab Experiment

Help

Concept: AUTOMATION

Definition: The performance of some task, manual or physical, in whole or in part, by a machine.

Instructions: Please select **as many** of those questions listed below that you think are a good way to assess or measure *Automation*, as defined above in red, or a *lack of Automation*.

(REMEMBER: You can select more than one question listed below)


- In your current job, how often are you exposed to whole body vibration (like operating a jack hammer or earth moving equipment)?
- In your current job, how often are you exposed to extremely bright or inadequate lighting conditions?
- How important is knowledge of biology to the performance of your current job?
- How important is working with computers to your current job?
- How important is a service orientation to the performance of the occupation?
- How important is controlling machines and processes to the performance of your current job?
- How important is monitoring processes, materials, or surroundings to the performance of your current job?
- How important is quality control analysis to the performance of the occupation?
- How important is equipment maintenance to the performance of the occupation?
- How important is economics and accounting knowledge to the performance of your current job?
- How important is knowledge of personnel and human resources to the performance of your current job?
- How important to your current job is keeping a pace set by machines?
- How much contact with others (by telephone, face-to-face, or otherwise) is required to perform your current job?
- How important is knowledge of medicine and dentistry to the performance of your current job?
- How automated is your current job?
- How important is mechanical knowledge to the performance of your current job?
- In your current job, how often do your decisions affect other people or the image or reputation or financial resources of your employer?
- How much time in your current job do you spend making repetitive motions?
- How often does your current job require that you become exposed to diseases or infection? This can happen in patient care, some laboratory work, sanitation control, etc.
- How important is operations analysis to the performance of the occupation?

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Manipulation: N / A

Change Factors

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eLab Experiment

Help

Concept: ROUTINIZATION

Definition: The extent to which when something happens at work, you know what that something is and you know exactly what to do in response. When routinization is very high, individual choice is simplified by the presence of clear rules and limited options for responding to specific events. Also, the greater the repetitiveness of individual activities (mental or physical), the greater the routinization of work.


Instructions: Please select **as many** of those questions listed below that you think are a good way to assess or measure *Routinization*, as defined above **in red**, or a *lack of Routinization*.

(REMEMBER: You can select more than one question listed below)

- Job requires being open to change (positive or negative) and to considerable variety in the workplace.
- Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems.
- How much time in your current job do you spend making repetitive motions?
- How important is knowledge of computers and electronics to the performance of your current job?
- How automated is your current job?
- How important is thinking creatively to the performance of your current job?
- How important is active listening to the performance of your occupation?
- How important is time management to the performance of the occupation?
- How often does your current job require that you be exposed to radiation?
- How important to your current job are continuous, repetitious physical activities (like key entry), or mental activities (like checking entries in a ledger)?
- How important is developing and building teams to the performance of your current job?
- How important is writing to the performance of the occupation?
- How regular is your work schedule on your current job?
- How important is operation and control to the performance of the occupation?
- How responsible are you for the health or safety of other workers on your current job?
- How important is knowledge of education and training to the performance of your current job?
- If someone were to be hired to perform this job, how much apprenticeship would be required?
- How important is providing consultation and advice to others to the performance of your current job?
- How much freedom do you have to determine the tasks, priorities, or goals of your current job?
- How important is cooperation to the performance of your current job?

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 Manipulation: N / A
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eLab Experiment

[Help](#)

Concept: SKILL REQUIREMENTS

Definition: The general level of experience, education, and/or specialization (meaning: special training) that is required to perform some task or occupation.

PLEASE NOTE: This definition refers to a general assessment of experience, education or skills specialization. We are NOT interested in measuring specific industry, or occupational skills (for example: medical knowledge, accounting skills, etc).

Instructions: Please select **as many** of those questions listed below that you think are a good way to assess or measure *Skill Requirements*, as defined above in red, or a *lack of Skill Requirements*.


(REMEMBER: You can select more than one question listed below)

- How frequently does your current job require telephone conversations?
- How important is developing and building teams to the performance of your current job?
- How important is knowledge of history and archeology to the performance of your current job?
- How important is systems evaluation to the performance of the occupation?
- Indicate the highest level of education that you have completed.
- In your current job? how often do you wear specialized protective or safety equipment, such as breathing apparatus, safety harness, full protection suits or radiation protection?
- If someone were being hired to perform this job, indicate the level of education that would be required.
- In your current job, how often are you exposed to extremely bright or inadequate lighting conditions?
- How important is knowledge of medicine and dentistry to the performance of your current job?
- How important is knowledge of personnel and human resources to the performance of your current job?
- If someone were being hired to perform this job, how much related work experience would be required? (That is, having other jobs that prepare the worker for this job)
- If someone were being hired to perform this job, how much on-site or in-plant training would be required? (That is, organized classroom study provided by the employer.)
- How important is establishing and maintaining interpersonal relationships to the performance of your current job?
- How important is persuasion to the performance of the occupation?
- What is the general level of skill or education required for this occupation?
- How important is identifying objects, action and events to the performance of your current job?
- How important is providing consultation and advice to others to the performance of your current job?
- How important is active listening to the performance of the occupation?
- How often does your current job require that you be exposed to radiation?
- How important is service orientation to the performance of the occupation?

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Concept: PROGRAMMED ENDS

Definition: A clear understanding of what work needs to be done, when that work has been accomplished, and/or whether that work has been done well. At the highest levels of programmed ends, work output, outcomes, or goals have been clearly defined (for example: standardized products, clear measurement of completed work, explicit expectations).

Instructions: Please select **as many** of those questions listed below that you think are a good way to assess or measure *Programmed Ends*, as defined above **in red**, or a *lack of Programmed Ends*.


(REMEMBER: You can select more than one question listed below)

- How important is organizing, planning, and prioritizing work to the performance of your current job?
- How much freedom do you have to determine the tasks, priorities, or goals of your current job?
- How often does your current job require written letters and memos?
- How important is selling or influencing others to the performance of your current job?
- How important is developing objectives and strategies to the performance of the occupation?
- How often is dealing with violent or physically aggressive people a part of your current job?
- How important is knowledge of law and government to the performance of your current job?
- How important is clerical knowledge to the performance of your current job?
- How important is judging the qualities of objects, services, or people to the performance of your current job?
- How much time in your current job do you spend climbing ladders, scaffolds, poles, etc.?
- How important is integrity to the performance of your current job?
- How important is repairing and maintaining mechanical equipment to the performance of your current job?
- How important is evaluating information to determine compliance with standards to the performance of your current job?
- How important is dependability to the performance of your current job?
- How important is estimating the quantifiable characteristics of products, events, or information to the performance of your current job?
- How important to your current job is being very accurate or highly accurate?
- How important is working with computers to the performance of your current job?
- How important is thinking creatively to the performance of your current job?
- In your current job, how often do you wear specialized protective or safety equipment, such as breathing apparatus, safety harness, full protection suits, or radiation protection?
- How important is developing and building teams to the performance of your current job?

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Manipulation:

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eLab Experiment

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Concept: DISCRETION

Definition: The right to make choices about when your work is done, how it is done, and when it is done, within the bounds of established goals or strategies. Discretion can also be the right to make judgments about how much supervision is needed on a task, about how and when you can change work activities, and about how tasks are connected with one another.

Instructions: Please select **as many** of those questions listed below that you think are a good way to assess or measure *Discretion*, as defined above **in red**, or a *lack of Discretion*.


(REMEMBER: You can select more than one question listed below)

- In your current job, how much freedom do you have to make decisions without supervision?
- How automated is your current job?
- How much freedom do you have to determine the tasks, priorities, or goals of your current job?
- How important is estimating the quantifiable characteristics of products, events, or information to the performance of your current job?
- How important is operating vehicles, mechanized devices, or equipment to the performance of your current job?
- How important is public safety and security knowledge to the performance of your current job?
- How important is innovation to the performance of your current job?
- Job requires developing one's own ways of doing things, guiding oneself with little or no supervision, and depending on oneself to get things done.
- How important is writing to the performance of the occupation?
- How important is management of personnel resources to the performance of the occupation?
- How important is customer and personal service knowledge to the performance of your current job?
- How important is self-control to the performance of your current job?
- How important is making decisions and solving problems to the performance of you current job?
- How competitive is your current job?
- How important is concern for others to the performance of your current job?
- How important is staffing organizational units to the performance of your current job?
- How important is judging the qualities of objects, services, or people to the performance of your current job?
- How important is clerical knowledge to the performance of your current job?
- How important is coaching and developing others to the performance of your current job?
- How important is selling or influencing others to the performance of your current job?

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Help

Concept: RESOURCE CONTROL

Definition: Having the right to make decisions regarding the resources (for example: money, materials, people, or ideas) you and/or others need to get work done. Having the authority to prescribe for others the structure of their work relations (for example: who reports to whom, who gets hired, who does what), or the definition of the nature of materials and resources (for example: what tools to use, what materials to purchase).

Instructions: Please select **as many** of those questions listed below that you think are a good way to assess or measure *Resource Control*, as defined above **in red**, or a *lack of Resource Control*.


(REMEMBER: You can select more than one question listed below)

- How important is monitoring and controlling resources to the performance of your current job?
- How important is persistence to the performance of your current job?
- How important is repairing and maintaining electronic equipment to the performance of your current job?
- How often does your current job require that you be exposed to hazardous equipment? This includes working with saws, close to machinery with exposed moving parts, or working near vehicular traffic (but not including driving a vehicle)
- How important is knowledge of communications and media to the performance of your current job?
- How important is estimating the quantifiable characteristics of products, events, or information to the performance of your current job?
- In your current job, how important are interactions that require you to coordinate or lead others in accomplishing work activities? (not as a supervisor or team leader)
- How many hours do you work in a typical week on your current job?
- How important is knowledge of therapy and counseling to the performance of your current job?
- How important is negotiation to the performance of the occupation?
- How important is coordinating the work and activities of others to the performance of your current job?
- How important is social orientation to the performance of your current job?
- How important is scheduling work and activities to the performance of your current job?
- How frequently does your current job require electronic mail?
- How important is staffing organizational units to the performance of your current job?
- How important is public safety and security knowledge to the performance of your current job?
- In your current job, how often are you exposed to whole body vibration (like operating a jackhammer or earth moving equipment)?
- How important is knowledge of history and archeology to the performance of your current job?
- How important are interactions that require you to work with or contribute to a work group or team to perform your current job?
- If someone were to be hired to perform this job, how much apprenticeship would be required?

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 eLab Experiment

Help

After you answer the following set of questions and hit proceed, the study will be complete. We'd like to remind you that your responses to all the questions in this study will be kept confidential. Please answer the following questions by clicking the appropriate response.

Gender:

Year of Birth:

Ethnicity:


Is English your most proficient language?


Yes No

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eLab Experiment

Help

Conclusion

You are done with this survey. Thank you for your participation in the study. Your answers have been successfully received. We've automatically entered you into the \$50 prize drawing for this study. Once the data collection is completed and the lottery is drawn, we will contact you at elabadmin@owen.vanderbilt.edu if you are a winner.

In this study, we are interested in which questions seem to be the more reasonable and reliable measures of the concepts of interest. These concepts and questions are part of a larger study investigating how the nature of work might change given varying levels of automation alongside that work. We hope this research will aid in our understanding of the consequences of automation for the nature of work (for example, the skills and experience required for an occupation) and the structure of organizations.

We appreciate your contribution to our research.

[Click here to leave the experiment](#)

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Manipulation:

[Change Factors](#)

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