How Computerized Work and Globalization Shape Human Skill Demands

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1) Introduction

As this chapter is being written in the Summer of 2005 the United States labor market continues to recover from the 2000-2001 recession. Nearly four million more people are now working than were working three years ago. This employment growth is the net result of two forces. While employment expands in some occupations, work that can be done at less cost by a computer or by workers in lower wage countries continues to disappear. The result is both a changing mix of jobs and a changing mix of tasks within jobs. Our purpose in this chapter is to outline these changes and their educational implications from an economist's perspective. In sum, what education and skills are needed to earn a decent living in the labor market created by computers and globalization?

We begin with three caveats. First, where most chapters in this volume focus on aspects of globalization, this chapter will focus on the labor market impacts of both globalization and computerized work. As we will show, globalization and computerized work currently substitute for workers in similar occupations – they reinforce each other – and this reinforcement occurs in both in the U.S. and other advanced economies. As a second caveat, we were invited to write this chapter as economists but our argument also involves our crude understanding of cognitive psychology. We hope to keep the intellectual violence to a minimum.

A final caveat involves properly distributing credit. Many of the ideas in this paper began in joint work with our colleague, David Autor, now an Associate Professor of Economics at MIT.[2] Many of these ideas were also anticipated in a remarkably prescient 1960 essay by Herbert Simon[3] that we discovered after we had largely finished our own work. Because Simon was writing for a general audience, he did not present the explanatory theory that we lay out in this chapter. But the theory is implicit in the essay and Simon's ability to see the future in this essay was as remarkable as the rest of his career.

2) What Computers Do

We begin by asking the question: How do computers substitute for human work? Consider some examples:

- In U.S. airports, the job of dispensing an airline boarding pass, a moderately skilled job, is increasingly performed by self-service kiosks rather desk agents.

- When an outside caller calls the MIT general telephone number, a software-created voice asks the caller to speak the first and last names of the person they are trying to reach – e.g. "Larry Brown". The software matches the caller's response with data in the MIT telephone directory and then says, "Dialing the extension for Larry Brown" which it does. Human operators used to handle all of these tasks. Operators now only handle calls that the software fails to match.

- Recently, two interventional radiologists used computerized imaging to insert a stent into a large arterial aneurism near the brain of a young man. Fifteen years ago, the imaging did not exist, the operation would not have been attempted, and the young man would have soon died.

[2] In particular, see Autor, Levy and Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration", *The Quarterly Journal of Economics*, Volume 118, Issue 4, November 2003

[3] Herbert Simon, "The Corporation: Will it be Managed by Machines?" in M..L.Anshen and G.L. Bach (eds.), *Management and the Corporations*, McGraw Hill, 1960, pp. 17-55.

Why do we see this particular mix of outcomes? How do we explain the fact that computers *substituted* for human skills in the first and second tasks while computers *complemented* human skills in third task?

The answer begins with two ideas:

- All human work involves the cognitive processing of information. The financial analyst who reads numbers in a spreadsheet, the farmer who looks to the sky for signs of rain, the chef who tastes a sauce, the carpenter who feels his hammer as it hits a nail – all these men and women are processing information to decide what to do next or to update their picture of the world.

- Computers execute rules. Some of the rules involve arithmetic (6 x 9 = 54). Other rules involve logical conditions (If [AGE $\geq$ 35] Go to Statement 13). We can think of a properly running computer program as a series of rules that specify an action for each contingency.

When these two ideas are combined with common sense, they say that a computer can substitute for a human in processing information when two conditions are present:

- The information to be processed can be represented in a form that is suitable for use by a computer.

- The processing itself can be expressed in a series of rules.

The first condition is the common sense and we return to it below.

The rules to which the second condition refers can be either deductive or inductive. Deductive rules arise from the logical structure of the process. For example, in the case of the airline boarding pass kiosks, one deductive rule might be: ("Does this credit card number match a number in the reservation data base? Yes/No"). Information processing based on deductive rules is often described as rules-based logic.

Inductive rules - a more complicated situation - typically refer to the equations of regressions, neural nets and other statistical models whose parameters have been estimated on "training samples" of historical cases. The equations with their estimated parameters are then used to process new cases. Information processing based on inductive rules is often described as pattern recognition.

An example of pattern recognition is Fannie Mae's *Desktop Underwriter*, software now widely used by mortgage brokers to assess the risk of a mortgage application. Applying a regression-like technique to a large sample of previously approved mortgages, Fannie Mae statisticians estimated the relative importance of fourteen different application items in predicting whether a mortgage had defaulted in its first four years.[4] The result was a mortgage scoring model, an estimated equation (an inductive rule) that processed the fourteen application items into an *ex ante* probability of default. The estimated scoring model rule was built into software that now assesses risk in new mortgage applications.

Other examples of pattern recognition using inductive rules include models estimated on historical credit card purchases to flag the possibility of fraud and computer security software trained to recognize specific fingerprints. In all of these examples, the estimation of the inductive rules is equivalent to discovering a pattern in the historical information.

The ability to articulate rules – deductive or inductive – explains the first two of the three examples that began this section. The task of issuing a boarding pass can be fully expressed in deductive rules particularly since any unanticipated situation can trigger the message, "Unable to Continue: Please See a Desk Agent."

[4] The technique used was a logit, a regression-like model for cases where the dependent variable is either one or zero (i.e. no default or default). Persons familiar with statistics will recognize that only analyzing approved mortgages creates a sample selection problem since the estimate cannot incorporate information from rejected applications. When statisticians have access to full samples of applications (including those that have been rejected), they can apply statistical methods to correct for this problem which do not seem to make a significant difference in this case.

Similarly, speech recognition software can substitute for the simpler part of an MIT telephone operator's work. When an outside caller speaks the name they want to contact, the software's inductive rule filters out accents and "uh's" and constructs a digital representation of the name which it can then match against data in the MIT directory.

The third example is obviously different. Here, computers complement, rather than substitute for the radiologists' ability to insert the stent. We turn to this example next.

3) The Limits of Computer Substitution

A quick look at existing software is enough to confirm that deductive and inductive rules are sufficient to express an enormous number of information processing tasks. Nonetheless, a number of other tasks, including the radiologists' insertion of the stent, cannot be expressed in this way. In other words, computer substitution has its limits. Two limits stand out.

An Inability to Represent Information: In many workplace tasks, the information being processed is hard to represent in a form that computers can use. Consider an internist talking to a patient to make an initial diagnosis. The doctor is listening to the patient's words but also thinking about the patient's history and reading the patient's body language - the avoidance of eye contact or the broken off sentence that indicates holding something back. Or consider a truck driver making a left turn against traffic who is processing what he sees and hears from the street and the sidewalk, what he feels from the brake pedal and the steering wheel and so on. In these and many workplace tasks, it can be very hard to represent relevant information in a form that computers can analyze.

An Inability to Articulate Rules: The internist's conversation with the patient and the truck driver's left turn point to the second limit of computer substitution: Even if we could represent the information being processed, it is unlikely we could determine the rules that describe the processing. The problem is captured in Michael Polanyi's felicitous phrase, "We can know more than we can tell."[5] It is the problem of describing to your child how to ride a two-wheel bicycle. Nothing you can put into words will keep the child from falling at least a few times as he or she learns to ride.

The inability to determine rules is the major reason the task of inserting the sent cannot be computerized. Mentally processing real-time scanned images from a patient's vascular system into the hand movements manipulating a stent through an artery is an enormously complex process – too complex to articulate the processing in rules. But programmed rules can be used to process the body's absorption of x-rays into an image of the vascular system. By showing where the aneurism lies, the resulting CT-Scan strongly complements the doctor's surgical skills.

We will use the term "pure pattern recognition" to describe information processing tasks that - at least today - cannot be articulated in inductive or deductive rules.
Some of these tasks arise in "high skilled" work – the insertion of a stent or the process of writing a convincing legal brief. Some of these tasks arise in "low skilled" work – the process by which a janitor, entering an unfamiliar room, converts a two dimensional pattern of photons on his retina to a three dimensional mental image of the physical space.

A critical task that is hard to express in rules is the writing of the *new* rules needed to solve a new problem. As a consequence, most software is limited to solving the problems that programmers (the "rules writers") foresaw. Conversely, solving new problems is still

[5] Michael Polanyi *The Tacit Dimension*. New York, Doubleday (1966), p. 4.

human work. An example occurs in automobile repair shops. A customer brings in a newly purchased Ford Taurus with a non-functioning power seat. A technician uses a computerized diagnostic tool to search for problems engineers have foreseen: a faulty switch, a break in the wire connecting the switch to the seat motor, a faulty seat motor, and so on. But in a new car, the many new electronic components can interact in ways engineers have not foreseen. If the seat problem is caused by one of these unanticipated interactions, the factory-programmed rules will detect no error and the technician must solve the problem another way, perhaps by drawing an analogy to a previous experience.

Implicit in this discussion is the educational challenge addressed by several other authors in this volume. While everyone agrees that children need problem solving skills, "problem solving skills" have often been taught by focusing only on problems with rules-based solutions - algebra is an example. Solutions using rules are easy to teach and easy to test. But, as we now know, a problem that can be solved by rules can also be programmed on a computer and so this skill has little value in the labor market. This leads to the challenge identified in the chapters by Kai-ming Cheng and Peter Gärdenfors (Chapters XX and XX):[6] schools must teach children how to solve "new" problems where solution rules are not yet known. This is more subtle work and we shall return to it at the end of this chapter.

Our argument to this point is summarized in Figure 1 that lists a representative set of tasks in order of the increasing difficulty of computerization. Over the decades, many observers have predicted that computers would replace the highest skilled work – work

[6] These chapters will be based on: Kai-ming Cheng, "Learning versus Education: Challenges in Global Knowledge Society" and Peter Gärdenfors, "Understanding Cultural Patterns". Both papers were originally prepared for the *First International Conference on Globalization and Learning*, Stockholm, March 17-18, 2005.

that requires lots of “thinking”. Conversely, other observers have predicted that computers would replace the lowest skilled, “routine” work.

While the second prediction is closer to the mark, neither prediction was fully accurate. As shown in Figure 1 and as noted above, computers have difficulty with both many skilled cognitive tasks and many “unskilled” physical movements as well.

FIGURE 1

VARITIES OF HUMAN INFORMATION PROCESSING

Increasingly Hard to Program

	Conscious Application Of Deductive Rules (Rules-Based Logic)	Application of Inductive Rules (Pattern Recognition)	Rules Cannot be Articulated (Pure Pattern Recognition)
<u>Examples</u>	Arithmetic, Issuing a Boarding Pass	Predicting Mortgage Default, Recognizing a Spoken Name	Writing a Legal Brief, a Truck Driver Making a left turn against traffic

4) <u>Human Interaction</u>

Return for a moment to the case of the janitor entering an unfamiliar room. One factor that makes this case complex is the fact that we can only process information in context. Based on visual information alone, the janitor cannot know whether he is looking at a four foot high chair ten feet away or a 40 foot high chair 100 feet away. He resolves this ambiguity on the basis of past experience – information he already possesses.

Similarly, when a salesperson says you look perfect in lime green pants, you cannot know, based on the verbal information alone, whether the salesperson is being honest. The other things the sales person does – reading your body language, quickly correcting misunderstandings, smiling at appropriate times – is designed to establish a context in which you assume you are hearing the truth.

This ambiguity potentially exists in processing any information. Simon (1960) noted that in some cases, the ambiguity can be reduced by routinizing the context. For example, the person calling the MIT general number is instructed to state the person's first and last name and so the software knows exactly what information to expect. If the software had to process general conversation - "Oh, hi. I am looking for a professor in the physics department. Smith, I think her name is…" the processing task would be much more complicated.

In many other cases, standardizing the context is not possible and the resulting ambiguity underlies what might be called the dot.com fallacy regarding human interaction. At the height of the dot.com bubble, some business plans assumed a recipient of information would automatically interpret it just as the author had intended - no face-to-face contact needed. To disprove the assumption, you can hand a calculus book to a third grader and ask him or her to start taking derivatives or, closer to home, try to interpret email from your college age children - "Dad, I was only joking." Most business plans that relied on this assumption failed and human interaction to set a context remains central to many occupations – managing, teaching, selling, workplace teams – where the task is to exchange not just information but a *particular understanding* of information.

As Sussmith's chapter in this volume (Chapter XX)[7] illustrates, a globalized economy complicates this communication problem. When two people are from different cultures, we cannot assume they share a common context even when they are in the same line of work. Without a common context, even face-to-face contact may not be enough to create a shared understanding. Mutually beneficial exchanges will be that much harder to attain. Multinational firms have long recognized this problem and have specifically trained managers in such topics as how to do business in Japan. But as Susssmith argues, the expansion of globalization means such contacts are likely to occur among people in every walk of life, many of whom have little sense of what to expect.

5) <u>Computers and Offshoring</u>

To this point, we have argued that for a human task to be programmed, we must be able to construct a representation of the required information that is suitable for a computer, and we must be able to express the processing in deductive or inductive rules.

To the extent that a task fulfills these conditions, it is also a candidate for being moved offshore. The more a task can be specified in rules – the less it relies on tacit knowledge – the easier it is to explain to someone else without substantial misunderstanding and the easier it is to monitor.

This overlap suggests that computerization and offshoring should substitute for many of the same jobs and that is indeed the case. The call center work that moves offshore is heavily scripted – "rule-like" - while other call center work, as we have seen, is lost to speech recognition software. Assembly line work is lost to both offshore producers and to

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[7] This chapter will be based on Rita Sussmith, "The Urgent Need for Teaching Intercultural Skills- Challenges and Impacts of a Globalizing World on Education", paper prepared for the *First International Conference on Globalization and Learning*, Stockholm, March 17-18 2005.

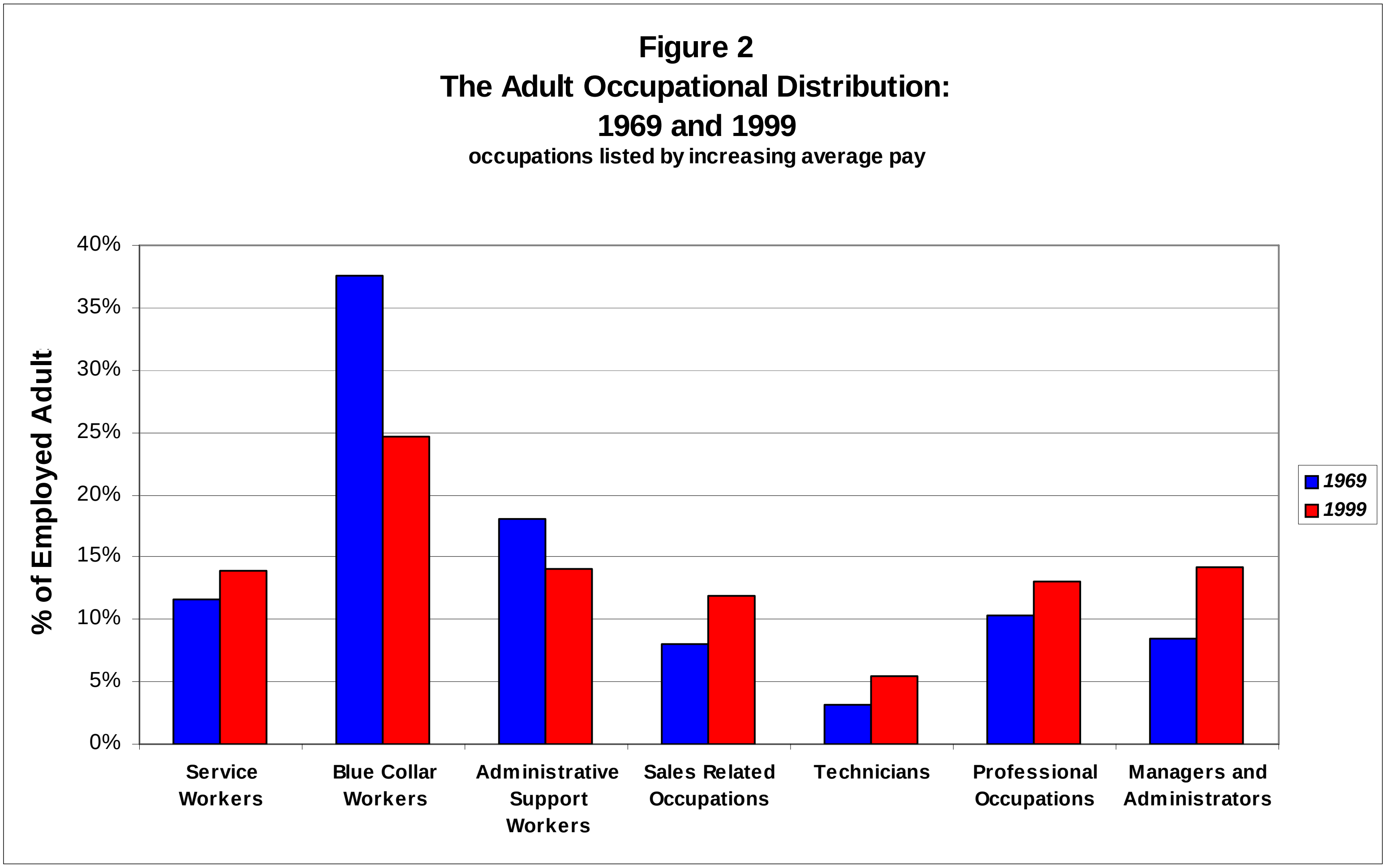
robotics. The preparation of basic tax returns is lost to offshore accountants and software like *TurboTax and TaxCut*.

Most of these are what we would call “moderate skilled” jobs. To the limited extent that higher skilled jobs have begun to move offshore, the majority are technical jobs in programming, engineering, financial analysis, etc. – jobs that combine tacit analysis with a heavy component of rules and standardized procedures.

In sum, in advanced economies globalization and computerization are taking many of the same jobs.

6) <u>What Jobs Will Be Available?</u>

How are computerization and globalization shaping available work? A rough first answer to this question is contained in Figure 2 which compares the U.S. adult occupational distributions for 1969 and 1999. Employment between these two years grew by 56 million (+ 70%). This employment growth is evidence that computers did not cause mass unemployment. But within the aggregate growth, some occupational categories grew faster than others and this *changing occupational mix* is one place where computers, international trade and, more recently, offshoring, have their impact.



In Figure 2, occupations are listed by increasing average pay. The graph's evolution is best described as a moderate hollowing out of the occupational distribution: Some growth in the lowest paying service occupations[8], shrinkage in blue collar and administrative support (clerical) occupations, and then growth in all higher paid occupations including sales.

Multiple forces are at work in Figure 2 - computerization, trade and offshoring but also the rising fraction of employed women and the rising education level of the

[8] Service *occupations* - e.g. janitors, security guards – should not be confused with jobs in the service *sector*. Service sector employment includes service occupations but also include jobs like school teacher, brain surgeon, airline mechanic, financial analyst, etc.

workforce. Nonetheless, the shifts in the distribution are consistent with the story we have outlined. Specifically:

- The growth of Service Occupations (janitors, cafeteria workers, security guards) reflects the inability of rules to capture human optical recognition and many physical movements and the fact that many of these tasks must be performed in this country and so cannot be offshored.

- The growth of Sales Occupations (a broad category that runs from fast food clerks through bond traders) reflects an increased flow of new products – driven in part by computers – which increases the need for selling, and the inability of rules to describe the exchange of complex information that salesmanship requires. [9]

- The growth of Professional, Managerial and Technical occupations reflects the inability to express high end cognitive activities in rules: formulating and solving new problems, exercising good judgment in the face of uncertainty, creating new products and services.

- In contrast, many Blue Collar occupations - particularly assembly line work - and Administrative Support (clerical) occupations can be described by deductive or inductive rules and this accounts in large part for the decline in these two categories through both direct substitution and computer-assisted outsourcing.

As we have suggested, this "hollowing out" is not unique to the United States. The Japanese word "kudoka" refers to a similar phenomenon in that country. Recent papers also demonstrate this pattern for England and Germany.[10] The process represents a potential problem because the demand side of the labor market can change much more rapidly than people can change their skills. Thus "hollowing out" can create a labor market imbalance where too many moderate skilled workers are chasing too few

[9] But sales occupations may not grow as rapidly in the future. While many sales transactions require actual "selling" – i.e. convincing a customer to buy – other sales transactions deal with customers who know exactly what they want and so the jobs are more clerk-like. This second group of transactions can now be handled over the internet through websites like Amazon.com.

[10] Maarten Goos and Alan Manning, "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain", Centre for Economic Performance, London School of Economics, September 2003. Alexandra Spitz, "Computer Use, Job Content and Educational Attainment", Center for Economic Research (Manheim Germany), July 2004.

moderate skilled jobs and end up competing for lower skilled jobs The result is a widening wage gap between higher and lower paid workers.

6) What Skills are Now Required?

To this point, we have discussed the changing nature of work in terms of the changing occupational mix. For purposes of education, the question is what these occupational mean for the skills workers require. In work with David Autor[11], we have categorized human skills into five broad categories:

- **Expert Thinking**: Solving problems for which there are no rule-based solutions. Examples include diagnosing the illness of a patient whose symptoms seem strange, creating a good tasting dish from the ingredients that are fresh in the market that morning, repairing an auto that does not run well but that the computer diagnostics report has no problem. These problems require what we have called pure pattern recognition – information processing that cannot now be programmed on a computer. While computers cannot substitute for humans in these tasks, computers can complement human skills by making information more readily available.

- **Complex Communication**: Interacting with humans to acquire information, to explain it, or to persuade others of its implications for action. Examples include a manager motivating the people whose work she supervises, a sales person gauging a customer's reaction to a piece of clothing, a biology teacher explaining how cells divide, an engineer describing why a new design for a DVD player is an advance over previous designs.

- **Routine Cognitive Tasks**. Mental tasks that are well described by deductive or inductive rules. Examples include maintaining expense reports, filing new information provided by insurance customers, and evaluating applications for mortgages. Because these tasks can be accomplished by following a set of rules, they are prime candidates for computerization.

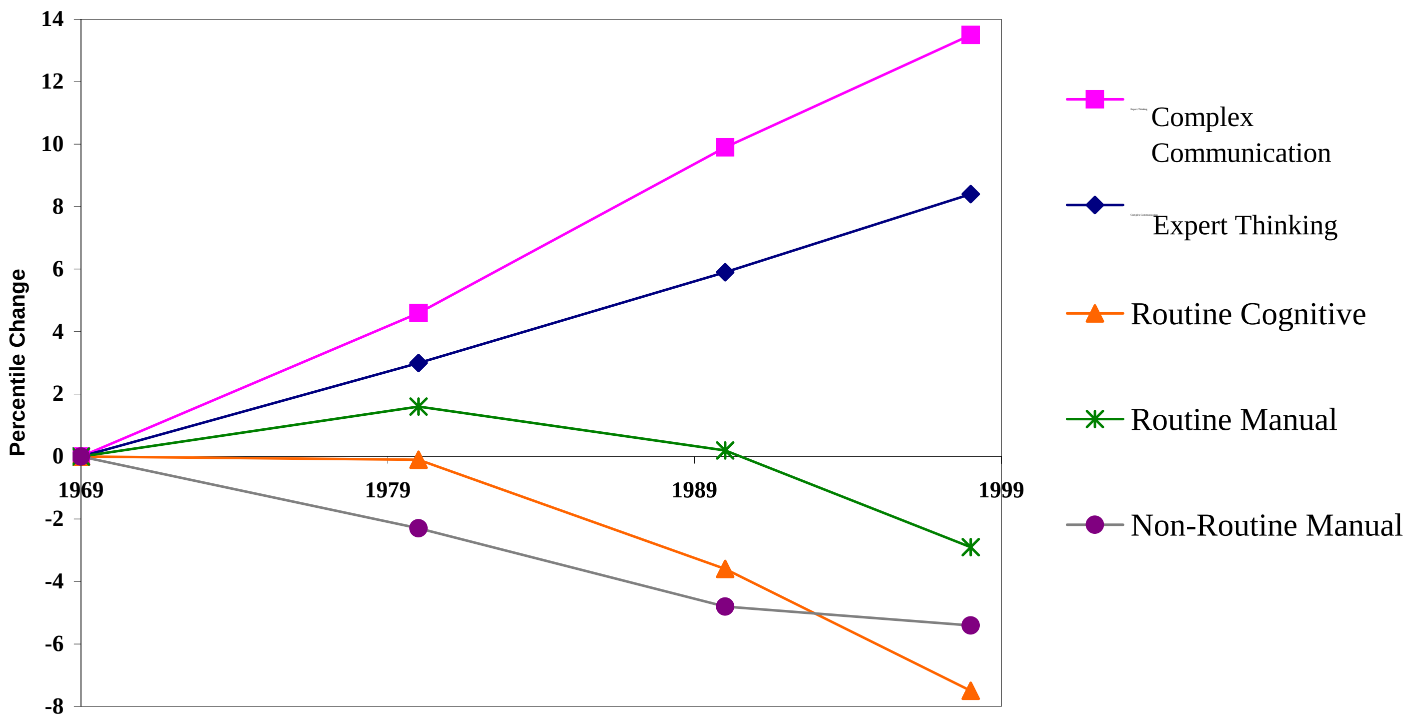
- **Routine Manual Tasks**. Physical tasks that can be well described using deductive or inductive rules. Examples include installing windshields on new vehicles in automobile assembly plants, and counting and packaging pills into containers in pharmaceutical firms. Since these tasks can be defined in terms of a set of precise, repetitive movements they are also candidates for computerization.

[11] Autor, Levy and Murnane, op. cit

- **Non-routine Manual Tasks**: Physical tasks that cannot be well described as following a set of If-Then-Do rules because they require optical recognition and fine muscle control that have proven extremely difficult to program computers to carry out. Examples include driving a truck, cleaning a building, and setting gems in engagement rings. Computers do not complement human effort in carrying out most such tasks. As a result, computerization should have little effect on the percentage of the workforce engaged in these tasks.

Figure 3 displays a conservative picture of how these tasks have evolved since 1969. The picture is conservative because available data limits the figure to skill changes caused by the changing occupational mix.

Figure 3: Economy-Wide Measures of Routine and Non-Routine Task Input: 1969 - 1998 (1969 = 0)



Source: Autor, Levy and Murnane, op. cit.

In reality, we know a large or larger source of changing skill demands comes from within occupations. Today's bank teller spends more time selling financial services and far less time with the routine cognitive tasks of processing deposits and withdrawals – tasks largely performed by ATM machines. Similarly, 25 years ago, auto mechanics did not have to read to learn their jobs - they could learn by watching other mechanics. But the evolution of automobile electronics has transformed many visible, mechanical components into opaque electronic modules. As a result, a mechanic can no longer function without the ability to read, to work with computerized testing equipment and to construct mental models of a problem. If these within-occupation changes were added to Figure 3, the trends would be sharper.

Going forward, we can expect these trends in skill demands to continue and, if anything accelerate. Because Figure 3 is based on 1969-98 data, it reflects the impacts of computerization and traded goods. But the impact of traded services – offshoring – only appears at the end of the period and will continue to eliminate routine cognitive jobs in the future. Similarly, the available measures of Complex Communication are based on the U.S. economy of roughly two decades ago and so fail to capture how globalization is now raising the bar on communication skills (e.g. Sussman, Chapter XX)

In summary, the trends in Figure 3 indicate demand is shifting toward a higher skilled, more flexible labor force. The question, at least for the U.S., is how such a labor force can be attained.

7) <u>The Educational Implications</u>

At various points in our history, the United States has experienced a substantial increase in the educational attainment of the labor force. These episodes suggest the country's institutions and population will, over the long run, respond to the rising skill demands that the combination of globalization and computerized work are creating.

Nonetheless, we should not expect an easy transition. Teaching Expert Thinking and Complex Communication will require significant adjustments and the nation's demographics are not on our side.

Begin with the demographics. As we have seen (e.g. Figure 2), skill requirements have been rising for some time. For much of the 1970s and 1980s, the baby boom's entrance into the labor force permitted the supply of skilled workers to meet demand. As a fraction of the labor force of that time, the baby boom cohorts were very large and they were much better educated than the cohorts that preceded them. These factors together allowed the average educational level of U.S. workers to increase rapidly. While our descriptions of Expert Thinking and Complex Communication involve more than just years spent in a classroom, the rapid increases in educational attainment suggests these particular skills were increasing as well.

Neither demographic factor operates today. The baby-boom cohorts are now part of the current labor force and the demographic cohorts now entering the labor force are relatively small by comparison. In addition, the educational attainment of these entering cohorts is no longer substantially higher than the cohorts who immediately preceded them. David Ellwood has estimated that under optimistic projections of existing trends, the proportion of the labor force with college educations will have risen from about .30 in the year 2000 to .35 in 2020, a fraction that likely lags behind the shift in employer demand toward more educated workers.[12] In sum, it is likely that significant numbers of jobs – some high skilled but most moderately skilled – will continue to be lost to computers and foreign workers. Without concerted efforts at retraining, the likely result

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[12] David Ellwood, "The Sputtering Labor Force of the 21'st Century: Can Social Policy Help?," National Bureau of Economic Research working paper 8321, June 2001.

is the scenario sketched above: growing inequality as significant numbers of moderately skilled workers are displaced and must compete for lower skilled jobs. This competition for lower wage jobs will occur even as employers continue to push for higher quotas on skilled immigration.

This brings us to the question of how to teach Expert Thinking and Complex Communication. To be clear, we are not suggesting that these skills are additional subjects. Rather, they are taught by approaching existing subjects in a somewhat different way.

Begin with Expert Thinking – the ability to solve problems that, unlike algebra, lack explicit rules-based solutions. These problems must be solved through some form of pattern recognition. Rules-based solutions must still be part of a curriculum – i.e. students still need to know subjects like algebra. But a curriculum must recognize that a rules-based solution is usually the second part of a two-part problem solving process. The first part of the process – the part that retains labor market value - is the ability to recognize which rules-based solution applies in a particular case. For example, a mechanical engineer is valued for her ability to formulate a problem as a particular mathematical model. Once the model is formulated, a computer – not the engineer – will apply rules to calculate the actual solution.

How does the engineer choose the correct mathematical model? As with the earlier case of the auto mechanic, the engineer likely relies on analogies with past experience. In cognitive terms, analogies often involve a kind of pure pattern recognition in which a person recognizes similarities between features of the current problem and features of earlier relevant problems. In (Chapter XX) Peter Gärdenfors makes an argument in this spirit when he advances the hypothesis that “understanding consists of seeing a pattern” (pp XX). Learning this kind of pattern recognition takes practice. In particular, it requires going beyond traditional assignments where a student knows that the problems at the end of a chapter on long division can all be solved using long division – no need to think about which rules apply.

In subjects like history or literature, the equivalent of rules-based solutions is a focus on narrow facts – e.g. dates and names and little more. In this case, going beyond rules-based solutions means teaching the underlying relationships among narrow facts. These relationships form the basis for the analogies needed to solve new problems.

An example from a National Research Council Report nicely illustrates the distinction.

> *Student 1*:
>
> Q. What was the date of battle of the Spanish Armada?
>
> A. 1588.
>
> Q. How do you know this?
>
> A. It was one of the dates I memorized for the exam.
>
> Q. Why is the event important?
>
> A: I don’t know.
>
> *Student 2*:
>
> Q. What was the date of battle of the Spanish Armada?
>
> A. It must have been around 1590.
>
> Q. How do you know this?
>
> A. I know the English began to settle in Virginia just after 1600, although I’m not sure of the exact date. They wouldn't have dared start overseas explorations if

> Spain still had control of the seas. It would have taken a little while to get expeditions organized, so England must have gained naval supremacy somewhere in the late 1500s.
>
> Q. Why is the event important?
>
> A. It marks a turning point in the relative importance of England and Spain as European powers and colonizers of the New World.[13]

The skill of Complex Communication – making effective oral and written arguments, eliciting information from others - can similarly be taught using existing subject matter. But teaching this skill requires both a change in emphasis and additional time - the time needed to review and grade oral presentations and frequent student essays. In practice, computers may be of some help here. Recognizing good writing, like recognizing a friend's voice, rests on inductive rules. Researchers have made significant progress in estimating these rules – the general patterns of word use that experts recognize as good writing. These inductive rules now form the basis of software to grade student essays.[14] This software cannot replace a skilled writing teacher but it can create a better writing experience than many U.S. children now receive.

The potential of machine graded essays may overlap with what is the biggest potential issue in teaching Expert Thinking and Complex Communication: the way these skills often conflict with mandatory state tests (assessments) that are part of the educational standards movement. Most states now mandatory assessments as part of a program to improve educational accountability. In many states, these assessments have been

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[13] This example is adapted from James Pellegrino, Naomi Chudowsky and Robert Glaser, *Knowing what Students Know: The Science and Design of Educational Assessment*,, National Academy Press, 2001.
[14] See, for example, Jill Burstein, Martin Chodorow, and Claudia Leacock, "*CriterionSM* Online Essay Evaluation: An Application for Automated Evaluation of Student Essays" at http://ftp.ets.org/pub/res/erater_iaai03_burstein.pdf

designed toward minimizing costs while producing numerical scores that can be compared across districts or over time. In a subject like history, a multiple-choice test is more likely to meet these criteria than an essay needed to demonstrate Complex Communication. In an area like math, a multiple-choice test based on the right answer is cheaper and more "objective" than grading how a student chooses a solution method - a demonstration of Expert Thinking. In the drive for educational accountability, teachers have strong incentives to teach to the test and so it is particularly important that we get the tests right.

8) <u>Conclusion</u>

In this chapter, we have outlined a theory of the way in which computers and globalization are changing available work. The changing nature of work is only result of our increasingly globalized society but it is clearly an important one. The argument we have presented can be summarized in three points:

- At least for the moment, there is a strong overlap between the jobs threatened by globalization and the jobs threatened by computerized work.
- Jobs lost to both forces tend to "hollow out" the occupational distribution leaving employment more concentrated at the low and high end of the skill distribution.
- It is possible to say a fair amount about the generic skills required in this evolving economy and the educational challenges involved in teaching these skills

As in any short summary, there are many points we have missed but we believe the arguments present offer a useful introduction to the future of work in industrial countries and the educational challenges that result.

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