Cyberpsychology: An Introduction to Human–Computer Interaction

Kent L. Norman

University of Maryland

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Nine

Individual Differences

People, Performance, and Personality

Scenario 1

Following the breakup of Macrosoft into the ten new Nanosofts and Groogle's introduction of the RainbowGroogleTop, different types of OSs proliferated. Instead of just Windows, Mac OS, and Linux, there were so many different styles and approaches to organizing desktops and files and controlling the functions of computers that no one knew what to choose. It was a mess until CompuMatchMe.com stepped in to match up people with OSs. The idea was that each user has a different makeup of cognitive abilities and styles and preferences. CompuMatchMe.com developed an algorithm for matching the user's personal profile with the ideal OS. Their slogan was "We help you to find your OSoul mate."

Scenario 2

A language instructor was explaining to her class that French nouns, unlike their English counterparts, are grammatically designated as masculine or feminine. Items such as "chalk" or "pencil," she described, would have a gender association, although in English these words were neutral.

Puzzled, one student raised his hand and asked, "What gender is a computer?"

The teacher was not certain which it was, so she divided the class into two groups and asked them to decide whether a computer should be masculine or feminine. One group was comprised of the women in the class, and the other, of men. Both groups were asked to give four reasons for their recommendation.

The women concluded that computers should be referred to in the masculine gender because

- *To get their attention, you have to turn them on.*
- *They have a lot of data, but are still clueless.*
- *They are supposed to help you solve your problems, but half the time they ARE the problem.*
- *As soon as you commit to one, you realize that, if you had waited a little longer, you could have had a better model.*

The men, in contrast, decided that computers should definitely be referred to in the feminine gender because

- *No one but their creator understands their internal logic.*
- *The native language they use to communicate with other computers is incomprehensible to everyone else.*
- *Even your smallest mistakes are stored in long-term memory for later retrieval.*
- *As soon as you make a commitment to one, you find yourself spending half your paycheck on accessories for it.*

Overview

As indicated in the previous scenarios and the one from Chapter 2, both humans and computers differ in a lot of ways. A fundamental principle in HCI is that there should be a match of some sort between the human's abilities, experience, cognitive style, and mode of operation and the computer's mode of operation, characteristics, and specifications. Whether personality type is the critical factor is not clear, but certainly cognitive strengths and weaknesses, as well as cognitive dissonance, are important considerations.

This chapter discusses individual differences in relation to issues in HCI. First, we look at differences in IQ, verbal comprehension, quantitative skills, and specific cognitive abilities, such as spatial visualization ability and perceptual speed, and how they relate to performance. Second, we look at age, gender, and differences in experience. Finally, we look at personality differences and attitudes about computers. The importance of these individual differences is assessed relative to their impact on HCI. Factors that may be very important in interpersonal relationships, such as gender and introversion, may not be that relevant when it comes to computers. However, other individual differences that may be of little interest to people, such as the ability to manipulate spatial objects in your head, may be very important in using computers. We explore the idea of matching abilities and cognitive styles to the interface to improve usability, performance, and user satisfaction. Finally, we see that the HCI is a prime area for assessing individual differences. In the past, testing was done with paper-and-pencil forms and personal interviews. Computerized testing has proven not only successful, but is in many cases superior to traditional methods.

Factors of Differences

Across brands and models, computers vary in many different ways such as processor speed, memory capacity, graphics capabilities, communications, etc. Operating systems and software also vary in many ways from purely alphanumeric (e.g., UNIX, DOS) to rich GUIs such as the Apple Macintosh OS and MS Windows. Within programs, the style, the "look and feel," the "personality," the vocabulary, and the artwork can vary greatly along many different dimensions. Within a system or a program, users can change preferences and layouts. Computer designers consider these factors when they develop a new model or version. What is the best system we can build for a particular price?

Computers are designed and built. Not so with users. In organizations, users are often tested and selected to use a computer and are then trained. As personal consumers, users choose what system to buy and use and then decide what training they need. For either situation, we now focus on the composition and characteristics of the user. What individual differences do they bring to the human–computer interface that need to be factored into the mix? Although we can select and train users, it is perhaps easier to design interfaces around the human rather than reinvent humans to fit the characteristics of the computer. To do this, we must answer two questions: 1) What are the factors (metrics) that matter?, and 2) Can we design the computer interface to accommodate for these differences?

Designers of computer systems have long been encouraged to carefully consider the diversity of their users. The term "user-centered" design emphasizes the importance of taking into consideration the needs and characteristics of the users over other programming issues (Norman, 1986).

The study of individual differences has been a major area of psychology since its beginning. The variability of human abilities, performance, characteristics, and personality has been studied extensively in the area called "psychometrics," which literally means "to measure the mind" (Anastasi & Urbina, 1996; Michell, 1999; Nunnally & Bernstein, 1994). We start from these metrics and then use experimental and correlational methods to determine whether there is a relationship with factors in computer use such as performance and satisfaction. Research on individual differences has proven to be extremely important in understanding user behavior in HCI (Dillon & Watson, 1996).

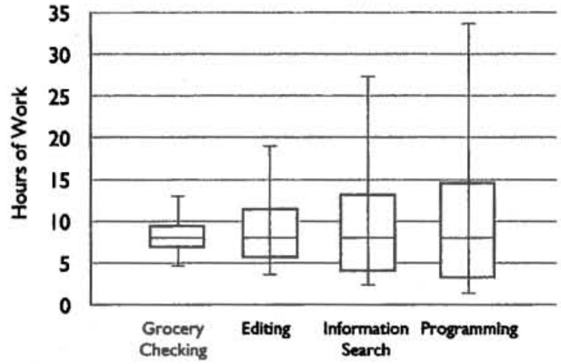

Figure 9.1. Distributions of completion times for grocery store cashiers and three HCI tasks. For each task, the fiftieth percentile has been set at 8 hours. The tops and bottoms of the boxes represent the seventy-fifth and twenty-fifth percentiles. The "whiskers" represent the best and worst performance. (From Egan, 1988.)

Performance Differences

It is clear that people differ greatly when it comes to using computers to perform tasks. Egan (1988) initially surveyed the size of differences in performance on several different tasks such as text editing, information search, and programming reported in a number of published studies. For each task, the performance measure was the amount of time to complete the task. To put the differences into perspective, he included the time it takes to check groceries by a cashier and then graphed the distributions as shown in Figure 9.1, setting the median or fiftieth percentile of each performance at the same level.

In each case, the ranges are very large compared to grocery checking. For editing, the ratio between the best and the worst is 5 to 1, for information search 9 to 1, and for programming 22 to 1. Even the ratios between the seventy-fifth and twenty-fifth percentiles in each distribution are 2 to 1 or 3 to 1. To further emphasize the magnitude of these differences Egan (1988, p. 551) wrote:

> After a group of 30 people complete a training course on text editing, we could expect that the top performer might be able to complete in one day what the poorest performer would take a week to do. After 30 people take a programming course, one student might take a year to program what another could do in two weeks!

When it comes to computers, performance differences between people in training classes are larger than one would expect. For some reason, computers tend to amplify differences between people. Norman (1994) suggested that this is because of a multiplicative effect between human cognitive abilities and computer empowerment. Those with high mental abilities are facilitated by computers. Those with low abilities are not facilitated and may in fact do worse with computers. The challenge to interface designers is to facilitate those that need help rather than to leave them in the dust. Assistive technologies are meant to do this and are discussed in Chapter 14. At this point, we need to understand the cognitive factors that give rise to performance differences.

Cognitive Factors

The penultimate measure of cognitive ability is IQ, an assessment of overall intelligence. We define intelligence as the set of mental abilities necessary to adapt to and shape the environment (Neisser et al., 1996; Sternberg, 1997). This definition is particularly relevant in HCI. Intelligence is not merely answering questions, knowing information, or reacting to the world, but it is also actively changing and manipulating the world around us. Moreover, intelligence is context dependent. The intelligent response to the word "EXIT" is quite different when it is above a doorway than when it is in a pop-up window.

The questions that we ask as psychologists are the following: "Is intelligence something inherited and inborn, or is it learned?"; "Is there one kind of intelligence, or are there different kinds of intelligence?"; and "Can intelligence be broken down into different factors or abilities?" The most contentious questions have had to do with differences in intelligence between males and females and among different racial/ethnic groups and their impact on socioeconomic factors.

Historically, psychometrics started with Sir Francis Galton (1822–1911), a British mathematician and naturalist who made contributions to many fields of science as well as eugenics. He introduced the idea of using questionnaires and surveys to measure just about everything in human communities. Galton was a half-cousin of Charles Darwin by a common grandparent Erasmus Darwin. When Darwin proposed his theory of evolution, Galton decided to apply the principle of natural selection to human traits to explain why some families, like his, were successful and others were not. He founded a eugenics movement to breed humans in much the same way as is done in animal husbandry. Thus, individuals with positive traits and high intelligence should be encouraged to marry and have children, whereas those with negative traits and low intelligence should not. Consequently, Galton set about developing statistical methods for measuring these traits. His major contribution was the idea of a correlation coefficient that measured the degree to which one variable such as intelligence is related to success. Although the errors of eugenics have been largely averted in modern society, the statistical measurement of correlation has been accepted. Moreover, the idea of assessing traits and abilities to predict future performance has particularly been embraced in education and in the workplace. Finally, in the area of HCI, there has been a particularly strong interest in identifying individual differences that correlate with performance.

Galton believed that he could measure intelligence by seeing how quickly and accurately people responded to stimuli. His measures of sensory abilities, reaction times, and physical measurements of head size and muscular strength did not actually correlate with accepted criteria of intellectual functioning at the time (Sharp, 1898; Wissler, 1901). Interestingly however, sensory abilities and speed of processing have become increasingly relevant in predicting performance at the human–computer interface today. One wonders how things might have been different had computers been around in Galton's day.

A much more successful attempt to measure overall intelligence was made by Alfred Binet who had been hired by the French school system to develop an inexpensive test to determine which children were in need of special education. His approach was to test mental abilities using a battery of tests of typical things that one would expect children of different ages to be able to do. In these tests, Binet emphasized mental reasoning and problem-solving abilities needed in the classroom rather than sensory and motor skills needed in the workplace. Binet hinged his measure on age because children increase dramatically in their verbal and mental abilities between the ages of 5 and 18 years. His reasoning was that if a 10-year-old child performed at the level of an "average" child of 8 years, he was in need of special help in the classroom and would need additional tutoring.

The IQ test came to America through the work of Goddard (1913) and Terman (1916), and resulted in the Stanford-Binet test. At this point, it was given a scoring system to divide the child's mental age by his or her chronological age and multiply by 100. So, a 10-year-old child performing at the mental age of 8 years has an IQ of $(8/10)(100) = 80$.

Interestingly, the aging effect is reversed for computers. The speed and power of a computer does not increase with age but remains constant at best, whereas younger, newer computers tend to be faster and more powerful. Thus, older is slower and younger is faster, resulting in a reversed quotient.

The intelligence quotient based on mental age and chronological age worked well for children, but not for adults, whose mental abilities level off at ages 18 to 20 years and then are not strongly related to chronological age. When Wechsler developed an intelligence test for adults, the solution was to set the average IQ at 100 and the standard deviation at 20. The result was the infamous bell curve for IQ shown in Figure 9.2. The implications of the bell curve are astounding and highly controversial (Gould, 1996; Jensen, 1982; Neisser et al., 1996). Much heated debate surrounds the use of IQ as a measure that has the potential to label, stereotype, and discriminate against individuals and groups. For example, Gould (1996) wrote that "the abstraction of intelligence as a single entity, its location within the brain, its quantification as one number for each individual, and the use of these numbers to rank people in a single series of worthiness, invariably to find that oppressed and disadvantaged groups – races, classes, or sexes – are innately inferior and deserve their status" (pp. 24–25). Assigning numbers to individuals through testing can have significant negative effects. We tend to

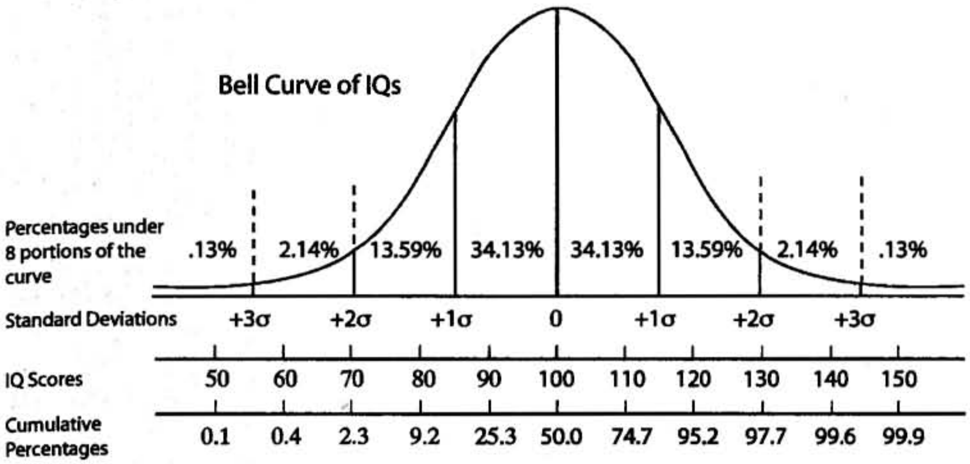

Figure 9.2. Bell curve for IQ showing the proportions of the distribution scoring in different internals.

expect people with low scores to perform worse than people with high scores even though the correlations are far from perfect. We then label students as "slow" or "challenged" on the basis of their scores. These labels stick, and students live up to these expectations or the lack thereof.

In the area of computers, one can point to the use of the pejorative term "dummy" in the more than 250 "...for Dummies" books. Even though the publisher emphasizes that the books are not literally for dummies, the subtitle for every book, "A Reference for the Rest of Us," implies that they are for individuals excluded from the upper tail of the distribution. To make matters worse, the dozen or so "Complete Idiot's Guide to..." on computers and the Internet use an even stronger term to label people. Consequently, there may be a serious self-fulfilling prophecy concerning individual differences with regard to computers as we label ourselves as "dummies" or savvy users, "geeks," "hackers," or "nerds."

Overall IQ is correlated with performance on tasks that require similar mental abilities. The correlation between IQ and grades in school is about 0.50, and between IQ and job performance 0.54. Today, in an environment where both schools and workplaces are permeated with computers, we continue to expect that performance will be correlated with IQ. But now the question is what proportion of the relationship is due to the task being done versus the interface being used? Take, for example, balancing a checkbook using a spreadsheet program. Part of the performance will be due to the mental abilities of dealing with numbers and sums, but another part will be due to the interface, entering numbers in boxes, following menus, and selecting functions. We are interested in isolating the cognitive abilities that pertain specifically to the interface rather than the general task.

Interestingly, intelligence scores are also related to physical attributes of the nervous system. Just as you would expect the intelligence of a computer to relate to its hardware characteristics, human IQ is correlated with brain size

(Tisserand, Bosma, Van Boxtel, & Jolles, 2001), speed of neural transmission, and brain efficiency (Vernon, Wickett, Bazana, & Stelmack, 2000).

Although the concept of an overall IQ has been a compelling idea, for a long time psychologists have used psychometric methods to identify separate factors that make up the composite. The first to identify two such factors was Spearman (1927). He labeled one factor "g" for general intelligence and the other "s" for specific abilities. Thurstone (1938) used factor analysis to identify seven primary mental abilities: verbal comprehension, number ability, word fluency, spatial visualization, associative memory, reasoning, and perceptual speed. Each factor will contribute with different weighting, depending on the task being performed (e.g., balancing a checkbook vs. proofing a paper). Moreover, each factor may contribute to different degrees, depending on the human–computer interface being used (e.g., a command-line interface vs. a GUI).

In the past few decades, new approaches to intelligence have been taken. The first is to emphasize that intelligence is not one monolithic factor but is composed of a number of component abilities (Sternberg, 1988). Gardner and others have emphasized "multiple intelligences." Gardner (1983, 1999) listed eight intelligences:

The Thought Intelligences:

Verbal-linguistic is the ability to use words and language. Those high in this intelligence are facile at writing and speaking. To the extent that the interface relies on language input/output, this intelligence will correlate with performance.

Logical-mathematical is the ability to work with numbers, abstractions, and logic. This intelligence favors mathematics and computer programming. To the extent that the interface requires logic, programming, and computation, it will relate to performance.

Naturalistic has to do with the ability to recognize, categorize, and characterize things in the natural environment. Although aimed at nature, in a virtual sense it also pertains to one's ability to recognize characteristics in computer environments, screen layouts, and backgrounds.

Sensate Intelligences:

Visual-spatial is the ability to think three dimensionally, manipulate objects in space mentally, and work with shapes and figures. Because computer interfaces are graphical and rely heavily on spatial metaphors, this skill will be involved in performance.

Bodily-kinesthetic has to do with motor coordination, movement, and position. Interfaces that require good hand–eye coordination, mouse movements, or hand and body movements, as in virtual reality systems, will require this skill.

Auditory-musical involves the sensitivity to pitch, melody, rhythm, and tone. Interfaces that use auditory and multimedia modes will require this skill.

The Communicational Intelligences:

Interpersonal skills involve the ability to understand and effectively interact with others. Individuals high in this skill are outgoing, leaders, charismatic, and diplomatic. In the past, there has been a stereotype that interpersonal skills are lacking in individuals with computer skills. However, there are many áreas of HCI in which people skills are important (e.g., help desks).

Intrapersonal abilities involve understanding one's own thoughts, motives, faith, and philosophy. Those high on intrapersonal skills are often seen as introverts. Although this intelligence does not seem to be directly related to HCI, it may deal with mental models and the perception of the self.

Factor analytic, component process, and multiple intelligence approaches allow us to explore individual differences at a more granular level. Essentially, we can get a profile of the user across each dimension or type and correlate these scores with performance measures at the human–computer interface. This approach helps us identify those factors of individual differences that play a part in the interface rather than the task per se.

Cognitive Abilities: Factor Referenced Tests

Many different tests have been developed to measure specific cognitive abilities. These tests range from size of working memory, to perceptual skills, to attentional abilities, etc. (Ekstrom, French, & Harman, 1976).

Vicente, Hayes, and Williges (1987) gave a battery of these tests to students and then correlated the scores with their performance at finding information in a computer system requiring paging, scrolling, and searching. Although numerous cognitive abilities were correlated with performance, they found two tests that were clearly the best predictors of computer performance: verbal comprehension and spatial visualization ability. The verbal comprehension test required the individual to read a passage and answer information about its content. The spatial visualization ability test has to with mentally manipulating objects in space and was measured using the conceptual paper-folding task shown in Figure 9.3. Each problem starts with a set of figures showing how a square piece of paper is being folded. The last figure has one small circle drawn to show where the folded paper has been punched through. You are to select one of the five figures to show where the holes will be when the paper is completely unfolded.

Numerous studies have shown fairly strong correlations ranging from 0.35 to 0.50 between spatial visualization ability and performance on computer search tasks (Norman & Butler, 1989), menu selection and navigation tasks (Chen & Rada, 1996), and command and control tasks (Murphy, 2000).

Why is spatial visualization ability such an important cognitive ability in HCI? Apparently, it has to do with the fact that the human–computer interface has many spatial aspects to it. HCI invokes the same cognitive abilities as mentally folding a surface, creating an effect, unfolding the surface, and

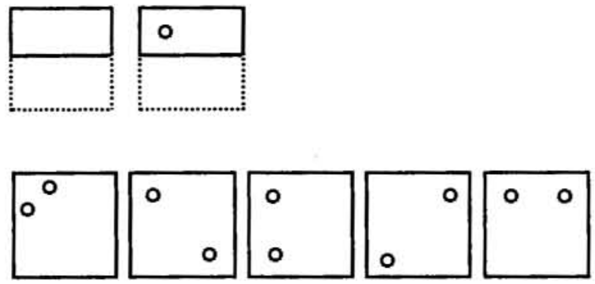

Figure 9.3. Paper-folding task. Example problem from instructions. (From Ekstrom et al., 1976.)

inferring what you have created or where you are. The human–computer interface, particularly the GUI, is essentially a flat, narrow, and convoluted passageway into a multidimensional, hierarchical space. To select options, we follow cascading pull-down menus, pop-up menus, and sequences of selections that drill down to the goal. To work with documents, we manipulate layers of overlapping windows, multiple scroll bars, and tabs. For some reason, the current computer interface from OSs and applications to databases and the Web rely highly on spatial visualization abilities, and the trend is increasing.

Demographics

Demographics are those variables that are temporal (age, experience, educational attainment), organic (gender, genetics), situational (income, socioeconomic status, employment, location of residence, marital status), and social (race/ethnicity, religion, language, nationality). Many demographic variables are determined for us, such as gender, age, and ethnicity. Others are under our own control, such as marital status, residence, and employment. Demographic variables contribute to individual differences, but again the question is whether they make any difference when it comes to HCI.

Age

Age is a very strong predictor of performance on computer-related tasks, even when experience is held constant. Most studies find age differences for complex computer tasks. Greene, Gomez, and Devlin (1986) found that age had a large effect on producing errors in information search. Across different designs of the interface, the average correlation between age and errors was 0.57. As the tasks become more complex, the effect of age on performance becomes even larger. However, differences due to age can be reduced. When users of different ages learned a display editor that had a simple set of function keys rather than complicated commands requiring the correct syntax, the effect of age was greatly reduced (Egan & Gomez, 1985).

Age can become a particularly detrimental factor when associated with loss of memory and cognitive abilities and motor and sensory impairment. These extremes are discussed in Chapter 14.

Age in demographics can also be expressed in terms of a generational or birth cohort, which is defined as "the aggregate of individuals (within some population definition) who experienced the same event within the same time interval" (Ryder, 1965, p. 845). Because the introduction of computers in society has occurred only over the past few decades, generational cohorts differ greatly with respect to experience with computers. Current cohorts in the United States include the following (adapted loosely from Strauss and Howe, 2003):

- *Postwar Cohort* (born from 1928 to 1945) – experienced sustained economic growth, the Cold War, and McCarthyism with characteristics of conformity, conservatism, and family values. This cohort was introduced to computers later in life, close to or after retirement. Only a small portion has adopted the use of computers for e-mailing their children and for word processing when typewriters became obsolete.
- *Baby Boomers Cohort 1* (born from 1946 to1954) – experienced the leading edge of the computer revolution, the rise of credit cards, the environmental movement, and the walk on the moon, with characteristics of being experimental, individualistic, and social cause oriented. This cohort was introduced to computers in midlife. Most have had to make the transition to computers later in their careers, some reluctantly, and have often been of two minds about paper versus electronic media.
- *Baby Boomers Cohort 2* (also called *Generation Jones*; born from 1955 to 1964) – experienced the proliferation of the personal computer (Apple II Computers, IBM PCs, MS-DOS), the Cold War, and gasoline shortages, with characteristics of being less optimistic, having a distrust of government, and being generally cynical. This cohort was introduced to computers in their twenties and thirties. They were compelled to make the transition to computers in their jobs and worried about the computer literacy of their children.
- *Generation X* (born from 1965 to 1981) – experienced the introduction of the GUI, e-mail, edutainment, multimedia, video games, the dot.com crash, the Challenger explosion, and social malaise, with characteristics of searching for emotional security, being entrepreneurial, and desiring informality. This cohort was introduced to computers and video games in high school and college and brought computers into their new homes.
- *Generation Y* (also called the *Millennial Generation*; born from 1982 to 2000) – experienced the rise of the Internet (Internet Explorer, Amazon.com, Google), September 11 terrorist attacks, and cultural diversity, with characteristics of searching for physical security and safety. They are connected, immediate, social, and technically savvy. This cohort grew up with computers at home, in the classroom, and everywhere. This group has always had video games, mobile devices, cell phones, and computers

in their lives, but are experiencing the metamorphosis of computers into an entertainment media with MP3 players.

- *Generation Z* (also known as *the iGeneration*; born from 2001 on) – growing up in a world with information at their fingertips with devices such as the iMac, iPod, and iPhone. They are the twenty-first century's first generation. They are digital natives who personify our future. In population size, they are the smallest of the living generations, with the fewest siblings, and born to the oldest mothers whose median age is 33. They are the most financially endowed generation and will be the most technologically empowered generation with the largest number of entertainment options for music, movies, Web sites, and video games.

Consequently, generational cohorts differ not only in chronological age and amount of experience, but also in the age at which technologies were introduced into their lives, social context, and social perspectives. These issues become extremely important when designing interfaces for, and training users on, interfaces for different ages.

Experience

Experience and educational attainment are usually highly correlated with performance on computer tasks such as programming and working with computer applications (Chrysler, 1978; Rosson, 1983). Of course, the reason for this can be traced back to Chapter 6. With more experience, one learns more about the task and the interface, whether it is a programming language, the functionality of the program, or the procedures to complete tasks. Furthermore, educational attainment is partially determined by general intelligence and will in turn determine the amount of general knowledge acquired and one's experience with computers.

Generally, for research and interface design purposes, we tend to categorize users into the following classes of computer experience:

- *Novice*: first-time user; unfamiliar with the interface, program, and devices
- *Intermittent user*: somewhat familiar with the interface, program, and devices, but uses it only infrequently
- *Casual user*: familiar with the interface, but not as much as a frequent, full-time user
- *Expert user (level 1)*: trained user with much experience
- *Expert user (level 2)*: extremely well-trained user with insider knowledge of the interface, program, and devices

As one moves from novice to expert, there are at least two factors that drive performance. The first is that with more experience, there is more learning. The second is that less proficient individuals tend to drop out and do not pursue expertise if they are struggling to keep up. Consequently, expert users are those who excel in ability, performance, and knowledge.

In any usability study, we want to know about the person's previous experience with the system in order to account for initial differences, and in any work environment, we need to know about the employee's previous experience in order to place the person in the appropriate work situation or training schedule.

Gender Differences

As Scenario 1 suggests, gender differences are filled with stereotypes. Certainly, there are interesting differences between males and females when it comes to computers. The stereotype still prevails that computers are a "boy thing." The simplistic question is whether males or females are better at using computers. The serious question is why there is a "gender gap" between males and females pursuing careers in computer science and computer-related fields. The ratio of males to females who are programmers, information technology professionals, and technicians is around 7 to 1. The female computer science major is a rare thing and actually on the decline rather than increase (Goodwin, 2004).

Although computers themselves have no inherent gender bias, the ways they are used and the context in which they are used tend to result in large differences in expectation and measures of achievement between males and females. Numerous studies show consistent differences in terms of both skills and attitudes (Houtz, 2001; Kay, 1992). In a meta-analysis of a number of studies, Whitley (1997) reported that both men and boys exhibited greater gender role stereotyping of computers (i.e., working with computers is more appropriate for males than for females), higher computer self-efficacy (i.e., males excel and get higher scores in computer training than females), and more positive affect (i.e., males tend to like computers more than females).

Beyer, Rynes, Perrault, Hay, and Haller (2003) found that the primary driving factor behind the differences had to do with confidence in using computers. Males tended to have higher confidence than females. In fact, males not majoring in computer science had higher confidence about using computers than females majoring in computer science!

One hypothesis is that males and females have a different intellectual style. Males think in more abstract ways and females in more concrete ways. In terms of computer programming, men like to work with prepackaged routines ("black boxes"), and women prefer to see what is inside ("glass boxes"). Men prefer to send commands at a distance, and women seek closer and deeper communication in their programs (Turkle & Papert, 1990). Although these are fascinating ideas, there has been little or no empirical evidence for this effect. McKenna (2004) found no differences in the preferences of male and female programmers for types of routines that differed according to these dimensions.

However, to the extent that males and females differ in cognitive abilities that drive performance, some gender differences may be explained. De Lisi and Cammarano (1996) explored spatial visualization abilities using a test of mental rotation and found that males did better than females. Moreover, differences in self-reported computer use and self-efficacy were associated with differences on the test of mental rotation.

What can be done to reduce the gender gap? Educational programs have been developed to encourage females and to increase their sense of self-efficacy. Professional organizations have helped support women in computing. These have helped to reduce, but have not eliminated the differences. Interfaces designed by women for women, or that are at least pleasing to the eye, may also help. But in the long run, as the human–computer interface permeates more and more of everyone's life space, gender differences in computer use and skill should become negligible.

Socioeconomic Differences

Clear differences exist in levels of computer use, knowledge, and skills between those of low versus high socioeconomic status. This difference is sometimes referred to as the "digital divide" between the "haves" and the "have nots." Although other factors may be correlated with socioeconomic levels, such as attitudes about computers and self-efficacy, the most obvious reason for this difference is the cost of computers and, as a consequence, their accessibility to the individual. Well-to-do households typically have multiple state-of-the-art workstations and laptops, wireless networks, and high-speed connections to the Internet. Low-income households either have no computer at all or, at best, an obsolete computer with a slow dial-up connection. Figure 9.4 shows this difference in terms of computer use in homes and schools.

In the same way that public education and public libraries have reduced differences in literacy, it is hoped that access to computers through schools, community centers, and public libraries will eliminate the digital divide. Because the primary barrier of computer use is cost, it is expected that if the price of entry-level computers and laptops drops, accessibility will increase.

National, Ethnic, and Cultural Differences

The introduction of the computer follows the industrialization of nations, and in the same way, there are large differences due to the economic level of countries in the global community. The digital divide at the international level is a serious problem that needs to be addressed. It is the goal of the MIT Media Lab's $100 Laptop Project and the One Laptop per Child Organization to make large quantities of inexpensive laptops available to developing countries with the lowest levels of computer use by schoolchildren.

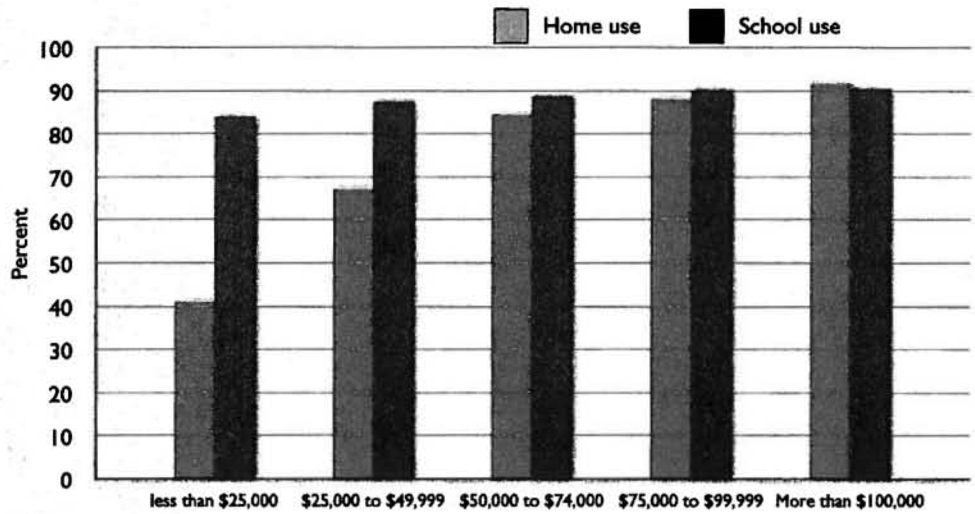

Figure 9.4. Percent of homes and schools with computers as a function of household income. (From U.S. Census Bureau, Current Population Survey, *October 2003, Day, Janus, & Davis, 2005.)*

Holding socioeconomic level and access to computers constant, are there individual differences due to nationality, ethnicity, and culture? Do different people groups have different attitudes and aptitudes with respect to computers? If so, should interfaces be designed differently for different nationalities and ethnic groups above and beyond language and keyboard differences, or can we aim for a universal, international design that will accommodate everyone (see Nielsen, 1990)?

Some interface designers believe that cross-cultural differences in terms of perception, values, thinking, and attitudes are so big that they must be taken into account in HCI. Marcus (2000) proposed that different GUIs should be designed for different cultures and nationalities. He suggests that the cultural dimensions proposed by Hofstede (1991) be used as a guide for design and gives a number of examples for how these dimensions express themselves in Web site design (Marcus & Gould, 2001). The dimensions and their characteristics are listed in Table 9.1.

Although Hofstede's cultural dimensions are compelling, his claims about the consequences of the dimensions and his analysis of the data have been seriously challenged (McSweeney, 2002). Above and beyond distinctive colors and graphics that may be used by different national and ethnic groups, the majority of cross-cultural studies indicates that differences due to culture are generally negligible. Even when differences do exist at the national or macro level, individuals within the groups vary so greatly that it overwhelms group differences. Moreover, when focusing on subgroups, such as business leaders in India, Norman and Singh (1989) found that their patterns of attitudes and expectations mirrored those of their American counterparts and did not need to be considered in issues of marketing or design.

Table 9.1. Hofstede's Five Dimensions of Culture (Hofstede, 1991)

Dimension	Description	Highest scoring	Lowest scoring
Power distance	The degree to which there is a disparity between people wielding greater power than others as opposed to the view that all people should have equal rights	Latin American and Arab nations	Scandinavian and Germanic nations
Individualism vs. collectivism	The extent to which people are expected to stand up for their individual rights as opposed to acting as members of a group	United States	Latin American nations
Masculinity vs. femininity	Masculine cultures value competitiveness, assertiveness, ambition, and the accumulation of wealth as opposed to feminine cultures that value a nurturing quality of life	Japan	Sweden
Uncertainty avoidance	The extent to which a society attempts to cope with anxiety by minimizing uncertainty, preferring institutional rules and structured situations	Japan	Mediterranean nations
Long- vs. short-term orientation	The extent to which a society has a future-oriented time horizon, and values investment and development over past heritage and tradition and present relationships and celebration	China	Pakistan

Personality Factors

As humans, when we think about other humans and individual differences, we think in terms of personality. *Personality* is defined as the consistent and distinctive thoughts, feelings, and behaviors of an individual. Personality is *consistent* in the sense that it is somewhat enduring over time and the same from one situation to another. Personality is *distinctive* in the sense that it sets one person apart from another. We observe personality in the thoughts, feelings, and behaviors of a person. Theories of personality and the assessment of personality factors date back to the early days of modern psychology.

The idea that computers have a personality is not new. My first personal computer was a SOL-20 dating back to 1976. Interestingly, even back then, it had what they called a "personality" card. It contained a ROM chip with a program that either ran the system as a dumb computer terminal to be connected via a modem to a dial-up mainframe or to run as a stand-alone personal computer. But to a very great extent, the OS and its settings determine the personality of the computer.

Given that we can measure personality traits or factors, the question is whether these have any impact or relevance at the human–computer interface. Do certain personality types work best with particular types of computers and OSs? Are there personality differences between MS Windows users and Apple Macintosh users?

In this section, we explore the factors of human personality and their relationship to performance and other measures at the human–computer interface. We explore the idea of computer personality in Chapter 13.

One of the earliest and most extensive lists of personality factors was derived by Cattell. The reasoning was as follows. Allport and Odbert (1936) hypothesized that "Those individual differences that are most salient and socially relevant in people's lives will eventually become encoded into their language; the more important such a difference, the more likely is it to become expressed as a single word." Allport and Odbert worked through two comprehensive English dictionaries and extracted 18,000 personality descriptor words. From this list, they extracted 4,500 personality adjectives that described relatively permanent traits. In 1946, Cattell organized the list into 181 clusters and asked subjects to rate people they knew using these adjectives. Using factor analytic methods like those used in intelligence testing, he identified twelve factors. He also generated four additional factors that he hypothesized were important. The 16PF Personality Questionnaire was then developed and is still in use today. Table 9.2 lists the sixteen primary factors and descriptors for the low and high ends of each factor.

The development of the California Personality Inventory (Gough, 1958) suggests that there are twenty-two factors. In contrast, others such as Eysenck (1947) claimed that only two orthogonal dimensions truly differentiate individuals: introversion-extroversion and neuroticism-emotional stability. Subsequent research has indicated that Cattell retained too many factors. In an attempt to simplify the situation and reduce the number of personality factors to more general dimensions, personality researchers reviewed the existing personality tests and decided that five factors would be sufficient. This work resulted in the Big Five personality traits (Goldberg, 1993). These traits are as follows:

- *Extroversion* – energy, surgency, and the tendency to seek stimulation and the company of others
- *Openness to experience* – appreciation for art, emotion, adventure, unusual ideas; imagination and curiosity
- *Agreeableness* – a tendency to be compassionate and cooperative rather than suspicious and antagonistic toward others

Table 9.2. Cattell's Sixteen Personality Factors (16PF)

Low-range descriptors	Primary factor	High-range descriptors
Impersonal, distant, cool, reserved, detached, formal, aloof (Sizothymia)	Warmth	Warm, outgoing, attentive to others, kind, easygoing, participating, likes people (Affectothymia)
Concrete thinking, lower general mental capacity, less intelligent, unable to handle abstract problems (Lower Scholastic Mental Capacity)	Reasoning	Abstract thinking, more intelligent, bright, higher general mental capacity, fast learner (Higher Scholastic Mental Capacity)
Reactive emotionally, changeable, affected by feelings, emotionally less stable, easily upset (Lower Ego Strength)	Emotional stability	Emotionally stable, adaptive, mature, faces reality, calm (Higher Ego Strength)
Deferential, cooperative, avoids conflict, submissive, humble, obedient, easily led, docile, accommodating (Submissiveness)	Dominance	Dominant, forceful, assertive, aggressive, competitive, stubborn, bossy (Dominance)
Serious, restrained, prudent, taciturn, introspective, silent (Desurgency)	Liveliness	Lively, animated, spontaneous, enthusiastic, happy-go-lucky, cheerful, expressive, impulsive (Surgency)
Expedient, nonconforming, disregards rules, self-indulgent (Low Super Ego Strength)	Rule consciousness	Rule conscious, dutiful, conscientious, conforming, moralistic, staid, rule bound (High Super Ego Strength)
Shy, threat sensitive, timid, hesitant, intimidated (Threctia)	Social boldness	Socially bold, venturesome, thick skinned, uninhibited (Parmia)
Utilitarian, objective, unsentimental, tough minded, self-reliant, no nonsense, rough (Harria)	Sensitivity	Sensitive, aesthetic, sentimental, tender minded, intuitive, refined (Premsia)
Trusting, unsuspecting, accepting, unconditional, easy (Alaxia)	Vigilance	Vigilant, suspicious, skeptical, distrustful, oppositional (Protension)
Grounded, practical, prosaic, solution oriented, steady, conventional (Praxernia)	Abstractedness	Abstract, imaginative, absent minded, impractical, absorbed in ideas (Autia)
Forthright, genuine, artless, open, guileless, naive, unpretentious, involved (Artlessness)	Privateness	Private, discreet, nondisclosing, shrewd, polished, worldly, astute, diplomatic (Shrewdness)
Self-assured, unworried, complacent, secure, free of guilt, confident, self-satisfied (Untroubled)	Apprehension	Apprehensive, self-doubting, worried, guilt prone, insecure, self-blaming (Guilt Proneness)

Low-range descriptors	Primary factor	High-range descriptors
Traditional, attached to familiar, conservative, respecting traditional ideas (Conservatism)	Openness to change	Open to change, experimental, liberal, analytical, critical, free thinking, flexible (Radicalism)
Group oriented, affiliative, a joiner and follower dependent (Group Adherence)	Self-reliance	Self-reliant, solitary, resourceful, individualistic, self-sufficient (Self-Sufficiency)
Tolerate disorder, unexacting, flexible, undisciplined, lax, self-conflict, impulsive, careless of social rules, uncontrolled (Low Integration)	Perfectionism	Perfectionistic, organized, compulsive, self-disciplined, socially precise, exacting willpower, control, self-sentimental (High Self-Concept Control)
Relaxed, placid, tranquil, torpid, patient, composed, low drive (Low Ergic Tension)	Tension	Tense, high energy, impatient, driven, frustrated, overwrought, time driven (High Ergic Tension)

Adapted from Conn and Rieke (1994).

- *Conscientiousness* – a tendency to show self-discipline, act dutifully, and aim for achievement
- *Neuroticism* – a tendency to easily experience unpleasant emotions such as anger, anxiety, depression, or vulnerability

With the development and interest in personality factors, there were great hopes and expectations that they would be extremely useful in giving guidance to the design of systems and the selection of applicants in the workplace. Despite their acceptance at face value, the empirical results have been very disappointing across the board. In a review of many studies on personality factors and their usefulness in personnel selection, Landy, Shandkster, and Kohler (1994) concluded that it is still too early to draw any reliable conclusions.

In the area of HCI, the idea that personality factors would predict success in programming was an appealing idea from early on (Weinberg, 1971). It was hypothesized that these factors would be related to performance on various computer tasks. However, nearly every study that has included personality factors as predictor variables has found no effect on learning or performance for tasks such as programming (Koubek, LeBold, & Salvendy, 1985), online searching (Bellardo, 1985), and text editing (Gomez, Egan, & Bowers, 1986). Bishop-Clark (1995) reported that most studies find no relationship between introversion/extroversion and computer programming.

In contrast, although personality factors may have little to do with performance, they may relate to other behaviors in HCI. For example, Landers and Lounsbury (2006) investigated the amount of self-reported time using the Internet for communication (including e-mail and chat), leisure (including music, role-playing, shopping), and academic reasons (research, course participation online). They found that Internet usage was negatively correlated with three of the Big Five factors (Agreeableness, Conscientiousness, and Extroversion) and with two additional factors ("optimism" and "work drive") and positively correlated with another factor ("tough mindedness"). However, the individual correlations were only in the range of 0.21 to 0.26, with an overall multivariate correlation of 0.35. This means that all of the personality factors together only accounted for 12 percent of the total variance in usage.

Cognitive Styles and Human–Computer Fit

"Cognitive styles" refers to relatively stable patterns in the way individuals think, perceive, and remember information, as well as the way in which they process information. As such, a particular cognitive style falls somewhere between a cognitive ability and a personality trait. A number of fascinating cognitive styles have been proposed and studied (Sternberg & Grigorenko, 1997). But even more than with personality theory, cognitive styles have often been promoted and marketed above and beyond any empirical evidence of their relationship with observed performance. Consider Scenario 1.

One of the main theories about cognitive styles in education and management is that if a teacher and pupil or a worker and manager share the same style, there will be a more positive learning experience or a more productive work environment than if there is a mismatch. Matching cognitive style helps individuals to feel more comfortable working with one another and more compatible in understanding and communication. Although this may have some merit, one could also argue that in many team situations having complementary cognitive styles would be more effective. Moreover, the problem may call for different styles at different points. In this section, we review some of the popular cognitive styles that have been promoted as individual differences relevant to HCI.

- *Field Dependence–Independence* (Witken, Moore, Goodenough, & Cox 1977). Those high in field independence have a tendency to provide structure to relatively unstructured situations. Individuals are able to overcome the organization of the field and restructure it. In contrast, those that are field dependent are oriented to the environment, and their perception of an item is strongly affected by the field. The favored measure for this cognitive style is the Group Embedded Figures Test (GEFT), as shown in Figure 9.5, and the Embedded Figures Test. Although numerous studies do show a relationship of field independence with programming achievement scores (Bishop-Clark, 1995), McKenna (1984) argued that it is not really due to style, but rather the fact that those with high GEFT scores have higher overall cognitive ability associated with perceptual skill.

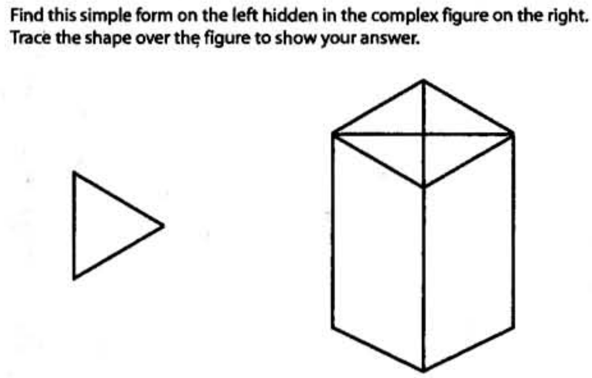

Figure 9.5. Example of a Group Embedded Figure Test item.

- *Analytic–Holistic* (French, Ekstrom, & Price, 1963). Analytic problem solvers reduce problems down to a base set of causes and factors and use structured approaches to decision making. Holistic thinkers emphasize common sense and intuition. They look for an overall pattern but tend to use more trial-and-error methods of problem solving. The Gestalt completion test shown in Figure 9.6 is often used to assess this style. The problem with the analytic–holistic dimension is that it is closely related to field independence. Studies looking at the relationship of this cognitive style with computer programming have had very mixed and questionable results.
- *Reflectic–Impulsive* (Kagan, Rosman, Day, Albert, & Phillips, 1964). Reflectic individuals think about different hypotheses in situations where there are many alternatives, and they tend to reflect on the consequences. Impulsives tend to choose the first alternative and go with it. The Matching Familiar Figures Test is the most popular method of assessing this cognitive style. It consists of items that start with a picture of a common object followed by several alternatives. One alternative is identical to the first picture, and the others are slightly different in one detail each. The subject is to pick the alternative that is identical, and the test is timed. Impulsives tend to pick the first alternative, and reflectics consider the figures in more detail. Figure 9.7 shows an example of one item. Research suggests an interesting link between programming experience and reflectivity. Programming experience may serve to increase reflectivity (Cathcart, 1990), and higher reflectivity results in higher programming achievement scores (VanMerrienboer, 1988).

Figure 9.6. Example of a Gestalt Completion Test item. (Picture A is an American flag, and Picture B is a bird.)

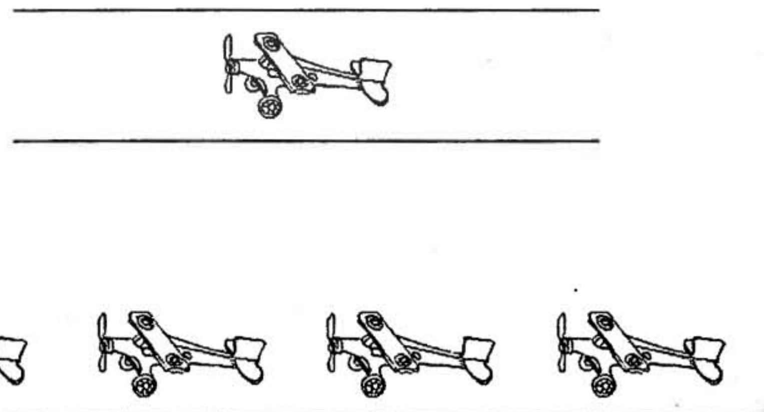

Figure 9.7. Example of a Matching Familiar Figures Test item. (The second alternative is the correct answer.)

- *Visualizer–Verbalizer* (Booth, Fowler, & Macaulay, 1987). Visualizers rely primarily on imagery processing when attempting to perform cognitive tasks. Verbalizers prefer to process information by a verbal-logical means. Although this seems to be an important individual difference, little is known about how it affects HCI.
- *Need for Closure* (Mills & Snyder, 1962). Individuals with a high need for closure have a desire to get a definite answer and will pursue the means to finish the job, make the decision, and get it done in a reasonable amount of time. Individuals with low need for closure will accept inconclusive results and have a tolerance for ambiguity. This cognitive style is measured using the Need for Closure Scale developed by Kruglanski, Webster, and Klem (1993). Need for closure and need for structure (analytic) are highly correlated. Need for closure may be related to information search and browsing the Web.
- *Locus of Control* (Rotter, 1966). Individuals with a strong *internal* locus of control believe that they influence events in their world and that their performance is the result of their own efforts rather than outside forces. Individuals with a strong *external* locus of control feel that outside forces control their performance and that they are helpless. The Rotter Locus of Control Scale (Rotter, 1966) is used to assess this dimension. Bishop-Clark (1995) reported that no reasonable conclusions can be drawn about the relationship between locus of control and programming performance. However, for general users, this may be an important individual difference when it comes to issues of who is in control at the human–computer interface, the user or the computer. We see in Chapter 12 that strong external locus of control is related to Internet addiction (Chak & Leung, 2004).
- *Convergent–Divergent Thinkers* (Hudson, 1966). The convergent thinker works for the best single answer to a problem. The divergent thinker moves outward from the problem to find many possible solutions. The Torrance

Test of Creative Thinking (Torrance, 1972) is used to measure divergent thinking. As suggested in Chapter 7, some creativity techniques may require a person to engage in both types of thinking at different stages of problem solving.

- *Adaptive–Innovative* (Kirton, 1976, 2003). Adaptors prefer to solve problems by time-honored techniques and within accepted paradigms, whereas innovators prefer to do things differently and strive to transcend existing paradigms. Again, a person may tend toward one of the other cognitive styles, but many situations may dictate which is more appropriate at a particular time. Moreover, it is not yet clear how these cognitive styles impact the way in which users interact with the human–computer interface.

At present, the idea of taking into consideration the user's cognitive styles seems promising. One of the models of HCI presented in Chapter 3 involves the idea of matching the characteristics of the human and the computer to create a synergistic combination. To an extent, this may be true, but humans tend to be very accommodating and can shift styles when needed. However, computers may provide a multiplying factor for some individuals, say, those with high spatial visualization ability, and a limiting factor for individuals with poor skills. If this is the case, we might find an increase in the disparity between different groups of computer users with different styles and abilities. Are there ways to reduce these differences? Is it possible for computers to provide scaffolding or bootstrapping for individuals who need help?

Assessment of Individual Differences: Online Testing and Measurement

Throughout this chapter, we have been talking about individual differences that are assessed by some sort of psychometric testing. Traditional methods have involved observing task performance, personal interview, and paper-and-pencil questionnaires. In the past few years, we have witnessed a steady shift from both face-to-face interview and paper-and-pencil testing to computerized testing and online surveys. Initially, there was some concern about the reliability and validity of online testing; however, in nearly every case, online testing has proven to be either equal or superior to traditional methods. Moreover, efficiency and cost effectiveness have made online testing the method of choice.

Studies indicate that, for the most part, the results are equivalent for online and paper-and-pencil surveys. Respondents tend to give the same answers whether the survey is printed or online (Huang, 2006). Moreover, a few positive factors have been observed.

Research indicates that people tend to be more honest and open about sensitive issues in online methods than face-to-face interviews. People tend to write more for open-ended questions on the computer than on paper (Slaughter, Harper, & Norman, 1994). College students prefer online questionnaires to paper-and-pencil forms. Surveys can be designed to be efficient and easy to navigate (Norman, Friedman, Norman, & Stevenson, 2000).

Online surveys, testing, and measurement have many advantages (Couper, 2000; Dillman, 1999). Obviously, online surveys and tests eliminate paper. They are electronically disseminated and collected, which avoids mailing and handling. They also help automate the data collection and analysis. Online surveys have the unique advantage of being dynamic. They can check for missing or incomplete answers. They can detect inconsistent answers (e.g., the respondent's age is 32, but he enters 30 for the age of his oldest child) and help the respondent correct any errors. They can automatically skip questions that are not appropriate given previous answers. One of the most compelling advantages to Web-based methods is that a number of survey tools are available on the Web that make it very easy to develop online questionnaires, automatically host them on the Web, and efficiently analyze the results.

However, there are also a few problems that one has to watch out for. The disadvantages are that computer problems can interfere with results. These include disconnects and problems with communications. It may also be difficult to get representative samples of the population.

End Thoughts

Individual differences have always been extremely important in psychology. Computer science took note of individual differences when computers were introduced to the masses and large differences in attitudes and performance were found between user groups. The popular method of "user-centered" design required that designers take into consideration individual differences. However, as the human–computer interface permeates more and more of the human environment, one wonders how and to what extent individual differences can really be accommodated. In much of our environment, we are accustomed to a "one-size-fits-all" solution. We do not have different doors for different heights of people, different roads for below average and above average drivers, and different public libraries for high verbal versus low verbal patrons. But within many systems, we do have choices and preferences. You can select the items that suit you and set the preferences in many applications that work best for you. Individual differences are accommodated by individual choice. Public libraries have large selections of books that cover the range of verbal abilities of the patrons.

Many individual differences have to do with job performance and are factors that help determine one's career path. Some people are good at programming, and others are not. Those who are good should be hired as programmers. Some people are good in art and graphic design. Some people are good at personal relations. Individual differences are assessed through applicant testing and screening and accommodated through career guidance and choice.

A large number of factors are discussed in this chapter that pertain to the measurement of individual differences and their subsequent impact on HCI. Some factors have been used to predict user performance such as IQ and spatial visualization ability. Others have been used to customize interfaces for different types of individuals. However, in many ways, the interface itself may serve to both assess individual differences and accommodate for them. As noted in other places, interactions at the interface can be captured, stored, and analyzed. These interactions, such as typing speed, mousing accuracy, programming patterns, and Web browsing, can all be used to profile individual differences. The methods of psychometrics from the 1900s using tests and questionnaires that capture only a few ratings and choices (e.g., <100) will undoubtedly be replaced in the near future with much more sophisticated data mining methods that tap into megabytes of interactive data stored in logs, cookies, and history files. These data will be used to assess a person's IQ, personality, cognitive styles, and abilities.

Suggested Exercises

1. Take a look at the profile or configuration of your computer. For a Mac user, go to the Applications folder, then the Utilities folder, and then run the System Profiler application. For a Windows-XP user, go to the Programs directory, then the Accessories directory, then the System Tools directory, and then run the System Information program. How do these specifications on the hardware and software map to individual differences among computers?

2. Write a description of yourself as a computer user. What are your demographics, abilities, attitudes, and so on?

3. Go to several of the online IQ and personality test Web sites. Take several of the tests and see if you agree with the results.

4. You can see how different programs and different Web sites are aimed at different user groups or types. See if you can find a Web site that matches each of the following stereotypes: teenage boy, teenage girl, geek, and retired person.

5. Go to one of the free online survey tools and develop your own survey on a topic of your choice.

References

Allport, G. W., & Odbert, H. S. (1936). Trait names: A psycho-lexical study. *Psychological Monographs, 47* (1 Whole No. 211).

Anastasi, A., & Urbina, S. (1996). *Psychological testing* (7th ed.). Upper Saddle River, NJ: Prentice Hall.

Bellardo, T. (1985). An investigation of online searcher traits and their relationship to search outcome. *Journal of the American Society for Information Science, 36*(4), 241–250.

Beyer, S., Rynes, K., Perrault, J., Hay, K., & Haller, S. (2003). Gender differences in computer science students. *Proceedings of the SIGCSE'03*, pp. 49–53.

Bishop-Clark, C. (1995). Cognitive style, personality, and computer programming. *Computers in Human Behavior, 11*(2), 241–260.

Booth, P., Fowler, C. J. H., & Macaulay, L. A. (1987). An investigation into business information presentation at human-computer interfaces. In: Bullinger, H. J., and Schackerl, B. (Eds.), *Proceedings of Human-Computer Interaction-INTERACT'87*, Elsevier, North-Holland. pp. 599–604.

Cathcart, W. (1990). Effects of LOGO instruction on cognitive style. *Journal of Educational Computing Research, 6*, 231–242.

Chak, K., & Leung, L. (2004). Shyness and locus of control as predictors of Internet addiction and Internet use. *CyberPsychology & Behavior, 7*(5), 559–570.

Chen, C., & Rada, R. (1996). Interacting with hypertext: A meta-analysis of experimental studies. *Human–Computer Interaction, 11*, 125–156.

Chrysler, E. (1978). Some basic determinants of computer programming productivity. *Communications of the ACM, 21*(6), 472–483.

Conn, S. R., & Rieke, M. L. (1994). *The 16PF Fifth Edition Technical Manual.* Champagne, IL: Institute for Personality and Ability Testing, Inc.

Couper, M. P. (2000). Web surveys: A review of issues and approaches. *Public Opinion Quarterly, 64*, 464–494.

Day, J. C., Janus, A., & Davis, J. (2005, October). *Computer and Internet use in the United States: 2003*. Current Population Reports P23-208. Washington, DC: U.S. Census Bureau. Retrieved March 20, 2008, from www.census.gov/prod/2005pubs/p23-208.pdf.

De Lisi, R., & Cammarano, D. M. (1996). Computer experience and gender differences in undergraduate mental rotation performance. *Computers in Human Behavior, 12*(3), 351–361.

Dillman, D. A. (1999). *Mail and Internet surveys: The tailored design method* (2nd ed.). New York: John Wiley & Sons.

Dillon, A., & Watson, C. (1996). User analysis in HCI – The historical lessons from individual differences research. *International Journal of Human–Computer Studies, 45*, 619–637.

Dillman, D. A. (1999). *Mail and Internet Surveys: The tailored design method.* (2nd ed.), New York: John Wiley & Sons.

Egan, D. E. (1988). Individual differences in human-computer interaction. In M. Helander (Ed.), *Handbook of human-computer interaction* (pp. 543–568). Elsevier Science.

Egan, D. E., & Gomez, L. M. (1985). Assaying, isolating and accommodating individual differences in learning a complex skill. In R. Dillon (Ed.), *Individual differences in cognition* (Vol. 2) (pp. 173–217). New York: Academic Press.

Ekstrom, R. B., French, J. W., & Harman, H. H. (1976). *Manual for kit of factor-referenced cognitive tests.* Princeton, NJ: Educational Testing Service.

Eysenck, H. J. (1947). *Dimensions of personality.* London, U.K.: Routledge & Kegan Paul.

French, J. W., Ekstrom, R., & Price, L. (1963). *Kit of reference tests for cognitive factors*. Princeton, NJ: Educational Testing Service.

Gardner, H. (1983). *Frames of mind: The theory of multiple intelligences*. New York: Basic Books.

Gardner, H. (1999). *Intelligence reframed: Multiple intelligences for the 21st century*. New York: Basic Books.

Goddard, H. H. (1913). The Binet tests in relation to immigration. *Journal of Psycho-Asthenics, 18*, 105–107.

Goldberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist, 48*, 26–34.

Gomez, L. M., Egan, D. E., & Bowers, C. (1986). Learning to use a text editor: Some learner characteristics that predict success. *Human–Computer Interaction, 2*, 1–23.

Goodwin, B. (2004, October 1). Number of women in IT industry falls by almost half in four years. *ComputerWeekly.com*. Retrieved March 20, 2008, from http://www.computerweekly.com/Articles/2004/10/01/205622/number-of-women-in-it-industry-falls-by-almost-half-in-four.htm

Gough, H. (1958). *Manual for the California Psychological Inventory*. Palo Alto, CA: Consulting Psychologists Press.

Gould, S. J. (1996). *The mismeasure of man*. New York: W. W. Norton.

Greene, S. L., Gomez, L. M., & Devlin, S. J. (1986). A cognitive analysis of database query production. *Proceedings of the Human Factors Society*, Dayton, OH, pp. 9–13.

Hofstede, G. (1991). *Cultures and organizations, software of the mind: Intercultural cooperation and its importance for survival*. New York: McGraw-Hill.

Houtz, L. (2001). Nebraska high school students' computer skills and attitudes. *Journal of Research on Computing in Education, 33*, 316–328.

Huang, H. (2006). Do print and Web surveys provide the same results? *Computers in Human Behavior*, 22(3), 334–350.

Hudson, L. (1966). *Contrary imaginations: A psychological study of the young student*. New York: Schocken Books.

Jensen, A. (1982). The debunking of scientific fossils and straw persons. *Contemporary Education Review, 1*, 121–135.

Kagan, J., Rosman, B., Day, D., Albert, J., & Phillips, W. (1964). Information processing in the child: Significance of analytic and reflective attitudes. *Psychological Monographs, 78*(1, Serial No. 578).

Kay, R. (1992). Understanding gender differences in computer attitudes, aptitude, and use: An invitation to build theory. *Journal of Research on Computing in Education, 25*, 159–172.

Kirton, M. (1976). Adaptors and innovators: A description and measure. *Journal of Applied Psychology, 61*(5), 622–629.

Kirton, M. J. (2003). *Adaption and innovation in the context of diversity and change*. London: Routledge.

Koubek, R. J., LeBold, W. K., & Salvendy, G. (1985). Predicting performance in computer programming courses. *Behaviour and Information Technology*, 4(2), 113–129.

Kruglanski, A. W., Webster, D. M., & Klem, A. (1993). Motivated resistance and openness to persuasion in the presence or absence of prior information. *Journal of Personality and Social Psychology, 65*, 861–876.

Landers, R. N., & Lounsbury, J. W. (2006). An investigation of Big Five and narrow personality traits in relation to Internet usage. *Computers in Human Behavior, 22*, 283–293.

Landy, F., Shandkster, L., & Kohler, S. (1994). Personnel selection and placement. *Annual Review of Psychology, 45*, 261–296.

Marcus, A. (2000). International and intercultural user-interface design. In C. Stephanidis (Ed.), *User interfaces for all* (pp. 47–63). New York: Erlbaum.

Marcus, A., & Gould, E. (2001). *Cultural dimensions and global web design: What? So what? Now what?* Emeryville, CA: Aaron Marcus and Associates, Inc.

McKenna, F. P. (1984). Measures of field dependence: Cognitive style of cognitive ability. *Journal of Personality and Social Psychology, 47*, 593–603.

McKenna, P. (2004). Gender and black boxes in the programming curriculum. *ACM Journal of Educational Resources in Computing, 4*(1), 1–12.

McSweeney, B. (2002). Hofstede's model of national cultural differences and their consequences: A triumph of faith – A failure of analysis. *Human Relations, 55*(1), 89–118.

Michell, J. (1999). *Measurement in psychology*. Cambridge: Cambridge University Press.

Mills, J., & Snyder, R. (1962). Avoidance of commitment, need for closure, and the expression of choices. *Journal of Personality, 30*(3), 458–470.

Murphy, E. (2000). *Beyond supervisory control: Cognitive issues in human interaction with autonomous satellites*. Unpublished Ph.D. dissertation. University of Maryland, College Park.

Neisser, U., Boodoo, G., Bouchard, T. J., Jr., Boykin, A. W., Brody, N., Ceci, S. J., et al. (1996). Intelligence: Knowns and unknowns. *American Psychologist, 51*, 77–101.

Nielsen, J. (Ed.). (1990). *Designing user interfaces for international use*. North Holland, Amsterdam: Elsevier.

Norman, D. A. (1986). Cognitive engineering. In D. A. Norman & S. Draper (Eds.), *User centered system design: New perspectives on human–computer interaction* (pp. 31–62). Hillsdale, NJ: Erlbaum.

Norman, K. L. (1994). Spatial visualization: A gateway to computer-based technology. *Journal of Special Education Technology, 12*; 195–205.

Norman, K. L., & Butler, S. A. (1989). *Search by uncertainty: Menu selection by target probability*. Technical Report CAR-TR-432. College Park: University of Maryland Center for Automation Research.

Norman, K. L., Friedman, Z., Norman, K. D., & Stevenson, R. (2000). Navigational issues in the design of on-line self administered questionnaires. *Behaviour and Information Technology, 20*, 37–45.

Norman, K. L., & Singh, R. (1989). Expected performance at the human/computer interface as a function of user proficiency and system power. *Journal of Behavioral Decision Making, 2*, 179–195.

Nunnally, J. C., & Bernstein, I. (1994). *Psychometric theory*. Hightstown, NJ: McGraw-Hill.

Rosson, M. B. (1983). Patterns of experience in text editing. *Proceedings of the CHI'83 Human Factors in Computing Systems*, pp. 171–175.

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Mongraphs, 80*, 1–28.

Ryder, N. B. (1965). The cohort as a concept in the study of social change. *American Sociological Review, 30*, 843–861.

Sharp, S. E. (1898). Individual psychology: A study of psychological method. *American Journal of Psychology, 10*, 329–391.

Slaughter, L., Harper, B. D., & Norman, K. L. (1994). Assessing the equivalence of the paper and on-line formats of the QUIS 5.5. *Proceedings of the Mid-Atlantic Human Factors Conference*, Reston, VA, pp. 87–91.

Spearman, C. E. (1927). *The abilities of man, their nature and measurement*. New York: Macmillan.

Sternberg, R. J. (1988). *The triarchic mind: A new theory of human intelligence*. New York: Penguin Books.

Sternberg, R. J. (1997). The concept of intelligence and its role in lifelong learning and success. *American Psychologist, 52*, 1030–1037.

Sternberg, R. J., & Grigorenko, E. L. (1997). Are cognitive styles still in style? *American Psychologist, 52*(7), 700–712.

Strauss, W., & Howe, N. (2003). *Millennials go to college: Strategies for a new generation on campus*. American Association of Collegiate Registrars. Washington, DC.

Terman, L. M. (1916). *The measurement of intelligence*. Boston: Houghton Mifflin.

Thurstone, L. L. (1938). *Primary mental abilities*. Chicago: University of Chicago Press.

Tisserand, D. J., Bosma, H., Van Boxtel, M. P., & Jolles, J. (2001). Head size and cognitive ability in nondemented older adults are related. *Neurology, 56*, 969–971.

Torrance, E. P. (1972). Can we teach children to think creatively? *Journal of Creative Behavior, 6*(2), 114–143.

Turkle, S., & Papert, S. (1990). Epistemological pluralism: Styles and voices within the computer culture. *Signs: Journal of Women in Culture and Society, 16*(10), 128–157.

VanMerrienboer, J. (1988). Relationship between cognitive learning style and achievement in an introductory computer programming course. *Journal of Research on Computing in Education, 29*, 181–185.

Vernon, P. A., Wickett, J. C., Bazana, G., & Stelmack, R. M. (2000). The neuropsychology and psychophysiology of human intelligence. In R. J. Sternberg (Ed.), *Handbook of Intelligence* (pp. 245–266). Cambridge University Press.

Vicente, K. J., Hayes, B. C., & Williges, R. C. (1987). Assaying and isolating individual differences in searching a hierarchical file system. *Human Factors, 29*(3), 349–359.

Weinberg, G. M. (1971). *The psychology of computer programming*. New York: Van Nostrand Reinhold.

Whitley, B. E. (1997). Gender differences in computer-related attitudes and behavior: A meta-analysis. *Computers in Human Behavior, 13*(1) 1–22.

Wissler, C. (1901). The correlation of mental and physical tests. *Psychological Review Monograph Supplement, 3* (Whole No. 6).

Witken, H., Moore, C., Goodenough, D., & Cox, P. (1977). Field-dependent and field-independent cognitive styles and their educational implications. *Review of Educational Research, 47*(10), 1–64.