

Errors in Interactive Behavior

Designing interactive systems to reduce error and increase error detection and recovery is an important and often frustrating goal. “Human error” is an everyday term with different meanings for different communities of practitioners and researchers, but the fact that different users of the same term may refer to very different phenomena does not seem to be widely recognized. A further difficulty is that although many researchers collect error data, there is no established research tradition to experimentally manipulate and study error as a phenomenon. In short, the subject of errors is broad, but the study of errors is shallow. After reviewing the state of the art in human error research, this article examines studies of the cognitive processes that lead to errors in interactive behavior.

Assessment of Current Research

Errors may affect productivity, user satisfaction, and the safety of property and lives. Errors may be diagnosed as training problems, design problems, system problems, or organizational problems, and the diagnosis will determine the remediation. Training problems are remediated by better documentation or user training. Design problems are fixed by redesign. Systems problems require a wider look at the complete task environment of the user to determine incompatibilities or conflicts between the design of multiple devices used by the same worker or in the functions and responsibilities of the worker. Finally, organizational problems (for example, strong pressures to reduce costs at the expense of all else, including safety) may require remediations as diverse as the adoption of new procedures, changes in organizational structure, or the replacement of top management.

Although legitimate, the breadth of phenomenon covered by the term “human error” has tended to get in the way of understanding its nature, detection, and correction. To some degree, these different

meanings have caused communication difficulties and have occasionally resulted in turf battles in which different communities argue for the primacy of their level of analysis (for instance, cognitive, systems, or organizational). More generally, these various meanings muddy the waters because distinctions that are important within one level of analysis are lost or blurred by attempts to cast all error phenomena within the same framework.

This situation holds even among the communities of researchers and practitioners interested in human factors and human-computer interaction. As one of the most influential thinkers on the topic complained, “the need for human error data for various purposes has been discussed for decades, yet no acceptable human error data bank has emerged” (Rasmussen 1987, 23). However, even within the human factors and human-computer interaction communities, these “various purposes” are somewhat independent and attempts to shoehorn them into one approach may not be the path to progress, but an obstacle to progress. For example, major reviews of human errors discuss the cognitive, systems, and organizational perspectives on human error. Although each perspective is important, it is difficult to know how progress in understanding the roots of error at, for instance, the organizational level, will either provide or be aided by insights into, for instance, the errors encountered in the course of routine interactive behavior.

Although a confusion of level of analysis is a major obstacle to understanding human error, it is not the only one. Perhaps equally damaging is the way in which errors are collected and classified. Following a tradition that goes back at least to William James, the most famous error taxonomies simply amass a large number of naturally occurring slips as reported anecdotally by friends, colleagues, the current researchers, and prior researchers. These errors are then subjected to a largely informal analysis that sort the errors into the taxonomic categories favored by the researchers. Attempts to compare how any given error is classified within or between taxonomies brings to mind the complaint that “cognitive theory is radically underdetermined by data” (Newell 1992, 426).

Although some of these taxonomies rely on cognitive theory as the basis of their classifications, all lack the mechanisms to predict errors. Hence, their explanatory power is only post hoc and incidental. Indeed, a 1997 survey by researchers Mike Byrne and Susan Bovair, led these researchers to conclude that errors in routine interactive behavior are regarded primarily as the result of some stochastic process. Such a view discourages the systematic study of the nature and origin of this class of errors.

Approaches to the Study of Error in Interactive Behavior

An analysis of errors at the cognitive level avoids neither the confusion nor the shallowness endemic to the study of human error. Arguably the dominant cognitive account of errors distinguishes among knowledge-based, rule-based, and skill-based errors. Knowledge-based errors occur when a user lacks the requisite knowledge—for example, if the only route you know from your home to work is habitually crowded during rush hour, you will undoubtedly spend a lot of time waiting in traffic. If you do not know an alternative route, then obviously you will not be able to take it.

Rule-based errors result from learning a mal-rule or applying the correct rule but on the wrong occasion. For example, if you know two routes to work and you also know that one is the fastest during rush hour and the other is the fastest on the off hours, taking the wrong route becomes a rule-based error. You have the correct knowledge, but you picked the wrong rule.

An error is “skill-based” when knowledge is available, the correct rule is selected, but a slip is made in executing the rule. For example, you intend to take your rush-hour route to work, but at the critical intersection you take the turn for the route that is fastest during the off hours.

The same behavior, e.g., “taking the wrong route during rush hour” can result from lack of knowledge, misapplication of a rule, or a slip. Hence, the knowledge-based, rule-based, and slip-based approach to errors is neither as neat and clean nor as theory-based as it may first appear. Whether an error

is classified as skill-based, rule-based, or knowledge-based may depend more on the level of analysis than on its ontogeny.

Unfortunately, the view that errors in routine interactive behavior are stochastic is reinforced by the difficulties of systematically studying such errors. Indeed, it is almost a tautology to assert that errors in routine interactive behavior are rare. This rarity may have encouraged the naturalistic approach in which researchers and their confederates carry around notebooks with the goal of noting and recording the occasional error. Naturalistic approaches have an important role to play in documenting the importance and frequency of error. However, they have not been particularly productive in understanding the cognitive mechanisms that determine the nature, detection, and correction of errors in interactive behavior.

New Directions

The rarity of errors requires research programs that will capture and document errors, not retrospectively, but as they occur. The systematic study of such errors of interactive behavior involves three interrelated paths. The first path entails creating a task environment designed to elicit a particular type of error. The second involves collecting errorful and error-free behaviors and subjecting both to a fine-grained analysis. A cost of these two approaches is that they require collecting vast amounts of correct behavior to amass a small database of errorful behavior. For example, in 2000 cognitive researcher, Wayne Gray, reported that out of 2,118 goal events (either initiating or terminating a goal) only 76 or 3.6% could be classified as errors. The third path entails building integrated models of cognition that predict the full-range of behavior, including reaction time, correct performance, and errors.

The study of the cognitive mechanisms that produce errors has been hampered by the long tradition in psychology of attempting to understand the mind by studying each mental function in isolation. Fortunately, contrasting trends exist. For example, the pioneering researchers, Stewart Card, Thomas Moran, and Allen Newell are credited with bringing to HCI the attempt “to understand in detail the

involvement of cognitive, perceptual, and motor components in the moment-by-moment interaction a person encounters when working at a computer” (Olson and Olson 2003, 493). Indeed, building on this work, the noted HCI investigator, Bonnie John developed a task analysis notation that captures the ways in which embodied cognition (cognitive, perceptual, and action) is responsive to small changes in the task environment. This approach is called CPM-GOMS (CPM<M>critical path method and cognitive, perceptual, and movement; GOMS<M>goals, operators, methods, and selection rules).

Despite a strong push from the cognitive HCI community, within the larger cognitive community the emphasis on an embodied cognition interacting with a task environment to accomplish a task has been a minority position. Fortunately, its status seems to have changed as we now have six approaches to embodied cognition and at least two mechanistic approaches capable of modeling the control of interactive behavior. The components of interactive behavior can be studied by focusing on the mixture of cognition, perception, and action that takes approximately 1/3 of a sec to occur. As human rationality is bounded by limits to working memory, attention, and other cognitive functions the exact mix of operations depends on the task being performed and the task environment. Understanding how the task environment influences the mix of operations is the key to understanding human error in interactive behavior, as the following four examples show:

A Goal Structure Analysis of the Nature, Detection, and Correction of Errors

In 2000 Gray provided a goal structure analysis of errors made programming a VCR. A cognitive model was written that used the same goal structure as humans with the goals and subgoals analyzed down to those that take approximately 1-s to occur (three times higher than required for the analysis of embodied cognition). This level of analysis allowed second-by-second comparisons of human behavior with model behavior (that is, model tracing).

Places in which the model and a given human on a given trial diverged were considered potential

errors. Each potential error was inspected to determine whether it represented a true error or a failure of the model to capture the richness and diversity of human goal structures. “True errors” were cataloged according to the actions that the model would have had to take to duplicate the error. This taxonomy avoided the use of more ambiguous terms such as “knowledge-based,” “rule-based,” and “slip-based” , or “capture errors,” “description errors,” and “mode errors.” Thus, model tracing was used to provide a rigorous and objective taxonomy with which to characterize the nature, detection, and correction of errors.

A Memory Activation Analysis of Postcompletion Error

Postcompletion errors are device-specific errors made after the target task has been accomplished. A classic postcompletion error is making copies of a paper but forgetting to remove the original. Computational modelers, Mike Byrne and Susan Bovair showed that a model that was sensitive to the working memory demands of the task environment could duplicate the pattern of human postcompletion errors.

Least-Effort Tradeoffs between Knowledge in-the-World and Knowledge in-the-Head

Researchers, Wayne Gray and Wai-Tat Fu were able to show an increase of errors in interactive behavior due to least-effort tradeoffs between reliance on knowledge in-the-world and knowledge in-the-head. Subjects in two conditions of a VCR programming task could acquire show information either by looking at a show information window (Free Access) or by moving the mouse and clicking on the gray box that covered a field of the window (Gray Box). Subjects in a third condition were required to memorize the show information before they began programming (Memory Test). Results showed that the Gray Box condition made the most errors, followed by Free Access, and then the Memory Test. The results were interpreted to mean that the increased perceptual-motor costs of information acquisition led the Free Access and Gray Box groups to an increased reliance on error-prone memory.

Integrated Model of Cognition

In a 2002 paper researchers Erik Altmann and Gregory Trafton proposed a goal-activation model of how people remember the states of the world they want to achieve. In subsequent work, this model was applied to yield predictions about the cognitive effects of interruptions on task performance (for instance, being interrupted by the phone while writing a paper). For the cognitive level of analysis, this work demonstrates that the basic research agenda of producing integrated models of cognitive processing is the key to understanding, detecting, and correcting human errors.

Applying a Bounded Rationality Framework

Errors are infrequent, but not rare. Their infrequency has discouraged many from studying errors within the experimental laboratory and may have discouraged a rigorous, theory-based approach to understanding how cognitive processes interact with the task environment to produce errors. The naturalistic approach to errors is enticing, but a hundred years of this approach has not yielded much progress. Although the importance of errors must be judged by their effect on everyday life, the study of the nature, detection, and correction of errors must be pursued in the laboratory.

For those concerned with human errors in HCI, a fruitful path is to pursue the errors that emerge from the interaction of embodied cognition with a task being performed in a given task environment. This bounded rationality framework focuses on the mixture of cognition, perception, and action that takes approximately 1/3 of a sec to occur. The goal of this work is the creation of powerful theories that would allow researchers and practitioners to predict the nature and probable occurrence of errors within a given task environment.

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See also Cognitive Walkthrough; User Modeling

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