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Process-Tracing Methods in Decision Making: On Growing Up in the 70s

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Abstract
Decision research has experienced a shift from simple algebraic theories of choice to an appreciation of mental processes underlying choice. A variety of process-tracing methods has helped researchers test these process explanations. Here, we provide a survey of these methods, including specific examples for subject reports, movement-based measures, peripheral psychophysiology, and neural techniques. We show how these methods can inform phenomena as varied as attention, emotion, strategy use, and understanding neural correlates. Two important future developments are identified: broadening the number of explicit tests of proposed processes through formal modeling and determining standards and best practices for data collection.

Keywords
process tracing, distortion risk, eye tracking, information boards, mouse tracking, neural techniques, verbal protocols

For centuries, those interested in understanding human decision behavior have observed choices to make inferences about the reasoning behind those choices. For example, researchers studying gambles derived predictions about choices based on risk preferences (Bernoulli, 1738), rational choice principles (Morgenstern & von Neumann, 1944), or psychological constructs like loss aversion (Kahneman & Tversky, 1979). Choice data were sufficient for examining these *algebraic* models that dominated the field. In the last 40 years, an increasing number of studies have included process-tracing data. These studies provided insight into the processes underlying choice and aided the development of more predictive explanatory models. This development was a natural complement to the "cognitive revolution" that shaped much psychological science in the second half of the 20th century. For decision research, this involved an increase in the building of models that describe in detail how an individual's actions can be linked back to its cognitive architecture. As a result, a substantial mass of process evidence as well as a slate of corresponding process-oriented theoretical accounts have been produced to improve and extend models of choice (e.g., Johnson & Ratcliff, 2014). In this paper, we illustrate the breadth of process-tracing methods (see Table 1) and offer a first attempt at a classification of this rich and developing set of techniques (see Fig. 1). Our goal is to assist researchers in considering such techniques to test and validate their theories, models, and hypotheses about processing constructs.

Process Tracing Defined

For the purposes of this paper, we operationally define process-tracing data as time-dependent, predecisional observations. These observations inform theories on the psychological mechanisms assumed to operate prior to choice. Table 1 displays the most commonly used process-tracing methods in decision research. We differentiate four groups of methods: *Subject reports* contain methods that target decision strategies through

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Table 1. Available Process-Tracing Measures and Their Hypothesized Underlying Decision Processes: Overview of Process-Tracing Methods Used in Decision Research

Method	Monitored behavior	Common measures	Targeted processes	Representative applications	Technical skills required	Threats to internal and external validity
			Subject reports			
Aspect listing	Retrospective or concurrent thought listing	Number and order of aspects	Importance of dimensions, decision strategy	Weber et al., 2007	Low	Changes of the recorded process (verbal utterance) directly through application of the method. Repeated questions may be disruptive to current activity. Relatively "slow" in measuring process.
Experience sampling	Self-reports	Cognitive and affective aspects of daily experiences	Emotional states, activities, environments	Csikszentmihalyi & Larson, 2014	Low	
Verbal protocols	Verbalized thoughts	Word frequency	Goals and decision strategies	Ranyard & Svenson, 2011	Low	
			Movement-based measures			
(Computer-based) Information boards	Information selected for inspection	Frequency, timing, and sequence of information acquisition	Attention, information search strategies	Willemsen & Johnson, 2011	Low	Prestructuring of information in uncommon formats might influence the acquisition process (e.g., matrix versus circular presentation setup).
Eye tracking	Position of eye gaze	Frequency, timing, and sequence of eye fixations; saccade vigor	Attention, information search strategies	Russo, 2011	Medium	
Joystick/slider bar	Joystick or slider position	Changes in position over time	Confidence, approach/avoidance motivation	Krieglmeyer, Deutsch, De Houwer, & De Raedt, 2010	Low	
Mouse tracking	Cursor position and trajectory	Changes in position, direction, velocity, etc.; deviations from ideal paths	Conflict, indecision, momentary preference, informational influence	Spivey & Dale, 2006	Low	
Reaching/pointing tracking	Finger/pointer position	Changes in position, direction, velocity, etc.; deviations from ideal paths	Conflict, indecision, momentary preference, informational influence	Burk, Ingram, Franklin, Shadlen, & Wolpert, 2014	Medium	

(Continued)

Table 1. (Continued)

Method	Monitored behavior	Common measures	Targeted processes	Representative applications	Technical skills required	Threats to internal and external validity
			Peripheral psychophysiology			
Pupilometry	Pupil dilation	Change in pupil size (by condition)	Arousal, cognitive effort, valuation	Beatty, 1982	Medium	Except for pupilometry and facial video monitoring: application of sensor on the body of the participant. A minority of participants do not show an EDA response.
Electrodermal activity (EDA)	Skin conductance, typically associated with increased sweating	Change in conductance (by condition)	Sympathetic arousal, stress	Bechara & Damasio, 2005	Low	
Muscle tension/ tone (EMG)	Electrogenic stiffness	EMG activity, muscle contraction/tension	Arousal	Lundberg et al., 1999	Low	
Facial muscle monitoring (fEMG)	Facial muscle contractions	Action units (FACS)	Emotion	Porter, ten Brinke, Baker, & Wallace, 2011	Low	
Facial video monitoring	Feature detection	Feature classification (FACS)	Emotion	Schuller, Rigoll, & Lang, 2003	Low	
Heart rate	Heart rate	Frequency, variability (HRV)	Sympathetic arousal, clinical classification	Crone, Somsen, Beek, & Van Der Molen, 2004	Low	
			Neural techniques			
EEG (electric fields)	Surface-level differences in electrical potential	Event-related potential (ERP), time-frequency analysis	Attention, memory, response preparation	van Vugt, Simen, Nystrom, Holmes, & Cohen, 2014	Medium	Application of sensors on the body of the participant. Recording conditions (e.g., fMRI tube) are "unnatural." Direct changes of the neural substrate (e.g., TMS). Can be used only for certain populations. Substantial apparatus and technical skills required.
fMRI, fNIRS (metabolic)	Neural metabolism (deoxygenated hemoglobin)	BOLD signal (differential neural response across conditions)	Task-dependent brain regions, connectivity	Figner et al., 2010	High	
MEG (magnetic fields)	Magnetic field differences in electrical potential	Neural response to stimuli, connectivity between regions	Task-dependent brain regions, connectivity	Giorgetta et al., 2013	High	
Neuron recordings	Rate of neuron firing	Change in firing rate by condition	Categorization, sensory discrimination, recall	Cerf et al., 2010	High	
tDCS (intervention)	Brain region inhibition or activation	n/a	Neural firing	Utz, Dimova, Oppenländer, & Kerkhoff, 2010	High	
(r)TMS (intervention)	Brain region inhibition or activation	n/a	Neural firing	Peters & Büchel, 2011	High	

Note: EMG = electromyography, FACS = Facial Action Coding System, fNIRS = functional near-infrared spectroscopy, HRV = heart rate variability, MEG = magnetoencephalography, (r)TMS = repetitive transcranial magnetic stimulation, tDCS = transcranial direct current stimulation.

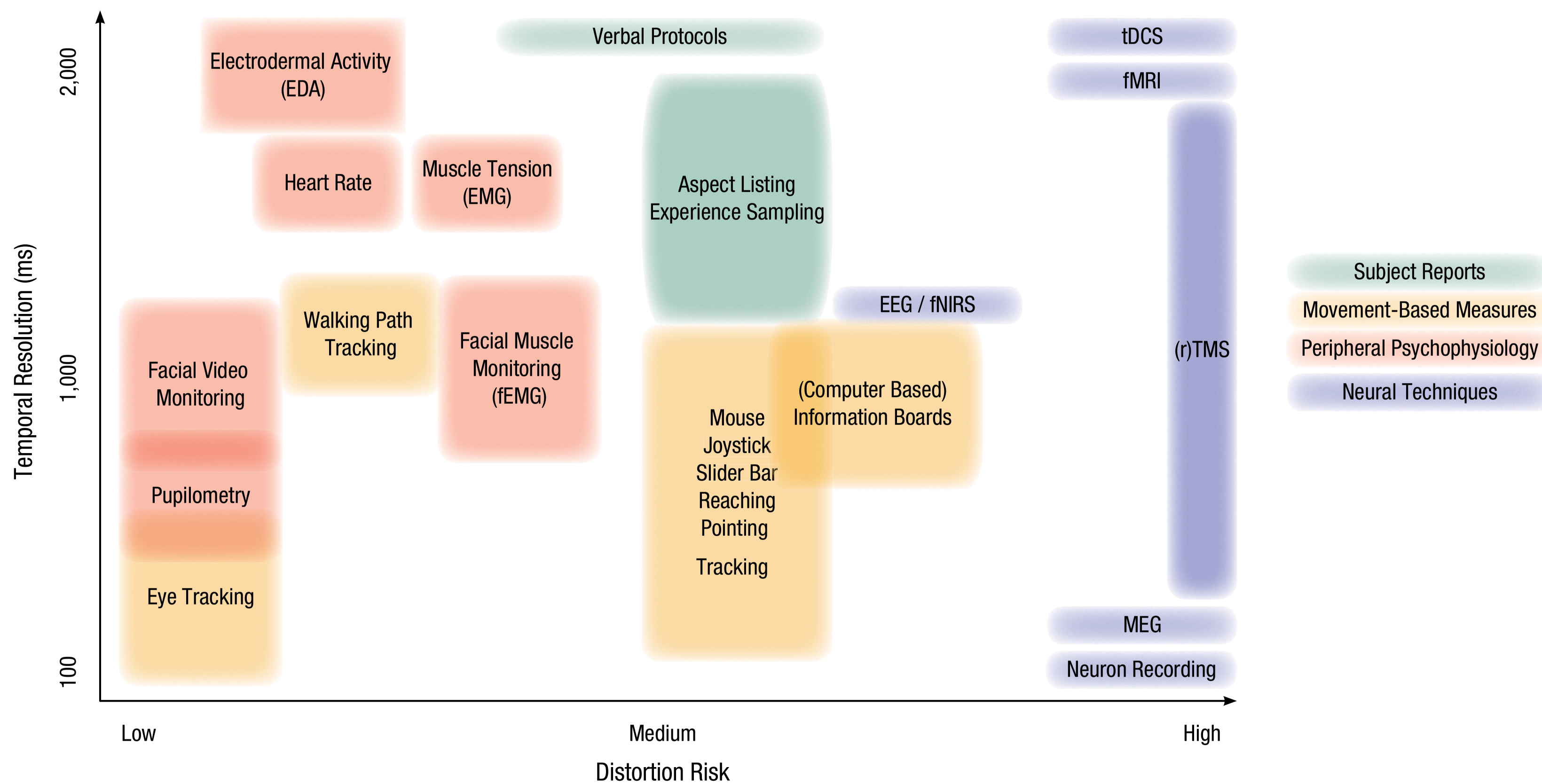

Fig. 1. Process-tracing methods divided into four groups—subject reports, movement-based measures, peripheral psychophysiology, and neural techniques—plotted with their distortion risk (how intrusively a process is measured assuming minimal invalidity of measurement; horizontal position and length indicate relative intrusion on the measured process) as a function of temporal resolution (vertical length of a label represents variability of the length of a measured process in a given method). See Table 1 for detailed descriptions and applications for each method. EMG = electromyography, fNIRS = functional near-infrared spectroscopy, MEG = magnetoencephalography, (r)TMS = repetitive transcranial magnetic stimulation, tDCS = transcranial direct current stimulation.

recording the verbalized thoughts of participants. *Movement-based measures* provide data on information search patterns. *Peripheral psychophysiological* measures quantify arousal and cognitive effort. Finally, elements of neural processes are studied using a vast array of *neural techniques*, such as functional MRI (fMRI), which collects estimates of neural metabolism as a proxy for neuron firing rates. Collectively, Table 1 provides a current snapshot of the impressive and diverse array of techniques sharing one element in common: the measurement of proxies for unobservable mental processes.

We next differentiate process techniques on two axes we feel are important for selecting any given method. First, *distortion risk*, is a potential barrier to theory testing; the more intrusive a method is on the measured process, the more careful one should be in interpreting the resulting data. Distortion risk includes at least three components: *demand effects* caused through applying a measurement (e.g., with cameras or microphones); *reactive effects* include distorting information by accessing it, for example through altering one's strategy based on information presentation formats; and degree of removal from a *naturalistic environment*, such as the artificial nature of lying in the bore of an MRI machine. Our second axis, *time resolution*, is instrumental to theory building and refinement, defining the possible measurement rate of a method. This assesses how closely each method maps a process.

Although it is clear that both distortion risk and time resolution have an effect in every measurement, we rated methods that potentially have more influence on the participant (e.g., the loud environment in an MRI tube) in one or more components further right on the *x* scale in Figure 1, compared to those methods with less influence on this dimension (e.g., remote eye-tracking). For most of these methods, the degree of distortion is not well understood, as it has not been investigated systematically (with some exceptions, e.g., Ericsson & Simon, 1992). Still, Figure 1 allows researchers to examine how the various techniques differ in their time resolution and potential risk of distorting the measured decision process.

What Can Process Data Do For You?

As theories in decision research become increasingly process-oriented, we argue here again that "process models deserve process data" (Johnson, Schulte-Mecklenbeck, & Willemsen, 2008, p. 263). In fact, process data are especially critical in areas where multiple theories propose different underlying mechanisms but make similar predictions for outcome variables such as choice or response time. Process data can provide evidence on theoretical positions, can illuminate regularities otherwise hidden, and can increase the predictive power of process models (e.g., Krajbich, Armel, & Rangel, 2010). Furthermore, they ultimately lead to the development or refinement of richer theories that are better specified at the process level. Below, we give several examples to elaborate on these points.

Analyzing subject reports for evidence of decision-making strategy

A concurrent verbal protocol is an articulation of thoughts occurring to a person as he or she undertakes a primary task. Verbal protocols featured prominently in problem-solving research during the 1960s and 1970s (Simon & Newell, 1972), especially for analytic thinking tasks such as logic or chess. Such tasks can provide valid verbal protocols when the contents of short-term memory during their execution are largely verbally encoded, requiring only articulation. Despite these influential early contributions, verbal protocols have had more limited success in recent decision research. Computerized transcription methods (e.g., Lin & Yu, 2015) may help ameliorate one barrier to use of this method by drastically reducing analysis time.

Recording movement-based measures to determine information used in decisions

Tracking eye movement has been used as a proxy for tracking attention and inferring thought processes in psychology for decades (Yarbus, 1967). Although the earliest techniques were often intrusive (using contact lenses), today eye trackers are either head mounted (e.g., via special glasses; Bulling & Gellersen, 2010) or remote mounted, via infrared cameras that record eye movements and map their positions on a computer screen without participants' awareness (Holmqvist et al., 2011). Measurements of attention, including where and how long the eyes rest ("fixations"), are assumed to indicate signal processing (Just & Carpenter, 1980), although such an assumption is still under critical examination (see Russo, 2011).

Recording peripheral psychophysiology to estimate valence

Linking facial expressions to emotions has been the realm of trained human coders for several decades. More recently, the development of fEMG and video-based facial expression analysis have revolutionized this field. In an fEMG study, sensors are placed on the participants' face recording muscle contraction—putting it higher on the risk of distortion. In video-based analysis, muscle movement is recorded via video camera and then compared to a database of classified facial expressions. Both methods are relatively new and are still evaluated more broadly (Stöckli, Schulte-Mecklenbeck, Borer, & Samson, 2017).

Neural techniques to look under the hood

As all decisions are ultimately the result of neuronal firing, understanding how neurons and clusters of brain regions respond and interact during choice can provide invaluable insights into decision processes. Currently, fMRI is perhaps the most popular technique for probing the decision process on a neural level. One drawback is fMRI's limited temporal and spatial resolution, often on the order of 1 to 3 s and 1 to 3 mm^3, due to both hardware constraints as well as the sluggishness of the blood-oxygen-level-dependent (BOLD) response it measures. With neuron firing rates on the order of milliseconds, this presents a significant limitation for capturing neural processes in real time as with other measures.

Validating Formal Mental Models With Process-Tracing Measures

Much of the empirical research compares measures collected from these techniques across discrete groups. Going a step further, process data from individuals can directly discriminate among sufficiently precise, process-level theoretical accounts. For example, although the drift diffusion model (DDM; Ratcliff, 1978) has provided a process-driven, accurate account for both choices and response time distributions, integrating eye-gaze data into the traditional DDM model fits data better and has been subsequently used as the foundation of new neural and psychological theories on the decision process (e.g., Krajbich et al., 2010). These models invoke constructs such as shifting attention toward different information, which produces changes in relative preference for each option over time. Additionally, Parallel Constraint Satisfaction (PCS) models suggest a reciprocal influence of momentary preference on subsequent information-seeking (see Busemeyer & Johnson, 2004, for comparison of these and other process models). Process measures can help us verify theoretical claims made about each of these. For example, eye-tracking can identify the shifting order of attention to different features in a choice setting, the relative time spent on a particular feature, sequential dependencies over time, and more (e.g., Stewart, Hermens, & Matthews, 2016). Relative preferences have been estimated by the physical movements in reaching for (or selecting with a computer mouse) competing choice options assumed to coincide with the ongoing cognitive process (Spivey & Dale, 2006). For decision research, this affords data-driven inferences about the approach tendency toward both foregone and selected choice options captured in real time during a choice, enabling us to test competing process models. Theories stand to benefit in unique ways from process tracing, such as in the growing body of research in neuroeconomics where eye-tracking data have helped to better understand strategic interactions and social preferences from a game theoretic perspective (e.g., Polonio, Di Guida, & Coricelli, 2015).

How To Get Started With Process Tracing—A Five-Step Approach

Given the broad range of techniques available, it can be somewhat daunting to explore the use of process tracing for the novice. We offer one way, in five steps, to approach the development and implementation of a successful study:

1) *Clearly articulate what mental "process" is involved and how it relates to the behavior under investigation.* As with any research program, developing research questions and hypotheses requires a solid grounding in psychological theory and the previous research findings.

2) *Determine (ideally multiple) ways to operationally define your processing constructs given the range of methods available.* Table 1 provides a way to begin the mapping of psychological constructs to process measures and variables and offers a classification of the required skill level for each of the listed methods.

3) *Consider among the viable methods those that meet design concerns, especially temporal resolution and distortion risk.* To address your question: What are acceptable levels of distortion? What would be the optimal time resolution for the key phenomena under study? Figure 1 allows one to estimate these dimensions and constrain the set of possible methods.

4) *Become acquainted with the technique(s) you've chosen by reading multiple methodological and application papers.* It is critical to develop the skills and knowledge required to collect, analyze, and interpret process-tracing data; for example, computer coding, advanced statistics, and learning established procedures may be needed. Table 1 lists one representative application for each method.

5) *Implement the technique carefully using the skills and knowledge you've gained, and explore various means of benefiting from the resulting data.* The abundant nature of process data lends itself to sophisticated approaches to drawing inferences, such as formal computational modeling of processes

informed and verified by the data, or estimating effects with multilevel statistical models to analyze repeated-measures data and heterogeneity.

Quo Vadis? Challenges and Opportunities

It is an ideal time for incorporating process-tracing data into research programs. Free software like Mousetracker (Freeman & Ambady, 2010) or MouselabWeb (Willemsen & Johnson, 2011) provides easy-to-use, flexible tools that can be adopted to new research questions, including online behavior (Goldstein, Suri, McAfee, Ekstrand-Abueg, & Diaz, 2014; Liu et al., 2017) or interactive games (Costa-Gomes, Crawford, & Broseta, 2001).

A major advantage of process-tracing techniques is their ability to both inform and build on our knowledge of cognitive neuroscience. For example, fMRI and EEG data have identified neural circuits involved in the decision process, as well as their temporal relationship (e.g., van Vugt, Simen, Nystrom, Holmes, & Cohen, 2014). Changes in heart rate and skin conductance have lent important insights into the cognitive process when anticipating losses in risky choices (Crone, Somsen, Beek, & Van Der Molen, 2004). Methods such as transcranial magnetic stimulation allow researchers to actively intervene in the neural substrates behind a decision process to observe behavioral change (Peters & Büchel, 2011). Furthermore, computational models are well equipped to formalize cognitive mechanisms to produce these data (see Forstmann, Ratcliff, & Wagenmakers, 2016).

New technologies let process-tracing experiments overcome limitations inherent in laboratory settings, like small samples, and thus improve external validity. Various "quantified self" devices allow for ongoing data collection on a large scale (Swan, 2009). Mobile phones, smartwatches, and even earbuds now can record many process measures, including heart rate, skin conductance, and geographic location, providing rich opportunities for mobile process tracing and experience sampling. In the lab, stationary eye trackers have improved in usability, resolution, data quality, and affordability. Portable eye trackers are now inexpensive enough for labs to run multiple eye trackers to investigate phenomena among groups of participants interacting with one another (Lejarraga, Schulte-Mecklenbeck, & Smedema, 2016). Scaling up this idea, it is also possible to simply use an available webcam on a participant's computer and access this information to track gaze for large samples online (Xu et al., 2015).

Looking back across many years of process-tracing research, methods have evolved from information displayed on bulletin boards and recording people's listed thoughts, to eye-tracking devices recording attention, information search, and arousal, to microcomputers running on mobile phones that can record movement patterns. That said, process tracing is still evolving as a scientific method to which we offer two important areas for further development. First, we must increase the number of actual tests of the proposed processes. There are many models available for making process predictions, but often these predictions are not directly tested. Second, having achieved a critical mass, there is a newfound need for norms and "best practices" that have not yet been established. Having developed from a niche area to hundreds of applications, process-tracing research needs standards for how to collect, report, archive, and share data (e.g., Fiedler, Schulte-Mecklenbeck, Renkewitz, & Orquin, 2017, as an example for eye tracking). An excellent start would be the exploration of the distortion risk components and other key constructs we have identified. More than 10 years ago, Ariel Rubinstein (2003) wrote, "We need to open the black box of decision making" (p. 1215). We believe that the methods in this review allow us to open the box wide and help us understand what we find inside.

Recommended Reading

Ashby, N. J., Johnson, J. G., Krajbich, I., & Wedel, M. (2016). Applications and innovations of eye-movement research in judgment and decision making. *Journal of Behavioral Decision Making*, *29*, 96–102. Lead article in a special issue on eye-tracking research in judgement and decision making providing many examples from theory to application.

Schulte-Mecklenbeck, M., Kühberger, A., & Johnson, J. G. (2018). *A handbook of process tracing methods*. New York, NY: Taylor & Francis. Comprehensive overview of 13 process-tracing techniques used in judgment and decision making.

Stewart, N., Hermens, F., & Matthews, W. J. (2016). Eye movements in risky choice. *Journal of Behavioral Decision Making*, *29*, 116–136. Bridging the gap between the recording attention and models like decision field theory, decision by sampling, or parallel constraints satisfaction.

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