Process tracing methods in decision making: on growing up in the 70ties

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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. The increasing number and variety of process-tracing methods has helped researchers test these process explanations. Here, we provide a survey of these methods, including specific examples for verbal protocols, information boards, and eye- and mouse-tracking tools to illustrate their research value and contributions to theory building and testing. We show how these techniques can inform phenomena as varied as attention, emotion, strategy use, and developing intentions. 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; measurement; verbal protocols; eye-tracking; information boards

INTRODUCTION

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 the *algebraic* models that dominated the field. In the last forty 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. Meanwhile, related research in economics and marketing spawned not only the new subfield of behavioral economics, but multiple Nobel laureates. For decision research, this involved a substantial increase in the building of models that describe in detail how an individual's actions can be linked back to their 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 change 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 Figure 1). Our goal in highlighting prominent methods and discussing their strengths and weaknesses is to assist the researcher considering using 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, pre-decisional observations. These observations inform theories on the psychological mechanisms assumed to operate prior to choice. In Table 1 we compiled the most commonly used process-tracing methods in decision research. Four groups of methods are differentiated: *Subject reports* contain methods that target decision strategies through recording, e.g., verbalized thoughts of participants. *Interactive measures* date back to physical information boards—notecards on a bulletin board turned over to reveal information—which provided data on information search patterns. *Peripheral psychophysiological* measures quantify arousal, emotions and cognitive effort, e.g., through the recording of skin conductance. Finally, elements of neural processes are studied using a vast array of *neural techniques*, such as 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: 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, *time resolution* is instrumental to theory building and refinement, defining a lower boundary or lowest possible measurement rate of a method. This assesses how closely each method maps a process. Some methods such as EEG, single cell recordings, and eye- and mouse-tracking can record on the order of milliseconds; other techniques such as fMRI, GSR and verbal protocols allow measuring cognitive processes at the level of seconds only. Our second axis, *distortion risk*, is a potential barrier to theory testing; the more intrusive or obtrusive 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: *practical effects* caused simply through applying a measurement, such as the damage caused when an electrode is inserted to measure neuron firing or the demand characteristics resulting from cameras or microphones; *psychological effects* include distorting information by virtue of accessing it, e.g., when collecting verbal protocols, or 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.

While it is clear that both time resolution and distortion risk 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) higher on the y-scale in Figure 1 than 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., Lohse & Johnson, 1996; 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.

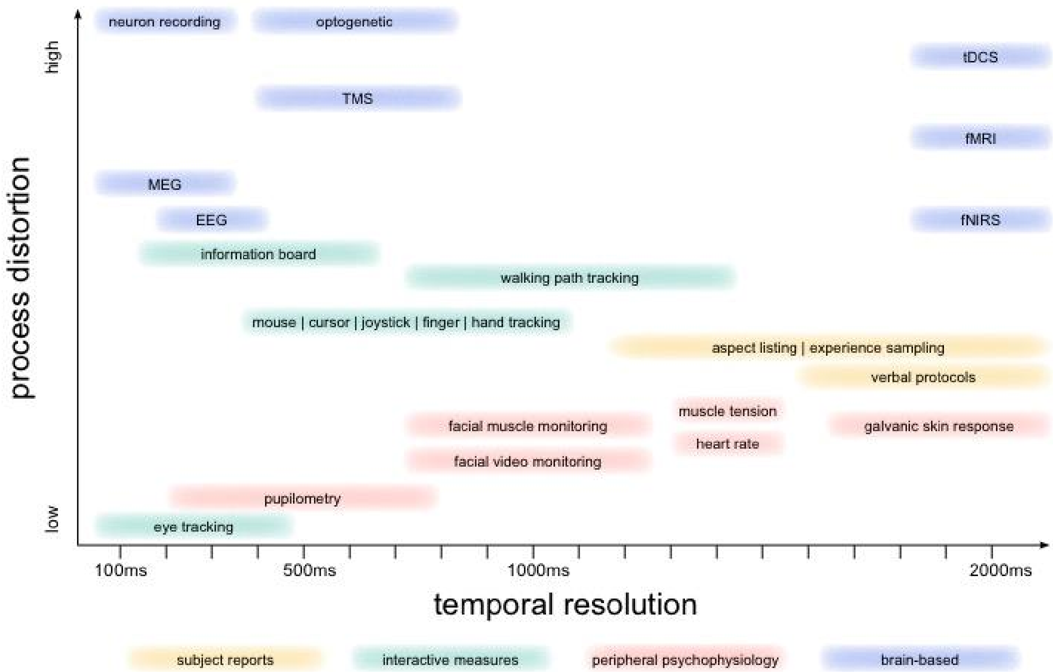

Figure 1. Process Tracing Methods divided in four groups (subject reports, interactive measures, peripheral psychophysiology and neural techniques) plotted with their temporal resolution (horizontal length of a label represents the length of a measured process) as a function of process distortion (how intrusively a process is measured assuming minimal invalidity of measurement, vertical position indicates relative intrusion on the measured process). See Table 1 for descriptions and applications.

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 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 while representing the great variety in type, history, targeted process, and application of process tracing methods.

Analyzing subject reports for evidence of decision-making strategy

Verbal protocols. A concurrent verbal protocol is an articulation of thoughts occurring to a person as they undertake 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, such as by experts in natural settings (Zsambok and Klein, 2014). Computerized transcription methods (e.g., Lin & Yu, 2015) may help ameliorate one barrier to use of this method by drastically reducing analysis time.

Recording interactive measures to determine information used in decisions

Eye-tracking. 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 plaster casts or contact lenses), today eye-trackers are either head mounted, for example via special glasses (Bulling & Gellersen, 2010) or remote mounted, for example via infrared cameras that record eye movements and map their positions on a computer screen without subjects' awareness (Holmqvist, et al., 2011). Eye-tracking provides a more direct and less distortive link to our attentional processes than other methods, such as using a mouse to acquire information or even turning over information cards on a table (see Figure 1). Measurements of attention, such as where 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). Nonetheless, the basic premise that attention reveals processing opens wide the door for applications. Researchers in marketing, naturally interested in how attention to advertisements is distributed (Wedel & Pieters, 2008), utilize eye-tracking technology as a research and evaluation tool.

Recording peripheral psychophysiology to estimate valence

Classifying Emotions with fEMG and video analysis. Linking facial expressions to emotions has been the realm of trained human coders for several decades. More recently the development of facial electromyography (fEMG) and video based facial expression analysis have revolutionized this field. In a 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 a video camera and then compared to a database of classified facial expressions. Both methods are relatively new and still lack a broader set of evaluation studies (but see: Lewinsiki et al., 2014; Stöckli et al., 2017).

Neural techniques to look under the hood

Functional magnetic resonance imaging (fMRI). 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 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 one to three seconds and one to three 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. Recently-developed multiband techniques drastically improve temporal and/or spatial resolution, for example reducing acquisition times to sub-second level (Feinberg and Setsompop, 2013). Moreover, fMRI can be coupled with other neural methods such as electroencephalogram (EEG) for, e.g., EEG-informed fMRI analyses, to provide finer temporal information (e.g., Sclocco et al., 2014).

Validating formal mental models with process-tracing measures

Much of the research introduced here compares measures collected from these techniques across groups. Going a step further, process data from individuals can directly discriminate among sufficiently precise, process-level theoretical accounts. For example, although accumulator-style computational models like the drift diffusion model (DDM; Ratcliff 1978) have 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 & Rangel, 2011; Vaidya & Fellows, 2015). These accumulation models invoke constructs such as shifting attention towards different information, which produces changes in relative preference for each option over time. Additionally, Parallel Constraint Satisfaction (PCS) models suggest an additional 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 towards 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 has helped us 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, the vast amount of data typically collected with process tracing measures, and the necessary computational, statistical, and other training requirement, 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 "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.

3) *Consider among the viable methods those that meet design concerns, especially temporal resolution and distortion risk*. To address your question, what would be the optimal time resolution for the key phenomena under study? What are acceptable levels of distortion, and which types should be minimized? Figure 1 allows one to estimate these dimensions and constrain the set of possible methods. Practically, what are your budget, facilities, skill level, and/or collaborative potential?

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 (e.g., computer coding or advanced statistics may be needed). In doing so, one should be aware of "best practices" across applications, and mindful of the measurement properties of the process tracing data, such as their construct validity or reliability.

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; estimating effects with multi-level statistical models to analyze repeated-measures data, heterogeneity, and other features. Especially popular are recent advances in theoretical approaches (e.g., Bayesian inference), scripted statistical languages (e.g., R) for reproducibility and consistency; and high-resolution, data-dense visualization methods (e.g., heat maps, icon graphs).

Quo vadis? Challenges and opportunities.

It is an ideal time for incorporating process tracing data into research programs. New technologies allow process tracing experiments to 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. 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 including 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). Free software like Mousetracker (Freeman & Ambady, 2010) or MouselabWeb (Willemsen & Johnson, 2011) provide easy to use, flexible tools that can be adopted to new research questions, including online behavior (Goldstein, Suri, McAfee, Ekstrand-Abueg, & Diaz, 2014) or interactive games (Costa-Gomez, 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, et al., 2004). Some newer methods, such as optogenetics and 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). Such models incorporating process data have been used as the foundation of new neural and psychological theories (e.g., Krajbich & Rangel, 2011) and have been shown to be able to describe the behavior down to the level of populations of neurons in primates (Platt & Huettel, 2008).

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 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., Schulte-Mecklenbeck, Fiedler, Renkewitz, & Orquin, in prep. as an example for eye-tracking).

More than 10 years ago Ariel Rubinstein (2003) wrote: "We need to open the black box of decision making …". We believe that the methods in this review can help open the box wide, and help us understand what we found inside.

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Table 1. Available process tracing measures and their purported underlying decision processes.

Table 1

Overview Process Tracing Methods

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	•	Changes of the recorded process (verbal utterance) directly through application of the method (but see Ericsson & Simon, 1993).
Experience sampling	Self reports	Cognitive and affective aspects of daily experiences	Emotional states, activities, environments	Csikszentmihalyi & Larson, 2014	•	Repeated questions may be disruptive to current activity.
Verbal protocols, Talking aloud	Verbalized thoughts	Word frequency	Goals and decision strategies	Ranyard & Svenson, 2011	•	
Interactive measures						
(Computer-based) Information boards	Information selected for inspection	Frequency, timing, and sequence of information acquisition	Attention, information search strategies	Willemsen & Johnson, 2011	•	Pre-structuring of information in uncommon formats might influence the acquisition process.
Eye tracking	Position of eye gaze	Frequency, timing, and sequence of eye fixations; saccade vigor	Attention, information search strategies	Russo, 2011	••	Participant is aware of tracking.
Joystick/slider bar	Joystick or slider position	Changes in position over time	Confidence, approach/avoidance motivation	Krieglmeyer et al, 2010	•	
Cursor position tracking	Cursor position and trajectory	Changes in position, direction, velocity, etc.; Deviations from ideal paths	Conflict, indecision, momentary preference, informational influence	Spivey et al., 2006	•	
Reaching/pointing tracking	Finger/pointer position	Changes in position, direction, velocity, etc.; Deviations from ideal paths	Conflict, indecision, momentary preference, informational influence	Burk et al., 2014	••	
Peripheral psychophysiology						
Pupilometry	Pupil dilation	Change in pupil size (by condition)	Arousal, cognitive effort, valuation	Beatty, 1982	••	Except for pupilometry and facial video monitoring: application of sensor on the body of the participant.
Galvanic skin response (GSR)	Skin conductance, typically associated with increased sweating	Change in conductance (by condition)	Sympathetic arousal, stress	Bechara et al, 2005	•	A minority of participants do not show a GSR response.
Muscle tension/tone (EMG)	Electrogenic stiffness	EMG activity, muscle contraction/tension	Arousal	Lundberg et al, 1999	•	fMRI: Low temporal resolution Awareness of tracking.
Facial muscle monitoring (fEMG)	Facial muscle contractions	Action units (FACS)	Emotion	Porter et al 2011	•	
Facial video monitoring	Feature detection	Feature classification (FACS)	Emotion	Schuller et al. 2003	•	
Heart rate	Heart rate	Frequency, variability (HRV)	Sympathetic arousal, clinical classification	Crone et al, 2004	•	
Neural techniques						

EEG (electric fields)	Surface-level differences in electrical potential	Event Related Potential (ERP), Time-frequency analysis	Attention, memory, response preparation	van Vugt, et al (2014)	••	Application of sensors on the body of the participant / "unnatural" recording conditions (e.g., fMRI tube) / direct changes on the neural level.
fMRI, fNIRS (metabolic)	Neural metabolism (deoxygenated hemoglobin)	BOLD signal (differential neural response across conditions)	Task-dependent brain regions, connectivity	Figner et al, 2010	•••	Can be used only for certain populations.
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	•••	
Neuron recordings	Rate of neuron firing	Change in firing rate by condition	Categorization, sensory discrimination, recall	Cerf et al, 2010	•••	
Optogenetics (intervention)	Ion channel opening	n/a	neural firing	Boyden et al, 2005	•••	
tDCS (intervention)	brain region inhibition or activation	n/a	neural firing	Utz et al, 2010	•••	
TMS (intervention)	brain region inhibition or activation	n/a	neural firing	Peters et al, 2011	•••	

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