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Neuroforecasting Aggregate Choice

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Abstract

Advances in brain-imaging design and analysis have allowed investigators to use neural activity to predict individual choice, while emerging Internet markets have opened up new opportunities for forecasting aggregate choice. Here, we review emerging research that bridges these levels of analysis by attempting to use group neural activity to forecast aggregate choice. A survey of initial findings suggests that components of group neural activity might forecast aggregate choice, in some cases even beyond traditional behavioral measures. In addition to demonstrating the plausibility of neuroforecasting, these findings raise the possibility that not all neural processes that predict individual choice forecast aggregate choice to the same degree. We propose that although integrative choice components may confer more consistency within individuals, affective choice components may generalize more broadly across individuals to forecast aggregate choice.

Keywords

fMRI, predict, forecast, individual, market, human, striatal, frontal, affect

In a film adaptation of the short story "The Minority Report," experts track the brain activity of a small group of "precognitive" mutants to forecast the crimes of citizens (Dick, 2002). Although the notion that brain activity in a few individuals could be used to forecast others' behavior might seem relegated to the realm of science fiction, recent technological advances have moved researchers closer to establishing "neuroforecasting" as a scientific fact.

Since the turn of the 21st century, improvements in the spatial and temporal resolution of neuroimaging methods have allowed researchers to visualize neural activity that can predict and promote individual choice (Knutson, Rick, Wimmer, Prelec, & Loewenstein, 2007; Plassmann, Doherty, Rangel, & O'Doherty, 2007). For instance, the spatiotemporal resolution (on the order of millimeters and seconds) of functional MRI (or fMRI) has allowed investigators to track changes in the neural activity (or oxygenation) of subcortical circuits implicated in appetitive and aversive motivation seconds before choice. These anticipatory changes in brain activity can inform predictions about individuals' tendencies to approach or avoid various options ranging from gambles to purchases to investments (Knutson & Greer, 2008; D. J. Levy & Glimcher, 2012), both during and after scanning (I. Levy, Lazzaro, Rutledge, & Glimcher, 2011) and even in the absence of conscious reflection (Tusche, Bode, & Haynes, 2010).

At the same time, the rise of large and novel Internet markets has opened up opportunities for tracking and even forecasting aggregate choice (Choi & Varian, 2012). These parallel developments raise the question of whether brain activity could be used not only to predict individual choice but also to forecast aggregate choice. Accordingly, researchers have begun to explore whether brain activity in laboratory samples can forecast aggregate choice in markets, how neural measures compare with more traditional measures (such as self-reported ratings and choices), and which markets best support forecasts. Below, we consider relevant theory, survey recent findings, and explore potential implications.

Scaling to the Aggregate

While the term "prediction" can refer to the use of an individual's neural data to predict his or her own behavior, we adopt the distinct term *neuroforecasting* here to refer to the use of brain activity from a group of individuals to forecast the behavior of a separate and independent group. Neuroforecasting further implies (but does not necessitate) that forecasts apply to the

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future behavior of larger groups. While neuroforecasting does not necessarily imply that neural data must provide better information than traditional behavioral measures (such as ratings or choice), demonstrations of added value might motivate and justify further research and development (Ariely & Berns, 2010).

But how might individual choice—or even its components—scale to inform forecasts of aggregate choice? While many theories make strong implicit assumptions about scaling from individual to aggregate choice, no explicit consensus exists. According to a *no-scaling* account, even if one could use neural data to predict individual choice, many factors (e.g., unsystematic individual preferences, gaming of others' systematic preferences, random noise) might conspire to obscure the influence of neural data at the level of aggregate choice. The efficient-market hypothesis, for instance, implies that individual choices should "wash out" at the aggregate level, such that no individual's choice provides information about future market behavior (Fama, 1970). Conversely, according to a *total-scaling* account, if one begins with an accurate model of a representative individual's choice, one could simply multiply that model (perhaps along with some noise) to derive an accurate estimate of aggregate choice. Expected utility theory, for instance, implies total scaling (Von Neumann & Morgenstern, 1944). Standing between these two extremes, we suggest an intermediate *partial-scaling* account, in which some choice components may generalize more across individuals than others (and by extension, more than individual choice itself, which constitutes the end point of all supporting components). If the partial-scaling account holds, then identifying choice components that generalize best across individuals could potentially improve forecasts of aggregate choice.

Neuroforecasting With fMRI

Motivated by theoretical challenges from economics (Bernheim, 2008) and the promise of practical applications (Smidts et al., 2014), researchers have begun to explore whether fMRI measures might inform not only predictions of individual choice but also forecasts of aggregate choice (only peer-reviewed, published findings are considered below; Karmarkar & Yoon, 2016). Although a few other published studies have attempted to forecast aggregate choice using other methods, such as electroencephalography (EEG; Boksem & Smidts, 2015; Dmochowski et al., 2014), we do not review them here because of their current inability to resolve subcortical sources of activity.

An initial and fortuitous example of neuroforecasting came from a study of peer influence, in which teenagers were exposed to music clips culled from an Internet site while undergoing MRI. Two years later, the researchers realized that they could obtain measures of aggregate song performance in the form of Internet downloads. By averaging brain activity and ratings (i.e., of liking) in response to these songs, the researchers found that the sample's averaged brain activity in the subcortical nucleus accumbens (NAcc) and cortical medial prefrontal cortex (mPFC) could forecast aggregate song downloads 2 years later (log-transformed). Moreover, increased NAcc activity could account for the positive association of mPFC activity with downloads. Averaged explicit ratings of liking collected from the laboratory sample, however, did not forecast aggregate song downloads (Berns & Moore, 2012). These findings were consistent with earlier speculation that "hidden information" in a group of individuals' neural responses might eventually allow investigators to forecast aggregate choice, even beyond more traditional behavioral measures (Ariely & Berns, 2010).

Other researchers then explored whether brain activity in a laboratory sample could account for aggregate responses to persuasive messages. They found that the sample's average mPFC response to different antismoking advertisements was associated with call volume in response to those ads, even when the activity in control regions (i.e., primary visual cortex, primary motor cortex, supplementary eye fields, and ventral striatum) and ad effectiveness ratings were not (Falk, Berkman, & Lieberman, 2012; see also Falk et al., 2016). These researchers later argued for a *brain-as-predictor* approach, in which brain activity predicts subsequent behavior—either in the same or in different individuals—as well as the possibility of neural activity improving predictions derived from traditional behavioral measures (Berkman & Falk, 2013, p. 45).

Following these initial demonstrations, a few studies explicitly sought to link brain activity in laboratory samples to aggregate choice (Table 1). In a study of microloan appeal success, researchers found that while NAcc and mPFC activity in response to microloan appeals predicted individual lending choices within a sample, only the sample's average NAcc activity (but not activity in other regions implicated in choice, including the mPFC, anterior insula, and amygdala) forecasted loan appeal success on the Internet—and did so to a greater extent than did the sample's choices. The sample's ratings of positive arousal in response to the loan appeals also continued to forecast loan appeal success on the Internet (Genevsky & Knutson, 2015).

In a study of advertising effectiveness, researchers collected multiple measures of neural, physiological, and behavioral responses to advertisements (including self-reported ratings, skin conductance responses, heart rate, eye tracking data, EEG, and fMRI). Similar to the findings of the microlending study, of these measures,

Table 1. Studies Forecasting Aggregate Choice With Functional MRI (as of July 15, 2017)

Study	Stimuli (number, length, mode)	*N*	Individual measure	Aggregate outcome	Neural analysis	Individual choice predictor	Aggregate outcome forecaster
Berns and Moore (2012)[a]	Songs (sixty 15-s clips)	32	Song ratings	Song downloads	Region + brain	—	NAcc
Falk, Berkman, and Lieberman (2012)	Ads (ten 30-s clips)	31	Ad ratings	Ad-related calls	Region	—	MFPC
Genevsky and Knutson (2015)	Loan appeals (eighty 6-s print)	28	Appeal ratings, lending choice	Loan rate, success	Region + brain	NAcc, mPFC	NAcc
Venkatraman et al. (2015)	Ads (thirty-seven 30-s clips)	33	Ad ratings, biometrics	Ad-related price elasticity	Region	Amygdala, mPFC	NAcc
Kühn, Strelow, and Gallinat (2016)[a]	Ads (six 3-s print)	18	Ad ratings	Ad-related sales	Region	—	NAcc + mPFC + others (combined)
Falk et al. (2016)	Ads (twenty 4-s print)	47	Ad ratings	Ad-related click-throughs	Region	—	mPFC
Scholz et al. (2017)[b]	News articles (eighty 10-s print)	41	Article ratings	Article forwards	Region + brain	—	NAcc + mPFC (combined)
Genevsky, Yoon, and Knutson (2017)[a,b]	Funding appeals (thirty-six 6-s print)	30	Appeal ratings, funding choice	Funding success	Region + brain	NAcc, mPFC	NAcc

Note: mPFC = medial prefrontal cortex; NAcc = nucleus accumbens.
[a]In these studies, sample assessment preceded aggregate outcome. [b]These studies included a replication sample.

only the sample's average self-report ratings and fMRI NAcc activity (but not activity in other regions implicated in choice, including the mPFC, dorsolateral prefrontal cortex, and amygdala) forecasted increased sales in markets where those ads were presented (Venkatraman et al., 2015). In another study of advertising effectiveness, researchers found that the sample's activity in a combined set of regions in response to ads (which prominently included the NAcc and mPFC) forecasted subsequent purchases of food (i.e., chocolates) placed near those ads in a supermarket, while the sample's rated ad preferences did not (Kühn, Strelow, & Gallinat, 2016).

Further, in a study of news virality, researchers found that a sample's combined NAcc and mPFC activity in response to news headlines with summaries, as well as rated intentions to share, forecasted the extent to which those stories were shared on the Internet (Scholz et al., 2017). Finally, in a study of crowdfunding appeal success, researchers found that while both NAcc and mPFC activity predicted individual choices to fund, only the sample's average NAcc activity forecasted crowdfunding appeal success on the Internet weeks later—despite the fact that the sample's average behavioral measures (including choices and affect ratings) did not forecast aggregate choice (Genevsky, Yoon, & Knutson, 2017).

Together, these findings not only demonstrate the plausibility of neuroforecasting but also raise the intriguing possibility that not all neural processes that contribute to individual choice equally forecast aggregate choice (Table 1). While the current number of relevant studies is small and so can support only qualitative impressions, most of these studies implicate regions associated with reward processing (i.e., the NAcc and mPFC) in forecasts of aggregate choice. This pattern of findings applies even after considering activity in other regions of interest or after performing whole-brain analyses. The few studies that have directly compared neural predictors of individual with aggregate choice, however, seem to implicate sampled NAcc activity in aggregate choice more often than mPFC activity (Genevsky & Knutson, 2015; Genevsky et al., 2017; Venkatraman et al., 2015).

Combined with the partial-scaling account, we suspect that an affect-integration-motivation (or AIM) framework inspired by research on neural predictors of individual choice could highlight which neural components are most likely to generalize from individual to aggregate choice (Samanez-Larkin & Knutson, 2015). According to this modular and hierarchical scheme, rapid neural signals from evolutionarily conserved affective circuits are cortically integrated with individual contextually relevant concerns and then relayed to motor preparatory circuits that can support motivated choice behavior (Fig. 1). Specifically with respect to fMRI markers, activity associated with gain anticipation in the ventral striatum (including the NAcc) and loss anticipation in the anterior insula is integrated with other factors related to personal relevance over time in the mPFC and then relayed up to the dorsomedial prefrontal cortex

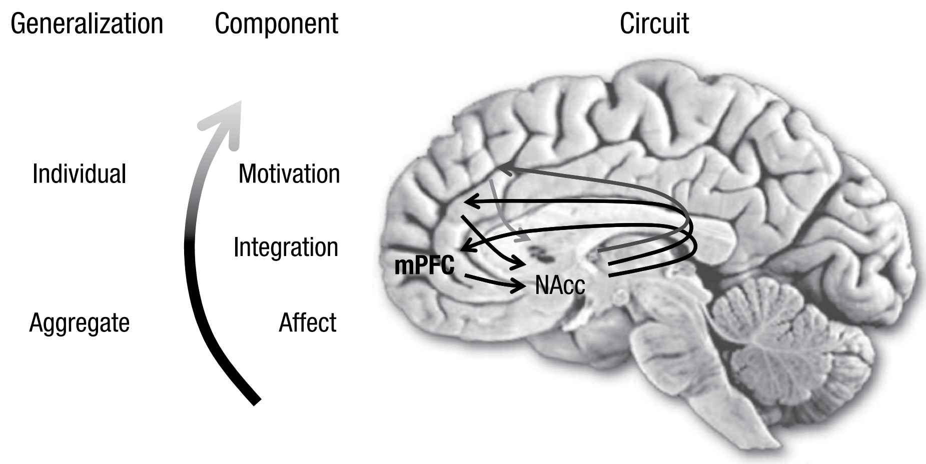

Fig. 1. Affect-integration-motivation (AIM) framework aligned with proposed gradient of choice generalization. Ascending circuits (right) implement component functions that integrate affective and other responses to motivate choice (center). Although higher integrative circuits may promote choice consistency within individuals, lower affective circuits may show broader generalization in forecasting choice across individuals (left). mPFC = medial prefrontal cortex; NAcc = nucleus accumbens.

and connected dorsal striatum to potentiate motivated behavior—including choice.

Combining partial scaling with the AIM framework implies that while both affective and integrative components might support individual choice, affective components may generalize more broadly across individuals than integrative components, which instead should show more precise sensitivity to idiosyncratic goals and contexts. For example, while both Alex and Brian might salivate when faced with a tray of warm soft chocolate chip cookies, Brian might grab one and gulp it down, while Alex abstains after contemplating the health implications of eating one. A counterintuitive implication of the AIM framework is that although affective components may reflect greater choice consistency across individuals (Knutson, Katovich, & Suri, 2014), integrative components may confer greater choice consistency within individuals (Camille, Griffiths, Vo, Fellows, & Kable, 2011). While Brian and Alex's shared affective neural responses make them both salivate in an appetitive response to cookies, their distinctive integrative neural responses lead them to make different choices with respect to consumption.

Future Directions

Brain activity might offer unique information capable of improving forecasts of aggregate choice. In some cases, the contribution of this "hidden information" may supersede even that afforded by individual choice itself or other traditional behavioral measures (such as self-report ratings). The potential for brain activity to forecast aggregate choice when behavior does not raises a *paradox of particularity*, in which only a subset of the components that produce individual choice generalize to forecast aggregate choice. The generalizable components may in turn afford more accurate forecasts of aggregate choice than individual choice itself. By implication, breaking down choice into its component processes could allow investigators to discover which of these components best scales to the aggregate. Neuroimaging might therefore provide a valuable tool for deconstructing choice components and testing their generalizability, both within and across individuals.

The AIM framework highlights which choice components might best forecast aggregate choice by implying that affective responses generalize more broadly than cognitive integrative responses (which nonetheless promote choice consistency in individuals). Indeed, in some studies, affective components (such as NAcc activity) appear to generalize best to forecast aggregate choice of goods (Berns & Moore, 2012; Genevsky & Knutson, 2015). Other findings, however, suggest that integrative components (such as mPFC activity) forecast aggregate responses to informational appeals (Falk et al., 2012). A different but complementary *market-matching* account might maintain that generalizable components of choice reflect the most relevant features of choice options for a given market. So appeals for gambling may prominently recruit positive affective circuits, whereas appeals for insurance might instead recruit negative affective circuits, and appeals to identity might instead recruit circuits relevant to personal goal relevance (Kuhnen & Knutson, 2005). If the market-matching account holds, then identifying which choice components best forecast aggregate choice could indicate the most salient features of associated markets, which might in turn suggest which interventions could exert the most leverage on choices in those markets.

After establishing the possibility of neuroforecasting, researchers can turn toward more specifically addressing how, when, and why neuroforecasting works. More sophisticated neuroimaging designs and analyses may improve forecasts, particularly if they can extract critical features from complex multivariate data, generalize to other samples, and replicate across scenarios (Grosenick, Klingenberg, Katovich, Knutson, & Taylor, 2013). Markers of individuals with more predictive neural activity (for instance, stronger neural signals or more similarity to market actors) remain to be characterized. Features of markets where neuroforecasting can add value to traditional measures need to be specified. While future research may move in diverse directions, it seems safe to claim that the path taken has already propelled neuroforecasting from the realm of science fiction into one of scientific fact.

Recommended Reading

Ariely, D., & Berns, G. S. (2010). (See References). A review of neuromarketing suggesting that brain activity could add value to conventional choice measures if it can reveal otherwise "hidden information."

Berkman, E. T., & Falk, E. B. (2013). (See References). Proposes the "brain-as-predictor approach" for using neural activity from focus groups to forecast the success of persuasive appeals.

Berns, G. S., & Moore, S. E. (2012). (See References). First demonstration that group functional MRI activity can forecast aggregate song downloads 2 years later—even when ratings cannot.

Genevsky, A., & Knutson, B. (2015). (See References). Direct demonstration that group brain activity can supersede group choice in forecasting microlending appeal success on the Internet.

Samanez-Larkin, G. R., & Knutson, B. (2015). (See References). Proposes the affect-integration-motivation (AIM) framework for using a hierarchical and ascending sequence of neural components to predict individual choice.

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