NEURAL BASIS OF CONSUMER DECISION MAKING AND NEUROFORECASTING

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Neuroscience, in recent years, has contributed significantly to a better understanding of how individuals make decisions and how these decisions are influenced by context, states, and individual traits. The past decade has seen the emergence of consumer neuroscience as an academic field of inquiry that applies tools and theories from neuroscience to better understand consumer behavior. These studies have primarily used functional magnetic resonance imaging (fMRI) and electroencephalography (EEG), although the field extends to a wider range of tools such as facial coding, eye-tracking, heart rate monitoring, and galvanic skin response.

Investigating meaningful questions with appropriately designed studies that leverage neuroscientific knowledge has allowed researchers to generate useful insights about consumers from both theoretical and practical perspectives. Plassmann et al. (2015) identified five concrete ways in which consumer neuroscience has been applied to improve understanding of consumer behavior. First, it can be used to validate, refine, or extend existing theories by elucidating the underlying mechanisms. It has also suggested empirically testable hypotheses about preferences, judgments, or choices (e.g., Ho & Spence, 2009; Wadhwa et al., 2008) that accord with an understanding of biology. Second, neuroscience techniques have provided information about implicit processes that are difficult to access using other methods (e.g., Plassmann et al., 2008; Yoon et al., 2006). Third, neural measures have been used to test for dissociations between psychological processes. For example, fMRI has been used in studies to examine the extent to which two different kinds of decisions use similar or different neural mechanisms and thus whether they are likely to use similar or different cognitive processes (e.g., decisions under risk and ambiguity; Hsu et al., 2005; I. Levy et al., 2010). Fourth, fMRI studies have tested whether different individuals perform the same decision task in different ways (e.g., using heuristic vs. deliberative decision strategies; Venkatraman et al., 2009). Fifth and finally, studies have incorporated neural measures into models of choice and decision making to improve predictions. Although all five ways are indeed important ways in which consumer neuroscience can contribute to knowledge about consumers, this chapter focuses primarily on reviewing the research related to neural predictions. We choose to do so, in part, because there are already a number of recently published review articles that have described the advantages of neuroscientific methods and their contributions to consumer research more generally (Karmarkar & Plassmann, 2019; Karmarkar & Yoon, 2016; Plassmann et al., 2015; Smidts et al., 2014). However, the main impetus for the present topic is that it is currently garnering much research interest among academic scholars and practitioners alike for holding the promise of expanding our insights about

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consumer decision making and improving predictions at the individual as well as aggregate level in real-world settings.

Prior studies have found that neural measures inform predictions of individual responses to social influence (Campbell-Meiklejohn et al., 2010; Klucharev et al., 2009; Zaki et al., 2011), health behavior change (Chua et al., 2009, 2011; Falk et al., 2010, 2011), and consumer decisions (Knutson et al., 2007; I. Levy et al., 2011). Building on this research, more recent investigations have focused on how neural activity of individuals can be used to predict large-scale, out-of-sample outcomes ranging from music album sales (Berns & Moore, 2012) and microfinancing outcomes (Genevsky & Knutson, 2015) to the virality of news articles (Doré et al., 2019).

In this chapter, we first provide a selective review of prior research findings about the neural processes underlying decision making. In so doing, we discuss how the insights about neural processes have served to provide a basis for research incorporating neural measures to improve within-individual predictions of preferences, choice, and decision making in consumer domains. The bulk of the chapter then discusses emerging research findings in neuroforecasting involving the use of neural data to forecast the aggregate behavior of a separate and independent group. We consider how the neuroforecasting findings can advance our understanding of real-world decisions and improve market-level predictions in a variety of choice domains, including consumption, health, and financial decision making. We highlight some notable gaps in knowledge and the challenges associated with conducting neuroforecasting studies. Finally, we discuss some future research opportunities and directions that hold promise for informing the design and selection of better marketing practices, as well as public policies and intervention programs.

NEURAL BASIS OF DECISION MAKING

Consumer researchers have traditionally used self-report and choice measures to predict future behavior despite their well-documented limitations. Prominent among these is the need to rely on participants to honestly and accurately report on the mental processes on which they are often unwilling or unable to accurately reflect. Indeed, we often require participants to respond regarding attitudes and behavior that will occur at some point in the future, an exercise we know people are generally unable to do accurately. In some cases, the very act of asking individuals to reflect on their internal processes fundamentally changes their experiences in a way that makes them incompatible with the real-world phenomena being examined. Use of neural data to capture what is hidden in consumers' brains to make predictions may thus provide a window into decision making processes that are informative in improving predictions. We review the research efforts from the past decade to understand consumers' neural processes associated with true underlying preferences and implicit processes.

Neuroscientific methods have developed to a point where they can indeed be used by themselves or to complement the traditional approaches to improve predictions of consumer preferences and behavior. Prior studies have incorporated neural measures into decision-making models to improve predictions of consumer-related behavior over and beyond the traditional measures. In particular, fMRI is the most commonly used method in academic consumer neuroscience research, followed by EEG (for a comprehensive discussion of neuroscientific methods, see Shaw et al., 2018). Accordingly, the vast majority of the studies dealing with neural preferences and choices reviewed in this chapter use fMRI.

Although preferences have received a great deal of research attention, the ways in which they are defined are surprisingly broad and diverse. Whereas some have conceptualized preferences as innate and biologically determined traits (e.g., Eysenck, 1990), the more common view is that they are dynamic, flexible, and frequently inconsistent representations of liking for different goods or entities. Consumer researchers have been heavily influenced by the economists' definition of preference, which entails a consistent ordering of choices based on relative utility. However, given that choices often reflect high variability and inconsistency, much of the prior research efforts have been devoted to exploring different models of stochastic preference rather than addressing the complexity around preferences. Understanding how consumer preferences for products or brands are represented in the brain and how they are influenced by contextual factors is an area of inquiry that has recently received more research attention.

Much of the neuroscience research on preferences has been done within the framework of understanding value-based decision making, which entails the idea that decision making is driven by, or reflects, underlying preferences or representations of value. A consensus view to emerge is that parts of the prefrontal cortex, together with the subcortical structures, play key roles in encoding subjective valuations (Kable & Glimcher, 2007). In particular, converging evidence indicates that the critical neural areas for subjective valuation include the orbital frontal cortex (OFC), ventromedial prefrontal cortex (VMPFC), and ventral striatum (VS). Moreover, there is commonality in the processes underlying subjective valuation, which has been termed a "common neural currency" (see D. J. Levy & Glimcher, 2012, for a meta-analysis). According to this view, neural responses in the areas implicated in subjective valuations are domain-general. That is, if one is faced with different types of value (e.g., primary rewards, secondary rewards), the valuation signals in the brain reflect direct comparisons that have been transformed onto a common scale. Increases in amounts of reward or affective value capturing the brain's value system have been found to scale with higher liking or pleasantness ratings, greater willingness to pay, and choice measures.

Converging evidence has suggested that the OFC is associated with the encoding of reward value underlying preferences (Padoa-Schioppa & Assad, 2006). The OFC has been implicated in representations of expected value for stimuli involving sensory processes such as taste (Plassmann et al., 2008; van den Bosch et al., 2014), touch (Rolls, 2004), and smell (Gottfried & Zald, 2005) and encoding of abstract stimuli such as aesthetics (Kawabata & Zeki, 2004), money (Elliott et al., 2000), facial attractiveness (Cloutier et al., 2008), and social stimuli (Rushworth et al., 2007; Spitzer et al., 2007).

Neuroimaging studies have documented a strong link between subjective value and activity in both the VMPFC and OFC. Initial studies examined the neural correlates of hypothetical preferences. In one study, participants viewing pictures of preferred (vs. nonpreferred) soft drinks had greater VMPFC and OFC activations (Paulus & Frank, 2003). In another study, male participants who viewed pictures of preferred (vs. nonpreferred) beer brands and female participants presented with pictures of preferred (vs. nonpreferred) coffee brands showed higher activations in the VMPFC and OFC (Deppe et al., 2005). Plassmann et al. (2007) scanned the brains of hungry participants while they placed bids for the right to eat 50 different snacks in a Becker–DeGroot–Marschak auction (Becker et al., 1964). The participants placed bids on 100 different trials, and on each trial, they were allowed to bid \$0, \$1, \$2, or \$3 for an appetizing snack that was visually presented. They found that the willingness-to-pay amounts for the items correlated with activation in the VMPFC and OFC. These studies have been interpreted as supporting evidence for a close correspondence in regional brain activity between the anticipation of rewarding events, the consumption of enjoyable goods, and the willingness to pay for them.

Although the OFC has been discussed as a leading candidate brain region for representing preferences that can predict choice at the time of decision, it does not have direct access to motor output networks supporting choice or action, unlike the cortical and subcortical regions of the brain that have been strongly associated with valuation. Insofar as the computing value is often associated with a decision involving an action or choice, a large body of neuroscientific research on decision making has focused on the VMPFC and VS as correlates of subjective utility that form the core of a valuation system supporting choice and decision making. These regions have consistently shown higher activity for more valuable items. A meta-analysis of 206 published fMRI studies found evidence of reliable correlates of a domain-general signal of subjective value in the VMPFC and anterior VS (Bartra et al., 2013). Positive effects in these regions were seen for both decision subjective value (i.e., when a decision is made) and experienced subjective value (i.e., when an outcome is experienced). As already mentioned, the positive effects in the VMPFC and VS were also evident in response outcomes for both primary (e.g., food) and secondary (e.g., money, social) rewards and serve to provide empirical support for the unitary neural system (i.e., common neural currency), representing different facets of an individual's value perceptions not only across different categories of goods but also features of the goods (Chib et al., 2009; D. J. Levy & Glimcher, 2011).

Prior studies have also examined the role of valuation signal in VMPFC and VS in more complex decision-making settings involving risk and ambiguity, intertemporal discounting, and social decisions (for a review, see Ruff & Fehr, 2014). I. Levy and colleagues found that activity in the VMPFC and VS correlated with predicted value during choice under both risk and ambiguity (I. Levy et al., 2010). In their fMRI study, participants made choices when presented with lotteries varying systematically in the amount of money offered and in the probability of winning the amount or the ambiguity around that probability. They found that activity in the VMPFC and VS correlated with subjective valuation under both conditions of risk and ambiguity. Kable and Glimcher (2007) tracked the participants' choices between immediate and delayed monetary payoffs while undergoing brain scans and found that VMPFC and VS activation varied with the subjectively discounted value of future rewards. In a study of social behavior involving charitable giving, Hare and colleagues showed that VMPFC correlated with the amount of money donated during free trials and provided evidence that valuation signals in the VMPFC represent an integration of input from neural regions involved in social cognition (Hare et al., 2010). In another study involving social situations, participants taking part in a social reward task in which they received positive evaluations of their personalities by others versus a nonsocial monetary gambling task (Izuma et al., 2008) showed activation in the VMPFC and VS. Similar patterns of VMPFC and VS activation have been found when participants are informed that others like (Davey et al., 2010), understand (Morelli et al., 2014), or want to meet them (Cooper et al., 2014).

NEURAL PREDICTORS OF DECISIONS

Some research efforts have focused on incorporating measures of activity in specific brain areas to complement existing psychological measures to predict outcomes within individuals. The idea was tested by Knutson and colleagues, who showed that predecisional activation in relevant brain regions predicted subsequent choice (Knutson et al., 2007). They distinguished between purchased-item and nonpurchased-item trials and found significant differences in activation in the nucleus accumbens (NAcc) part of the VS during product presentation and both medial prefrontal cortex (MPFC) deactivation and insula activation during processing of excessive prices. They estimated brain activity in these three regions of interest and entered them as covariates in logistic regression along with self-report measures of preference and net value to predict subsequent purchasing decisions. The results indicated that the full model (i.e., including the neural measures) provided significantly better predictive power than a model with only the self-report measures. Importantly, the study provided additional evidence of the representation of subjective value in the VMPFC and VS during the choice process. Even though the advantage of the full model including the neural measures was relatively small in this study, Grosenick et al. (2013), in a subsequent study, used multivariate methods to model the data from the Knutson et al. (2007) study and obtained substantial improvements in predictive validity.

A related question that stems from the evidence that the VMPFC and VS activation represent an integration of various inputs into a common neural currency is the extent to which the integration occurs automatically in response to exposure to stimuli regardless of whether a choice is hypothetical or even when no decision is currently needed. A study by Kang et al. (2011) found that VMPFC activity was associated with the decision value of an item even when the choice was hypothetical. Other findings have suggested that the valuation signals encode information that predicts subsequent behavior when it is implicitly processed and in the absence of a specific judgment or choice.

Lebreton et al. (2009) scanned participants while they rated the pleasantness of faces, houses, and paintings or made judgments about age. Outside of the scanner, they were then presented with pairs of the same images and asked to identify which one was more pleasant. They found greater VS and VMPFC activity for images that were subsequently preferred, suggesting an automatic valuation process even though the participants did not know they would be asked to make a choice before assessing the pleasantness of the images. Tusche and colleagues (Tusche et al., 2010) used a multivariate decoding approach in a study comparing the neural responses of participants in the high-attention group (i.e., paid attention to different products presented on the screen and rated their attractiveness) to participants in the low-attention group (i.e., attention directed away from the products on the screen). The participants in both groups were then asked to indicate their willingness to buy each product. A comparison of the activation patterns for the two groups during product exposure revealed similar activation patterns in the VMPFC and VS, such that choice could be predicted equally well in both attention groups. Thus valuation signals corresponded to the subjective value of an item that was implicitly processed.

Building on the studies by Lebreton et al. (2009) and Knutson et al. (2007), I. Levy et al. (2011) investigated the extent to which neural activity in the VS and VMPFC during passive viewing of consumer goods (e.g., CDs, DVDs, books, monetary lotteries) could predict subsequent consumer choices. They found that activation in the valuation areas in the absence of choices was indeed predictive of subsequent decision making. These findings suggest that there are elements of preference that are similarly represented in the brain, regardless of how the target is encountered. Whereas the aforementioned studies focused on within-subject classification or prediction, Smith et al. (2014) sought to predict out-of-sample choices from nonchoice neural activity. They had participants view images of 100 different snack foods while being scanned and did not tell them that they would be asked to make choices among the alternatives outside the scanner. Their findings provided further support for the idea that neural responses to products when participants are not making choice decisions could nonetheless be used to predict choices that people would make, especially in settings where actual choice data are difficult to obtain or do not exist.

While the findings reviewed thus far contribute to foundational knowledge for understanding consumer decision making, they are arguably more informative about the brain than consumer behavior. They are nonetheless important in expanding our understanding of decision processes that allow for productive ways to generate better predictions based on more refined models, assumptions, and hypotheses related to behavioral outcomes and patterns.

NEUROFORECASTING: USING NEURAL DATA TO FORECAST MARKETS

To this point, we have reviewed research in consumer neuroscience focused on understanding and predicting individual preferences and behavior. This body of work suggests that neural measures in specific areas of the brain can track decision attributes or the choice process across time even before a conscious decision is made. It further indicates that neural data may have a unique ability to predict an individual's future pattern of behavior from their own brain activations. This work has laid the foundation for an exciting new body of research focused on scaling predictions beyond the individual to account for aggregate-level behavior at the market and even population level. The term *neuroforecasting* has been used to describe this new direction of neural prediction—in which the focus is on forecasts of aggregate outcomes—and distinguish it from previous work focused on prediction of individual choice (Knutson & Genevsky, 2018).

Many of the most consequential decisions across business, economics, and public policy rely on information collected from a relatively small group of individuals to forecast the behavior of much larger groups. As an example, firms often use survey responses and focus groups to inform large-scale marketing strategies and campaigns. Advances in brain imaging design and analysis, and the increasing availability of market-level data, have allowed researchers to apply neural analyses to the forecasting of aggregate behavior (for reviews, see Hakim & Levy, 2019; Knutson & Genevsky, 2018). Even relatively small improvements in forecasting accuracy can have significant consequences across many domains. As one example, neural responses to health campaigns could be used to forecast how effective they will be in eliciting real and widespread changes in health behavior (Falk et al., 2010, 2011).

Evidence is mounting that neural measurements of less observable intervening processes responsible for the assessment and evaluation of incoming stimuli may be the most informative for improving forecasts of aggregate behavior. Due to the fact that neuroforecasting researchers are interested in scaling prediction beyond the individual to account for behavior at the aggregate level, there are important conceptual implications for how experiments are designed and analyzed. Typically, in conventional analysis, the individual is the unit of analysis. Data are collected (both neural and behavioral) in an effort to predict the choices of that individual. On the other hand, in neuroforecasting research, the focus is on prediction at the aggregate level. Data collected from a sample of individuals are used to predict the behavior of much larger groups. As a consequence, the unit of analysis becomes the stimulus itself, whose real-world impact on an outcome of interest is what we seek to predict.

In the next section, we begin by reviewing recent work in neuroforecasting that has shed light on the potential of neural data to improve forecasts of aggregate outcomes and also improve our understanding of how individual decision processes may scale to inform aggregate-level behavior. We then discuss the practical and theoretical contributions of this body of work and place it within the context of existing neural and behavioral marketing research. Finally, we conclude by highlighting some of the biggest questions currently facing neuroforecasting research and the directions the work is likely headed in the foreseeable future. A list of published articles on neuroforecasting is presented in Table 27.1.

fMRI Studies of Market Prediction

The first neuroforecasting study was conducted by Berns and Moore in 2012; though, of course, it was not called such at the time—the term would not be used until 2018. The authors had conducted a study a few years prior on an unrelated topic: the impact of social influence on music preferences. The stimuli they used in that study were songs uploaded by musicians to a popular social media website. Importantly, these bands were not well known at the time, and the songs were unfamiliar to the study participants. The participants listened to the song clips while being scanned in an MRI, and, thus, their neural responses to each unique clip were recorded. Participants also provided self-reported ratings regarding their preference for each of the songs. After a couple of years had passed, some of the songs had enjoyed a measure of commercial success. The authors realized that they could now look back at the original neural responses collected years earlier to see if the participants' responses (neural or behavioral) were at all related to the eventual real-world sales outcomes. They first looked at the subjects' own preference ratings and found that they were not predictive of the songs' market success. However, when they reanalyzed the brain data, they found that neural activity in the NAcc and MPFC, the same regions often associated with reward and valuation in studies of individual decision making, were also significantly associated with the aggregate-level commercial success. In other words, the authors found that a component of an individual's basic neural responses not only predicted their own music preferences but, once averaged across participants, also forecasted real-world aggregate-level outcomes. This first demonstration of neural data from a relatively small sample forecasting aggregate-level behavior signaled the beginning of neuroforecasting.

The work by Berns and Moore was soon followed by a study focused on public health messages conducted by Falk et al. (2012). Departing from traditional consumer behavior metrics (e.g., sales figures, willingness to pay, ad engagement), the authors sought to forecast the relative effectiveness of smoking cessation advertisements. Effectiveness in this context was defined as the number of

TABLE 27.1

Neuroforecasting Studies: Research Using Neural Activity Collected in a Laboratory Sample to Predict Real-World Aggregate-Level Outcomes

Authors	Year of publication	Method	Study stimulus	Aggregate outcome
Berns & Moore	2012	fMRI	Songs	Album sales
Falk et al.	2012	fMRI	Ads	Ad-related calls
Dmochowski et al.	2014	EEG	TV episodes; Video ads	Twitter activity; ad ratings
Genevsky & Knutson	2015	fMRI	Microlending requests	Loan funding rates
Venkatraman et al.	2015	fMRI, EEG	Ads	Sales elasticity
Boksem & Smidts	2015	EEG	Movie trailers	Box office sales
Baldo et al.	2015	EEG	Shoe products	Sales
Kuhn at al.	2016	fMRI	Ads	Ad-related sales
Dietz et al.	2016	EEG	Video ads	Online views
Scholz et al.	2017	fMRI	News articles	Online sharing
Genevsky et al.	2017	fMRI	Crowdfunding appeals	Funding success
Barnett & Cerf	2017	EEG	Movies	Box office sales
Guixeres et al.	2017	EEG	Video ads	Online views
Hakim et al.	2018	EEG	Video ads	Online views
Shestyuk et al.	2019	EEG	Television programs	Viewership and Twitter volume
Tong et al.	2020	fMRI	YouTube videos	Online views/duration

individuals in the target markets that subsequently called antismoking hotlines indicated in the advertisements. Participants in the study were presented with advertisements while being scanned in the MRI magnet. Their subjective ad effectiveness ratings were also subsequently collected. The authors found that neural activity in the MPFC while viewing the advertisements was significantly associated with their aggregate volume of calls to the hotline. This relationship held even when controlling for the self-reported effectiveness scores. This study was the first to explicitly advance the brain-as-predictor approach and also represents one of the first examples of directly testing the relative contribution of various neural and behavioral predictors.

In 2015, Genevsky and Knutson continued to build on these early examples, exploring forecasting of real-world prosocial behavior. Their study was set in the context of microlending—small, interest-free loans, typically made by a large number of donors to support people in need across the globe. In this study, the authors used neural activity recorded as participants were presented with real loan request pages scraped from the largest active microloan website on the internet (kiva.org). In response to each loan request, participants were also asked whether they would like to make a real donation using their own money and rated various features of the loan page and recipient. Subsequent analyses demonstrated that not only was the neural data associated with the real-world outcomes for these loans on the internet (i.e., whether they were funded) but they contributed predictive power above and beyond the participants' own lending behavior and subjective ratings. Given the large economic scale of online microlending in which millions of dollars are raised each year, even relatively modest improvements in forecasting represent substantial increases in overall giving.

The results reported by Genevsky and colleagues highlight an important aspect of current neuroforecasting research programs. Beyond demonstrating that neural activity is associated with aggregate-level behavior, researchers must remain mindful of the additional effort and cost associated with these methods and thus place their relative contributions in the context of traditional behavioral methods, such as consumer surveys and focus groups. Venkatraman et al. (2015) did exactly this in a study of advertising effectiveness. In fact, the authors directly contrasted the relative predictive powers of a number of traditional, neural, and physiological measures, including consumer surveys, psychological surveys, eye tracking, biometric measures (e.g., heart rate, respiration, skin response), EEG, and fMRI. While many of these measures, when considered separately, demonstrated an association with real-world advertisement effectiveness, only the fMRI measures were observed to improve forecasts beyond what was possible using traditional pencil-and-paper measures. This work made an important contribution because it demonstrated not only that neuroscientific methods can improve our ability to forecast real-world consumer behavior outside the laboratory but that we must focus on when and why individual methodological approaches might be most optimal.

In another innovative example of neuroforecasting being applied in a marketing-relevant context, Kühn et al. (2016) explored the effectiveness of point-of-sale supermarket advertisements on sales of chocolate. Participants in the study were presented with advertisements and products in the scanner and subsequently made subjective ratings of their liking of the products. After the neural data collection, the purchasing behavior of over 60,000 shoppers in a supermarket was recorded and analyzed. When the authors compared the ability of the laboratory measures to forecast the relative sales of the products, they found neural responses to both the advertisement and the product itself outstripped the predictive power of subjective ratings. Building on previous studies, this work is a useful demonstration of the potential for neuroscience-based forecasts to inform the kind of real-world marketing challenges often faced by firms.

Genevsky et al. (2017) went on to apply neuroforecasting to outcomes of crowdfunding campaigns, another growing market with significant financial implications. In this case, the participants' own funding behavior and an array of survey data, including liking, emotional responses, and estimations of the projects' likelihood of success, were all found not to be associated with the real-world outcomes of projects on the crowdfunding website. In other words, behavioral measures from the laboratory sample were not informative about the larger marketplace's funding behavior. However, neural activity collected while participants viewed the projects in the scanner was found to predict their success or failure months later on the crowdfunding website. Interestingly, while regions associated with both positive affect (NAcc) and value integration (MPFC) were associated with the participants' own individual funding decisions, only the NAcc activity effectively scaled to forecast aggregate-level outcomes. This observation raises the intriguing possibility that not all neural processes associated with individual decision-making processes may be implicated in forecasts of aggregate choice. This insight has led to follow-up work exploring the neural and psychological mechanisms underlying neuroforecasting, as described later in the chapter.

A study by Scholz et al. (2017) further demonstrated the potential of neuroforecasting to make an impact across a large range of market-relevant domains. The ubiquity of online content has made information-sharing behavior an integral element of understanding how consumers interact and engage with firms and their messages. Developing an understanding of why certain messages are shared more often, and even being able to predict which messages will become viral, is an invaluable tool in today's marketing environment. In this study, the authors presented a series of *New York Times* online articles to participants while they were in the scanner. They then attempted to forecast the real-world sharing volume of those same news pieces on the *New York Times* website. As hypothesized, activity in the aforementioned reward-related regions of the brain (i.e., NAcc and MPFC) was predictive of online sharing. In particular, the neural activity improved forecasts above and beyond what was possible using features of the articles themselves or the participants' own self-reported sharing intentions.

To this point, we have primarily described decision contexts in which individuals were making choices regarding financial resources. However, we are steadily moving toward a world in which a new currency is quickly becoming increasingly valuable. Our very attention and engagement, often measured by our allocation of time, increasingly represent the most valuable commodity to firms. This is particularly true in entertainment and online media platforms. A study by Tong et al. (2020) explored whether neuroforecasting can expand beyond traditional decision making to account for real-world engagement in these attention markets. To accomplish this, the authors extracted aggregate measures of engagement from YouTube (e.g., how many people watched a video per day and the average viewing duration of the videos they watched). Participants in the scanner watched the first few seconds of these same videos and then decided whether to continue watching. They also provided self-reported ratings regarding their viewing preferences. The authors found that the participants viewing behavior and their ratings were not significantly associated with the frequency of views on YouTube. However, the neural analyses indicated that activity in affective circuits was significantly associated with these real-world aggregate metrics. Importantly, the neural data could also forecast the aggregate view duration of the videos. This demonstration of a neural predictor of viewer engagement (and disengagement) has important implications for optimizing the design of online content and messaging.

EEG Studies of Market Prediction

The use of EEG has gained popularity in both academia and industry due to its relative affordability and ease of use when compared with fMRI. Indeed, EEG is the primary source of neural data collected in private industry and by commercial neuromarketing firms (Hakim & Levy, 2019). EEG studies have taken a different approach to aggregate prediction. Whereas fMRI studies largely leverage the spatial resolution afforded by functional imaging to localize and extract predictive brain activity, EEG studies generally rely on other types of analyses, including decomposition of frequency bands, symmetry of activity across brain hemispheres, and correlations of neural activity across individuals. In this section, we review the existing EEG studies of aggregate prediction.

One way EEG data can be used is by assessing the extent to which neural activity while experiencing a stimulus is correlated in time across individuals. Rather than imposing predefined models on the data, this intersubject correlation (ISC) analysis uses neural responses derived from a subject to predict responses in other subjects (see Hasson et al., 2004, 2010; Mukamel et al., 2005). Originally applied to fMRI data, ISC analyses are often used in EEG studies involving the reliability and synchronization of neural responses across individuals. In particular, when used in connection with dynamic stimuli (e.g., commercial advertisements, videos), the ISC purports to capture engagement as represented by activity common across viewers. This technique was used by Dmochowski et al. (2014) in their study of viewer engagement with popular media and advertising. First, EEG activity was recorded in a small group of participants while they watched episodes of the popular American television show *The Walking Dead*. Analyses found that the shared neural activity during the viewing period correlated with real-world engagement with those episodes by the viewing public. Specifically, the ISC was associated with the size of the viewership of the episodes and the volume of relevant tweets posted during airing of the episodes. Next, the researchers turned their attention to an exploration of Super Bowl advertisements. There, they found that the correlation of neural activity within a laboratory sample of participants was associated with the real-world ratings of the advertisements. Taken together, these studies suggest that correlated neural activity measured via EEG may represent a common form of engagement that can be informative in predicting market-relevant behavior.

A similar analysis of correlated neural activity across individuals was employed by Barnett and Cerf (2017) in their study of movie trailers. Eschewing the traditional laboratory environment, the researchers took the admirable step of collecting EEG data from individuals as they watched film trailers in a real movie theater. Despite the myriad technical challenges presented by this study, the authors found that the extent to which neural responses were correlated across viewers was associated with the real-world success of the films, as measured by box office sales. Additionally, the researchers compared the strength of this relationship against other more commonly collected types of viewer data, including the participants' own ratings of the movie trailers and their assessments of willingness to pay to view the full film. They found that of these measures, the EEG similarity metric demonstrated the strongest association with box office sales.

Another method utilized frequently in EEG analysis, termed spectral decomposition, separates the various frequencies of neural activity into defined bands, often associated with various psychological processes and states. As an example, Boksem and Smidts (2015) used spectral analysis of participants' neural activity as they watched movie trailers to forecast the real-world success of the films after release. As participants watched promotional trailers for the films, their neural responses were collected and subsequently decomposed into predefined frequency bands. The power of the signal observed in specific frequency bands was found to be positively associated with the real-world revenue of the films. In another example, Guixeres et al. (2017) utilized a variety of EEG analyses including spectral decomposition to forecast engagement with Super Bowl advertisements. Applying machine learning algorithms to a combination of EEG metrics, the authors could predict the number of YouTube views for the advertisements. The authors went on to compare the various measures and found that the asymmetry across brain hemispheres in a particular frequency range, interpreted as a measure of pleasantness, was the single best predictor of YouTube views.

A prime example of the movement of neuroforecasting research beyond simple existence proofs to more sophisticated analysis of the relative contributions of various methods and analysis techniques comes from a study by Hakim et al. (2018). In this work, the authors recorded EEG data from participants as they watched a number of video advertisements for various consumer products. They additionally collected survey data regarding the participants' preferences and intentions of purchasing those same products. While the questionnaire data could forecast the aggregate-level responses to the various products with 64.2% accuracy, adding the EEG measures improved the forecasts, reaching a rate of 68.5%. This relatively modest yet significant improvement in prediction suggests that despite the usefulness of traditional marketing measures, neuroscientific methods can contribute significant additional explanatory power to models attempting to predict behavior beyond the participant sample—a goal often at the forefront of modern-day marketing.

Up until this point, we have discussed academic research, primarily conducted in business schools at universities. However, as mentioned at the beginning of this section, due to the practical and logistical advantages of EEG, it has become the preferred method of neuroscientific research in neuromarketing departments of international firms, as well as a growing number of smaller dedicated neuromarketing firms. While the research published by these private organizations is not as easily interpretable due to proprietary methods and data sources, it remains informative to be aware of the work being done by these firms. In a study of Super Bowl advertisements, Deitz et al. (2016) at Sands Research used a proprietary EEG analysis method to predict advertisement view metrics on YouTube. In another example, Baldo et al. (2015), from Neuromarketing Labs, reported success using proprietary EEG metrics of emotional engagement to forecast shoe sales. These examples point to the growing use of neuroscientific methods in industry. The goals of these studies have shifted from gaining an understanding of consumer motivations to making actionable forecasts of consumer behavior.

Scaling Prediction: From Individual Decisions to Aggregate Behavior

The body of work reviewed leads us to a very important question: How can neural activation recorded in a laboratory sample predict aggregate behavior, at times better than self-report measures or observed behavior? More specifically, what are the mechanisms that support the scaling of prediction from the individual to the aggregate? While few studies have addressed these questions to date, they represent an important direction for continuing research.

One theory put forward by Knutson and Genevsky (2018) suggested that while a number of neural processes are involved in an individual decision-making process, only a subset of these regions may scale to inform forecasts of aggregate behavior. More specifically, basic affective responses indexed by evolutionarily conserved subcortical circuits may represent a more universal, or generalizable, measure of the response to a stimulus. The affect–integration–motivation framework describes a hierarchical model whereby a decision stimulus first elicits an affective reaction. This affective reaction is then integrated by higher order cognitive processes that include idiosyncratic preferences and concerns. This then leads to a motivational state, whether to approach or avoid the stimulus. Finally, the response is manifested as an observable behavior: the end point of the decision-making process.

Knutson and Genevsky (2018) offered an illustrative example of how neuroforecasting may play out. They painted an image of a researcher entering a crowded lecture hall carrying a tray of warm, freshly baked chocolate-chip cookies. As the delicious smell wafts throughout the room, the students likely experience a very similar and strong affective response. If those same researchers then stepped back and recorded the students' behavior (i.e., whether they took a cookie), they would observe a great variety of reactions. Similarly, if they surveyed the students regarding their behavior, the responses would likely include a great deal of idiosyncratic variability reflecting the individual students' dietary and motivational goals. However, if the researchers were able to capture that first affective response as the tray of cookies entered the room, they would have a more universal and generalizable index of the preference for that cookie. To complete the metaphor, the neural response, specifically that recorded in the NAcc, represents this generalizable response. Thus, these basic responses, unadulterated by idiosyncratic differences, offer the best opportunity to improve forecasts of the larger population's behavior.

One consequence of this framework is that it makes specific testable predictions. Forecasts based on generalizable neural activity should be less impacted by the representativeness of the sample to the population than forecasts that rely on less generalizable self-report measures. Recently, Genevsky and colleagues have tested this prediction. In unpublished work, they found that while the accuracy of behavioral forecasts based on traditional measures collected from a sample is highly impacted by the representativeness of that sample to the population, neural forecasts demonstrate a much lower impact of representativeness. This finding suggests that compared with observable behavior and self-report measures, neural activity may represent a more generalizable index of preference across individuals.

In this section, we have reviewed a new and growing literature on neuroforecasting. Across methodologies, there are now numerous examples of how neural data collected in the laboratory can make market-relevant predictions about outcomes in the real world. As the field continues forward, it is imperative that researchers continue to move toward studies that address how, when, and why neural forecasts work. This understanding can then be applied to optimize forecasts to achieve maximum prediction accuracy. The work reviewed earlier in the chapter on the neural mechanisms of individual choice has set the stage for neuromarketing to fulfill the potential of consumer neuroscience to make tangible and substantial contributions to the marketing fields in both academia and industry.

CONCLUSION

As the field of consumer neuroscience has continued to grow, there has been increasing interest in leveraging theoretical and practical insights from brain-based studies on decision making to improve within-individual predictions and aggregate-level forecasts. The work described in this chapter covers research advances and significant insights that serve to inform and guide better predictions in a variety of consumer domains. An important caveat to keep in mind is that the extent to which specific processes can be inferred from neural data is limited, and caution is warranted when interpreting brain data. In general, combining multiple complementary methods can offer benefits in terms of the researchers' ability to provide more definitive empirical evidence. We now have a critical mass of findings that we can draw on to reveal a distinct set of brain signals from consumers that can potentially outperform the commonly used behavioral measures. In parallel with advances in academia, practitioners' interest in applying neuroscience methods has been growing as a means for gaining insights into implicit or automatic processes.

Looking forward, neuroscientific studies can provide useful insight about the underlying causes and mechanisms that can be used to perform predictive analytics on problems in the age of big data. Predictive analytics essentially rely on vast amounts of past observations to connect inputs with outputs and typically do not account for underlying mechanisms. This black box approach without a sound understanding of the underlying forces that drive outcomes can lead to inadequate predictive models. The work on the neural basis of consumer decision making can be useful for understanding what actions and interventions are effective and ineffective under specific conditions and why they do or do not work. This work can help practitioners put structure on the question at hand so that unobserved and latent information can be properly accounted for when making inferences. It can ultimately guide practitioners and policy makers to be better at understanding cause-and-effect relationships between input and output variables, identifying real drivers of outcomes, and parsing out spurious patterns. For academic scholars, the work adds value to decision-making research by enhancing the ability to make inferences beyond our usual variables and paradigms, develop more comprehensive theories, and generate hypotheses that are empirically testable. This ultimately puts us in a better position to generalize this knowledge, understand the contextual influences on decision making, and create interventions or influence decisions more effectively. Such process knowledge can be important not just in consumer settings but in other settings such as those involving policy, legal, financial, or health decisions.

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