

Applications in consumer neuroscience: Decoding and neuroforecasting

Alexander Genevsky & Maarten Boksem
Rotterdam School of Management, Erasmus University

Abstract

Consumer neuroscience is an emergent field of academic research based on the foundations and principles of neuroeconomics, while maintaining a focus on real-world applications. The promise of consumer neuroscience stems from the potential of using modern neuroimaging methods to provide relevant and actionable insights into the mental processes underlying consumer and market behavior. In this chapter we provide a broad overview of the two areas of consumer neuroscience in which neuroeconomic perspectives and methods have shown the most promise. We first discuss the role of neuroimaging in the decoding of mental states and how these measures are informative for understanding consumers' responses, experiences, and associations. We then cover neuroforecasting, the use of neural data collected from laboratory samples to forecast market-level behavior. Finally, we close the chapter with an outlook for the future of the field.

1. Introduction

Over the past decade, the field of neuroeconomics has grown to include consumer neuroscience, an area of research focused on the application of neuroscientific methods and approaches to better understand consumer and market behavior. To this end, neuroimaging methods offer an important benefit over traditional behavioral methods by providing information about underlying mental processes without the need for participants to verbally articulate their thoughts, feelings and preferences^{1,2}. This represents a valuable opportunity for researchers and practitioners because many of the mental processes responsible for observed behavior occur below the level of conscious experience^{3,4}. Thus, research participants are often unable, or unwilling, to accurately report their true mental states and motivations⁵⁻⁷. The hope is that by applying neuroscientific methodologies we can gain insights that lead to a better understanding of consumers' mental processes, and subsequently to improved predictions of consumer behavior at the individual and aggregate levels.

From the outset, there has been enthusiasm that neuroscience would make significant impacts across a broad range of domains within consumer research¹. Indeed, valuable work in the field has applied neural data to marketing relevant topics including consumer valuation^{8,9}, branding^{10,11}, product design and aesthetics^{12,13}, and the integration of price information^{14,15} (for reviews see^{1,2,16-19}). However, to date, we find that the most promising contributions of consumer neuroscience to business practice fall into two categories: 1) the decoding of underlying mental states in response to marketing stimuli and the associated

consumer decision-making processes, and 2) the use of neural data to improve forecasts of market-level outcomes through neuroforecasting.

We begin with a discussion of the use of neural data to decode consumers' underlying mental states. This work has applied neuroeconomic approaches to explore consumers' emotional responses to marketing messages, the temporal experience of static and dynamic stimuli, and the assessment of consumer's perceptions of brand associations and image. Next, we consider the field of neuroforecasting, in which neural data is used to inform forecasts of real-world market-level consumer behavior. We discuss the origins of neuroforecasting, its unique experimental approach, existing empirical evidence, and theory building efforts.

2. Decoding mental states from the brain

2.1 Decoding Emotions

An extensive stream of literature in marketing has shown that emotions play an important role in how consumers respond to marketing stimuli^{20,21}. For example, it has been shown that advertisements high in emotional content generate more online search behavior²², that positive emotions lead to more positive attitudes to ads, products, and brands²³⁻²⁹, and that positive emotions lead to higher purchase intention and increased sales^{28,30} (see^{31,32} for meta-analyses).

However, measurement of these emotions is often difficult, in large part because individuals have limited access to their inner mental states^{4,33}. Even when aware of their emotional state, people often find it difficult to accurately identify or put them into words⁵⁻⁷. In some cases, participants may willfully misreport their feelings for reasons of social desirability^{7,34,35}. In addition, emotional ratings are often reported retrospectively, thus relying on how well they can be retrieved from memory. Moreover, emotions are dynamic processes, fluctuating considerably in short periods of time. Often it is precisely these fluctuations, opaque in retrospective reports, that can be of great importance for understanding the experience of a stimulus³⁶. For these reasons it is highly beneficial to be able to measure emotions with high temporal resolution, and without requiring retrospective self-report responses.

This is where neuroscience insights and methods play an important role. Modern neuroimaging methods provide researchers with insight into affective processes by directly observing them in real-time from the consumer's brain with relatively high temporal resolution^{1,2}. Importantly, emotions (as with other psychological processes) are considered distributed patterns of activations in a network of neural regions across the

brain^{37–39}. For these reasons, modern neuroscience makes extensive use of machine learning and pattern recognition techniques, referred to as multivariate pattern analysis (MVPA). This analytic approach is particularly suitable for analyzing distributed patterns of brain activation and how these patterns translate into psychological processes such as emotions^{40–42}.

In short, MVPA statistical models specify how patterns of activity across the brain combine to predict the identity or intensity of a mental process. While traditional (univariate) approaches in neuroscience are mainly focused on identifying the function of brain areas, the MVPA approach is mainly interested in identifying mental processes. This approach aligns well with the goals of consumer neuroscience researchers. For example, in marketing, one is less concerned with understanding which specific brain area is involved in a certain psychological process. Rather, the main goal is to establish which mental processes are evoked by marketing stimuli irrespective of the underlying brain network.

Over the past 15 years, several papers have demonstrated the possibility of decoding emotions from multivariate brain measurements. Researchers in affective neuroscience have found that it is possible to decode the neural substrate of discrete emotions (e.g. happiness, sadness, fear, anger and disgust) elicited by (audio)visual stimuli^{43–46}. However, most work has been focused on investigating the neural representations of the underlying emotional dimensions of valence and arousal. A seminal study in this area⁴⁷ showed that the pattern of brain activation evoked by emotional pictures could reliably predict the target emotion (see also⁴⁸).

Building on these findings and applying them in a marketing context, Eijlers, Boksem and Smidts⁴⁹ first classified neural activity in response to emotional pictures and subsequently used these representations to estimate the level of valence and arousal in response to advertisements. In this study, participants viewed 100 images from the IAPS image database⁵⁰ and 150 print ads from various product categories and brands, while EEG activity was recorded. The researchers used this neural data to train a statistical model to differentiate high and low emotional valence and arousal as evoked by the IAPS images. Subsequently, this model was used to obtain a measure of (neural) valence and arousal evoked by an independent set of print ads. Finally, they estimated the relationship between the decoded levels of valence and arousal evoked by the print ads and external measures of ad effectiveness (as measured by notability and attitude toward the ad in an independent consumer panel). The results showed that the neural measure of arousal was positively associated with the notability of ads in the population at large, but was negatively associated with the attitude toward these ads.

Although static stimuli such as print ads are still relevant for marketing, the trend is clearly towards video and interactive media. Chan and colleagues⁵¹ tested whether affective neural representations evoked by static emotional stimuli (IAPS images) can be used to decode emotional experiences evoked by dynamic advertising stimuli (video movie trailers). In this experiment, subjects were shown IAPS images and movie trailers in the MRI scanner. A support-vector machine (SVM) classifier was trained on the fMRI data obtained while viewing

the IAPS images and then tested on the movie trailer fMRI data. The results showed that patterns of activation in the brain could be used to accurately predict both the overall emotional content of the trailers, as well as the time course of the changes in both valence and arousal across the trailer. These findings provide evidence that neural affective representations extracted from episodic affective states correspond with those of more naturalistic and dynamic emotional experiences. We will further discuss the link between affect and forecasting in the section on neuroforecasting below.

2.2 Decoding the Consumer Experience

While most of the work on neural decoding, particularly where it relates to consumer behavior, has focused on emotions, the approach has broader applications. A key tool in this area is a meta-analytic database called Neurosynth⁵², which to date mines over 14,000 peer-reviewed neuroscientific publications for brain activation associated with a large range of concepts (e.g. ‘emotion’, ‘attention’, ‘memory’). The database provides a statistical brain map representing the relationship between the concepts and the neural activity reported across regions of the brain. By testing the similarity between patterns of brain activation elicited by (marketing) stimuli and the association maps obtained from Neurosynth it is possible to decode multiple underlying mental states simultaneously.

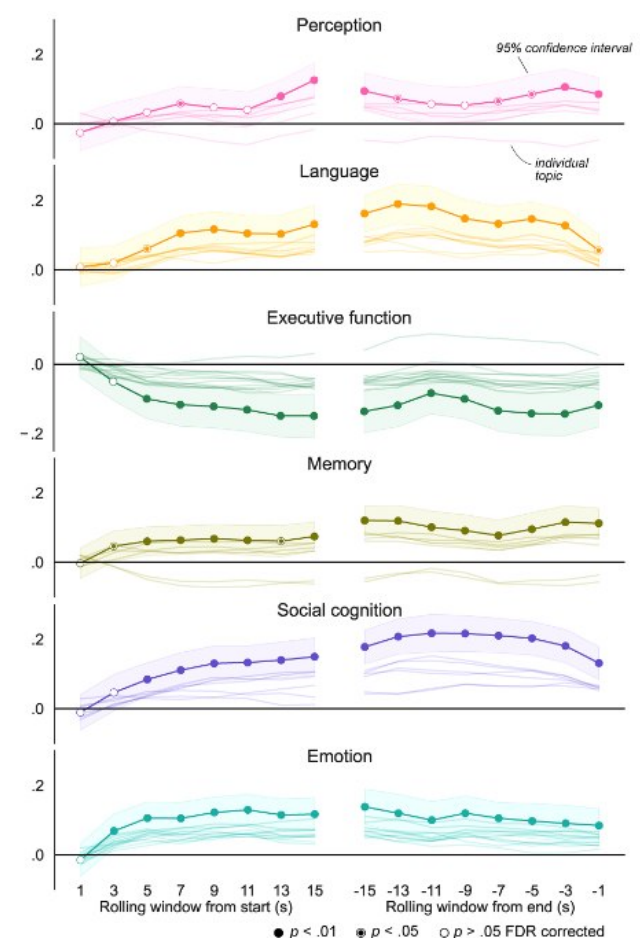


Figure 1. Time-Course of Decoded Mental Processes Predictive of Self-Reported Attitude to Advertisements. Adapted from Chan et al. (2023)

This is particularly relevant in consumer neuroscience because there is evidence from the marketing literature that mental states

other than emotions are important for effective communication. For example, perceptual and linguistic responses^{53,54}, memory, and attention⁵⁵ have all been associated with consumer preferences. In addition, executive functions impacted by processing fluency, such as deliberation and inhibitory control, have been found to interact with brand preference. On the other hand, social cognition, encompassing psychological processes such as empathy and mentalizing, is closely related to the advertising literature on narrative transportation⁵⁶.

Chan and colleagues⁵⁷ leveraged the power of meta-analytic decoding to investigate which mental processes were most closely associated with advertising success, and at which points during ad presentation these processes were most relevant. In their study, participants viewed ads while undergoing scanning in the MRI. Neural activity evoked by the ads was decoded using Neurosynth to capture the dynamics of the mental processes evoked by the ads. The decoded mental states were then subsequently compared to a measure of attitude towards the ad. The results showed that, in addition to emotions, a broad range of mental states were strongly associated with self-reported attitudes. Interestingly, it was observed that the temporal dynamics of these processes differed substantially (see figure 1). That is, the emotional response was found to be particularly important early on in the ad (within the first 3 seconds), but then dropped off slightly, while mental processes associated with social cognition (i.e. mentalizing) became important later in the presentation but then remained important. On the other hand, processes related to perception and executive functions (or lack thereof) were important for the closing stages of the commercial, suggesting that making consumers engage in effortful cognitive processing while viewing an ad leads to lower attitudes, confirming the long-standing observation that information complexity negatively impacts comprehension.

This work is a good example of how consumer neuroscience can provide specific recommendations for marketing in practice. Specifically, it suggests that it is important for effective ads to evoke an early emotional response, aligning with recent behavioral work indicating that consumers make up their mind about engagement within the first 10–15 seconds^{58–60}. In addition, these findings reveal the importance of eliciting processes associated with social cognition throughout the ad, echoing work showing that neural activity in the brain's social cognition system tracks message virality⁶¹ and that ad liking is associated with neural activity across participants at mentalizing regions in the brain⁶².

2.3 Decoding (Brand) Associations

In addition to evoking mental processes through advertising and communications, a central function in marketing is to create strong and specific brand images, the mental associations of the brand in the minds of consumers⁶³. For example, a beer brand may try to create associations between the brand and the concepts of 'young' and 'party' that conjure up images of trendy young people at a party. A breakfast cereal, on the other hand, may try to associate the brand with the concept of 'family' and an image of a loving family at the breakfast table. The extent to which these images and associations are elicited effectively and consistently in the minds of consumers is very difficult to

measure. We know that most people are simply not very good at thinking about internal mental processes and often cannot express them accurately. An additional problem with asking people about brand associations is that it is difficult to determine whether the reported associations are actually retrieved from memory, or are constructed on the spot in response to the researchers' questions⁶⁴. Moreover, people are more inclined to offer associations with familiar and innocuous brands like McDonalds than those with more complex social connotations like Durex⁶⁵. For these reasons, directly reading mental associations from the brains of consumers offer a more reliable way of measuring these brand images.

Findings from cognitive neuroscience support the idea that imagery and perception of specific visual content might be represented in the same cortical regions and in a similar representational format. In other words, models trained on fMRI data recorded during the visual perception of stimuli can decode which of these stimuli are then imagined at a later time^{66–68}. Indeed, the content of working memory -- what people are thinking of at any moment without relying on direct visual input -- can be decoded from the brain^{69,70}. These findings suggest that it may indeed be possible to extract visual imagery from activity patterns within the brain, potentially allowing for brand images to be decoded from consumers' neural responses.

Chan, Boksem and Smidts⁷¹ tested this hypothesis by asking participants to create a mental image that best fits a number of well-known brands (e.g., Apple, Disney, Heineken, Red Bull, Kellogg's, Microsoft and Durex). They were then placed in an MRI scanner and asked to recall the mental images they constructed previously while presented with the brand logos. In addition, participants viewed a large set of photos depicting different social situations: people working in an office, partying with friends, being intimate with a romantic partner, socializing with family, etc. In order to reveal the extent to which the association with the brand (the 'brand image') resembles the images of the different social scenes, a classification model was trained on the brain activity evoked while looking at photos of these situations, and those evoked while thinking about the brands. Thus, a neural profile in terms of the similarity of each brand to the different social settings was created (see figure 2). It was observed, for example, that when participants thought about Heineken, their brain activity was similar to how the brain responds to 'party' photos, but also that Heineken was fairly strongly associated with 'work', but clearly considered less sexy than Red Bull. An additional insight from this study indicated that when the neural profiles of two brands are very similar, such as that of Apple and Beats, consumers reported that they would be more interested in co-branded product. This method could be a useful tool for marketers to predict which brand collaborations might be most successful.

A slightly different approach was taken by Chen, Nelson and Hsu⁷². In this study, the researchers attempted to decode the personality traits associated with brands, rather than their brand images⁷³. As in the previous study, participants viewed the logos of different brands in the MRI scanner and were asked to freely express the associations they had with these brands. A classifier was then trained to associate the patterns of brain activity

acquired while participants viewed the brand logos with the personality characteristics as measured by a brand association scale⁷³. The results showed that personality characteristics associated with a brand can be reliably decoded from patterns of brain activity.

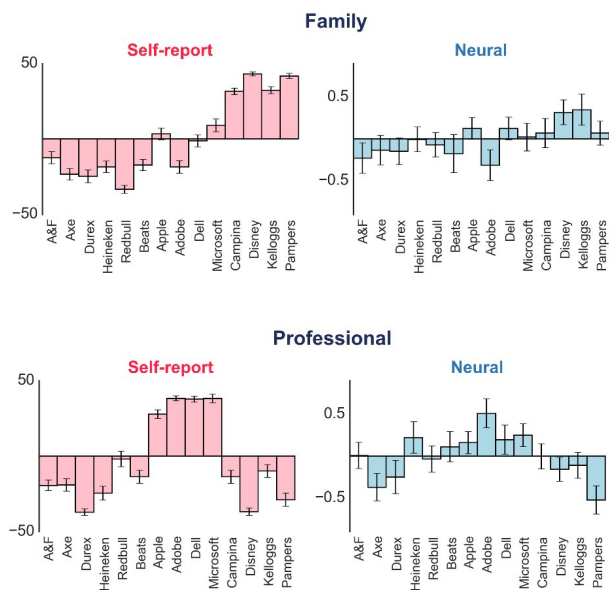


Figure 2. Self-reported brand perceptions (pink) and neural context scores (blue) for the Family context (top) and the Professional context (bottom). Neural context scores represent the pattern similarity between the neural responses evoked by the brand imagery and the different social contexts. Adapted from Chan et al., 2018.

2.4 Interim Summary

In this section, we have presented an overview of how contemporary methods from neuroscience provide a unique opportunity to capture measures of psychological processes, including emotions and mental associations, that are highly relevant for marketing. As reviewed above, there is growing evidence that mental states and mental associations can indeed be decoded from the brain and provide valuable insights for researchers and practitioners interested in understanding associations and mental states evoked in consumers by marketing stimuli.

3. Neuroforecasting

The decoding of mental states has proven valuable for exploring the processes underlying individual consumer decision-making. In practice, however, the value of understanding the motivations driving consumer behavior largely rests on its ability to inform managerial decision making and improve predictions at the aggregate level. In this section we address the application of neuroeconomic methods to the forecasting of real-world market-level outcomes, a recently established and quickly growing field of research called neuroforecasting.

Previous research in neuroeconomics, much of which has been covered in earlier chapters, has demonstrated that neural activity in specific brain areas can track decision-making processes and predict behavior, even before a conscious choice is made. This foundational work has paved the way for neuroforecasting, which aims to predict aggregate-level behavior, such as market

or population trends, based on neural data collected in the laboratory. Unlike traditional methods that focus on individual choices, neuroforecasting uses data from a small sample to forecast the behavior of much larger groups, at the market, or even population levels.

In the following sections, we begin by addressing the key elements of neuroforecasting research and empirical design. We then review the foundational neuroforecasting studies, exploring their methodological and theoretical contributions and placing them within the broader context of consumer research. We do not delve into the fine details of each study, as there are a number of comprehensive reviews available for that purpose^{74–77}. We end with a discussion of ongoing work aimed at understanding the mechanisms, optimization, and boundary conditions that define neuroforecasting in practice.

3.1 Empirical approach

Neuroforecasting research, which aims to predict behaviors at the aggregate rather than individual level, necessitates a different empirical approach than utilized in traditional neuroeconomic studies. Typically, in psychology and neuroeconomics, data analysis focuses on individual-level predictions. In these contexts, data collected from an individual (neural and behavioral) are used to predict that individual's preferences and behavior. Thus, in these experimental designs the independent and dependent variables are elicited from the same source. Alternatively, in neuroforecasting, the unit of analysis shifts from the individual (or sample) to the stimulus itself. The goal now is to understand and predict the broader impact of the stimulus at the aggregate level, rather than any individual response. The focus no longer lies on how differences in neural responses to a set of stimuli within an individual predict their relative preferences or choice, but rather, how shared responses across individuals to unique stimuli forecast their real-world, market-level outcomes (see figure 3).

An important consequence of this empirical approach is that it requires aggregate-level dependent variables that serve as the targets of our forecasts. Whereas traditional neuroeconomic experiments may rely on preference and choice data collected in the laboratory, neuroforecasting studies require access to market-level data. These data often represent a significant challenge for researchers. In many cases, market data are difficult to obtain and less controlled than traditional in-laboratory stimuli. Market outcome data collected by private firms, such as information about customers, sales figures, and online engagement metrics, are often highly proprietary and rarely shared outside of the company for competitive and legal reasons. Even when market data is available, one must carefully consider the numerous exogenous influences that impact their outcomes. For example, differences in promotional activities, communications, and availability might account for variance in real-world sales outcomes, but are presumably not associated with the neuropsychological processes driving choice that researchers are most interested in identifying and leveraging.

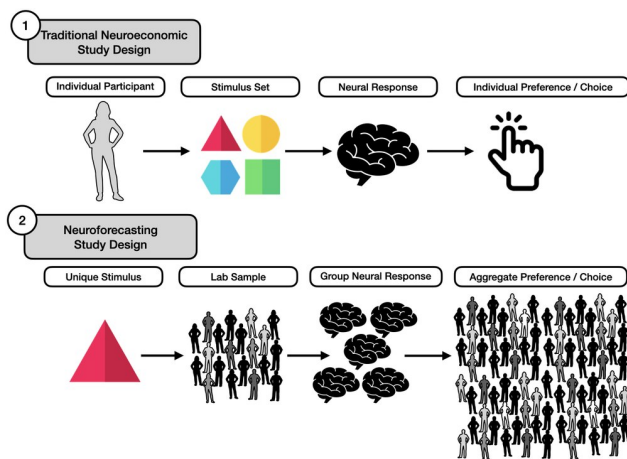


Figure 3. The Anatomy of a Neuroforecasting Study 1) In traditional neuroeconomic studies, an individual is shown a set of stimuli or makes a series of decisions. Neural responses are recorded and used to predict the individual's preferences and choices regarding those stimuli. 2) In neuroforecasting experiments, stimuli are presented to a sample of laboratory participants. The sample's pooled neural responses (and behavioral metrics) are subsequently used in forecasts of aggregate outcomes at the market or population level.

3.2 Primary findings in the field

Although the term "neuroforecasting" wasn't coined until 2018⁷⁶, the roots of the field can be traced back to a 2012 study by Berns and Moore on the forecasting of music preferences⁷⁸. The authors used data collected previously in a study on social influence in which adolescents underwent fMRI while listening to unfamiliar songs. Years later, once market-level success of the songs became available, the neural and behavioral data was re-analyzed. The authors discovered that participants' self-reported preferences did not predict market success, but neural activity in the nucleus accumbens (NAcc) did. This work represents the first application of neural data to the forecasting of market-level outcomes.

This work was followed by focused efforts to explore the use of neural data for aggregate-level forecasts across a variety of domains. Falk, Berkman, and Lieberman⁷⁹ applied neuroforecasting in the public health domain, evaluating the effectiveness of neural responses to forecast the success of smoking cessation advertisements. They found that neural activity collected as participants viewed anti-smoking ads in the scanner predicted the volume of calls to smoking cessation hotlines better than self-reported effectiveness scores.

Genevsky and Knutson⁸⁰ further expanded the application of neuroforecasting to prosocial behavior in a study of online microlending. In this study, participants in the fMRI scanner were presented with real microloan requests selected from a large online microloan platform. Initially, the goal of the study was to assess which features of loan requests most effectively elicited giving behavior from individual lenders. However, having access to the real-world outcomes for these loan requests, the authors went on to forecast their relative success or failure on the internet. Using the laboratory participants' self-report ratings, observed lending behavior, and fMRI data, they found that neural responses to loan requests (specifically in the NAcc) significantly improved forecasts of the funding success of the

loans. Further, the neural forecasts outperformed those based on the participants' subjective ratings and donation behavior.

Together, these studies demonstrated that the inclusion of neural data could indeed improve aggregate-level forecasts and highlighted the potential social and economic impact of even modest improvements in forecasting accuracy. Importantly, Venkatraman and colleagues⁸¹ validated the use of neuroforecasting by comparing the predictive value of various traditional, neural, and physiological measures, including consumer surveys, psychological surveys, eye tracking, biometric measures (e.g., heart rate, respiration, skin response), EEG, and fMRI. They found that of the metrics they collected, only their fMRI metric significantly improved forecasts beyond traditional surveys responses. This work underscores the value of neuroscientific methods to augment established methods for the prediction of consumer behavior, and suggests that brain imaging data may represent a unique source of predictive information.

Genevsky, Yoon and Knutson⁸² went on to apply neuroforecasting to predictions of crowdfunding campaigns. While in the scanner, participants were presented with crowdfunding projects from kickstarter.com and asked to choose which they would prefer to contribute to. Because these campaigns were newly listed, their final real-world outcomes were not known to the researchers at the time of data collection. Once the funding window for all of the projects on the website had closed, the authors assessed which laboratory measures, either behavioral or neural, best forecasted project success or failure. They found that while activity in several neural regions were associated with individual funding choices, only activity in the NAcc effectively predicted the real-world crowdfunding campaign success more accurately than behavioral measures.

Over the last ten years, the applicability of neuroforecasting has been demonstrated across a diverse range of market relevant domains. Kühn, StreLOW and Gallinat⁸³ tested neuroforecasting's application in retail marketing in a study on the impact of supermarket advertisements on chocolate sales, finding neural responses to ads and products predicted sales better than subjective ratings. In a pair of studies, Scholz et al.⁶¹ and Dore et al.⁸⁴ showed that neural activity in reward-related brain regions predicted the sharing volume of New York Times articles better than article features or self-reported sharing intentions. Tong et al.⁶⁰ then extended neuroforecasting to "attention markets" utilizing the engagement metrics of YouTube videos and demonstrating that neural activity, rather than self-reported viewing preferences, predicted real-world video engagement on the internet. Indeed, there is even emerging evidence that neural activity in the NAcc might hold predictive information regarding large-scale equity investment markets^{85,86}. In separate studies by Stallen, Borg, and Knutson⁷⁴, and Van Brussel, Boksem and Smidts⁸⁶, activity in the NAcc of amateur and professional investors were better predictors of stock performance than investor choices or self-report measures.

Despite the early predominance of fMRI studies in the neuroforecasting literature, the relative affordability and accessibility of EEG has gained popularity in the field. In particular, the practical and logistical advantages of EEG have

led to its widespread use in industry, particularly in private neuromarketing firms. Unlike fMRI studies, which typically emphasize spatially isolated neural activity in forecasting analyses, EEG studies often utilize alternative methods based on the increased temporal and spectral resolution of EEG data. For example, Boksem and Smidts⁸⁷ applied spectral decomposition of participants' neural responses (the analysis of neural frequencies) to film trailers to predict the commercial success of movies. They found that particularly oscillations in the gamma range (>30Hz) were predictive of the box office revenue for the movies, and that gamma improved these predictions beyond self-report measures. Guixeres and colleagues⁸⁸ combined various EEG metrics to predict Super Bowl advertisement engagement, finding brain asymmetry in specific frequency ranges was the best predictor of YouTube views. Finally, Hakim et al.⁸⁹ used EEG data to improve forecasting accuracy of consumer responses towards commercials.

Dmochowski et al.⁹⁰ used Inter-Subject Correlations (ISC) to analyze the synchronization of neural activity across participants and found that correlated EEG activity while viewing television programs predicted real-world viewership and social media activity. Barnett and Cerf⁹¹ used a similar approach with movie trailers, finding that EEG data collected from viewers in theaters predicted box office success better than traditional ratings. Neural synchrony has also been found to contain predictive information regarding popularity on streaming music platforms⁹², and out-of-sample preferences for video stimuli⁶².

3.3 Understanding neuroforecasting

This body of research provides substantial evidence for the ability of neural data to improve forecasts of real-world market-level outcomes of interest to researchers and practitioners. However, a significant question remains regarding the mechanism that might explain the effectiveness of neurally derived predictions. How is it possible that neural data collected from a relatively small laboratory sample can significantly improve behavioral forecasts of market-level outcomes? Further, how can we understand results indicating that in some cases, forecasts based on the neural responses of laboratory respondents out-perform forecasts based on the self-reported preference and observed behavior from those same individuals?

A first clue can be found in the Genevsky et al. (2017) neuroforecasting paper on crowdfunding⁸². The authors find that neural activity in both primary affect (NAcc) and value integration (medial prefrontal cortex, MPFC) regions predicted individual funding decisions, but only activity in the NAcc scaled to effectively forecast aggregate outcomes. Subsequently, Knutson and Genevsky⁷⁶ proposed that while various neural processes contribute to decision-making at the individual level, only a specific subset of these processes may remain relevant for predicting aggregate behavior. They argue that individual choice is a function of both primary affective responses, which are more widely shared across people, and deliberative processes which are more idiosyncratic to the individual. Thus, self-report and choice data collected at the individual level are a combination of both generalizable and idiosyncratic component processes. In neuroforecasting, where the aim is to forecast aggregate-level variables, the shared components of choice offer the most

valuable and predictive source of information. On the other hand, while more idiosyncratic deliberative processes may account for the consistency and reliability in choice behavior within an individual, they represent unsystematic noise at the aggregate level.

Previous work in neuroeconomics provides some hypotheses regarding which components of the decision-making process might generalize best across individuals to subsequently account for aggregate level behavior. In particular, the Affect Integration Motivation (AIM) framework⁹³ offers a useful framework through which to study neuroforecasting (see figure 4). The AIM framework suggests that choice stimuli initially evoke affective responses (either positive or negative) activating subcortical and cortical regions including the NAcc and Anterior Insula. This initial response is then further integrated through deliberative and reflective cognitive processes unique to the individual. Finally, the integrated representation generates a motivational state, to approach or avoid the stimulus, which subsequently manifests as self-report and observable behavior. This framework suggests that initial affective responses to choice options (e.g., NAcc activity) may represent a more universally shared component of the decision-making process than later integrative neural responses (e.g., associated MPFC activity). Further, self-report and choice behavior then include both generalizable and idiosyncratic components of choice. As a result, forecasts based on only the more generalizable choice components indexed by primary affective responses in the brain may result in increased forecasting accuracy. Conversely, forecasts containing idiosyncratic components, including self-reported and choice, may result in decreased accuracy due to the addition of non-generalizable noise into aggregate forecasts. In a test of this hypotheses, Genevsky and colleagues⁹⁴ found that neural activity associated with early affective processing was more widely shared across individuals than later integrative or deliberative processes, and subsequently led to improved forecasts of aggregate behavior.

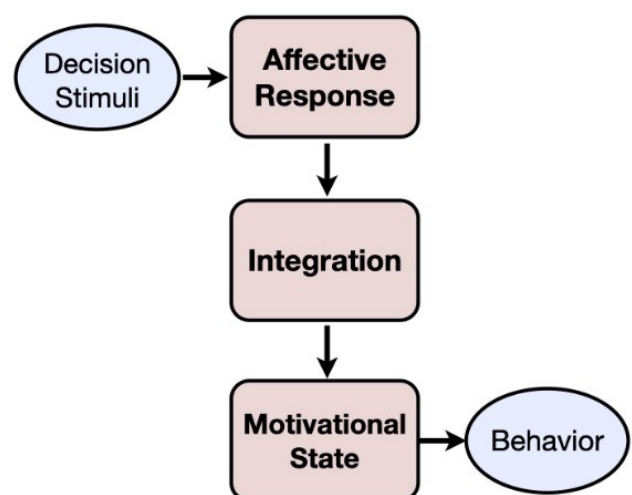


Figure 4. The Affect Integration Motivation (AIM) framework

3.4 Open questions and future directions in Neuroforecasting

In addition to the exploration of an underlying mechanism discussed above, many open questions in neuroforecasting

revolve around issues of optimization and boundary conditions. Taking into account both theoretical and practical considerations, it becomes important that we understand when neural data may be most informative, and thus cost-effective to collect, and when it might not. For example, does neuroforecasting work equally well across contexts and choice domains? Based on the findings reviewed above, with a few notable exceptions, neural forecasts have been most broadly supported by generalizable neural activity associated with affective processes. This suggests that forecasts of consumer decisions in domains that heavily involve affective considerations, such as those related to hedonic and experiential products, might benefit most from neural data. However, it must be noted that in the existing neuroforecasting literature, studies of affectively oriented decisions are over-represented, and thus may have led to findings specific to these domains. Whether or not neuroforecasting can be equally effective for forecasting outcomes in markets with more deliberative considerations is a topic of ongoing research.

There are also important open questions regarding the optimization of empirical approaches in neuroforecasting research (i.e., experimental designs and analysis methods). The initial set of neuroforecasting experiments reviewed above are almost exclusively characterized by efforts to forecasts which stimuli within a set will perform better or worse at the aggregate level. Little work has explored how to optimize forecasting accuracy using different experimental designs, stimulus selection criteria, identification of critical stimulus features, and which tasks participants should perform while in the scanner. To date, empirical design choices have largely been based on existing paradigms from other neuroeconomic disciplines, not necessarily constructed to optimize the generalizable neural responses critical for neuroforecasting. Better understanding regarding how to conduct neuroforecasting research most efficiently and effectively represent a promising direction for future research and would offer substantial benefits for researchers and practitioners interested in addressing the scope of neuroforecasting's potential to inform real-world market decision making.

Questions also remain regarding the relationship between the experimental sample and the aggregate market of interest. Does the effectiveness of neuroforecasting rely on the similarity between the sample and market? Using two independent neuroforecasting datasets, Genevsky and colleagues⁹⁴ found that the accuracy of market forecasts derived from neural data were less impacted by the representativeness of the sample to the market than forecasts based on behavioural data. This suggests that neural activity capturing generalizable components of affect and value processing in the brain may represent a more universal index of preference across individuals compared to observed behaviour and self-report measures.

Finally, while we have seen that multivariate pattern analysis has been pivotal in decoding consumer mental states, work on neuroforecasting has predominantly relied on univariate analysis approaches. However, in a recent study by Chan et al.⁵⁷, a first step has been made to combine the decoding of mental states with neuroforecasting. The authors found that patterns of neural activity, particularly those associated with social-affective

responses, improved the prediction of out-of-sample liking ratings for advertisements compared with traditional anatomically based neuroimaging measures and self-report measures. These findings align well with predictions derived from the AIM framework (see figure 4); that (social) affective processes may account for the ability of brain measures to forecast market-level behavior. The use of more nuanced approaches to neural analyses, as in this example, will become increasingly important as the field of neuroforecasting continues to grow and develop.

4. Conclusion

Over the past decade, the application of neuroeconomic approaches to business-relevant questions has propelled the development of the field of consumer neuroscience. This area of research is committed to applying the lessons and methods from the disciplines of neuroscience and neuroeconomics to better understand and predict consumer psychology and decision-making. While we remain optimistic about the potential for consumer neuroscience to contribute across a broad range of domains, reflection on the last 10 years of work indicate the greatest contributions have come from research on the decoding of consumer mental states and the forecasting of market-level outcomes.

The temporal resolution and real-time nature of neuroimaging methods have removed the limitations of black-box models of consumer behavior, in which we only have access to stimulus inputs and resulting behavior. Using neural data related to psychological processes, researchers are able to decode emotions, consumer experiences, and brand associations. These methods have opened new avenues of research on consumer responses to marketing stimuli and their resulting decision-making process. In particular multivariate analysis methods have proven particularly useful for the decoding and prediction of emotional and cognitive states. The ability to record brain responses in real time, unobtrusively, without requiring overt responses from participants that may interfere with ongoing mental processes, gives consumer neuroscience a unique advantage in providing insights on the experiences and cognitions underlying consumer behavior that are critical for the development of effective business strategies.

Finally, the evolving field of neuroforecasting has extended the applications of consumer neuroscience beyond the individual (or sample). A growing body of research has demonstrated the effectiveness of neural data to improve forecasts of real-world market-level outcomes across a wide range of product domains and consumer contexts. This work has shown that the brain responses of laboratory samples, primarily in affective and value-based neural circuits, holds hidden information capable of improving the accuracy of predictions of aggregate-level preference and behavioral outcomes. As the field continues to develop, ongoing work must focus on optimizing empirical designs, establishing boundary conditions, and exploring generalizability across product and consumer domains. In addition, neuroforecasting research on the generalizability of individual decision-making processes to aggregate-level

behavior may contribute to the neuroeconomic literatures on affect and value-based decision-making.

In summary, the application of neuroeconomics in the form of consumer neuroscience has made significant contributions over the last decade. Still a nascent field, the continued integration of basic neuroscientific approaches to business-relevant research questions represents a promising direction. In particular, the use of neural metrics for the decoding of mental processes and the forecasting of market behavior offers the potential for improved communications, more effective intervention strategies, and better informed strategic decision-making in business and public policy.

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