Updated Reviews and Trends in Consumer Neuroscience☆

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Abstract

Consumer neuroscience methods have become prevalent in marketing research. Despite their proven significance, very little marketing research has addressed their applications in Asia. Thus, this review aims to introduce practical integrations with consumer neuroscience and marketing research and how they can be carefully applied to these fields, with some identified caveats. Specifically, I review the recent literature from top marketing and science journals to (1) highlight substantial applications of updated neuroscientific methods to marketing research and neuroforecasting approaches, (2) discuss the additional potential of computational models in these applications, and (3) offer a simple framework that adopts a multi-method approach intended to enhance both the external and ecological validity of neuroscientific findings. Along with the need for embracing scientific rigor and marketing theory, more guidelines are also needed to improve the validity issues of neuroimaging uses and highlight practical directions in the nascent field of consumer neuroscience.

Keywords: Consumer neuroscience, Neuroimaging, Computation model, Data triangulation, Validity

1. Introduction

Since the advent of a special issue on consumer neuroscience[1] in the Journal of Marketing Research (JMR) in 2015 (Plassmann et al. 2015), the field has significantly advanced in both theory and practice and has garnered a plethora of excitement in marketing research. With proven publication records in top marketing journals using neuroscientific techniques, practitioners' interest in this area has considerably been noted as well. The World Neuromarketing Forum has been held over the last 10 years for marketers and practitoners, with a substantial rise in companies and agencies using neuroscience tools (e.g., Nielson, Mars Inc, Ipsos, HP, and Hyundai). Further, renowned figures in business schools, including INSEAD (Hilke Plassmann), Michigan Ross (Richard Bagozzi and Carolyn Yoon), Wharton (Gideon Nave and Michael Platt), Caltech (Colin Camerer), Berkeley Haas (Ming Hsu), Columbia (Moran Cerf), MIT (Drazen Prelec), UCSD (Uma Karmarkar), Temple Fox (Vinod Venkatraman and Crystal Reeck), and Erasmus Rotterdam (Ale Smidts and Marten Boksem), have been pushing the field to embrace cognitive neuroscience in MBA programs (Financial Times 2018). While neuroscience applications' visibility in premier marketing journals has been relatively newer compared to very high-impact science journals (e.g., PNAS, Nature, Science), these leading business schools have been willing to accept such work to better understand consumer behaviors and decisions.

However, in contrast to such efforts, neuroscientific applications in Asian business schools (except Zhejiang University) and marketing journals have been limited and underdiscussed, with a predominant focus on conventional approaches, specifically the three mainstream research agendas in behavior, quant, and strategy. By contrast, in practice, there have been continuous endeavors to promote the applications of neuroscience in Asian startups and conglomerate (e.g., Looxid Labs and Hyundai), in conjunction with the widespread acceptance of artificial intelligence

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[1] It is defined as applying "tools and theories from neuroscience to better understand decision making and related processes (Plassmann et al. 2015; p.427), which is an interdisciplinary subfield of neuroeconomics (or decision neuroscience).

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technology. Does this insinuate that consumer neuroscience in academia advances in Western countries but not in Eastern countries?

Our answer to this question leans toward saying no; however, caveats still exist when applying neuroscience findings in marketing practice and theory. These shortcomings are also impeding the progress of consumer neuroscience in leading business schools and premier marketing journal publications. Over the past two decades, neuroscientists focusing on decision neuroscience (or neuroeconomics) have made significant contributions to understanding the fundamental neural mechanisms underlying human decision-making and judgment (e.g., Glimcher 2022; Kable and Glimcher 2009). However, despite such ample progress made in basic science, the practical application of these findings to marketing practices has faced setbacks for several important reasons. These reasons include the steep learning curve associated with acquiring technical skill sets, the high costs involved, the lack of scalability, the challenges of interdisciplinary collaboration, and issues related to the validity of neuroscientific findings. In this review, I aim to address these limitations by introducing practical implementations of integrating cognitive neuroscience into consumer psychology and marketing research. Additionally, I outline the necessary steps to enhance scientific rigor and ecological validity within the field of consumer neuroscience.

This review is organized as follows (see Fig. 1): First, I conduct a systematic review of the existing literature on the updated deployment (i.e., mediating processes and multivariate pattern analysis) of neuroscientific tools (i.e., functional magnetic resonance imaging, electroencephalography, and eye-tracking) and neuroforecasting techniques (using neuroimaging data to forecast markets) in marketing research. Second, I delve into the potential significance of employing computational models (e.g., drift diffusion modeling) in these applications. Third, I emphasize the importance of employing a multi-methodological approach that integrates psychometric, behavioral data, computational models, and neuroimaging data, rather than solely relying on one tool in marketing research. I explore how such an approach can enhance both external and ecological validity. Lastly, I shed light on the marketing and practical implications of adopting consumer neuroscience, providing step-by-step guidelines to promote the field in Asian business schools and academic journals.

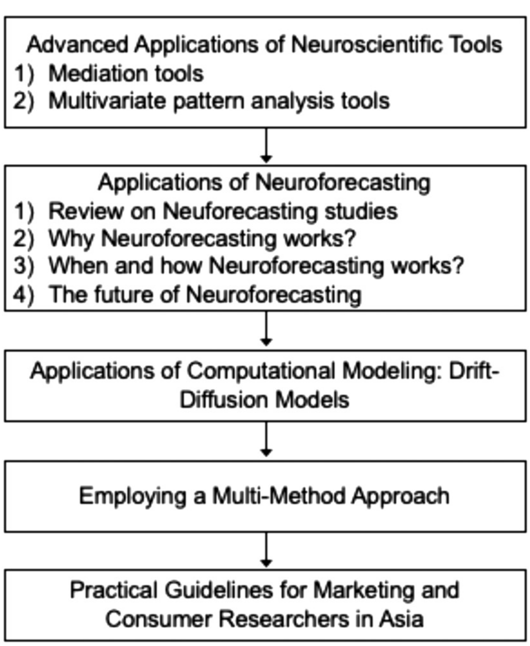

Fig. 1. The flow logic of the current review paper.

2. Applications of neuroscientific tools

Since the first pioneering paper in consumer neuroscience (McClure et al. 2004), the field has considerably contributed to both consumer behavior and marketing research. The works started to appear in top-tier consumer and marketing papers, including the *Journal of Consumer Research (JCR), Journal of Marketing Research (JMR), Journal of Consumer Psychology (JCP), and Journal of the Association for Consumer Research (JACR),* which fueled immense interest among marketing scholars. The topics covered in utilizing neuroscientific methods span a variety of consumer psychology and marketing theories. They range from judgment and decision-making (Hedgcock and Rao 2009; Karmarkar, Shiv, and Knutson 2015), advertising (Beard, Henninger, and Venkatraman 2022; Craig et al. 2012; Venkatraman et al. 2015, 2021), branding (Chan, Boksem, and Smidts 2018; Chen, Nelson, and Hsu 2015; Reimann et al. 2012; Yoon et al. 2006), design (Reimann et al. 2010; Warren and Reimann 2019), and pricing (Laurent and Vanhuele 2023; Plassmann and Weber 2015; Plassmann et al. 2008). These enlightening publications have provided invaluable insights into understanding consumer behavior and marketing theories, serving as an important complement to conventional methods.

Through the pursuit of profound inquiries and the orchestration of well-crafted studies that harness the depths of neuroscientific knowledge, neuroscientists have successfully divulged invaluable insights into the intricate realm of consumer behavior, seamlessly bridging theoretical contemplation with practical applications. In the illustrious review paper of

Plassmann et al. (2015),[2] five distinct avenues emerge, showcasing the triumphant integration of consumer neuroscience in the relentless pursuit of unraveling the mysteries underlying consumer behavior. These five main points take an important step forward in unpacking the black box of the consumers' minds and behaviors, particularly by using functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) technologies.

1) The application of neuroscience data enables researchers to authenticate, enhance, or validate existing theories by elucidating the psychological mechanisms that underlie them.
2) The incorporation of neuroscientific tools has bestowed upon us valuable insights into the implicit processes that elude conventional methodologies.
3) Moreover, it serves as a medium to unveil the dissociation between psychological processes, such as the interplay between System 1 and System 2, unraveling the multifaceted nature of human decision-making.
4) Neuroscience empowers us to uncover the wellsprings of consumer heterogeneity, facilitating a comprehensive comprehension of individual differences.
5) Lastly, the integration of neural data into decision-making models transcends the confines of traditional data, enabling the better prediction of population-level or market-level phenomena.

These concrete points serve as readily accessible guidelines for marketing scholars, offering a clearer pathway to comprehend how neuroscience data can illuminate and enrich the realms of consumer behavior and marketing research. Shaw and Bagozzi (2018) also outline an excellent review of consumer neuroscience on each marketing topic, address an important comparison across different modalities (e.g., fMRI, EEG, transcranial magnetic stimulation, eye-tracking, genetics, etc.), and exemplify future avenues of neuroscience in marketing. Though these points and reviews are indeed crucial in clarifying how neurobiological tools can be adopted, next, I review more recent works to practically guide marketing scholars to apply updated tools in studying (1) psychological mechanisms of mediating processes, and (2) multivariate (or multi-voxel) pattern analysis (MVPA) for more advanced techniques such as decoding (or machine learning) and representational similarity. I also provide custom Python code for future marketers to apply fMRI MVPA on a single trial (or trial-by-trial),[3] which is a necessary step for decoding and representational similarity analysis.

2.1. Mediating tools in elucidating psychological mechanisms

Traditionally, consumer researchers have been long using the mediating processes underlying the certain effect an experimental condition on dependent measures to explain why they occur (Laghaie and Otter 2023). More recently, consumer neuroscientists found a nuanced way to use neurophysiological or neuroimaging data as a mediator to describe behavior or self-reports. In other words, a captivating advancement in the field involves investigating whether neurophysiological measurements play a formal mediating role in consumer behavior or align with self-reports provided by individuals. Plassmann and Mormann (2017) kindly reviewed such methods to understand psychological underpinnings and their choice architecture. This groundbreaking approach initially emerged in Tor Wager's lab where brain imaging data was employed to examine the brain's mediators in pain placebo effects (Atlas et al. 2010). To facilitate this endeavor, his team developed an openly accessible mediation toolbox that caters to both single-level and multilevel analyses.[4]

Brain mediators encompass a range of tools, including neuroimaging techniques (EEG and fMRI), eye tracking, and psychophysiological measures. These tools enable researchers to investigate processes occurring both during consumer behaviors related to marketing stimuli and before or after such behaviors take place. Marketing researchers can gain valuable insights into the mechanisms underlying consumer behaviors and the temporal dynamics surrounding these behaviors. For example, the recent paper (Ling et al. 2023) used multilevel moderated mediation

[2] For those interested in basic illustrations of consumer neuroscience studies, this review paper is highly recommended to read. In addition, there are numerous literature reviews on this field introducing diverse brain tools, explaining applications, and pinpointing limitations, so our review does not cover these basic introductions.

[3] The neuroimaging study employs a within-subject repeated measures design (see Plassmann et al. 2015 for design details). To predict neural responses (or beta estimates) of brain activity based on experimental conditions/regressors (e.g., familiar vs. unfamiliar brands), the analysis utilizes general linear modeling (GLM). Typically, researchers aggregate repeated trial data within each condition (fixed effects) and perform group-level analysis to make inferences about brain activity at the population level (mixed effects). However, since trials within the same condition show variation, extracting a single trial (single beta estimate) could offer additional valuable information. This approach is particularly crucial when employing the MVPA method (e.g., extracting a single beta estimate from each trial and conducting a classification analysis using leave-one-subject-out cross-validation to predict a familiar vs. unfamiliar brand). The code is available at GitHub: https://github.com/drjyun/mvpa_trial_level.git.

[4] https://github.com/canlab/MediationToolbox

approaches to understand how valence and arousal of an affective state (i.e., winning incidental rewards) can jointly influence the evaluation of experiences (i.e., wine tasting) by using skin conductance, facial responses, and fMRI techniques. Moreover, Mormann, Nowlan, and Kahn (2016) demonstrated that the extent to which consumers incorporate specific past prices as reference points in their decision-making process is influenced by the level of attention allocated to these prices, as measured using eye tracking. Directing attention towards higher prices can result in an upward shift of the reference point, while directing attention towards relatively lower prices can lead to a downward shift of the reference point. This highlights the role of attention in shaping consumers' perception of pricing and their subsequent decision-making. In cognitive neuroscience, multilevel mediation results explained how humans process noxious heat stimuli into pain via a distinct EEG pattern, offering mechanistic insights into how the brain can subserve different dimensions of pain (Tiemann et al. 2018).

2.2. Multivariate pattern analysis tools

Over the past decade, applying multivariate techniques (MVPA) on neuroimaging data such as pattern classification or decoding to predict decisions has been extensively explored in cognitive neuroscience (Haxby, Connolly, and Swaroop Guntupalli 2014; Mumford, Davis, and Poldrack 2014; Wagner, Chavez, and Broom 2019). This allows neuroscientists to analyze brain activity patterns and make predictions about cognitive processes or decisions. In fMRI, this MVPA approach[5] differs from univariate methods, which typically examine the average activity within voxel sets (Haxby 2012). Instead, multivariate methods aim to explore whether the activity patterns across voxels within specific brain regions contain discernible information that can differentiate between different stimuli or conditions (i.e., the rows are number of trials or conditions and the columns are voxels represented in a certain brain region). For instance, when investigating whether the voxel pattern differs between iconic brands and unfamiliar brands, it has been observed that numerous brain regions carry information about the stimulus category, even if the overall activity level for iconic versus unfamiliar brands remains similar. Further, in using EEG modality, the objective is to ascertain the representation of stimulus-evoked information within the brain at a specific temporal instance. One can utilize decoding techniques on averaged event-related potentials (ERP) waveforms with the intention of increasing the signal-to-noise ratio and optimizing the capability to detect subtle neural signals.[6]

Despite its popularity in cognitive science and neuroscience, Chen, Nelson, and Hsu (2015) published in JMR was the first study in consumer neuroscience to predict what brand a consumer is thinking about when brand personality traits exist a priori inside consumers' minds. This study marked a paradigm shift in consumer neuroscience, moving the focus from identifying "where" in the brain to extracting "what" information can be obtained from marketing stimuli. The previous works predominantly concentrated on revealing anatomical distinctions in the brain under different experimental conditions (e.g., when looking at preferred versus nonpreferred brands). However, this approach was limited to uncovering the specific cognitive processes underlying the observed effects. For instance, the activation of the insula region, found to be related to brand love, could also be involved in unrelated tasks/states like empathy (Li et al. 2020), interoceptive processes (Ernst et al. 2013), or even aversive states (Berret et al. 2019). This limitation has been a significant drawback in the field, as it fails to address the practical question of understanding which specific psychological state a region is associated with, leaving marketers without actionable insights. Chen, Nelson, and Hsu (2015) tackled the issue by employing a "decoding" approach to learn the representation space widely distributed across the brain and gain a finer-grain understanding of the brand personality information that can be extracted from a brand.

In a more recent study, Chan, Boksem, and Smidts (2018) made significant advancements in the application of the fMRI MVPA method within the field of consumer neuroscience. They built a customized neural profile of different brand images (e.g., Apple and Disney) and compared the neural patterns during passive viewing of brand logos with passive viewing of naturalistic pictures as visual templates (e.g., intimate vs. professional images). In contrast to the assumption made by Chen, Nelson, and Hsu (2015), which posited that brand perception remains consistent among consumers, Chan, Boksem, and Smidts (2018) hypothesized that brands can change over time either by endogenous (brand repositioning) or exogenous (changes of market trends) drivers. To address these challenges, they introduced an

[5] This method is known by various names, including MVPA, classification, and decoding.
[6] Unfortunately, there is no EEG study using the MVPA method in consumer neuroscience. An example paper in cognitive neuroscience would be by Bae and Luck (2019), in which they used ERP-based machine learning or decoder to predict a random dot movement and direction.

alternative approach: they first extracted top voxels from a separate localizer task (i.e., mental images evoked during visual templates) and then mapped these onto mental associations with specific brands. To achieve this, they employed an MVPA decoding method, which enabled them to classify four distinct types of visual templates (namely, intimate, professional, communal, and familial). They then identified the top voxels from this classification as a brain template and compared them with activated voxels obtained from participants viewing a variety of brand logos. Additionally, they examined the suitability of co-branding by constructing a brands-brands similarity matrix based on participants' passive viewing of different brands. This matrix allowed them to predict the compatibility of different brands for co-branding purposes (e.g., Apple and Disney). Furthermore, they utilized inter-subject neural profiles to predict the strength of each brand image. Despite the methodological complexity, the study showed a possibility to infer brand image strengths and extract brand information without resorting to explicit verbalization. This again corroborates a paradigm shift in our understanding of the brain, focusing on "what" information can be acquired rather than "where" it is located in the brain. Accordingly, this opens up new possibilities for studying how our brains process and perceive brand associations.

The MVPA, a data-driven approach, is indeed a fundamental technique that must be effectively utilized in consumer neuroscience. Past literature predominantly focused on finding the functional roles of a brain region and may have overlooked other important aspects of brain information. The main reason behind this custom is probably due to traditional ways of conducting behavioral experiments in consumer research. I have been using a group-averaged effect within the condition or between the conditions on behavioral data (following the Gaussian distribution), without caring so much about individual differences (or consumer heterogeneity). A typical example includes manipulating the experimental condition and reporting that the experimental condition has a greater main effect than the control condition *on average* (Speelman and McGann 2013). The second reason would be technical barriers, particularly the coding part, whereby the learning curve of MVPA is immense for consumer researchers. This is a challenging issue even for quantitative researchers since neuroimaging analyses usually require substantial effort to collect the data and learn a completely new analysis pipeline (including both machine learning and advanced statistical methods), making the need to acquire such skills less apparent. However, the value of learning the advanced method offers new insights into understanding consumer behavior and decision-making that should not be underestimated. Next, I will continue emphasizing the value of using neuroscience data by reviewing practical applications of neuroforecasting, which has so much potential to forecast the population level and the market from small sample neural data.

3. Applications of neuroforecasting

3.1. Neuroforecasting studies

Since the publication of the first consumer neuroscience paper in JCR by Yoon et al. (2006), marketers have been intrigued by the practical application of neural data in marketing research. This curiosity has spurred a concerted effort to integrate neural measures into existing psychometrics, aiming to predict individual choices. The groundbreaking work by Knutson et al. (2007), initially validated this idea, demonstrating that activations in predefined brain regions such as the nucleus accumbens (NAcc) and medial prefrontal cortex (MPFC) could forecast subsequent purchase decisions. Moreover, they successfully amalgamated these neural data with self-reported information, revealing that combining both types of data yielded the highest predictive power compared to models relying solely on self-reported data. Building upon these findings, Levy et al. (2011) examined how valuation areas, specifically the ventral striatum (NAcc is the main part of it) and ventromedial prefrontal cortex, could anticipate future choices during passive viewing of consumer goods. Notably, decision-making did not occur within the confines of an fMRI scanner; instead, participants were presented with identical products outside the scanner and subsequently made decisions. This study effectively demonstrated the value of utilizing neural data even when consumers were not actively making choices, as it successfully predicted the decisions they would ultimately make. While these initial findings contributed to a rudimentary knowledge gap in consumer decision-making and judgment, these works were perhaps more informative about the brain mechanism than marketing implications.

If I can predict individual choices, can I also forecast aggregate-level decisions at the population level and the market? This question laid the groundwork for ample evidence aimed at scaling predictions beyond the individual, the term coined as *neuroforecasting* (Knutson and Genevsky 2018). A large body of these works have been showcasing the predictive power of using neural data above and beyond self-reports in diverse domains (see Table 1 for summary), ranging from the music market success (Berns and Moore

Table 1. Key summary of neuroforecasting studies.

Authors	Method	Predictors	Aggregate outcome	Explained variance
Berns and Moore (2012)	fMRI	Self-reported liking and fMRI measures	Number of albums sold, 3 years later	Moderation, and Structural Equation Model
Falk, Berkman, and Lieberman (2012)	fMRI	Self-reported liking, ad effectiveness rating, and fMRI measures	Ad effectiveness	Weighted Kendall's tau
Boksem and Smidts (2015)	EEG	Self-reported liking, ranking, WTP of movies, and EEG Gamma band	U.S. box office movie sales	Explained variance
Knutson and Genevsky (2018)	fMRI	Self-reported affect, lending choices, and fMRI measures	Internet lending rates for requests from kiva.com	Explained variance, and AIC
Venkatraman et al. (2015)	fMRI, EEG, biometrics	Survey, IAT, eye-tracking, heart rate, SCR, EEG, and fMRI measures	Ad elasticity for 37 ads	Explained variance
Barnett and Cerf (2017)	EEG	Self-reported WTP, liking, and free recall, and EEG measures	U.S. box office movie sales	Coefficients
Genevsky, Yoon, and Knutson (2017)	fMRI	Self-reported affect, success, funding choices, and fMRI measures	Crowdfunding decisions on kickstarter.com	Explained variance, and AIC
Tong et al. (2020)	fMRI	Choices, self-reported affect ratings, and fMRI measures	Metadata from Youtube.com	Explained variance, AIC, and RMSE
Stallen, Borg, and Knutson (2021)	fMRI	Stock investment choices, and fMRI measures	Stock price dynamics	Explained variance, and AIC
Varga et al. (2021)	fMRI	Market, survey, purchase choices, and fMRI measures	Sales of newly introduced products and food	Coefficients, and MAPE

Notes: WTP = willingness to pay, IAT = implicit association test, SCR = skin conductance response, AIC = Akaike information criterion, RMSE = root mean square error, MAPE = mean absolute percentage error.

2012) to smoking cessation ads (Falk, Berkman, and Lieberman 2012), ads elasticity (Venkatraman et al. 2015), crowdfunding success (Genevsky, Yoon, and Knutson 2017), movie ticket sales (Barnett and Cerf 2017; Boksem and Smidts 2015), Youtube video success (Tong et al. 2020), stock price dynamics (Stallen, Borg, and Knutson 2021), and sales of new products (Varga et al. 2021). The mounting evidence supports the validation of the neuroforecasting approach, where neural responses in less observable intermediary processes can account for real-world outcomes. An illustrative example of this is the role of ventral striatum activity, as measured by fMRI, as the most robust predictor of real-world market responses to advertising when compared to other measures such as EEG, eye-tracking, biometrics, implicit measures, and self-reports (Venkatraman et al. 2015). This finding highlights the added value of conducting fMRI research, as it allows for tracing real-world outcomes beyond what traditional methods (and even above other neurophysiological methods) can achieve. Yet, collecting EEG data can be still invaluable in forecasting movie box office sales (Barnett and Cerf 2017). This study took a commendable step to collect data in a real movie theater and found that neural activity correlated (or synched) across the individuals was a stronger predictor of ticket sales than their own liking and willingness to pay self-ratings. These examples crystallize a shift from obtaining a basic understanding of brain mechanisms to making a practical forecast of consumer behavior.

3.2. Why neuroforecasting works?

These neuroforecasting studies lead to asking *why* this occurs. In other words, what are the specific mechanisms that produce robust support of scaling forecasts from the individuals to the aggregate? Knutson and Genevsky (2018) put forth a compelling proposition, arguing that although numerous neural processes contribute to an individual's decision-making, only a specific subset of these regions (i.e., Nacc and MPFC) may have significance in predicting aggregate market behavior. The key aspect emphasized is the primal affective responses governed by subcortical circuits (i.e., the NAcc in the ventral striatum), which have evolved over time and can potentially serve as a more universally applicable gauge of how individuals react to stimuli. The affect-integration-motivation (AIM) framework presents a hierarchical model wherein a decision stimulus initially triggers an affective response. This response then undergoes processing by higher-level cognitive functions that integrate individual preferences and concerns. Consequently, a motivational state emerges, dictating whether the stimulus should be approached or avoided. Ultimately, the decision-making process reaches its culmination in observable behavior, representing the final outcome.

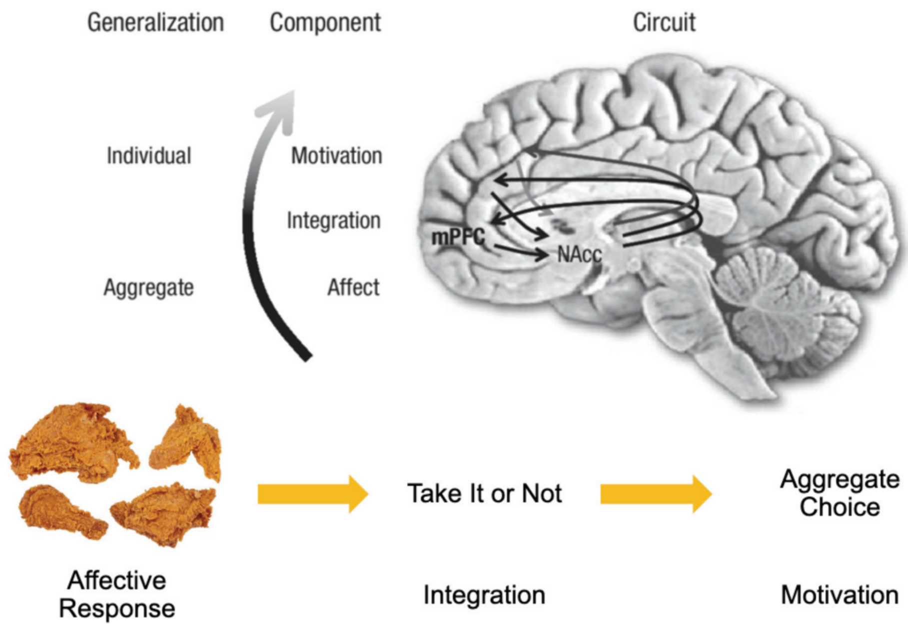

Fig. 2. Affect-Integration-Motivation (AIM) framework. Notes: From Knutson and Genevsky (2018) with an illustrative example. mPFC = medial prefrontal cortex, NAcc = nucleus accumbens.

To illustrate the AIM theory (see Fig. 2), let's consider a classroom scenario involving a group of students. Imagine a pair of researchers entering the lecture room, carrying a tray filled with deliciously cooked, fried chickens. As the aroma of the fried chicken spreads through the air and the students catch sight of it, they experience strong affective reactions towards the food. These initial responses vary from student to student based on their individual preferences and dietary goals. Now, suppose the researchers decide to survey the students, asking them about their choices and responses regarding whether they would eat the fried chicken. This survey would reveal a wide range of individual differences, influenced by each student's personal goals and dietary considerations. What's particularly interesting is that if the researchers were able to capture the students' early affective reactions when the tray of fried chicken entered the room, they would obtain a more universally applicable and generalizable measure of the students' overall preference or choice regarding the chicken. In this context, the activity in the NAcc could generalize this affective response, while the MPFC activity would integrate these idiosyncratic individual behaviors. This integration process would ultimately enhance predictions of the broader market's behaviors, in this case, representing the students' aggregate behavior towards the fried chicken. Following this logic, generalizing from more idiosyncratic components may reduce prediction accuracy due to individual noises (e.g., having different dietary goals when seeing fried chickens), whereas generalizing from more universal (less idiosyncratic) choice components may improve prediction accuracy (undergrad students generally love fried chickens).

3.3. When and how neuroforecasting works?

To verify this hypothesis, Genevsky, Tong, and Knutson (2021) recent working paper further delved into the degree to which the neural data can generalize to the representativeness. They pushed one more step by showing that even in the less well-represented market (less representing the lab sample), the neural data is a stable predictor while the behavioral data becomes less stable. But in the well-represented market, both measures exhibited stable predictions. This research has significant implications for neuroforecasting studies, as it demonstrates how affective responses, captured through neural data, can be generalized to forecast aggregate choices, whereas behavioral data may not provide the same level of stability. To address the cost limitations associated with fMRI, the researchers employed bootstrapping iterations to demonstrate that p-values derived from NAcc activity remained consistent after reaching a certain threshold ($p = 0.05$) with a relatively small number of subjects (14 subjects). In contrast, the behavioral data did not reach significance even as the sample size increased and failed to surpass the threshold. Based on these initial findings, it suggests that compared to traditional self-report measures, neural measures obtained from a smaller sample size may serve as a more universally applicable and generalizable indicator of choice and preference in both well-represented and less-represented markets. Thus, the final goal of the field would be examine when, how, and why neural forecasts work (Genevsky and Yoon 2021).

3.4. The future of neuroforecasting

To also note, the first review in consumer neuroscience was written by Ariely and Berns (2010), who introduced the concept of using neuroimaging data as a neuroforecasting tool (though this 'neuroforecasting' term was not used by them). Their review paper has become the most cited publication in consumer neuroscience, with 1462 citations. Collaborating on this work, Dan Ariely, a highly influential figure in psychology and marketing, and Gregory Berns, a cognitive neuroscientist, recognized the value of consumer neuroscience a decade ago. In fact, they even predicted how marketers could leverage neuroimaging data for their practical implementations. In their paper (p. 287), they stated:

> *"With increasing stimulus complexity, simple interpretations of brain activation will become more difficult. However, for real-world marketing applications, it may be more important to predict future behavior than to understand the 'why' of behavior. Such a data-driven application of imaging (perhaps even lacking an underlying theory) is analogous to identifying a genetic polymorphism associated with a particular cancer without understanding what that gene does..."*

This forward-thinking perspective emphasized the importance of focusing on the predictive capabilities of neuroimaging data in marketing, rather than solely seeking to understand the underlying brain's area function. Today, I have made significant progress and now have the validated theory of the AIM framework to support the predictive nature of this approach. Moreover, our suggestion also aligns with Ariely and Berns' proposition for a more data-driven approach (e.g., MVPA) to be appropriately practiced in the field. Lasltly, I also suggest a few more concrete points to advance the field:

1) A need for more EEG research in neuroforecasting: I urge more research using EEG and other biometrics to advance the field of neuroforecasting. Although several past studies using EEG found how it can forecast, I need a more relevant theory pertaining to the EEG and/or other biometrics measures (e.g., pupil dilation and facial affect responses to capture emotional arousal). Though EEG data alone cannot directly capture subcortical circuits such as the NAcc, it has the advantage of a better scalable measure in marketing practices. A future research question would be to identify the ideal EEG metric (e.g., inter-subject correlation in an alpha band or ERP-based decoding) that can effectively explain these processes.
2) A need for more advanced MVPA method: Future studies should incorporate more MVPA methods to uncover more interesting research questions. For example, Lee et al. (2022) developed a whole-brain decoder (from fMRI data) using thresholded partial least squares (T-PLS) to predict intertemporal decisions in out-of-sample data. They extended the PLS method by incorporating tuning parameters and cross-validation techniques, which improved computational efficiency and accuracy performance.
3) A need for adding neural data: Consumer behavior studies conduct multiple experiments in both the lab and the field settings. I also urge consumer researchers to learn neuroimaging methods to at least unravel the underlying mediating mechanisms. Despite the popularity of using text mining data, field data, and secondary data along with behavioral experiments, the inclusion of neural data remains relatively rare in consumer behavior research. Still, Wang, Zhu, and Handy (2016) added the ERP data in Study 2 to illustrate underlying empathic responses towards misfortune. Wiggin, Reimann, and Jain (2018) also added the fMRI data (i.e., the insula activity) to explain how curiosity can drive indulgent decisions. In general, combining multiple methods can reap benefits in tandem with researchers' main arguments to offer more definitive evidence.

4. Applications of computational modeling

Along with applying neuroscience data in consumer behavior and marketing research, recent trends in psychology, cognitive science, and neuroeconomics have embraced the use of computational modeling works. Despite the significant value of better understanding human behavior and decision-making, its application in marketing research has been uncommon. Almost every paper in our field boils down to identifying research gaps by collecting empirical data and reporting p values.[7] Computational modeling is not commonly featured in consumer and

[7] Reporting Bayes factor results is still an uncommon practice in consumer behavior and marketing research.

marketing scientific endeavors or Asian marketing journals. Nonetheless, marketers can gain profound insights and explore alternative perspectives by delving into the computational implications of their ideas, surpassing the common practices of reporting statistical mean differences, mediations, or moderations. This approach not only aids in theory building but also enhances practical implementation, particularly in comprehending the intricate relationship between behavior and the brain (Guest and Martin 2021). Thus, to advocate for the practical adoption of computational modeling in our field, I review recent literature and outline how these methods can synergize with neuroscience data.

In terms of theory building with the use of computational modeling, the most representative example of theory in psychology and economics is prospect theory (Kahneman and Tversky 1979). Prospect theory has been also hotly debated in the field of consumer behavior and marketing research to articulate the mechanisms behind consumers' loss aversion (Mrkva et al. 2020; Novemsky and Kahneman 2005; Rick 2011). To explain why individuals tend to avoid the losses than the equivalent gains, the dominant account was that they overweigh losses compared to gains (i.e., valuation bias), requiring an additional amount of gains (or premium) to accept a mixed gamble. Recently, an alternative account was proposed, suggesting that individuals may have a predisposition to avoid losses that could interrupt their current status quo (i.e., response bias) (Sheng et al. 2020). Coupled with eye tracking, pupillometry, and computational modeling, decomposing loss aversion into two distinct biases was proven for the first time. Valuation bias was selectively indexed by preferential gaze allocation to losses, and response bias selectively indexed by pupil dilation. Specifically, the authors applied a drift diffusion model (DDM; see Fig. 3 for illustrations) on both behavior and physiological data to unfold a process of evidence accumulation over time that culminates in decision-making. The study not only showed the first evidence of response bias but manifested individual heterogeneity underlying loss aversion by DDM and neurophysiological methods that are otherwise indistinguishable using conventional data of mean differences.

DDM has been extensively used in psychology and neuroeconomics to draw inferences on latent aspects of the binary decision process (a two-alternative forced choice) from behavior choices and response times (Ratcliff and McKoon 2008). This model assumes that a representation of the subjective value can guide the final choice, the relative decision value accumulates over time, and when the accumulation process reaches one of the two boundaries, that option

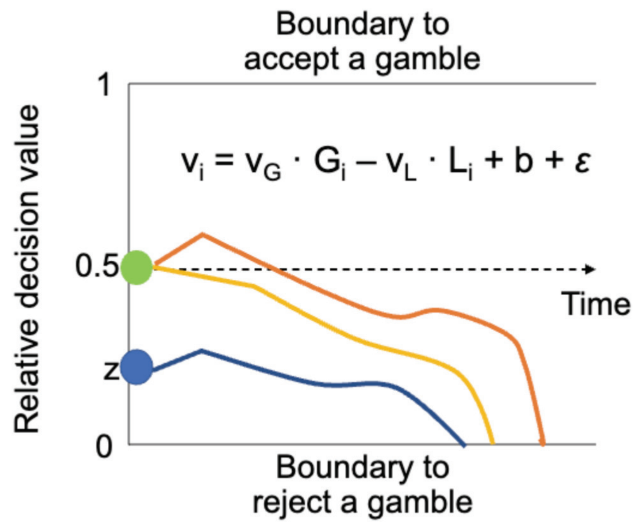

Fig. 3. Drift Diffusion Model (DDM) framework. Notes: From Sheng et al. (2020). The acceptance or rejection of a mixed gamble was assumed to be the result of a noisy evidence accumulation process that drifts between two response boundaries. When the process reaches the upper boundary (referred to as 1), the gamble is accepted, and when it reaches the lower boundary (referred to as 0), the gamble is rejected. The starting point of the process is represented by the variable z. The velocity of the drift process, known as the drift rate, is determined by certain factors. Specifically, the magnitudes of potential gain and loss are represented by G and L, respectively, while v_G and v_L represent their respective weights. The intercept is denoted as b, and ϵ represents random noise following a standard normal distribution. Additionally, variables of non-interests, namely non-decision time (t) and boundary separation (a), are also included in the model.

is finally chosen (Krajbich 2019; Krajbich, Armel, and Rangel 2010). This method is not only applicable in behavioral data but eye tracking data. The attentional DDM (aDDM) assumes that the drift rate varies as a function of gaze fixation area, unlike the behavior DDM. The relative decision value fluctuates according to the equation below. Att denotes gaze fixation area and takes the value 1 when the right eye is fixated and 0 otherwise. θ denotes the influence of attention on the relative decision value and takes a value between 0 and 1.

$$V_t = V_{t-1} + \text{att}_t[d(r_{\text{right}} - \theta_{\text{left}} r_{\text{left}})] \\ + (1 - \text{att}_t)[d(\theta_{\text{right}} r_{\text{right}} - r_{\text{left}})] + \varepsilon_t$$

The aDDM was first proposed by Krajbich, Armel, and Rangel (2010), and the idea was then applied to organizational behavior and consumer psychology practices (D'Ambrogio et al. 2023; Fisher 2021; Martinovici, Pieters, and Erdem 2023). Particularly, the aDDM approach was able to unveil the mechanisms underlying the effect of celebrity endorsement in advertising (D'Ambrogio et al. 2023). This research revealed that choosing a product with a celebrity endorsement is associated with smaller pupil dilation, potentially indicating higher confidence in the decision-making process. Celebrity endorsers also captivate consumers' attention, requiring comparatively less evidence to reach the decision threshold. In addition, a more recent study demonstrated a systematic "double attention lift" for the chosen brand, as it received increased attention in the moment of choice compared to competing brands. It also found that owned brands held attention early in the decision-making process (Martinovici, Pieters, and Erdem 2023). The authors extended the aDDM method to incorporate eye movements, attention trajectories, and utility accumulation, even in the absence of pupillometry data. Together, these studies allowed marketers to have a more comprehensive understanding of the psychological mechanisms underlying celebrity effects and selected brands.

5. Employing a multi-methodological approach

So far, I have covered a wide range of applications of neuroscience data in recent consumer and marketing research, as well as the use of computational models. Herein, I also propose how marketers can employ a multi-methodological approach to improve both external and ecological validity. Cao and Reimann (2020) posited that the validity of fMRI findings can be improved by the data triangulation of (1) careful design of neuroimaging studies and analyses of data, (2) meta-analysis (from an automated meta-analysis tool *Neurosynth*), and (3) the integration of psychometric and behavioral data with neuroimaging data. I will briefly address these points and suggest additional guidelines to improve the external and ecological validity as well as the validity in other modalities (i.e., EEG and eye-tracking).

While the following points primarily discuss fMRI applications in consumer neuroscience, their relevance extends to other tools as well. Firstly, it is crucial for marketers to understand the specific psychological or cognitive implications behind the activation of distinct anatomical regions (referred to as reverse inference). Cao and Reimann proposed Bayes' theorem as a means to mitigate false positives in reverse inference:

$$P(COG|ACT) = P(ACT|COG)P(COG)/P(ACT)$$

Here, COG represents the cognitive process of interest or specific task, and ACT represents the brain region activation. Increasing $P(COG \mid ACT)$ allows for confident claims regarding the association between certain brain activity and a particular mental process. However, the value diminishes when a brain region is involved in multiple functions (e.g., the insula region), as P(ACT) increases and leads to reverse inference issues. Yet, careful experimental design and systematic literature review can mitigate the implications of this interpretation. For instance, Zhang et al. (2023) developed an fMRI paradigm to investigate how a reasonable person can effectively differentiate visually similar products, contributing to the application of neuroscience in the field of law. Despite the multifunctional nature of the fusiform gyrus, they independently localized this region to enhance functional specificity by controlling for the baseline of P(ACT). By focusing on the visual cortex area (fusiform gyrus) and disregarding alternative functional theories, their study cleverly addressed the objective of discerning visually similar products. Furthermore, when utilizing neuroimaging data for forecasting purposes (the prediction becomes valid itself whether or not one cares about certain cognitive processes) or employing the MVPA approach, false positive issues become less significant.

Secondly, effectively estimating $P(COG \mid ACT)$ and addressing the validity of reverse inference can be achieved by leveraging sizable evidence from previous studies to ensure consistency and specificity. Neurosynth, the most widely used automated meta-analysis database in neuroimaging (Yarkoni et al. 2011) (https://neurosynth.org/), proves invaluable in this regard. By employing text-mining and meta-analytic methods, this open-source, large-scale database encompasses fMRI data from over 14,300 published papers. Researchers can search for relevant cognitive terms (e.g., reward, social, cognitive control) and access meta-analytic brain maps for download. To alleviate reverse inference issues, a comparison between Neurosynth maps and activation maps from a specific task can be performed. Various options are available for employing this database tool, but it is advisable to (1) conduct a conjunction (or overlapping) analysis between Neurosynth maps and one's activation maps and (2) input the coordinates of the peak voxel activation in Neurosynth to generate a table under the "Associations" tab.

Additionally, I propose alternative methods such as topic-based decoding approaches that can help interpret the psychological meaning. This can be achieved by decoding activation maps and estimating spatial correlations between Neurosynth maps and activation maps. Neurosynth includes a decoder tab in its menu, allowing researchers to upload their activation maps and extract Pearson's correlation from the most similar to the most dissimilar terms. Alternatively, spatial correlations can be calculated to derive the most similar topics from activation maps. Python's NIMARE packages (Salo et al. 2022) provide a straightforward means to execute this multi-process topic-based decoding method. For instance, Koban et al. (2023) recently employed this approach to estimate spatial similarity using Pearson's *r* for the delay discounting brain marker and identify the topics associated with each brain activation map. This method not only mitigates the issues of reverse inference but also quantitatively informs us about the extent and direction of previously identified brain maps' contribution to task activation maps.

Unfortunately, there is currently no meta-analysis-based database available for EEG or other biometric modalities. However, a recent study by Speer, Smidts, and Boksem (2021) aimed to overcome this limitation by implementing an independent localizer task, specifically the Stroop task. They computed Spearman correlations to directly compare the EEG time-frequency data from the localizer task with the time-frequency data from their own task (spot the difference task to detect cheating behaviors). By utilizing the well-established and validated Stroop task, they were able to establish a link between the neural marker of cognitive control (in the theta power band) and mental processes of the spot the difference task, particularly when participants were allowed to cheat for monetary rewards. This approach allowed them to make confident claims, bypassing reverse inference problems, that cognitive control processes are indeed recruited when individuals attempt to cheat. In future studies involving neurophysiology, it is advisable to incorporate the design of localizer tasks to elicit the underlying neural and mental processes specific to a newly developed task. This strategy will provide researchers with a more inclusive understanding of the mental mechanisms associated with the task at hand.

Thirdly, integrating psychometric, behavioral, and computational model data with neuroimaging data can significantly enhance external and ecological validity. Self-reported data collection can be incorporated either within the neuroimaging experiment itself and/or through out-of-sample data collection. By incorporating these multiple data sources, I can increase both P(COG) and subsequently P(COG | ACT). Given the common practice of employing multi-method approaches combining lab and field studies in consumer research, incorporating neuroscientific data further strengthens the validity of findings. First, leveraging the neuroforecasting approach contributes to improved convergent, external, and ecological validity. This approach validates neural data collected in the lab and extends its generalizability to the population level and real-world applications. An illustrative example is the first neuroforecasting research by Berns and Moore (2012) published in JCP. While self-reported liking alone failed to forecast album sales, the NAcc activity was able to significantly forecast, which demonstrated generalizability to real-world sales data. Second, an influential paper by Richard Bagozzi's team (Dietvorst et al. 2009) published in JMR exemplified the integration of neural data with traditional methods, establishing convergent, discriminant, and nomological validity. The study employed multimethods such as self-reported confirmatory factor analysis, structural equation modeling, multitrait-multimethod matrix, and fMRI studies. This groundbreaking research shed light on better understanding salespeople's ability to engage in interpersonal mentalizing. Third, marketers can also consider using computational models (e.g., DDM) to glean insights into mechanisms underlying consumers' decision-making processes. Sheng et al. (2020) combined the DDM work with eye-tracking data to gain a deeper understanding of the two distinct biases that lead individuals to avoid losses. Fourth, marketers can enhance ecological validity by conducting mobile neurophysiological studies in more realistic settings (Stangl, Maoz, and Suthana 2023). Since theories and models developed in lab settings also should hold in real-world settings, wearable technologies (e.g., mobile EEG) to record physiological brain data outside of the lab have untapped potential to study naturalistic consumer behaviors. The utilization of web-based eye-tracking applications (e.g., Madsen et al. 2021) is another recent technique that enables the tracking of eye gaze allocation while subjects browse real online shopping websites. This approach holds significant potential for running large-scale online studies (e.g., Prolific, MTurk, or CloudResearch), thereby increasing ecological validity in consumer research. Overall, incorporating psychometric, behavioral, and computational model data, along with neuroimaging data, leads to a more comprehensive and robust understanding of consumer behavior, improving external and ecological validity while bridging the gap between laboratory findings and real-world applications.

6. Practical guidelines for marketing and consumer researchers in Asia

The field of marketing has extensively borrowed theories and methods from psychology, economics, and statistics. Consumer researchers utilize conventional methods from psychology in various research settings, including scale development, lab, online, and field experiments, and both quantitative and qualitative research. Quantitative modelers also employ a wide range of methods from statistics, economics, and computer science, such as econometric models, secondary data analysis, big data analysis, and real-world data analysis. Moreover, Malter et al. (2020) presented future research questions and directions, highlighting three broad topics concerning consumer research methods in 2030: (1) The utilization of cutting-edge technologies, including machine learning algorithms and artificial intelligence, (2) The importance of method transparency, open access to data and materials, and pre-registered studies to enhance the reliability and reproducibility of findings, and (3) The increasing demand for more applications of big data, more experimental studies in a single paper, and the incorporation of real-world data. In addition to these guidelines, the adoption of cognitive neuroscience theories and methods will be needed for gaining a deeper understanding of consumers' thoughts, feelings, and behaviors. Therefore, there is a need for concrete future directions and guidelines in consumer neuroscience.

However, despite the ongoing applications of neuroscience in top business schools in western countries, facilities and labs dedicated to neuroscience in Asian business schools are not common. To our knowledge, the neuromanagement lab at Zhejiang University in China is the only known facility that actively promotes the use of neuroscience in a business school. This lab is equipped with portable devices such as EEG and eye-tracking, and it has been successful in recruiting world-class young neuroscientists. Yet, some efforts have been made in Korea, with a few papers published in the Korean Journal of Marketing and Asia Marketing Journal (Lee, Kim, and Choi 2017; Roshchupkina, Kim, and Lee 2023; Yang et al. 2015). However, in order to expand the application of neuroscience and establish interdisciplinary labs similar to Zhejiang University, I propose practical guidelines for marketing and consumer researchers in Asian business schools.

1) Hire young neuroscientists from prestigious institutes: Asian business schools should prioritize the recruitment of young neuroscientists who have received comprehensive training in marketing, psychology, and cognitive neuroscience. By hiring such experts in these areas, the burden of marketers acquiring neuroimaging skills during their professorship career can be significantly reduced. Trained cognitive neuroscientists can contribute to the field more effectively, given their existing knowledge and experience.
2) Foster interdisciplinary collaborations: Once young neuroscientists are hired, senior marketers who are interested in the field should actively seek out interdisciplinary collaborations with them. These collaborations should extend globally to connect with renowned researchers in top western business schools. It is essential to recognize that approaching experts without any training in the field may be impractical and challenging. However, young neuroscientists who have received extensive training in this field already possess networks and connections with global experts, making continued collaboration feasible.
3) Promote diversity within the lab: To establish an interdisciplinary and collaborative lab in business schools, it is crucial to acquire relevant funding and expand the team to include researchers from diverse disciplines, such as consumer researchers, psychologists, statisticians, computer scientists, and neuroscientists. The Wharton School of Business serves as an example, with diverse experts who have obtained doctoral degrees in various fields such as psychology, neuroscience, computer science, physics, etc. Unfortunately, it is still uncommon to find scholars in Asian business schools who have earned doctoral degrees outside of business-related majors. Promoting diversity in terms of mindsets, expertise, knowledge, and backgrounds will facilitate a more collaborative and effective functioning of the lab.
4) Recruit doctoral Students from non-business backgrounds: Asian business schools should actively recruit doctoral students who have obtained undergraduate degrees in diverse majors, rather than limiting themselves to business degrees. These schools should also establish a dedicated program for students interested in consumer neuroscience and decision-making. This program should provide opportunities for students to spend a semester or two in world-class institutes, enabling them to collaborate with established labs and researchers. By attracting students from varied academic backgrounds, the program can enhance its interdisciplinary nature and foster innovative thinking and approaches.

Leveraging neuroscience in marketing and consumer research in Asian business schools and industries requires a multifaceted approach. It demands investment in neurotechnology, human resources, collaboration, computational training, and open science practices,. I offer a few more conceivable guidelines in Table 2 at an individual level for doctoral students and faculty, which can serve as a roadmap for establishing a thriving ecosystem for consumer

Table 2. Practical guidelines for individual marketing scholars in Asia.

Suggestions	Contents
1. Focus on fostering abilities in data science, machine learning, and computational mindsets. Cognitive neuroscience is based on these skill sets.	If students and/or faculty are reluctant to the use of neurobiology in business fields, focusing first on computational thinking process, such as coding, using chat AI, and understanding mathematical modeling is recommended.
2. Invest in cutting-edge neuro technologies	Training in the usage of biometrics, neurophysiology, and neuroimaging tools should be provided, and applying for the government fund is needed.
3. Tone down the gap between Quant vs. CB divides by creating specialized courses and training programs	Short-term workshops, invited seminars, and doctoral training programs in behavioral economics, data science, AI deep learning, and psychology can be organized.
4. Attend the summer school programs	Strongly encourage doctoral students to attend the summer schools held by top institutes (e.g., MindCore Neuroeconomics Summer School, Neuromatch Academy).
5. Promote collaboration with top institutes and attend the relevant international conferences	Exchange programs for doctoral students and faculty can be developed for international collaborations with top institutes. Attend the Association Consumer Research (ACR) special sessions, Interdisciplinary Symposium on Decision Neuroscience (ISDN), and Consumer Neuroscience Satelite at the Society for NeuroEconomics (SNE).
6. Engage with industry and communicate its impact	Encourage industry-funded projects and measure the impact of neuroscientific insights on marketing strategies and communicate them clearly to stakeholders. The selling point is essential to bridge the gap with the industries by addressing their takeaways.
7. Mandate open science practices	This is not limited to the field of consumer neuroscience. But, to expand the area, align with global trends, and increase the reliability of valid findings, adopting scientific practices of open data and script sharing, method transparency, and pre-registered studies is recommended. Journal of Marketing Research announced such practices recently.

neuroscience in Asia, leading to more nuanced and effective interdisciplinary studies.

Taken together, cultivating open mindsets for interdisciplinary collaborations is crucial for advancing the field of consumer neuroscience and gaining recognition in business journals and schools in Asia. Historically, marketers have successfully used theories and methods from disciplines outside of business majors. By taking another step forward and embracing interdisciplinary collaboration, the field of consumer neuroscience can thrive and establish a strong presence in Asia. This will contribute to the growth and development of the field, leading to enhanced recognition and impact within the academic and business communities. *Behavior and judgment come from human brains and minds.*

Conflict of interest

There is no conflict of interest.

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