Out of Control:

Utilizing Implicit Data for Behavioral Science

Hauke Roggenkamp

ORCID: 0009-0005-5176-4718

Research Proposal

2024-08-01

Institute of Behavioral Science and Technology

University of St. Gallen

Submitted in partial fulfilment of the requirements of the degree of Doctor of Philosophy under supervision of Christian Hildebrand and Johannes Boegershausen

Table of contents

Abstract

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Nunc malesuada massa eget sem fringilla vehicula. Donec pulvinar diam dolor, sed egestas sem fringilla quis. Integer vitae gravida ante. Sed mauris nisl, luctus a mi ut, hendrerit dapibus tortor. Sed maximus consectetur metus sit amet aliquam. Donec eu orci sit amet neque pretium euismod. Donec egestas aliquam ex, ac dapibus nunc maximus quis. Pellentesque in accumsan purus, dignissim interdum turpis. Etiam sed dignissim ex, quis congue nulla. Phasellus accumsan ullamcorper leo ac iaculis. Vivamus tempor sapien tortor, in tincidunt lorem imperdiet in. Ut convallis imperdiet nisl at eleifend. Fusce tincidunt nunc ut metus fermentum vestibulum. Suspendisse vel molestie arcu. Curabitur eu diam vitae tortor placerat gravida eget ac urna. Sed quis leo a augue dapibus aliquet ac ac metus. Mauris sit amet convallis felis, nec ullamcorper velit. Aliquam congue est sed augue porttitor, pellentesque ullamcorper lacus fermentum. Nunc metus mi, consectetur et est sed, vulputate dignissim risus. Nulla et nibh lacus. Praesent commodo metus ut tellus aliquet, ut vehicula augue elementum.

Part I.

INTRODUCTION

Praesent urna magna, tincidunt at consectetur a, facilisis consequat magna. Mauris viverra hendrerit tempus. Mauris faucibus, nisi quis auctor volutpat, dui augue accumsan justo, ut auctor tellus augue quis metus. Interdum et malesuada fames ac ante ipsum primis in faucibus. Nulla et ornare tortor, non imperdiet leo. Praesent imperdiet odio arcu, at porttitor nulla hendrerit nec. Fusce tempor mattis neque ac elementum. Suspendisse enim dolor, scelerisque ut viverra tincidunt, hendrerit non dolor. Etiam sagittis magna id ex maximus, vel scelerisque nunc placerat. Phasellus ornare sapien ac justo pharetra accumsan. Sed mollis tincidunt semper. Curabitur et iaculis dui. Interdum et malesuada fames ac ante ipsum primis in faucibus. Vivamus a finibus purus, consectetur interdum quam. In semper, sem in varius commodo, sapien leo efficitur magna, rhoncus rhoncus lectus nulla sit amet lectus.

Vestibulum ut eleifend purus. Suspendisse id enim velit. Proin iaculis maximus elit, ac tempus sem placerat ut. Mauris aliquet eget nibh sit amet malesuada. Phasellus facilisis porta justo, nec tincidunt justo. Nunc consectetur nibh eget quam tristique tincidunt. Sed a odio gravida, eleifend mauris quis, sodales erat. Curabitur id magna placerat urna aliquam commodo ac id mauris. Proin porttitor eleifend tellus at congue. Etiam elit tellus, semper vel blandit tempor, sagittis quis risus. Ut fringilla dui vitae elit volutpat, elementum lobortis quam scelerisque. Duis euismod quam sit amet sollicitudin vehicula. Curabitur pulvinar leo eu nulla aliquam gravida quis in sem. Morbi eget facilisis urna.

Ut hendrerit risus nibh. Suspendisse vehicula, lectus sit amet tincidunt tempor, erat lacus maximus turpis, non eleifend neque massa eget ipsum. Sed vulputate rutrum dolor nec ullamcorper. Aliquam eu risus sit amet neque interdum placerat sit amet at nisl. Quisque ac sapien eros. Maecenas vulputate volutpat accumsan. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia curae; Nam sit amet finibus nisl. Integer id aliquam ex. Praesent id enim sapien. Nullam posuere tellus a arcu ullamcorper, nec bibendum mauris feugiat. Duis non porta quam. Donec eget lectus aliquam, commodo lorem nec, auctor orci. Fusce vitae aliquam turpis, sit amet sodales urna.

Donec eleifend cursus tellus, quis tempor arcu hendrerit tempor. Maecenas non ornare nunc, et lacinia diam. Nulla eget nunc odio. Mauris ultricies diam et ante dapibus, et posuere ligula auctor. Pellentesque vel est metus. Nullam posuere maximus tincidunt. Ut varius orci ut placerat pellentesque.

Pellentesque pretium porta ipsum, mattis sodales lacus vestibulum vitae. Praesent eget vestibulum nibh. Ut id purus enim. Phasellus sed varius velit. Nunc gravida orci sit amet odio bibendum varius. Sed dapibus arcu eros, sed eleifend nisl luctus vel. Morbi gravida dignissim felis ut posuere. Quisque dapibus convallis est, at rutrum dui tempus eget. Aenean molestie justo in eleifend placerat. Curabitur malesuada suscipit nulla, sit amet viverra eros rutrum eget.

1. Research Overview

Throughout this research proposal, I will refer to my research projects either using their title or a descriptive acronym. Table 1.1 lists my three dissertation projects and reports the respective authors, the title, the target journal alongside their submission- or publication status as well as the said acronym. Each acronym is a hyperlink that directs the interested reader to the corresponding OSF repository. The repositories contain anonymized raw data, code, and experimental stimuli. If not stated otherwise, we pre-registered the sample size, predictions, analysis strategy, and data-exclusion criteria for each study of each project.

This section outlines the projects briefly to then describe how the sum of these projects relates to the overall goal of the dissertation. The subsequent sections then describe the individual projects on a more granular level.

Table 1.1.: Project Overview

Acronym/OSF	Authors	Title	Target Journal	Status
DICE	Roggenkamp, Boegershausen & Hildebrand	Digital In-Context Experiments (DICE): Enhancing Ecological Validity and Causal Inference in Social Media Research	Journal of Marketing	RR
CIVILITY	Roggenkamp	The Price of Civility: Economic and Social Returns on Investment in Toxicity Moderation	Marketing Letters	
SOUND	Gaerth, Roggenkamp & Hildebrand	The Sound of Certainty: Assessing Paralinguistic Indicators of Decision Confidence	Journal of Marketing Research	

Part II.

INDIVIDUAL PROJECTS

Maecenas vehicula vestibulum dolor, sit amet pellentesque lacus sagittis at. Duis elit elit, iaculis sit amet magna eget, elementum iaculis ante. Fusce ultricies felis non ornare gravida. Praesent tempor bibendum augue sit amet porta. Nam aliquam auctor lectus vitae rhoncus. Donec eget tortor purus. Cras bibendum lacinia tortor. Aliquam erat volutpat. Donec efficitur tempus tellus, iaculis ultricies tellus posuere ac. Pellentesque ut placerat mi. Interdum et malesuada fames ac ante ipsum primis in faucibus. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Nam at auctor sapien.

Maecenas metus tellus, blandit at venenatis at, consectetur vitae tellus. Nunc nec feugiat metus. Nulla nec iaculis dui. Vestibulum pretium ullamcorper pharetra. Nullam vehicula nibh in nunc fermentum sollicitudin. Phasellus massa erat, finibus at turpis a, aliquet tempor metus. In hac habitasse platea dictumst. In eros lorem, sodales id nisl vitae, lacinia mollis dui. Vivamus mollis vel libero quis malesuada. Pellentesque viverra blandit faucibus. Mauris posuere sodales nisl vel ullamcorper.

Sed imperdiet lectus id est malesuada consectetur. Suspendisse et elit sed ante porta egestas a rhoncus nulla. Mauris quis ex quam. Morbi nec porta odio. Aliquam sit amet elit vel est egestas ultrices vel malesuada arcu. Cras vitae urna in ipsum iaculis vestibulum sit amet vel nulla. Nam imperdiet tristique tincidunt. Donec nec mauris erat. Morbi blandit nulla ante, id posuere nisi gravida vitae. Mauris odio mi, vulputate a mattis in, posuere sit amet nisi. Morbi id nisi vel turpis efficitur ultrices vel vitae dolor. Morbi a facilisis erat, facilisis malesuada velit. Sed lacinia bibendum enim, eu molestie est euismod in. Praesent in est at dolor bibendum laoreet. Morbi ullamcorper nisi et pellentesque venenatis.

Nullam rutrum id felis a euismod. Nam ac risus in nisi congue commodo. Donec placerat lobortis enim id viverra. Ut venenatis augue magna, eu cursus mauris ultrices nec. Nulla vel dui vitae diam mattis ullamcorper. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia curae; Etiam iaculis dapibus orci ut semper. Donec sagittis risus nunc, quis egestas est tempor non. Sed condimentum finibus mattis.

2. Digital In-Context Experiments (DICE)

Co-authored with Johannes Boegershausen (Rotterdam School of Management) and Christian Hildebrand (University of St. Gallen), we are finalizing the data collection and the manuscript for a re-submission at the Journal of Marketing's special issue on *"Marketing Impact with Research-Driven Apps"*.

2.1. Introduction

With 4.76 billion social media users in 2023 (i.e., approximately 60% of the world's population) and an average daily social media usage of more than 2.5 hours (Kemp 2023), understanding the consequences of social media use carries tremendous economic and societal weight (e.g., Ahmad et al. 2024; Anderson and Wood 2021; M. Appel, Marker, and Gnambs 2020; Orben and Przybylski 2019; Stephen 2016). Consequently, the last two decades have seen an explosive growth of research examining consumer and firm behavior on social media platforms (for recent reviews, see Aridor et al. 2024; Leung, Gu, and Palmatier 2022; Shankar et al. 2022; G. Appel et al. 2020). Consumer attention and engagement on social media platforms have become key assets in the digital (attention) economy, driving billion-dollar valuations of companies and leading to major investments by brands to harness these platforms effectively.

To better understand attention and engagement on social media, researchers strive to get access to proprietary data directly from these platforms as they own granular data that is less susceptible to selection issues such as algorithmic interference Xu, Zhang, and Zhou (2020) than what is publicly available. However, most researchers do not have the option of using confidential data because platforms are hesitant to share these data (due to perceived regulatory, legal, or competitive risk). Even when platforms provide data another challenge may arise because researchers may be limited to studying topics that could benefit the company, or, at the very least, will not hurt it (Farronato, Fradkin, and Karr 2024, 4).

To address these challenges and to provide researchers with an accessible method for studying social media behavior, this paper introduces Digital-In-Context-Experiments (DICE). DICE is an open-source tool that allows researchers to mimic and manipulate social media feeds and track study participants' interactions with that feed, offering a novel approach to understanding user behavior on social media platforms. This method complements and extends existing research paradigms in our field, which has primarily employed four approaches: scenario-based vignette studies, observational social media studies, online platform studies, and browser extensions.

Scenario-based vignette studies typically use a set of static vignettes (e.g., an image or screenshot of a single or a few selected Twitter posts) and are the back bone of consumer research. They offer high levels of internal validity, yet they can be criticized for being too artificial (Morales, Amir, and Lee 2017). In online platform studies researchers can use social media platforms as hidden recruitment tools and disguise their stimuli as ads that are displayed to the social media platforms' real user base. Importantly, researchers can make use of "A/B testing" functionalities and expose different variants of the ads to different users. However, this approach scores low on internal validity because, unlike in experiments, the assignment of users to these ad variants is affected by a platform's algorithms (Braun et al. 2024) and thus, not random. Observational study designs are yet another, non-experimental approach to study social media. They leverage proprietary datasets, web scraping, or application programming interfaces (API) to capture archival data from social media platforms (Boegershausen et al. 2022). While such data captures actual behavior, these gains in realism typically come at the expense of construct validity, internal validity, and endogeneity issues. Jointly, these factors exacerbate the detection of causal effects and require sophisticated econometric modeling approaches (Goldfarb, Tucker, and Wang 2022) as well as natural experiments. However, these are challenging to find, provide information about only specific causal effects, and involve assumptions that are difficult to validate empirically (Grosz et al. 2024). Hence, researchers in neighboring disciplines have started to use custom software (i.e., browser extensions) to conduct experiments. Under this paradigm, recruited participants install software which can implement interventions while tracking consumer behavior online (see, e.g., Farronato, Fradkin, and Karr 2024; Aridor 2024; Allcott, Gentzkow, and Song 2022). Whereas this approach offers experimentation in realistic environments as well as stable and random group assignment, it usually requires software development making it inaccessible for many researchers. In fact, to the best of our knowledge, there are no published studies in the field of marketing using this paradigm to date.

In summary, *accessible* approaches to derive causal inference in realistic social media settings remain limited and, none of them captures the actual context of social media experiences: vignette studies intentionally neglect contextual factors, platform studies do allow the manipulation of contexts and do not report contextual data whereas observational studies' archival data can capture these data but may be affected by algorithmic interference. Consequently, researchers are often unable to fully control, manipulate, or even observe the contextual factors that have been shown to affect consumer behavior (see, e.g., study 3 in Berger and Milkman 2012; or Schmitt 1994). Furthermore, none of the approaches reports granular data that describe individual browsing behavior. Instead, vignette studies often elicit self-reports whereas platform- and observational data provide behavioral data such as clicks or likes on an aggregate level. Whereas these data are important to inform (conscious) psychological processes and ecologically valid behavior, they tend to miss out on unconscious and passive user behavior, that is, internal processes that do not translate into mouse clicks (Baumeister, Vohs, and Funder 2007).

DICE addresses these limitations by making three key contributions. First, it maintains the high internal validity characteristic of static scenario-based vignette studies while enhancing ecological validity by creating interactive stimuli in realistic look-and-feels. Second, it provides researchers with control over context that also allows them to create interventions that manipulate it. This essentially enables them to systematically vary individual social media posts or even complete social media feeds to examine how different (contextual) factors influence user behavior. Third, it enables unobtrusive tracking of implicit behavioral data, measuring the duration and timing of a participant's interaction with each social media post. This provides metrics that are highly used by platforms internally (see, e.g., Berger, Moe, and Schweidel 2023; Cramer 2015; Yi et al. 2014) but unavailable through any accessible research paradigm.

`[Taken together, DICE provides a tool to work on research questions that couldn't be answered before... and in a way that was not accessible before.]`

We developed DICE with the aim to complement (and not replace) existing research paradigms—static scenario-based vignette studies, observational studies, and online platform studies. We also designed it to be useful to a broad range of marketing stakeholders, such as brand managers, influencers, agencies, and policy makers—with and without programming experience. For this reason, the software consists of two components. At its core, DICE is an oTree app (Chen, Schonger, and Wickens 2016) that can be extended and customized by stakeholders *with* basic programming experience. In addition, we created a web interface (www.dice-app.org) designed for stakeholders *without* programming experience. To further increase its ease of use, we designed DICE as a module that can be embedded in the experimentalists' typical workflow as it is compatible with recruitment procedures in behavioral labs or Prolific and survey tools such as Qualtrics.

While developing DICE, we applied principles of the Open Science movement to make research software widely available, interoperable, and reusable. We hope that by leveraging oTree, which is frequently used in incentive-compatible group experiments but, admittedly, not yet established in marketing research, other researchers can add to DICE's functionalities. For instance, to adapt media platform or to mimic the interface of the social also mimic mass media feeds, product review platforms or web shops.

In what follows, we first provide a critical synthesis of the three dominant research paradigms employed in extant social media research and their implications for validity (see Table 1) to derive our first contribution: the enhancement of ecological validity while maintaining high internal validity. Next, we introduce DICE, its configuration, workflow, integration with existing research tools, participant and data management, and its novel behavioral tracking capabilities. Subsequently, we present two case studies that further illustrate the workflow and the obtained data. Importantly, these studies showcase how to leverage the control over context as well as the implicit behavioral data, supporting our second and third contributions respectively. The first case study demonstrates how DICE allows for precise manipulation of social media contexts, enabling researchers to examine the impact of varying environmental factors on user behavior. The second case study highlights DICE's capacity to capture fine-grained behavioral metrics, such as dwell time and scrolling patterns, providing insights unavailable through traditional methods. Finally, we conclude with a roadmap on how DICE might be leveraged to shape future social media research and offer directions for key stakeholders in the social media ecosystem (e.g., brands, influencers, and public policy).

2.2. Research paradigms in social media research

This section also discuss the implications of these paradigms for construct validity, internal validity, and ecological validity given their critical role for the quality of the inferences made in marketing research and are critical during the review process at top marketing journals (Jacoby 1978; J. G. Lynch, Osselaer, and Torres 2024; Sridhar et al. 2022). Construct validity, with its focus on the validity of inferences about higher order constructs, and internal validity, with its focus on the validity of causal relationships (Shadish, Cook, and Campbell 2002; Xu, Zhang, and Zhou 2020), are often considered necessary but not sufficient for high-quality marketing research (e.g., Schmitt et al. 2022; Heerde et al. 2021). Specifically, scholars continue to call for greater realism and external validity in marketing research (e.g., Jedidi et al. 2021; Morales, Amir, and Lee 2017; Jr. Lynch John G. 1982). External validity concerns whether the cause-effect relationship holds over variations in study design, setting, samples, and measurement variables (@ Shadish, Cook, and Campbell 2002). Because every result is valid to some setting and no result is externally valid to all settings, we focus our discussion to the related, yet distinct concept of ecological validity. It refers to the extent to which research findings can be generalized to real-life settings. It focuses on how closely the study's methods, materials, and setting approximate the real-world situation under investigation. High ecological validity means the study's conditions are similar to those in the real world, making the results more likely to be applicable in natural contexts. When deciding between different research paradigms, scholars often face a trade-off between different types of validity, as we will detail in the following.

`[Limit Scope and mention that real RCTs are impossible without the platforms' data and that browser extensions are equally inaccessible.]`

2.2.1. Scenario-based vignette studies

Scenario-based vignette studies typically feature an image of a single social media post that varies the focal construct(s) of interest between different experimental conditions. For example, participants in Study 2 of Zhou, Du, and Cutright (2022, see Web Appendix F for the stimuli) were randomly shown one of two images displaying only a single tweet ostensibly from the brand KitKat. The image of the tweet either praised a competitor or featured a control message. Subsequently, study participants reported their attitudes toward both Kit Kat and a competitor brand (i.e., Twix).[1] Among the three accessible paradigms of social media studies, scenario-based vignettes offer the highest level of internal validity as researchers have full control over the treatment (e.g., experimental manipulations), measurement of variables, and the randomization process. By carefully designing their stimuli and measures, researchers can also achieve high levels of construct validity (i.e., close alignment between the specific operationalization and the higher-order theoretical construct). These studies are generally easy to design, execute, and analyze.

[1] The authors used three seven-point scales (i.e., "negative/positive" "dislikeable/likeable" and "unfavorable/favorable").

However, experiments with static vignettes are often criticized for their low levels of ecological validity (Morales, Amir, and Lee 2017) and as "research-by-convenience" (Ferber 1977; Baumeister, Vohs, and Funder 2007) failing to sufficiently mimic an environment that would be informative of consumers' actual responses observable in a real consumption setting. Static vignette studies also magnify the salience of the focal aspects of the treatment (e.g., a particular post from a brand), which increases the risk of demand effects and may overestimate the size of the observed effect compared to a more noisy field setting (see, e.g., Simonsohn, Montealegre, and Evangelidis 2024) `(e.g., Dubois et al. 2021)`.

A particular concern for social media research is that the prototypical vignette social media study lacks the rich context of the actual user experience on social media sites. Rather than seeing a single post, consumers browse endless feeds in which many posts compete for their attention and engagement. Thus, static vignette studies may lead participants to adopt overly analytical mindsets that diverge from how they would approach the same post while browsing social media platforms (see, e.g., Pham (2013)'s 6th sin of consumer psychology).

`[Also mention that this focus on single posts limits the research questions on can answer.]`

2.2.2. Online platform studies

Given these limitations online platform studies have emerged as an increasingly popular third paradigm in social media research. Since 2021, more than thirty articles in the leading marketing journals have used such study designs (Cornil et al. 2023). Specifically, researchers use the A/B testing functionalities provided by social media platforms, such as Meta (i.e., Facebook and Instagram), Twitter, or LinkedIn to compare the effect of different ads in a naturalistic social media environment (Braun et al. 2024). The A/B testing functionalities offered by these platforms are primarily intended for advertisers, fairly easy to use, and provide an opportunity to study consumer behaviors in the wild by tracking conversion outcomes across the purchase funnel such as impressions, clicks `[or likes and comments?]`.

Another benefit of these online platform studies is that online ad platforms provide some functionalities to target users based on demographics or "user interests" based on their past online behavior (Cornil et al. 2023). For example, in Study 1 of Zhou, Du, and Cutright (2022), 13,719 Facebook users saw an ad for the Facebook page of a fictional car wash provider. The authors use three different ads featuring either a self-promotion, an external endorsement, or a brand-to-brand praise message from the car wash company. Like other online platform studies, Zhou, Du, and Cutright (2022) leverage the aggregate summary statistics (i.e., clicks/impressions) provided by Facebook to compute and compare the clickthrough rates of these three different ad creatives. Online platform studies promise higher ecological validity as they excel in realism and naturalism, given that they are conducted directly on social media sites used by major advertisers, while still allowing researchers (limited) control of the stimuli and the users exposed to the stimuli.

While the A/B testing functionalities of social media platforms might appear to be randomized controlled trials (RCTs) run in a naturalistic environment. If they were indeed RCTs, online platform studies would be the gold standard in social media research. Yet, by using the A/B testing functionalities provided by digital platforms, researchers relinquish control over critical elements of the study design to the digital platform. Specifically, online platforms employ post-randomization targeting algorithms that prevent clean random assignment of participants to different treatments. Researchers' stimuli (i.e., ads) compete in a bidding system in the digital advertising marketplace, producing a so-called "divergent delivery" across different ads (i.e., conditions) that emerges as the platform selects users based on expected audience reaction and bid amount (Braun and Schwartz 2023; Johnson 2023).

Additionally, at any given point in time, social media platforms are likely to run numerous A/B tests of their own to optimize their platform that are unobservable to researchers and may comingle with their study. These concerns about construct validity and internal validity severely limit the quality of inferences from these studies (see also Gordon, Moakler, and Zettelmeyer 2022). Unfortunately, many social media platforms like Meta do not present the mechanisms underlying these types of studies (i.e., so-called split or A/B tests) and their limitation very transparently (Langhe and Puntoni 2021).

Another limitation of online platform studies is that they only provide aggregate data. While the summary data of clicks and impressions allows researchers to generate datasets for analysis, it prevents any serious individual-level analysis of the psychological processes driving consumer responses (e.g., clicking sequence, time spent on a post). At present, and despite their increasing popularity in marketing research, it is unclear whether online platform studies have sufficient levels of internal and construct validity to be informative for academic research at all Braun and Schwartz (2023). Yet, it is already clear that online platform studies are not a panacea to offset the limited realism of typical static scenario-based vignette studies.

`[Make clear that online platform studies are not necessarily social media studies. Often they just use social media as a recruitment platform that is unnoticed by its participants. Many online platform studies are as much about social media as prolific studies are about online behavior. Just because someone is recruited in an social media or online environment, it does not mean that one studies behavior in there.]`

2.2.3. Observational social media studies

A third, non-experimental paradigm, observational social media studies, directly accesses existing social media data. Typically, researchers collect such datasets themselves via web scraping or application programming interfaces (Boegershausen et al. 2022), or purchase them from proprietary sources (e.g., social media agencies in Wies, Bleier, and Edeling 2023). Various social media sites such as Twitter (#2, N = 27) and Facebook (#6, N = 13) are among the most frequently scraped sources in articles published in the leading marketing journals (Boegershausen et al. 2022). An example of such an observational social media study is the pilot study of Zhou, Du, and Cutright (2022), featuring 8,393 tweets from three gaming console manufacturers between September 1st, 2016 to September 30th, 2017 collected via the Twitter API. The authors coded the tweets for their focal construct of interest (i.e., whether they mentioned a competitor) and compared aggregate user reactions to the different types of tweets (i.e., number of likes, number of retweets). A critical advantage of such observational data is that it features consequential dependent variables (e.g., likes, comments, and retweets/reshares) of interest to marketing managers, content creators, and other decision-makers (Inman et al. 2018). As researchers can collect such data unobtrusively, these studies are unlikely to be affected by demand effects and help identify ecologically valid effects "in the real world".

Yet, observational studies are likely affected by "algorithmic interference" (Boegershausen et al. 2022), which is the effect of personalization algorithms on information display and retrieval (Xu, Zhang, and Zhou 2020). This interference occurs both during the data generation stage (e.g., which tweets users are exposed to) and the data retrieval stage (e.g., which tweets researchers can retrieve). These concerns are particularly pronounced for social media research that draws from online platforms heavily relying on sophisticated, dynamic, black-box algorithms (Aridor et al. 2024). The opaqueness and lack of control over these algorithms that shape the data-generating process on social media platforms make it difficult to address these concerns, reducing construct and internal validity in observational social media studies (e.g., Davidson et al. 2023; Xu, Zhang, and Zhou 2020).

Because observational social media studies are based on archival data, researcher cannot intervene to exogenously manipulate treatment variables. Hence, these datasets require careful consideration of the familiar methodological challenges encountered with organically generated data, due to potential as endogeneity issues (see, e.g., Rutz and Watson (2019); Goldfarb, Tucker, and Wang (2022)). To overcome these challenges, researchers typically exploit natural experiments in which the assignment of treatments to users is "as good as random" (Angrist and Pischke 2009) because it is chosen by nature or policy rather than an experimenters. They then and apply regression discontinuity, difference-in-differences as well as instrumental variable designs to these natural experiments to identify causal effects. However, natural experiments are rare to find and the corresponding methods involve postulates, that is, assumptions that are difficult to validate empirically (Grosz et al. 2024).

Finally, given the increased privacy regulations in the EU and other major markets, most observational studies only contain limited individual-level data and data granularity to explore the psychological processes producing consumer reactions to content.

2.3. App Implementation

> *Submissions to the special issue should include a new section titled "App Implementation." In this section, the author(s) should: (1) Describe the problem solved by the app and how it supplements the research contribution of the manuscript. (2) Define the audience or the end users targeted by*

the app and the usefulness of the app to this audience over and above the current situation or available (software or other) solutions. The audience can be broad and include managers, executives, researchers, consumers, policy makers, government, media, general public, other marketing academics, and students. (3) Provide a secure, anonymous relatively permanent link to the app, with appropriate instructions on how to use the app and interpret the results. Share open-source access to the app to allow accelerated dissemination upon publication.

Ideally, the app implementation informs the problem statement and intended contribution of the research and manuscript.

2.4. Case Studies

The following case studies demonstrate the practical application and novel capabilities of DICE. They not only showcase the tool in action but also highlight its key contributions, particularly by manipulating entire feed contexts and in measuring dwell time. By presenting these studies, we aim to provide a blueprint for researchers interested in adopting DICE for their own studies The first case study illustrates the tool's capacity for manipulating and controlling entire feed contexts whereas the second focuses on measuring participant engagement through dwell times. Together, these studies exemplify how our tool can enhance ecological validity while maintaining high levels of internal validity as discussed above.

2.4.1. Context Case

Brand safety refers to strategies and measures ensuring that a brand's content, particularly advertisements, does not appear in contexts that could harm the brand's reputation (e.g., Bellman et al. 2018; Lee, Kim, and Lim 2021; Hemmings 2021). These measures are especially crucial in social media, where platforms use automated systems to place ads in dynamic, rapidly changing, and user-generated content environments. These automated systems often lack the nuanced understanding that humans possess, potentially leading to ad placements in contexts that are only superficially fitting but, ultimately, inappropriate.

In our hyper-connected world, such of misplacement can rapidly propagate, potentially magnifying reputational damage beyond the initial exposure (Swaminathan et al. 2020). Accordingly, Ahmad et al. (2024) found that most brand managers have a strong preference to avoid misplacement (and also that most of them are unaware that their companies' advertising appears on misinformation websites).

To illustrate the unique capabilities of DICE, we propose a simple study that extends beyond altering individual posts to modifying entire feeds: Unlike traditional online platform studies, we hold the ad copy and creative constant while manipulating the surrounding context between-subjects. Doing so, we test the intuitive hypothesis that an inappropriate (compared to a generic) context negatively affects brand attitudes. To better understand whether the effect is also driven by implicit memory effects (Schmitt 1994), we also control for aided and unaided recall.

Experimental Design

We simulated a scenario where an airline inadvertently promotes a travel destination recently impacted by a natural disaster.[2] More specifically, we exposed participants in the treatment group to a simulated Twitter feed that consisted of real tweets describing the severe flooding affecting Brazil in 2024. Within this feed, we included a fictitious sponsored post by KLM, advertising flights to Brazil with the following copy:

> Brazil's wild beauty calls! Experience nature like never before. Book your breathtaking adventure with KLM.

`[Add creative saying "Brazil. Wild Beauty. Book flight.]`

In contrast, the control group was exposed to the same ad but in a different context which did not contain any tweets covering the flooding.[3] Instead, the control condition's feed covered other real topics such as *Madonna*'s free concert that was attended by 1.6 million people in Rio de Janeiro at that time.

Procedure and Measures: `[Describe procedure briefly.]` After participants were exposed to their assigned social media feed, they evaluated the target brand (KLM) on three seven-point scales presented in a random order (1 = "Negative/Unfavorable/Dislike" and 7 = "Positive/Favorable/Like"), which we average into a single measure. `[We also measure recall.]`

Participants: We recruited 299 participants (M_{age} = 37 years; 49% female) from the US using Qualtrics and randomly assigned them to one of two conditions "safe", i.e., general feed content, vs. "unsafe", i.e., flooding-related content in a between-subjects design. All participants who started the experiment and read the instructions (N=317), submitted the social media feed. 299 finished the qualtrics survey. Of these 299 participants, 111 have been assigned to the unsafe condition, specifically, the misplaced advertisement. The subsequent table demonstrates that the two treatment groups do not exhibit significant differences in observables. Nevertheless, the unsafe condition tends to skew slightly younger, as indicated by column 2 in Table 2.1. Moreover, we do not observe selective attrition and are confident that the group assignment was indeed random—an assumption that is generally accepted in vignette studies, but cannot be presumed in observational studies.

[2] This approach mirrors real-world practices; for instance, the German airline Lufthansa actively monitors news coverage and maintains a blacklist of affected travel destinations to avoid such misplacements.

[3] You can browse the flooding-related feed here and the more general feed here.

Table 2.1.: Balance Across Conditions

Characteristic	Beta	95% CI	p-value	Beta	95% CI	p-value
condition						
safe	—	—		—	—	
unsafe	0.04	-0.08, 0.15	0.5	-2.6	-5.3, 0.11	0.060

Implementation

This is how we implemented it technically. `[Add description of csv file.]`

Results

`[WIP]`

Brand attitude. As pre-registered, we conduct a simple OLS regression where the unsafe feed ($M_u = 3.96$) resulted in significantly less favorable brand evaluations than the more general feed ($M_s = 4.65$, $F(1, 296) = 21.71$, $p = 0.000$, Cohen's d $= 0.56$).

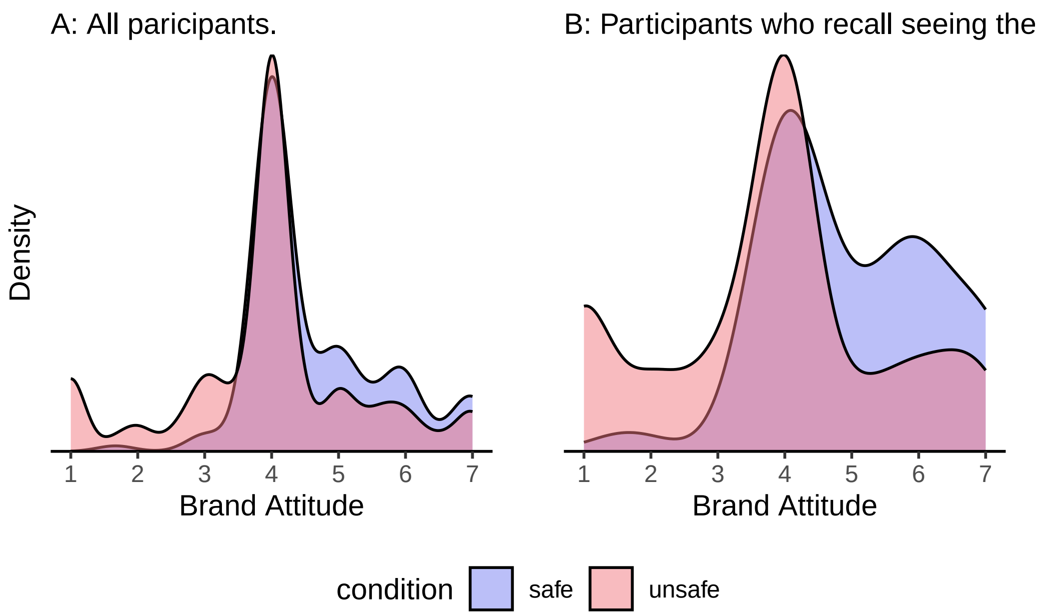


Figure 2.1.: Effect of Misplaced Ad on Brand Evaluations

This effect becomes even stronger if we only consider those participants who recall seeing the ad: The unsafe feed ($M_u = 3.81$) resulted in significantly less favorable brand evaluations than the more general feed ($M_s = 5.02$, $F(1, 296) = 21.71$, $p = 0.000$, Cohen's d $= 0.8$). `[Check wheher there are differences between` recall measures (aided vs. unaided) to better understand implicit memory effects.]

We illustrate both effects in panel A and B of Figure Figure 2.1, respectively. Comparing both panels, one can see that the density around the center diminishes once one considers only those participants who remember (aided recall) that they have been exposed to an ad.

Recall. [If we use this study to demonstrate the context-contribution, we don't need dwell time analyses here.] A logit regression provides correlational evidence which indicates that an additional second in the viewport increases the odds of recall by about 3% holding other factors constant ($p = 0.01$). Controlling for the experimental condition this value changes only slightly[4]. The interaction's large standard error in Model 2 presented in Table 2.2 indicates that this correlation is robust across conditions.

Table 2.2.: Logit Results

Characteristic	**OR**	**p-value**	**OR**	**p-value**	**OR**	**p-value**	**OR**	**p-value**
seconds_in_viewport	1.03	0.008	1.05	0.025				
condition			1.72	0.13			1.84	0.12
seconds_in_viewport * condition								
seconds_in_viewport * unsafe			0.97	0.2				
relative_dwell_time					24.1	0.091	268	0.057
relative_dwell_time * condition								
relative_dwell_time * unsafe							0.01	0.3

[Because we analyze dwell time in the next study in more detail, we should use it here to exclude participants who have not paid attention to the ad: either exclude them or control for dwell time on focal post.]

2.4.2. Dwell Time Case

Lorem ipsum.

[4] An additional second in the viewport increases the odds of recall by about 1.05% ($p = 0.02$)

2.5. Future Opportunities from using DICE in Marketing Research

The current paper proposes a novel paradigm, DICE, to conduct research that has the capacity to keep the advantages of classic vignette studies (e.g., high experimental control to maximize internal validity) and advantages of observational and online platform studies (e.g., high realism to maximize ecological validity) while eliminating their main disadvantages and methodological issues discussed in prior work (see Table 1). DICE also enables researchers to measure content engagement with maximal resolution at the individual level, which was not possible in any of the currently used social media research designs (e.g., millisecond dwell time response measures at the feed level or sequential content browsing trajectories during a session). These features allow researchers to pursue entirely new lines of inquiry in future social media research. In what follows, we discuss the methodological contributions and offer directions for future work and how DICE could be utilized to make better-informed decisions for key players in the social media ecosystem (e.g., brands, influencers, platform providers, agencies, and public policy).

2.5.1. Methodological Implications

The methodological contributions of DICE directly address several challenges in the research designs employed in prior social media research. First, DICE ensures stable group assignment by eliminating divergent delivery and issues with potentially multiple exposures in online platform studies. DICE, therefore, directly addresses the limitations of "black box" engagement algorithms on all major social media platforms and the lack of control for researchers to study truly causal effects on these platforms.

Second, and as a consequence, DICE offers high ecological value that closely mimics the environments in online platform studies or observational studies but with the additional advantage of offering feed composition controls in which researchers can directly specify the mode and sequence of how content should be delivered across conditions. This researcher-controlled delivery overcomes the methodological drawbacks of typical observational studies (e.g., endogeneity) and online platform studies (e.g., divergent delivery), while offering a similar level of control as vignettes.

Third, DICE offers the ability to measure content engagement with high resolution at the individual level, which was not possible before without extensive monetary and time investments. DICE allows researchers to track millisecond dwell time content engagement and sequential content trajectories at the individual level. Thus, researchers can directly measure the relative content engagement, a proxy for consumer attention, at a highly atomized level for every single post or item in a feed and the sequence of content consumption (e.g., whether users read a post, then scroll down and up again). The metrics produced from this tracking data in DICE offer a new lens to study attention-related mechanisms in future social media research (see our future research directions section).

Fourth, DICE directly integrates crowdsourcing platforms for participant recruitment, such as Prolific or Amazon Mechanical Turk, to track participant identifiers across the entire duration of a study and also integrates with survey management platforms, such as Qualtrics, to follow up with post-survey measurements after exposure to different treatment conditions. Thus, our paradigm combines behavioral tracking data and traditional survey instruments within a single study. While the tracking data is theoretically available in online platform studies, it is typically inaccessible for researchers as it is used to “optimize” engagement metrics (and, in turn, jeopardizes the possibility of drawing causal inferences). Finally, we designed DICE as an easy-to-use, low-cost, open-source environment to promote replicability and transparency for all researchers. Our aim is to offer a paradigm and platform to conduct robust, high-quality social media research studies, that directly address the lack of transparency, replicability, and customization on major social media platforms.

2.5.2. Future Research Directions

In what follows, we outline future directions for key actors and stakeholders in the social media ecosystem (i.e., marketing scholars, brands, influencers, agencies, and public policy) on how DICE offers the possibility to explore either new phenomena or to utilize the methodological advantages to deepen our understanding of previously studied phenomena. We offer a summary of selected and exemplary questions in Table 2.

2.6. Concluding Thoughts

In this paper, we have introduced DICE, a novel experimental paradigm, along with a user-friendly, open-source research app that resolves key methodological issues in social media research while enhancing ecological value and causal inference. DICE represents a synthesis of the advantages of high experimental control (and therefore internal validity) found in scenario-based vignette studies with the advantages of high realism (and therefore ecological validity) of observational and platform studies. Our DICE paradigm, along with the behavioral tracking possibilities to assess attention and scrolling trajectories with high resolution at the individual level, offers new avenues for rigorous, realistic, and ultimately relevant marketing research for a wide range of stakeholders within the social media ecosystem. Given DICE’s modular nature, it is also possible to further adapt the environment to just any other platform featuring scrollable content streams. `[Show how and under which conditions in Appendix.]` For example, professional networks like LinkedIn, online review platforms like Yelp or e-commerce sites like Amazon could be modeled to test messaging effects on engagement, recruitment, product search, and purchasing behavior with high resolution. This adaptability of DICE underscores its capacity for broad application across various online environments, each with its idiosyncratic user engagement dynamics and commercial and theoretical implications (see also Swaminathan et al. 2023). In summary, DICE presents a novel research paradigm to examine important marketing questions in social media and other digital contexts.

3. The Price of Civility: Economic and Social Returns on Investment in Toxicity Moderation

Meta estimates its users create approximately one billion stories—ephemeral posts—daily. Stylistically, each additional post augments the appeal of platforms like Meta, TikTok, and X because it contributes potentially novel and diverse content to a massive content pool. To tame the scale of these content pools and to ensure that its size indeed augments a platform's appeal, one of the platforms' most critical functions is to distribute the most relevant content per user.[1] Well-designed content recommendations tend to positively affect the duration of user engagement (Aridor et al. 2024), which is crucial for platforms because advertisers are interested in capturing users' attention and pay these platforms to gain a share of it. This is so significant that digital advertising, a substantial portion of which is placed on social media, now accounts for most of global advertising expenditures (Deisenroth et al. 2024).

Formally, a social platform chooses a targeting rule that picks, for each user i, a personalized subset $\mathbf{x}_i$ from the total pool of posts to show the user. A post is characterized by a vector of characteristics, $x \in \mathbb{R}^K$ which can include, for example, toxicity or sentiment expressed. Platforms choose the posts that maximize the revenue-weighted time spent ($t_i(\mathbf{x}_i)$) on the platform. $\alpha(\mathbf{x}_i)$ represents the monetary gains the platform gets per unit of time spent from showing $\mathbf{x}_i$ to i (Aridor et al. 2024, 3). In addition, the platform faces costs $c(\mathbf{N}, \mathbf{M})$ that increases in the total numbers of users $\mathbf{N}$ and posts $\mathbf{M}$. These may include the technical infrastructure as well as labor costs.

$$\max_{\{\mathbf{x}_i\} \subseteq U; \mathbf{x}_j^p} \left(\sum_i \alpha(\mathbf{x}_i) t_i(\mathbf{x}_i) - c(\mathbf{N}, \mathbf{M}) \right)$$

One specific driver of costs is content moderation: Despite selecting potentially relevant content per user, platforms also have to filter content that should *not* be displayed to any user. Because platforms cannot control the content production directly, they typically set rules that define which type of content shall (not) be displayed. However, actively moderating the content production by enforcing these rules and sanctioning

[1] In addition to facilitating the content production and consumption, the core of a platform's business is to distribute the content to its consumers. Due to the unprecedented scale of content production, social media platforms cannot expose all of its users to all the available content. Instead, they curate personalized subsets of content. In contrast to traditional media outlets, where editors select content for a broad audience, recommender systems on these platforms generate tailored lists of content for individual users.

violations is costly because platforms need to design algorithms that flag potentially unwanted content and employ human moderators who evaluate the flagged posts. These are considered *direct* costs and represented by $c(\mathbf{N}, \mathbf{M})$.

In addition, there may be *indirect* costs because field experimental evidence suggests that the removal of harmful content[2] reduces content consumption. Hence, and perhaps counterintuitively, $t(\cdot)$ decreases in $\mathbf{x}_i$'s civility. However, anecdotal evidence suggests that advertisers react to harmful content by withdrawing their campaign budget for platforms that promote such content. In November 2023, CNN reported that at least a dozen major brands, such as IBM or Disney, halted their ad spending over concerns about antisemitism and hate speech on X. Such *brand safety* measures indicate that $\alpha(\cdot)$ may increase in $\mathbf{x}_i$'s civility. Moreover, Ahmad et al. (2024) find that most brand managers prefer their advertisements not to be displayed on websites that distribute misinformation and lack civility.

Focusing on one specific form of uncivil content, it is not clear how the product of $\alpha(\cdot)t(\cdot)$ is affected by toxicity. This study aims to find out.

[2] This includes hate speech and misinformation, for instance, and is considered harmful as the literature works with the assumption that such content imposes negative externalities on groups of the population (Beknazar-Yuzbashev et al. 2022, 8)

4. The Sound of Certainty: Assessing Paralinguistic Indicators of Decision Confidence

Co-authored with Max Gaerth (Wharton) and Christian Hildebrand (University of St. Gallen), we have completed a pre-test as well as the first study. We are currently refining two additional studies, for which the experimental designs and software have already been developed, while the fourth study has not yet commenced. We plan to submit our findings to the Journal of Marketing Research, which is renowned for welcoming methodological contributions and for its high visibility within our research community.

4.1. Introduction

The average adult makes about 35,000 remotely conscious decisions each day. In fact, we make 226.7 decisions each day on just food alone `(Hoomans 2015)`. Many of which can be thought of as trade-offs (see, e.g. Shaddy, Fishbach, and Simonson 2021 for a recent review). Think of a restaurant customer who chooses a protein for her ramen soup. She can choose between pork or chicken, for instance, and intuitively decides whether and how much to satisfy one consideration at the expense of another.

To understand how consumers resolve such trade-offs, prior research has established that the strength of consumer preferences, defined as the confidence with which consumers hold their preferences and the stability of their preferences over time, plays a pivotal role (e.g., Amir and Levav 2008; Yoon and Simonson 2008). To measure preference strength, researchers have traditionally relied on retrospective methods, such as questionnaire measures and conjoint analayses. These *direct* approaches rely on two strong assumptions: people are able to introspect their psychological states, and they are willing to report correctly the results of their introspection (Fischer et al. 2023, 2). To relax these assumptions, researchers have begun to append direct measures with response times. Response times are a promising *indirect* measure, that can be elicited unobtrusively and that reveals more information (than discrete choices stated in retrospective methods) because it is continuous. An extensive body of literature established that longer response times are associated to lower preference strength (see, e.g., Luce 1991; Bergert and Nosofsky 2007; Bhatia and Mullett 2018). However, response times can be noisy as they also capture many constructs unrelated to decisions (Konovalov and Krajbich 2019).

This research also focuses on *how* decisions are transmitted but considers vocal instead of manual communication. Vocal communication involves more than just the words that echo a decision (Mehrabian 1971; Gorodnichenko, Pham, and Talavera 2023) and comprises non-verbal elements such as tone, pitch, or pace (see, e.g., Zierau et al. 2023; Melzner, Bonezzi, and Meyvis 2023). These so-called *paralinguistics* can not only be measured continuously but also less controllable and more immediate. Contemplation, for instance, is associated with slower speech with longer pauses (Dasgupta 2017), anger is often associated with louder speech, and fear with greater pitch variability (Juslin and Laukka 2003; Clark 2005). Hence, paralinguistics offer a unique and unintended lens to reveal one's inner thoughts and feelings that cannot be retrieved from text transcript.

Consider the ramen example again. Suppose we are attempting to determine which of two people, Peter or Bob, is more confident in his choice and suppose that both order pork with the exact same wording. With just this information there is no way to distinguish between them. Now suppose Peter orders loudly and clearly, whereas Bob may speak more quietly, raising the intonation at the end of the statement as if he was asking a question. Who has a stronger preference for one protein over the other? Since Peter communicated his choice more confidently than Bob, it is likely that he found it more delicious. In other words, Peter's relative preference for pork was likely stronger than Bob's; he was farther from indifference (i.e., the point at which she is equally likely to choose either option). Of course, if Peter and Bob differ on relevant characteristics such as age or culture, we might be misled about their preferences. It is thus an empirical question whether our example is actually feasible or speculation. This is a key question that we tackle in this paper.

The answer to this question has practical implications because voice analytics (i.e., the computational extraction of paralinguistics) is increasingly available to marketers as voice data is becoming ubiquitous. Due to the rise of voice-enabled technology and chat interfaces, consumers who used to search for information, make bank transactions, and choose products using only their keyboard or mouse, can now perform almost any computer-based task using voice commands. In 2022, it was estimated that 62% of all Americans aged 18 or older used some type of voice-enabled technology (e.g., smart devices), and of these, 57% indicated using voice technology daily (NPR and Edison Research 2022). Notably, one can easily imagine the adoption to further increase as major companies, such as Apple, released the first version of *Apple Intelligence*, its suite of artificial intelligence features that will improve their voice assistant Siri based on OpenAI's ChatGPT (Malik 2024).

Building on the findings on preference strength, we hypothesize that certain vocal features will change as a function of consumers' strength of preferences. To test this hypothesis, we utilize the technological advances mentioned above, chat interfaces and large language models, in a series of four studies that we outline below.

4.2. Study 1

The goal of Study 1 was to examine (a) whether preference strength on a given trial predicted how participants vocalized their choice (i.e., vocal features) and (b) whether vocal features could be used to predict preference strength.

Participants: 242 Prolific panelists (M_{age} = 39.96, SD_{age} = 13.14; 36% female) completed the study. We based our sample size on past work using within—subjects designs and a mouse—tracking task (cite). The study employed a 2 (conflict: low vs. high) $\times$ 2 (gender model: male vs. female) $\times$ 2 (replicates) within-subjects design.

Procedure and stimuli: Participants completed eight choice trials between two models. To induce differences in participants' preference strength across all eight trials, we manipulated the decisional conflict associated with these choice trials. We pre-tested a variety of model headshots to identify pairs with high decisional conflict (where both models were equally attractive) and low decisional conflict (where one model was perceived as being more attractive on average). More information on the pre-test as well as the specific stimuli can be found in Section A.1 and Section A.2, respectively. Importantly, the presentation order of the models as well as pairs was randomized within participants. For each choice trial, participants were asked to say out loud which of the two models they find more attractive. After each choice, participants indicated the strength of their preference on a 101—point slider scale (i.e., 0 = Strong preference for Model X, 1 = strong preference for Model Y) on a separate page.

Before the start of the study, participants completed two trial rounds to familiarize themselves with the recording interface and test (or adjust) their settings to ensure a high audio quality. Subsequently, participants were led through the choice task described above. Lastly, participants indicated their age, gender, and environmental factors that could affect the quality of their recordings or trigger self-presentational concerns. Accordingly, they indicated whether they were alone or in a public space and whether they disguised their voice.

Results: These results suggest that vocal features can be a sensitive metric for strength of preferences within a given decision and that the variance is distinct from established implicit measures, such as response time.

Discussion:

4.3. Study 2

Participants will be randomly assigned to a 10-trial repeated measures design. They will indicate their preferred product version between two options (e.g., Diet Coke vs. Coke Zero) using a voice interface designed with oTree (Chen, Schonger, and Wickens 2016) and OpenAI's *Whisper API*.[1]

Subsequently, participants will engage in a titration task for each of the 10 trials, where the price of the preferred product version will be increased incrementally (from 5% to 40% in 5% steps). For each price premium, participants will indicate whether they would choose to buy the preferred product version, or the less preferred product version.

This process will allow us to determine our outcome variable: the maximum acceptable price premium (MAPP) a participant would pay before switching to the less preferred product. Specifically, we will examine the relationship between preference strength,

[1]Our oTree app extends functions provided in McKenna (2024)

as measured by paralinguistic features, and MAPP. We hypothesize that consumers' preference strength for one product over the other (which we approximate using the paralinguistic features) will significantly predict MAPP.

4.4. Study 3

In a first study, we ask whether we can learn how hard a decision is not by listening to *what* consumers say but *how* they say it.

Experimental Paradigm: We employ a Multiple Price List design (see, e.g., Andersen et al. 2006) and expose study participants to a series of ten decisions that differ with respect to their decision difficulty. More precisely, participants choose between two artificial products that differ only in their product ratings. Whereas the lower-rated product has a fixed price in each decision, the price of the higher-rated product varies between decisions. Table 4.1 summarizes these decisions.

Table 4.1.: Manipulation of Dicision Difficulty

Decision	Quality A	Quality B	Price A	Price B
1	3.8	4.2	200	200
2	3.8	4.2	200	204
3	3.8	4.2	200	209
4	3.8	4.2	200	213
5	3.8	4.2	200	218
6	3.8	4.2	200	226
7	3.8	4.2	200	232
8	3.8	4.2	200	240
9	3.8	4.2	200	246
10	3.8	4.2	200	254

Because both products share the same price in the first decision but differ with respect to their quality, product B weakly dominates product A. With these information being salient, consumers should choose product B and, importantly, they should be confident in choosing between the two.

As the price of product B increases over the course of the following decisions, the consumers face a trade-off between price and quality. Notably, this trade-off becomes more difficult as the price increases up to the point where product B becomes too expensive. From that so-called switching point on, the trade-off difficulty should decrease again. `[How does decision difficulty relate to decision confidence?]`

As a consequence, we expect the confidence with which consumers make these decisions to exhibit a U-shaped pattern that we illustrate for 100 simulated participants in Figure 4.1.

Crucially, participants communicate their decisions verbally as they make their respective choices. This enables us to not only measure *what* they say (to localize their

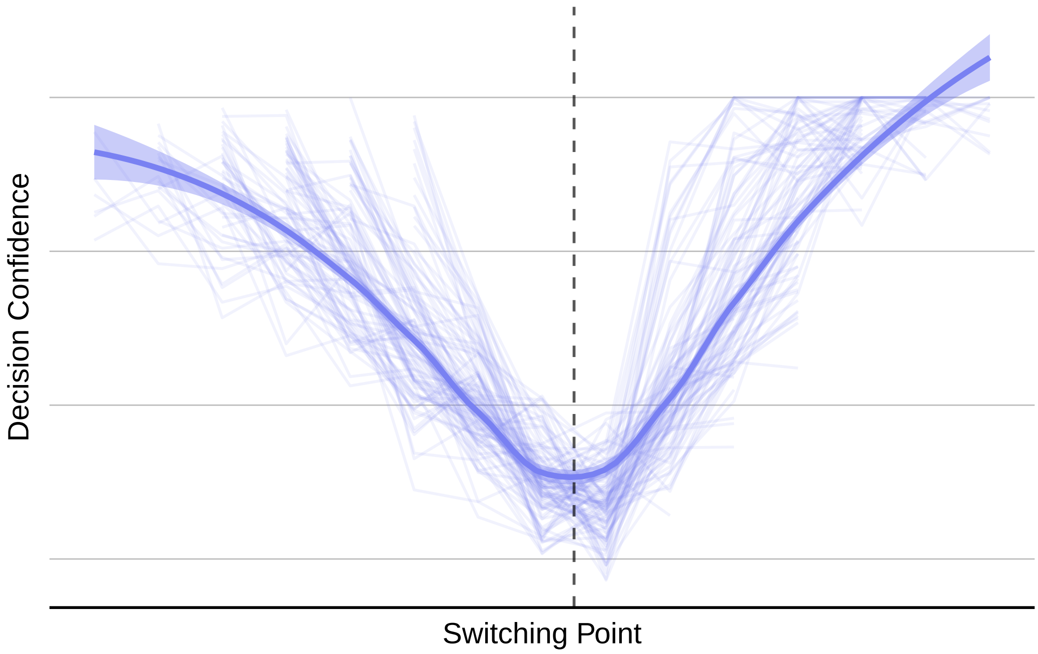


Figure 4.1.: Expected U-Shape Pattern in Choice Confidence

switching points) but also to measure *how* they say it during a time closely aligned with their decision-making process.

To sum up, we build on an established paradigm that yields clear and intuitive predictions and modify it to record rich audio information which we can decode, transcribe and analyze to get a glimpse into the underlying psychological states that drive decision-making.

Validation: We tested this prediction in pre-test that was conducted online and where participants entered their preference strength manually using a slider. We recruited participants via Prolific and classified 68 participants as rational because they were only switching once. The resulting pattern, illustrated in Figure 4.2, matches the prediction.

Identification: To learn whether we could describe the latent consumer confidence, we build on the experimental paradigm and the expected confidence pattern described above and illustrated in Figure 4.1 and Figure 4.2. In addition to the pre-test reported above, we will run another study where we will change the modality and ask participants to voice their decision. This will yield ten voice recordings per participant which we will use to extract the same vocal features we extracted in the previous studies. Building on the findings of Study 1 and Study 2, we can put the features with the highest predicted power to yet another test and (correlate and) plot them against the U-shape derived above.

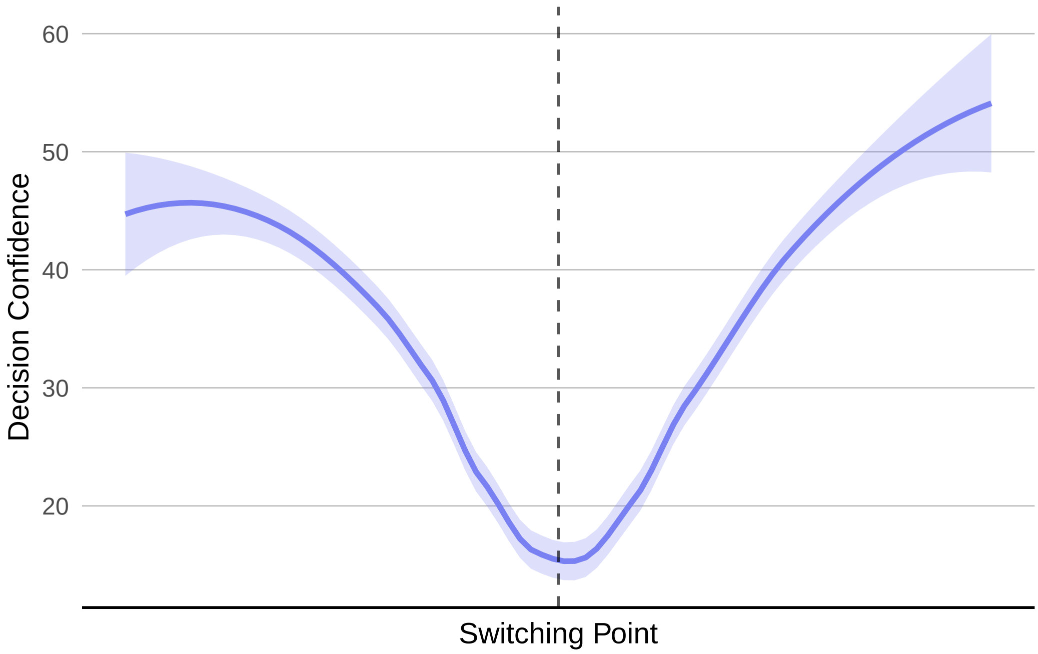


Figure 4.2.: Fitted Pattern in Self-Reported Choice Confidence

4.5. Study 4

To promote the consumption, adoption, and ongoing usage of our research findings, we plan to develop a customized deep learning model for detecting preference strength in speech. To this end, we hire 24 North American voice actors and actresses who will speak statements in with varying degrees of certainty (uncertain, neutral, certain) and recruit Prolific participants for validation. Using these data, we will follow Gorodnichenko, Pham, and Talavera (2023) and use Librosa, a Python package, to extract vocal features. More specifically, we will extract 128 mel spectrogram frequencies which allows us to determine the level of loudness of a particular frequency at a particular time for each recording. In addition, a chromagram with 12 chroma coefficients will be extracted. The chromagram reflects the distribution of energy along 12 chroma bands (i.e., C, C#, D, D#, E, F, F#, G, G#, A, A#, and B) over time and, hence, can capture melodic and harmonic characteristics of audio. Moreover, we will extract 40 mel-frequency cepstral coefficients (MFCCs), which are discrete cosine transformations of the mel frequency spectrogram (as Gorodnichenko, Pham, and Talavera (2023) found it to improve their model).

After extracting the vocal features from each recording our data, we have a labeled dataset that split into training and testing data. We use the training subset to build and fine-tune a neural network using an established deep learning framework such as *Keras*.[2] The testing data will then be used to evaluate the model's performance using

[2]Alternatively, we can also try to fine-tune an existing model such as Facebook's Wav2Vec, which is

the following accuracy score:

$$\text{Accuracy}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^{n} \mathbf{1}\{\hat{y}_i = y_i\}$$

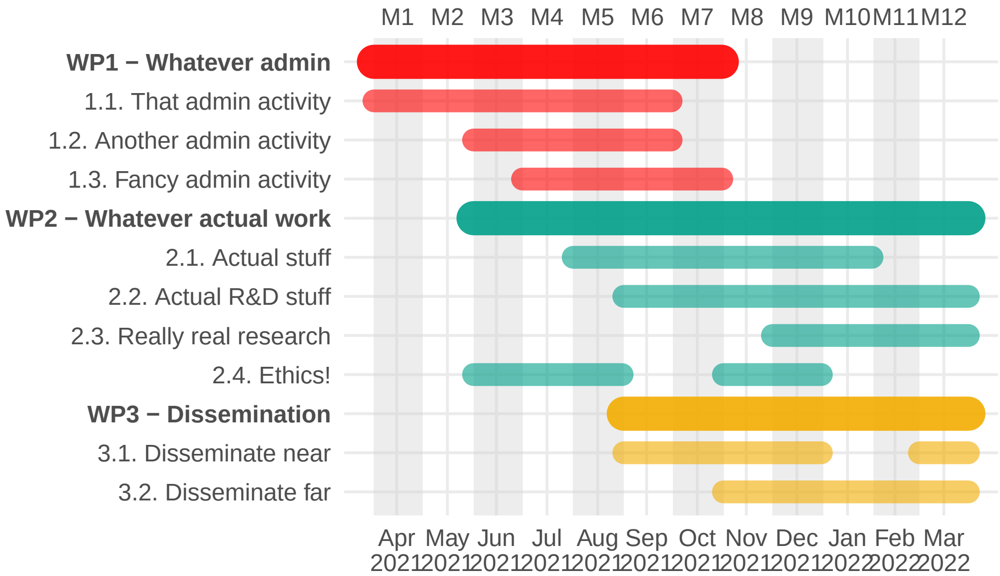
where y and $\hat{y}$ are the true and the predicted levels of certainty, respectively, and n is the number of audio files in the testing dataset.

described here.

Part III.

OUTLOOK

5. Work Plan


M1
M2
M3
M4
M5
M6
M7
M8
M9
M10
M11
M12
WP1 − Whatever admin
1.1. That admin activity
1.2. Another admin activity
1.3. Fancy admin activity
WP2 − Whatever actual work
2.1. Actual stuff
2.2. Actual R&D stuff
2.3. Really real research
2.4. Ethics!
WP3 − Dissemination
3.1. Disseminate near
3.2. Disseminate far
Apr 2021
May 2021
Jun 2021
Jul 2021
Aug 2021
Sep 2021
Oct 2021
Nov 2021
Dec 2021
Jan 2022
Feb 2022
Mar 2022

6. Outcomes and Impact

Mention expected outcomes here.

References

Ahmad, Wajeeha, Ananya Sen, Charles Eesley, and Erik Brynjolfsson. 2024. "Companies Inadvertently Fund Online Misinformation Despite Consumer Backlash." *Nature* 630: 123–31. https://doi.org/10.1038/s41586-024-07404-1.

Allcott, Hunt, Matthew Gentzkow, and Lena Song. 2022. "Digital Addiction." *American Economic Review* 112 (7): 2424–63. https://doi.org/10.1257/aer.20210867.

Amir, On, and Jonathan Levav. 2008. "Choice Construction Versus Preference Construction: The Instability of Preferences Learned in Context." *Journal of Marketing Research* 45 (2): 145–58. https://doi.org/10.1509/jmkr.45.2.145.

Andersen, Steffen, Glenn W. Harrison, Morten Igel Lau, and E. Elisabet Rutström. 2006. "Elicitation Using Multiple Price List Formats." *Experimental Economics* 9 (4): 383–405. https://doi.org/10.1007/s10683-006-7055-6.

Anderson, Ian A., and Wendy Wood. 2021. "Habits and the Electronic Herd: The Psychology Behind Social Media's Successes and Failures." Journal Article. *Consumer Psychology Review* 4 (1): 83–99. https://doi.org/10.1002/arcp.1063.

Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton university press.

Appel, Gil, Lauren Grewal, Rhonda Hadi, and Andrew T. Stephen. 2020. "The Future of Social Media in Marketing." Journal Article. *Journal of the Academy of Marketing Science* 48 (1): 79–95. https://doi.org/10.1007/s11747-019-00695-1.

Appel, Markus, Caroline Marker, and Timo Gnambs. 2020. "Are Social Media Ruining Our Lives? A Review of Meta-Analytic Evidence." Journal Article. *Review of General Psychology* 24 (1): 60–74. https://doi.org/10.1177/1089268019880891.

Aridor, Guy. 2024. "Measuring Substitution Patterns in the Attention Economy: An Experimental Approach." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4069567.

Aridor, Guy, Rafael Jiménez-Durán, Ro'ee Levy, and Lena Song. 2024. "The Economics of Social Media." *Journal of Economic Literature*. https://doi.org/10.2139/ssrn.4723727.

Baumeister, Roy F., Kathleen D. Vohs, and David C. Funder. 2007. "Psychology as the Science of Self-Reports and Finger Movements: Whatever Happened to Actual Behavior?" *Perspectives on Psychological Science* 2 (4): 396–403. https://doi.org/10.1111/j.1745-6916.2007.00051.x.

Beknazar-Yuzbashev, George, Rafael Jiménez Durán, Jesse McCrosky, and Mateusz Stalinski. 2022. "Toxic Content and User Engagement on Social Media: Evidence from a Field Experiment." SSRN Working Paper. SSRN. https://doi.org/10.2139/ssrn.4307346.

Bellman, Steven, Ziad H. S. Abdelmoety, Jamie Murphy, Shruthi Arismendez, and Duane Varan. 2018. "Brand Safety: The Effects of Controversial Video Content on Pre-Roll Advertising." *Heliyon* 4 (12): e01041. https://doi.org/10.1016/j.heliyon.2018.e01041.

Berger, Jonah, and Katherine L. Milkman. 2012. "What Makes Online Content Viral?" *Journal of Marketing Research* 49 (2): 192–205. https://doi.org/10.1509/jmr.10.0353.

Berger, Jonah, Wendy W. Moe, and David A. Schweidel. 2023. "What Holds Attention? Linguistic Drivers of Engagement." *Journal of Marketing* 87 (5): 793–809. https://doi.org/10.1177/00222429231152880.

Bergert, F. B., and R. M. Nosofsky. 2007. "A Response-Time Approach to Comparing Generalized Rational and Take-the-Best Models of Decision Making." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 33 (1): 107–29. https://doi.org/10.1037/0278-7393.33.1.107.

Bhatia, S., and T. L. Mullett. 2018. "Similarity and Decision Time in Preferential Choice." *Quarterly Journal of Experimental Psychology* 71 (6): 1276–80. https://doi.org/10.1177/1747021818763054.

Boegershausen, Johannes, Hannes Datta, Abhishek Borah, and Andrew T. Stephen. 2022. "Fields of Gold: Scraping Web Data for Marketing Insights." *Journal of Marketing* 86 (5): 1–20. https://doi.org/10.1177/00222429221100750.

Braun, Michael, Bart de Langhe, Stefano Puntoni, and Eric M Schwartz. 2024. "Leveraging Digital Advertising Platforms for Consumer Research." *Journal of Consumer Research* 51 (1): 119–28. https://doi.org/10.1093/jcr/ucad058.

Braun, Michael, and Eric M Schwartz. 2023. "Where AB Testing Goes Wrong: What Online Experiments Cannot (and Can) Tell You about How Customers Respond to Advertising." *SMU Cox School of Business Research Paper*, no. 21-10. https://doi.org/10.2139/ssrn.3896024.

Chen, Daniel L., Martin Schonger, and Chris Wickens. 2016. "oTree—an Open-Source Platform for Laboratory, Online, and Field Experiments." *Journal of Behavioral and Experimental Finance* 9: 88–97. https://doi.org/doi.org/10.1016/j.jbef.2015.12.001.

Clark, Anita V. 2005. *Psychology of Moods*. Nova Publishers.

Cornil, Yann, Shanwen Yi, Johannes Boegershausen, and David J. Hardisty. 2023. "Testing the Digital Frontier: Validity Tradeoffs in Online Platform a/b Tests." Unpublished Work. University of British Columbia, working paper.

Cramer, Henriette. 2015. "Effects of Ad Quality & Content-Relevance on Perceived Content Quality." In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 2231–34. CHI '15. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/2702123.2702360.

Dasgupta, Poorna Banerjee. 2017. "Detection and Analysis of Human Emotions Through Voice and Speech Pattern Processing." *CoRR* abs/1710.10198. http://arxiv.org/abs/1710.10198.

Davidson, Brittany I., Darja Wischerath, Daniel Racek, Douglas A. Parry, Emily Godwin, Joanne Hinds, Dirk van der Linden, Jonathan F. Roscoe, Laura

Ayravainen, and Alicia G. Cork. 2023. "Platform-Controlled Social Media APIs Threaten Open Science." Journal Article. *Nature Human Behaviour* 7 (12): 2054–57. https://doi.org/10.1038/s41562-023-01750-2.

Deisenroth, Daniel, Utsav Manjeer, Zarak Sohail, Steven Tadelis, and Nils Wernerfelt. 2024. "Digital Advertising and Market Structure: Implications for Privacy Regulation." NBER Working Paper w32726. National Bureau of Economic Research. https://doi.org/10.3386/w32726.

Eckles, Dean, Brett R. Gordon, and Garrett A. Johnson. 2018. "Field Studies of Psychologically Targeted Ads Face Threats to Internal Validity." *Proceedings of the National Academy of Sciences* 115 (23): E5254–55. https://doi.org/10.1073/pnas.1805363115.

Farronato, Chiara, and Andrey Fradkin. 2022. "The Welfare Effects of Peer Entry: The Case of Airbnb and the Accommodation Industry." *American Economic Review* 112 (6): 1782–1817. https://doi.org/10.1257/aer.20180260.

Farronato, Chiara, Andrey Fradkin, and Chris Karr. 2024. "Webmunk: A New Tool for Studying Online Behavior and Digital Platforms." 32694. National Bureau of Economic Research. https://doi.org/10.3386/w32694.

Ferber, Robert. 1977. "Research by Convenience." Journal Article. *Journal of Consumer Research* 4 (1): 57–58. https://doi.org/10.1086/208679.

Fischer, Thomas, Donald C. Hambrick, Gwendolin B. Sajons, and Niels Van Quaquebeke. 2023. "Leadership Science Beyond Questionnaires." *The Leadership Quarterly* 34 (6): 101752. https://doi.org/10.1016/j.leaqua.2023.101752.

Goldfarb, Avi, Catherine Tucker, and Yanwen Wang. 2022. "Conducting Research in Marketing with Quasi-Experiments." Journal Article. *Journal of Marketing* 86 (3): 1–20. https://doi.org/10.1177/00222429221082977.

Gordon, Brett R, Robert Moakler, and Florian Zettelmeyer. 2022. "Close Enough? A Large-Scale Exploration of Non-Experimental Approaches to Advertising Measurement." *Marketing Science* 42 (4): 768–93. https://doi.org/10.1287/mksc.2022.1413.

Gorodnichenko, Yuriy, Tho Pham, and Oleksandr Talavera. 2023. "The Voice of Monetary Policy." *American Economic Review* 113 (2): 548–84. https://doi.org/10.1257/aer.20220129.

Grosz, Michael P., Adam Ayaita, Ruben C. Arslan, Susanne Buecker, Tobias Ebert, Paul Hünermund, Sandrine R. Müller, Sven Rieger, Alexandra Zapko-Willmes, and Julia M. Rohrer. 2024. "Natural Experiments: Missed Opportunities for Causal Inference in Psychology." *Advances in Methods and Practices in Psychological Science* 7 (1): 1–15. https://doi.org/10.1177/25152459231218610.

Heerde, Harald J. van, Christine Moorman, C. Page Moreau, and Robert W. Palmatier. 2021. "Reality Check: Infusing Ecological Value into Academic Marketing Research." *Journal of Marketing* 85 (2): 1–13. https://doi.org/10.1177/0022242921992383.

Hemmings, Mike. 2021. "Ethical Online Advertising: Choosing the Right Tools for Online Brand Safety." *Journal of Brand Strategy* 10 (2): 109–20. https://www.ingentaconnect.com/content/hsp/jbs/2021/00000010/00000002/art00003.

Inman, J. Jeffrey, Margaret C. Campbell, Amna Kirmani, and Linda L. Price. 2018. "Our Vision for the Journal of Consumer Research: It's All about the Consumer." Journal Article. *Journal of Consumer Research* 44 (5): 955–59. https://doi.org/10.1093/jcr/ucx123.

Jacoby, Jacob. 1978. "Consumer Research: How Valid and Useful Are All Our Consumer Behavior Research Findings?: A State of the Art Review." Journal Article. *Journal of Marketing* 42 (2): 87–96. https://doi.org/10.1177/002224297804200213.

Jedidi, Kamel, Bernd H. Schmitt, Malek Ben Sliman, and Yanyan Li. 2021. "R2M Index 1.0: Assessing the Practical Relevance of Academic Marketing Articles." Journal Article. *Journal of Marketing* 85 (5): 22–41. https://doi.org/10.1177/00222429211028145.

Johnson, Garrett A. 2023. "Inferno: A Guide to Field Experiments in Online Display Advertising." Journal Article. *Journal of Economics & Management Strategy* 32 (3): 469–90. https://doi.org/10.1111/jems.12513.

Juslin, Patrik N., and Petri Laukka. 2003. "Communication of Emotions in Vocal Expression and Music Performance: Different Channels, Same Code?" *Psychological Bulletin* 129 (5): 770–814. https://doi.org/10.1037/0033-2909.129.5.770.

Kemp, Simon. 2023. "Digital 2023: Global Overview Report."

Konovalov, Arkady, and Ian Krajbich. 2019. "Revealed Strength of Preference: Inference from Response Times." *Judgment and Decision Making* 14 (4): 381–94. https://doi.org/10.1017/S1930297500006082.

Langhe, Bart de, and Stefano Puntoni. 2021. "Are Personalized Ads a Waste of Money?" Journal Article. *Harvard Business Review Digital Articles*. https://hbr.org/2021/12/are-personalized-ads-a-waste-of-money.

Lee, Chunsik, Junga Kim, and Joon Soo Lim. 2021. "Spillover Effects of Brand Safety Violations in Social Media." *Journal of Current Issues and Research in Advertising* 42 (4): 354–71. https://doi.org/10.1080/10641734.2021.1905572.

Leung, Fine F., Flora F. Gu, and Robert W. Palmatier. 2022. "Online Influencer Marketing." Journal Article. *Journal of the Academy of Marketing Science* 50 (2): 226–51. https://doi.org/10.1007/s11747-021-00829-4.

Luce, R Duncan. 1991. *Response Times: Their Role in Inferring Elementary Mental Organization*. Oxford University Press.

Lynch, John G., Stijn M. J. van Osselaer, and Patricia Torres. 2024. "Inside Baseball: How Our Stereotypes of 'Good Theory' Undermine Perceived Relevance of Marketing Scholarship." Journal Article. *Journal of Consumer Research* forthcoming.

Lynch, Jr., John G. 1982. "On the External Validity of Experiments in Consumer Research." *Journal of Consumer Research* 9 (3): 225–39. https://doi.org/10.1086/208919.

Malik, Aisha. 2024. "How Apple Intelligence Is Changing the Way You Use Siri on Your iPhone." 2024. https://web.archive.org/web/20240727192450/https://techcrunch.com/2024/07/11/how-apple-intelligence-is-changing-the-way-you-use-siri-on-your-iphone/?guccounter=1.

Matz, S. C., M. Kosinski, G. Nave, and D. J. Stillwell. 2018. "Reply to Eckles Et Al.: Facebook's Optimization Algorithms Are Highly Unlikely to Explain the Effects of Psychological Targeting." *Proceedings of the National Academy of Sciences* 115 (23): E5256–57. https://doi.org/10.1073/pnas.1806854115.

McKenna, Clint. 2024. "oTree Whisper." https://github.com/clintmckenna/oTree-Whisper.

Mehrabian, Albert. 1971. *Silent Messages: Implicit Communication of Emotions and Attitudes*. Belmont, CA: Wadsworth Publishing.

Melzner, Johann, Andrea Bonezzi, and Tom Meyvis. 2023. "Information Disclosure in the Era of Voice Technology." *Journal of Marketing* 87 (4): 491–509. https://doi.org/10.1177/00222429221138286.

Morales, Andrea C, On Amir, and Leonard Lee. 2017. "Keeping It Real in Experimental Research—Understanding When, Where, and How to Enhance Realism and Measure Consumer Behavior." *Journal of Consumer Research* 44 (2): 465–76. https://doi.org/10.1093/jcr/ucx048.

Orazi, Davide C., and Allen C. Johnston. 2020. "Running Field Experiments Using Facebook Split Test." Journal Article. *Journal of Business Research* 118: 189–98. https://doi.org/10.1016/j.jbusres.2020.06.053.

Orben, Amy, and Andrew K. Przybylski. 2019. "The Association Between Adolescent Well-Being and Digital Technology Use." Journal Article. *Nature Human Behaviour* 3 (2): 173–82. https://doi.org/10.1038/s41562-018-0506-1.

Pham, Michel Tuan. 2013. "The Seven Sins of Consumer Psychology." *Journal of Consumer Psychology* 23 (4): 411–23. https://doi.org/10.1016/j.jcps.2013.07.004.

Rutz, Oliver J., and George F. Watson. 2019. "Endogeneity and Marketing Strategy Research: An Overview." *Journal of the Academy of Marketing Science* 47 (3): 479–98. https://doi.org/10.1007/s11747-019-00630-4.

Schmitt, Bernd H. 1994. "Contextual Priming of Visual Information in Advertisements." *Psychology & Marketing* 11 (1): 1–14. https://doi.org/10.1002/mar.4220110103.

Schmitt, Bernd H., June Cotte, Markus Giesler, Andrew T. Stephen, and Stacy Wood. 2022. "Relevance—Reloaded and Recoded." Journal Article. *Journal of Consumer Research* 48 (5): 753–55. https://doi.org/10.1093/jcr/ucab074.

Shaddy, Franklin, Ayelet Fishbach, and Itamar Simonson. 2021. "Trade-Offs in Choice." Journal Article. *Annual Review of Psychology* 72 (Volume 72, 2021): 181–206. https://doi.org/10.1146/annurev-psych-072420-125709.

Shadish, William, Thomas D Cook, and Donald Thomas Campbell. 2002. *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*. Book. Boston: Houghton Mifflin.

Shankar, Venkatesh, Dhruv Grewal, Sarang Sunder, Beth Fossen, Kay Peters, and Amit Agarwal. 2022. "Digital Marketing Communication in Global Marketplaces: A Review of Extant Research, Future Directions, and Potential Approaches." Journal Article. *International Journal of Research in Marketing* 39 (2): 541–65. https://doi.org/10.1016/j.ijresmar.2021.09.005.

Simonsohn, Uri, Andres Montealegre, and Ioannis Evangelidis. 2024. "Stimulus

Sampling Reimagined: Designing Experiments with Mix-and-Match, Analyzing Results with Stimulus Plots." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4716832.
Sridhar, Shrihari, Cait Lamberton, Detelina Marinova, and Vanitha Swaminathan. 2022. "JM: Promoting Catalysis in Marketing Scholarship." Journal Article. *Journal of Marketing* 87 (1): 1–9. https://doi.org/10.1177/00222429221131517.
Stephen, Andrew T. 2016. "The Role of Digital and Social Media Marketing in Consumer Behavior." Journal Article. *Current Opinion in Psychology* 10 (1): 17–21. https://doi.org/https://doi.org/10.1016/j.copsyc.2015.10.016.
Swaminathan, Vanitha, Cait Lamberton, Shrihari Sridhar, and Detelina Marinova. 2023. "Paradigms for Progress: An Anomaly-First Framework for Paradigm Development." Journal Article. *Journal of Marketing* 87 (6): 816–25. https://doi.org/10.1177/00222429231201959.
Swaminathan, Vanitha, Alina Sorescu, J. B. E. M. Steenkamp, Thomas C. O'Guinn, and Bernd H. Schmitt. 2020. "Branding in a Hyperconnected World: Refocusing Theories and Rethinking Boundaries." *Journal of Marketing Research*. https://doi.org/10.1177/0022242919899905.
Wies, Simone, Alexander Bleier, and Alexander Edeling. 2023. "Finding Goldilocks Influencers: How Follower Count Drives Social Media Engagement." Journal Article. *Journal of Marketing* 87 (3): 383–405. https://doi.org/10.1177/00222429221125131.
Xu, Heng, Nan Zhang, and Le Zhou. 2020. "Validity Concerns in Research Using Organic Data." *Journal of Management* 46 (7): 1257–74. https://doi.org/10.1177/0149206319862027.
Yi, Xing, Liangjie Hong, Erheng Zhong, Nanthan Nan Liu, and Suju Rajan. 2014. "Beyond Clicks: Dwell Time for Personalization." In *Proceedings of the 8th ACM Conference on Recommender Systems*, 113–20. RecSys '14. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/2645710.2645724.
Yoon, Song-Oh, and Itamar Simonson. 2008. "Choice Set Configuration as a Determinant of Preference Attribution and Strength." *Journal of Consumer Research* 35 (2): 324–36. https://doi.org/10.1086/587630.
Zhou, Lingrui, Katherine M. Du, and Keisha M. Cutright. 2022. "Befriending the Enemy: The Effects of Observing Brand-to-Brand Praise on Consumer Evaluations and Choices." Journal Article. *Journal of Marketing* 86 (4): 57–72. https://doi.org/10.1177/00222429211053002.
Zierau, Naim, Christian Hildebrand, Anouk Bergner, Francesc Busquet, Anuschka Schmitt, and Jan Marco Leimeister. 2023. "Voice Bots on the Frontline: Voice-Based Interfaces Enhance Flow-Like Consumer Experiences & Boost Service Outcomes." *Journal of the Academy of Marketing Science* 51 (4): 823–42. https://doi.org/10.1007/s11747-022-00868-5.

A. The Sound of Certainty

A.1. Pre-Test

The document processes and analyzes data generated in a pre-test. The pre-test aimed to identify pairs of model headshots between which participants found it hard (easy) to decide. The identified pairs of two serve as stimuli for the high (low) conflict condition in *Study I*.

Procedure: We conducted two online experiments to pre-test eighteen pairs of female headshots as well as eleven pairs of male headshots in October 2022 and August 2023, respectively. Both pre-tests followed the same procedure and led participants through a series of decisions in which they were exposed to two model headshots. For each of these pairs of headshots their task was to indicate which they find more attractive and how difficult they found the decision to be.

Participants: 131 Prolific panelists (M_{age} = 24.28, SD_{age} = 2.76; 40% female) completed the pre-test studying female headshots whereas 100 Prolific panelists (M_{age} = 39.72, SD_{age} = 14.24; 43% female) completed the pre-test studying male headshots.

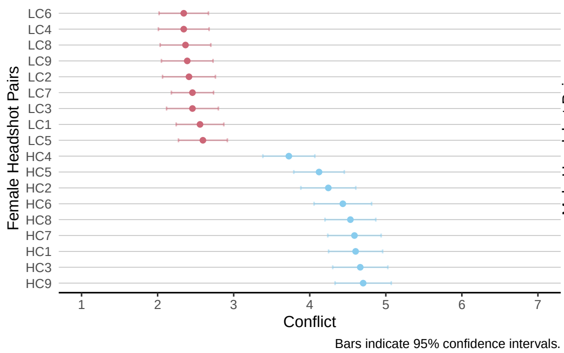


Figure A.1.: Pre-Test Female Headshots

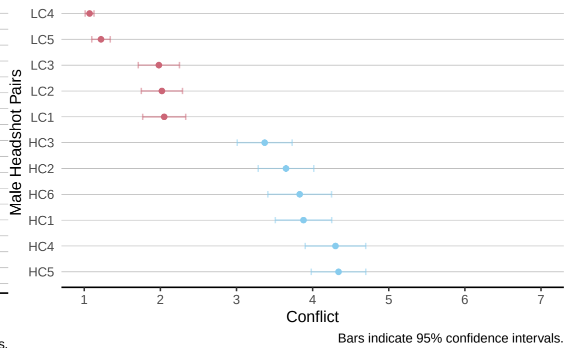


Figure A.2.: Pre-Test Male Headshots

The visualizations show on two accounts that the low conflict pairs (abbreviated with `LC` and colored in red) are perceived significantly different than the high conflict (`HC`, blue) pairs.

The visualizations also show that there is some variation within these two conditions. We'll choose the pairs that are the most extreme: e.g. we pick the pairs that represent the highest (lowest) `conflict` for the `HC` (`LC`) condition.

Hence, we implement the pairs listed in the following table. The first column refers to the codes used in this analysis (displayed in the visualizations). The second column refers to the gender of the models shown in each pair and the last columns displays the file names implemented in oTree.

Code	Gender	File Names
HC3	female	HCP1A, HCP1B
HC9	female	HCP2A, HCP2B
HC4	male	HCP3A, HCP3B
HC5	male	HCP4A, HCP4B
LC8	female	LCP1A, LCP1B
LC9	female	LCP2A, LCP2B
LC5	male	LCP3A, LCP3B
LC4	male	LCP4A, LCP4B

A.2. Stimuli

All stimuli can be found in our Github repository.