Disrupting System 1 Thinking: Better Science for Smarter Marketing

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Executive Summary

Since the publication of Daniel Kahneman's *Thinking Fast and* Slow in 2012, there has been an explosion of interest in System 1 versus System 2 thinking (aka Dual Process Theory) and its applications to marketing in particular. But what if we have it wrong? Are we using the latest and best science appropriately? The conventional wisdom is that most decisions are made by System 1, and only occasionally does System 2 kick in to override System 1. Additionally, System 1 decisions are thought to be very resilient, and the biases impossible to break. These "new" laws of human behavior have fueled dubious claims about related phenomena, such as 95% of behaviors are driven by non-conscious processes, cognition and emotion are two separate and independent processes, emotion is entirely non-conscious and measuring it is exclusively the domain of neuroscience, and cognition is entirely conscious and easily accessible by asking questions.

While the narrative is easy and compelling – that emotions help overcome our cognitive limitations by facilitating rapid non-conscious responses – it does not represent the complex and adaptive nature of the decision-making process. A fundamental paradigm shift is happening in the scientific literature away from the canonical Dual Process Theory (DPT), and marketing must keep pace lest we miss out on important and valuable insights.

The traditional, "System 1, then sometimes System 2" sequence is not supported by the data—people engage in both automatic and deliberative thinking at the same time, sometimes in conflict. Cognitive processing is not binary, but falls along a continuum, ranging from slow/deliberative to fast/automatic. An independent, regulatory process monitors and guides the cascade of processes, literally disrupting automatic responses and allowing a decision or behavior to be adapted dynamically, based on the context and availability of resources. All of this is deeply influenced by the context, goals, prior associations and experiences stored in memory, and the bodily sensations that combine with these other factors to produce emotions.

In this work, we have crystallized the latest science into a new model for human experience and decision making. This model disrupts the myths that have grown out of the prior generation of science and addresses some of the most important marketing questions of today: What causes marketing disruption? How can I design, evaluate and optimize products and experiences that disrupt default behavior? How can I create emotional experiences that will support adaptive decisions and stimulate behavior change? We discuss the evolution of the proposed model and its scientific basis. Then, we discuss results from our research on how disruption influences adaptive decision making and changes behavior in marketing and other domains, with empirical examples from advertising research and the changing shopping behaviors around the COVID-19 public health crisis.

The Prevailing Narrative

The idea that there are two distinct modes of thinking, System 1 and System 2, has been very influential in marketing and market research since Daniel Kahneman won the Nobel Prize in Economics in 2002 and published *Thinking Fast and Slow* in 2011 [1]. This idea has a longer history in cognitive and social psychology where it is known more generally as Dual Process Theory (DPT) [2]. Kahneman popularized a version of the theory called default interventionist DPT that argues that, when making a decision, people will first rely on the more automatic, System 1 (the default), then sometimes switch to the deliberative System 2 (intervening and overriding the default response).

This approach has spawned a wide array of myths and misconceptions in marketing about the primacy of automatic and non-conscious processing, the independence of emotion and cognition, and confusion about the relevance and utility of various research methods, including surveys and neuroscience methods. At its most extreme, the presumption among some companies, sparked by some consultants who rely more on popular science, is that consumer decisions are dominated by a cluster of conflated processes that includes System 1 emotions, all presumed to be non-conscious in nature.

The latest science shows that the dominant System 1/System 2 narrative in marketing and policymaking is an over-simplified view -- human psychology is more complex. This is particularly important in today's disruptive digital world, where individuals are bombarded with influences and the cost of getting marketing wrong is massive. Specifically, several researchers have criticized DPT, pointing to the variability in dual-processing accounts, the vagueness of its definition, and lack of coherence and consistency in the cluster of attributes for each "system" [3, 4]. Similarly, parallel developments in cognitive neuroscience and developmental psychology have also challenged the core tenets of DPT [5, 6].

New Behavioral Science Evidence

Over the years, the results of a number of studies have challenged the prevailing DPT narrative. First, these results challenge the notion that the two systems engage sequentially (System 1 and then System 2) and that the automatic System 1 responses lack any form of regulatory control and detection of conflict. Let's take the example of the classic Cognitive Reflection Test question known as the bat and ball problem [7]. In this problem, a bat and a ball together cost $1.10 and the bat costs $1 more than the ball. Research participants are given this problem and asked to report the cost of the ball. The common (incorrect) response of $0.10 is often used to illustrate the default interventionist idea as the biased, automatic "System 1" response. Implicit in this assumption is the implication that participants are ignoring key aspects of the problem in providing a fast response.

What happens if we create an easy version of the bat and the ball problem, where participants are just told that both cost $1.10 and the bat costs $1 (rather than "the bat costs $1 *more* than the ball")? The default response of $0.10 is now the correct response. Critically, do participants process the two problems similarly? According to the prevailing DPT narrative, participants should engage identical processes in both versions of this problem when providing the $0.10 response. However, across a range of studies from different labs using a variety of problems similar to the one above, research shows that people answering the original "hard" version take longer [8], fixate their eyes on the "harder" parts of the problem like the comparison prompts [9], recall the hard parts better [10], express less confidence in the response [11], exhibit more autonomic nervous system response in the form of increased skin conductance [12], and show more activation in the areas of the brain associated with conflict detection and executive control [13-15]. Together, these findings challenge some fundamental premises of DPT, both in terms of the sequential "System 1, then System 2" argument, as well as the engagement of regulatory processes in System 1 response. On the other hand, these problems suggest that people detect conflict and recruit additional processes even when engaging in biased automatic reasoning and fast automatic responses.

Multiple paths to "System 1" response. Another implication of DPT is that there is often a single biased System 1 response, which could get overridden by a deliberative System 2 response. However, across the experiments, findings suggest that some people are able to get the correct (unbiased, System 2-like) response ($0.05 in the hard bat and ball problem above) very quickly, a response referred to as "logical intuition". To explore this further, experimenters have asked participants to provide a fast response first and a second more deliberative response after a delay. Traditional DPT argues that the majority of responses during the early stage should be incorrect ($0.10), which then shifts to the correct response ($0.05) after deliberation. However, a significant proportion of people arrive at the correct response even without deliberation, through logical intuition. These effects persist even when System 2 processing resources are "knocked out" by engaging people in a demanding memory task (e.g., remembering spatial patterns presented on the screen) [14].

Together, these findings suggest that multiple threads of processing (biased heuristic, logical intuition, deliberative) get activated in parallel and that regulatory control processes are engaged fairly early in the decision processing pipeline, presenting serious challenges to default interventionist DPT.

The Role of Control in Adaptive Processing: Neuroscience Evidence

A central dogma in much of the early work in the field of decision neuroscience argued that rational and irrational behaviors result from the activation of distinct and independent systems for cognition and emotion respectively [16] [17] [18] [19]. However, subsequent papers started challenging this dogma [6], with evidence in favor of a more distributed and integrated processing across emotional and cognitive regions in multiple domains like intertemporal choice [20]; loss aversion [21]; and risk strategies [22]. Similar findings also began to emerge in the developmental literature challenging the view that logical intuitive reasoning and mathematical cognition were distinct and independent [5]. Instead, the ability of humans to detect conflict, inhibit responses, and shape behavior in a flexible manner has been attributed to the adaptive use of cognitive control [23].

The current view argues that irrationality and biases do not necessarily reflect a failure of brain systems for cognitive control; instead, control systems may lead to distinct choices adaptively depending on context. In other words, the extent of deliberative versus automatic processing is an adaptive function of cognitive control and executive processing.

Based on these novel insights from the scientific literature, we outline a new decision-making framework that makes three important advances over the prevailing "System 1, then sometimes System 2" idea:

1. New behavioral science evidence shows that when confronted with a decision to be made, **multiple processes** are launched and operate in parallel. These threads unfold, cross-feed, are abandoned, resumed, and iterated across the course of time, from milliseconds to days, depending on the context and the need for action.
2. These cognitive processes fall along a continuum or **gradient of cognitive effort** from fast/automatic to slow/deliberative.
3. There is a regulatory or **adaptive process** in the brain that modulates or guides this cascade of processes and selects a strategy or response that is best adapted to the current decision context.

Contextual Factors in Adaptive Processing

Rationality sometimes assumes that individuals have stable well-defined preferences that pervade across all contexts. Under this view, each option or choice is associated with a fixed utility that depends entirely on the option and the ability of the individual to compute it. Yet, the limitations of human processing often lead to bounded rationality, where preferences are often constructed in making a decision, and not merely revealed [29]. An important implication of constructed preference is that choices are often highly contingent on a variety of factors characterizing the decision environment – decision context, task framing, goals, knowledge, attitudes, and emotional states.

Context plays a critical role in decision making by influencing how individuals perceive and process the choice options**.** For example, the same option (e.g., a dictionary with 10,000 words in brand new condition or a dictionary with 20,000 words that has a torn cover) may be evaluated differently based on whether it is presented in isolation or in the presence of the other alternatives within the choice set [30, 31]. Another classic example is the attraction effect [32], where the inclusion of an irrelevant and dominated "decoy" option (print only subscription to Economist at $129) influences the relative preference between two other choice alternatives (online subscription for $69 versus a combined online and print subscription for $129). In this study, 68% of the people prefer the $69 online-only subscription in the absence of decoy, but only 16% prefer this option in the presence of the decoy [33]. Finally, preferences are also influenced by how the question is framed – strategically equivalent methods for eliciting preferences (e.g., do you like an item versus how much will you pay for an item) can lead to systematically different decisions [34].

Preferences also depend critically on the goals of the decision maker [35]. These goals could be related to minimizing the effort needed to complete the task, maximizing the accuracy of the decision, minimizing the possibility of regret associated with the decision, or a combination of these. Goals can directly influence the attention paid to stimuli, making some information more salient than others [36]. Goals can also influence the interpretation and meaning associated with the input information, particularly through the explicit integration of prior knowledge and experience [37]. Finally, goals also influence the degree of control and effort, leading to differences in the processing strategies and behavioral outcomes [29, 38]. For example, the processing strategies and response to the hard bat and ball problem introduced earlier may be very different depending on whether it is part of a longer online survey or a job interview. Critically, goals can also be manipulated experimentally (e.g., asking individuals to make decisions under time pressure, or emphasizing accuracy).

Preferences are also influenced by knowledge, long-term memory, and attitudes. Preferences are not always constructed, and individuals are also likely to have well-formed and stable preference especially when they are familiar with the choice option or have made similar decisions in the past [39]. Past knowledge or schemas influence the degree of processing and control associated with different choice scenarios, such as prior exposure and familiarity with the bat and ball problem influencing the strategies used by individuals in other related problems. Additionally, individual attitudes and traits also play a key role in influencing the degree of effort, salience of goals, and framing of input information [40]. In the context of marketing, a consumer's past experience with products and services will feed into their future decisions and can ultimately lead to more automated processing and formation of habits. Integrating these elements into the model is therefore critical for understanding the decision process.

Last but not the least, emotions also play a key and integrated role in decision making. In the words of Herbert Simon, "*In order to have anything like a complete theory of rationality, we have to understand what role emotion plays in it".* Emotions can be classified into four broad categories – ambient or incidental emotions which are not directly related to the task, task-integral emotions arising from the nature of the task itself, and affective reactions related to the experienced and anticipated outcomes. These different emotions can then influence goals, beliefs, and cognitive effort [41]. A particularly important framework for integrating these different categories of emotions is the *Somatic Marker Hypothesis* formulated by Antonio Damasio and his associates, which proposes that emotional processes guide (or bias) behavior [42]. "Somatic markers" are feelings in the body that are associated with emotions, such as the association of rapid heartbeat with anxiety, or of nausea with disgust. According to the hypothesis, these somatic markers or bodily sensations are generated both by past associations as well as by anticipating future outcomes and can strongly influence subsequent decision-making strategies.

Therefore, we extend our proposed adaptive decision-making framework that challenges DPT by integrating context, goals, long-term memory and knowledge, and bodily sensations to build our more comprehensive Ipsos Dynamic Decision-Making Model (DDMM, Figure 1). In this model:

- Stimulus context, goals/motivation, long-term memory/knowledge/self and body states all influence the nature of adaptive processing and cognitive control, leading to engagement of different strategies that lie along the continuum of automatic and deliberative processing.
- These different factors also interact and influence each other (e.g., specific goals can be influenced by long-term memory and lead to different body sensations)
- These factors are also updated based on the outcome of decisions and may have differential influence on similar decisions in the future

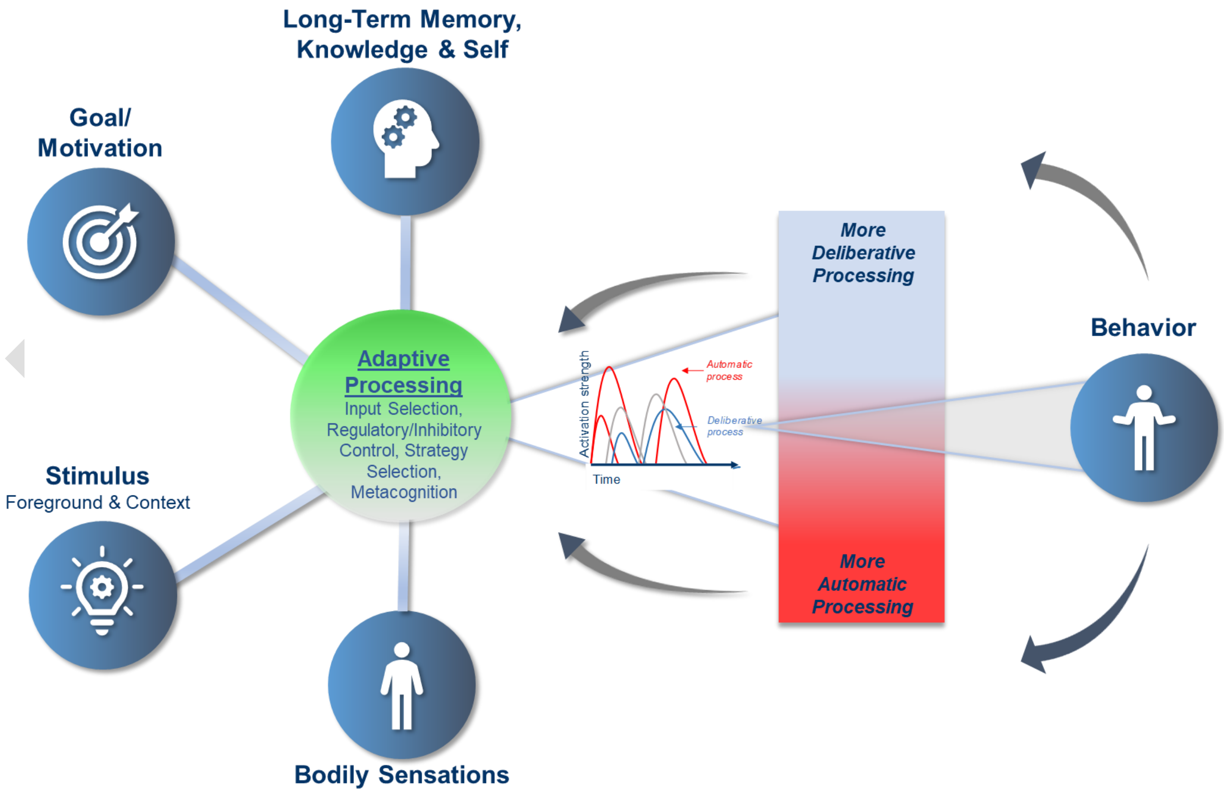

Figure 1: Ipsos Dynamic Decision-Making Model (DDMM)

Case Studies

Our proposed DDMM is sufficiently flexible to apply to almost any decision made by individuals across a wide array of contexts. Naturally, questions arise about how it can be applied and interpreted in different decisions and contexts? While the framework is broad, it provides clear hypothesized relationships where the components that are more influential will vary from scenario to scenario and not all components of the model have to be explicitly involved in each and every case. At the same time, it is also important to appreciate the limitations based on the constraints of the current scenario and measurement tools, and temper expectations and inferences accordingly. At Ipsos, we have embarked on a series of R&D studies that are designed to explicitly characterize the dynamic nature of decision-making process in different domains through the use of unique experimental designs, survey questions, response time measures, and other relevant methods. In this section, we highlight two such examples of adaptive processing in decision making in the domains of advertising and shopping behavior research.

Case Study 1: Disruption Through Advertising

Advertising is the primary mechanism through which companies inform potential customers of their products, educate them, and attempt to influence their preferences. This is a key domain where the more nuanced approach to decision making can help identify distinct opportunities to influence behavior for marketers over simplistic dual system approaches.

In this study, we sought to understand how consumers choose between different brands, and whether and how we can disrupt this choice. Specifically, based on the proposed model, can we identify which consumer is likely to be influenced and switch their preference following exposure to an ad? We recruited 300 participants for a decision-making task involving four competing food brands in a specific subcategory (the four brands comprise of a leader brand A, a competitor brand B, and two other brands C and D; names of the brands and specific category are anonymized to maintain client confidentiality). Using prescreening, we only recruited consumers who prefer the leader brand A. Therefore, these consumers are motivated, based on past knowledge and experience, to prefer the leader brand A against all other competitors. However, they should be more open minded in choices involving the other brands in the absence of the leader brand.

The study was divided into four phases. First, while all participants were selected to prefer leading brand A, they were asked to indicate their curiosity as well as their degree of anticipated regret for not choosing competitor brand B. These measures provide an indicator of their degree of affinity to the leader brand. In the second phase, participants completed a series of binary choice trials. First, they completed a few calibration trials where they had to choose between two distinct random brands. Subsequently, we presented them with three randomized pairs of binary choices involving brands from the relevant food category (A vs. B, A vs. C, B vs. C). In addition to their preferences (i.e. their explicit selection in each binary choice), we also measured their speed of response. The calibration trials allowed us to account for individual variability in the speed of response. After completing the paired choices, participants moved to phase three where they were exposed to a series of four video ads. For half the participants (test group, N=150), these included an ad for competitor B. No such relevant ad from the chosen food category was shown to the other half of the participants (control group, N=150). After viewing the ads, participants were asked a few additional questions about one focal ad. Finally, in phase four, they repeated their decisions from phases one and two again.

We hypothesized that traditional DPT would simply predict that participants will be faster in selecting leader brand A, their preferred brand, when it is available as an option, regardless of whether it is paired against B or C or if participants are exposed to a competitor ad. Therefore, all participants should continue to choose the leader brand A in both groups regardless of the distractor ad because it is their preferred brand. They should also be faster post exposure because of familiarity with the task and learning effects. On the other hand, our proposed DDMM argues that the competitor ad will disrupt the automatic processing and force people to adapt their response even to the preferred brand. While some people will switch choices and choose competitor brand B now, others may continue to choose leader brand A despite the conflict. Regardless of switching, those in the test group will be relatively slower in making their decisions than those in the control group because exposure to an ad for competitor brand B disrupts their processing. Critically, the proposed model also argues that customers who indicated greater regret when choosing the leader brand initially are also likely to experience the greatest conflict as measured by post-ad response duration or brand switching behavior.

Our findings were consistent with the predictions. Despite the respondents' initial preference for leader brand A, there was considerable variability in their curiosity and degree of regret about competitor brand B consistent with individual differences in the degree of affinity and conviction. These in turn led to differences in the degree of processing and control when making additional choices involving the leader brand A. Critically, there was no difference in these measures between the test and control groups, consistent with a random assignment of participants to these groups. We found that participants preferred leader brand A relative to brands B and C, and competitor brand B over C (see Figure 2). Participants took significantly longer in choosing between B and C, relative to choices involving leader brand A as reported in Figure 3, consistent with lack of familiarity with brands B and C.

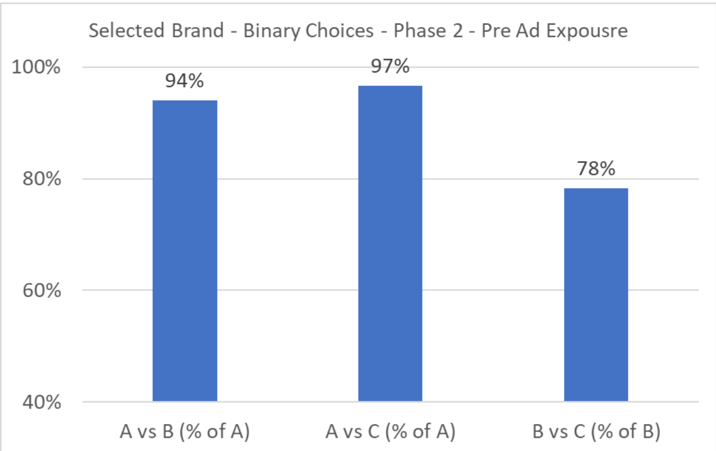

Figure 2: Aggregate preferences during the binary choice task pre ad exposure. Respondents selected their preferred brand (A) both over B and C as expected.

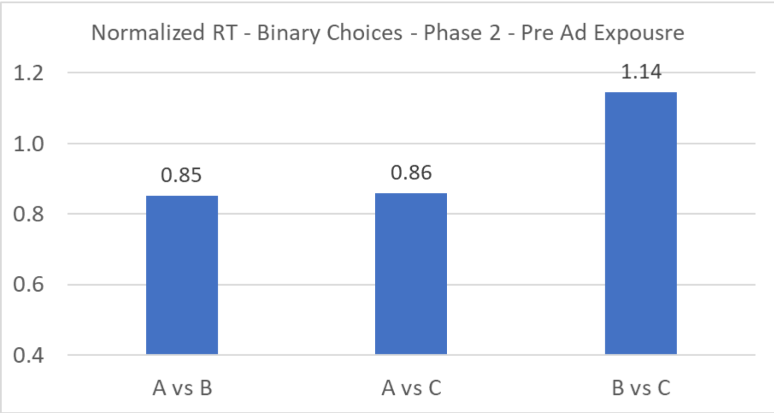

Figure 3: Average response times for the binary choice task pre ad exposure. As expected, respondents took longer when their preferred brand (A) was not included in the choice set.

We found that preference for the leader brand reduced significantly in the test group after exposure to competitor ad from 96% to 72% (X^2 (1,150) = 30.4, p < 0.001), but not in the control group. After accounting for learning effects by normalizing the response times to the calibration trials and focusing on individuals who did not change their preference (i.e., continued to choose leader brand A even after exposure to the ad), we still found that these participants in the test group were significantly slower in the A vs. B trials relative to the control group, consistent with the competitor ad disrupting choice and creating conflict. Figure 4 illustrates the comparison where the change in test group shows significantly slower response times than the control group (one sided t-test p=.035). While most individuals overcome this disruption and continued to choose leader brand A, a significant number of them switched to competitor brand B after exposure to the ad. In addition to the ad creating conflict in preference for the leader brand A, we also found facilitation effects where those exposed to the ad also selected competitor brand B at higher levels over the other challenger brand C post exposure. However, no such difference in relative preference between brands B and C was found in the control group.

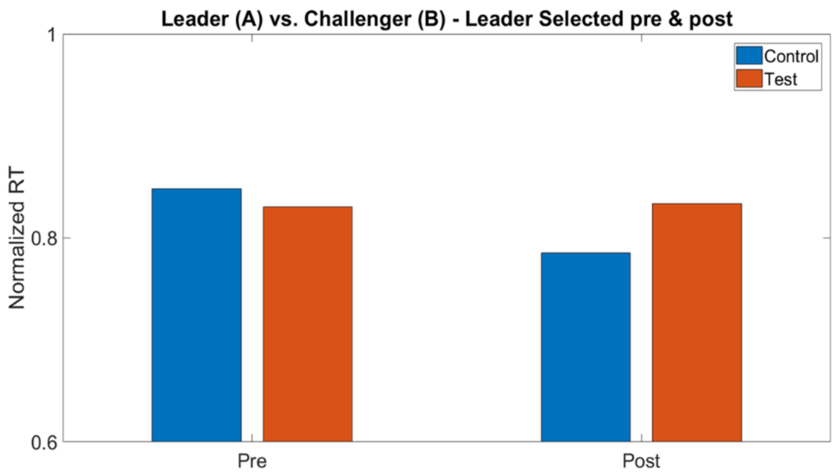

Figure 4: Exposure to the ad for challenger brand B slows down respondents when selecting leader brand A for the test group, but not control group.

Critically, is the switching behavior related to the initial degree of conviction for the leader brand A? We found that participants who did switch to the competitor brand B after exposure to the ad had indicated significantly greater anticipated regret at not choosing the competitor brand during the initial exposure to the brands in phase 1 (mean regret switchers = 70.5, mean regret non-switchers = 46.3, $t(280) = -4.46$, $p<0.001$).

In summary, our findings are consistent with DDMM such that context (prior experience and knowledge of the different brands could vary among the users of the leader brand) influences decisions and disrupts preferences, and the differences in conflict can be measured using a combination of self-report measures and response times. In future studies, we seek to extend these findings by including participants who are not users of the leader brand to start with. Additionally, we also plan a multi-method approach involving EEG, heart rate, eye tracking, galvanic skin response and facial coding to obtain additional measures of the adaptive processing.

Case 2: Shopping Behavior in the Time of COVID

With the lockdowns caused by COVID-19 in many countries, there has been an increasing tension among individual's desires to stay at home and their desire to resume normal activities such as shopping. To evaluate the nature of these preferences, we conducted studies with 1,000 respondents each in the US, China, France and Italy in May/June of 2020 after the lockdowns in France and Italy were lifted and as things seemed settled in China before the later re-emergence of clusters in Beijing. Comparing the results from the different countries allows identifying some key insights about behavioral change as well as distinctions driven by culture and their stage in the pandemic.

It may be tempting to think of staying home vs. going out as two ends of a spectrum of personal preferences. Here, we challenged this simplistic traditional view and tested its accuracy by independently measuring an individual's preference to go out and shop at stores like they did before the pandemic and their preference to stay home and protect themselves and others. Consistent with DDMM, we found that evaluation of preferences and the adaptive process varied across the multiple markets.

First, we found that these preferences are not two ends of a spectrum but separate aspects on which individuals can hold simultaneous conflicting views, with strong preferences for both. In Table 1, we can see that a substantial number of individuals indicated a preference for both wanting to stay home for protection ***and also*** for wanting to go out and shop again as they had previously. Critically, these proportions varied across markets, as a function of the phase of the pandemic reflected in the market at the time of data collection. While the data was collected in a fairly fluid environment and reflect only one point in time, nevertheless it is clear from Table 1 that individuals showed higher preference for both behaviors in the US, which was earlier in its phase of the pandemic relative to the other markets.

Table 1: Preferences across Staying Home and Shopping Behaviors (T2B)

	US	China	France	Italy
Neither Behavior	11%	10%	20%	17%
Only Shopping	24%	37%	39%	33%
Only Staying Home	27%	26%	25%	25%
Both Behaviors	39%	26%	17%	25%

To explore these market-based differences further, we also employed Ipsos's approach of enhanced causal Bayesian Network Modeling and identified that there were clear distinctions in the relationships between the two behavioral preferences. In our full analysis of over 20 dimensions (such as motivations, perceived abilities, psychological processing, emotions, physical environment and social context) tapping into views of behavior change around each preference, we actually found that there was no direct relationship between the preferences of staying home and going to shop in the US market. There was a modest negative relationship between the two in France and Italy at that time and it was reciprocal, feeding in both directions. This contrasted with the strong one-way direction in China where shopping desire was one of the top determinants among the full set of psychological measures around staying home and protecting oneself and others. Thus, culture and the phase of the pandemic across markets led to very distinct causal patterns between these two fundamental constructs as illustrated in Figure 5.

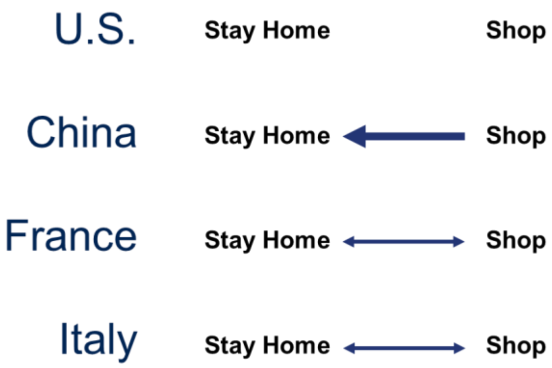

Figure 5: Relationship between staying home and shopping preferences across the different markets (excerpts from full Ipsos Bayes Nets models). Based on structural models, we predict that increasing one's preference to shop will lead to a modest decline in their desire to stay home, and vice versa, in France and Italy. In China, the predicted impact is stronger but only in one direction and there is no predicted relationship between the two in the US.

Along with cultural distinctions, the phase of COVID-19 in each locality affected how individuals were connecting their attitudes in their evaluations. In fact, in each market, we also found different psychological drivers of the preferences for staying home from those for shopping, further distinguishing between these as two distinct and separate constructs. These drivers in each market map nicely onto the different contextual dimensions of the DDMM framework like goals and motivations, knowledge and bodily sensations.

Second, in terms of adaptive processing, as we saw in the first case of advertising behavior, perceived regret is often a good indicator of conflict. Following the questions on how much the individuals want to engage in each of the behaviors separately, they were also asked how much they may regret that decision. For those individuals identified as having strong preference for both protection and shopping, we found that they expressed significantly greater levels of regret for their decision compared to those in the other conditions whose views did not conflict across all countries (Figure 6). The consistent findings with anticipated regret in both cases suggest that survey questions can tap and identify differences in conflict, and this is not only identifiable through neuroscience measures.

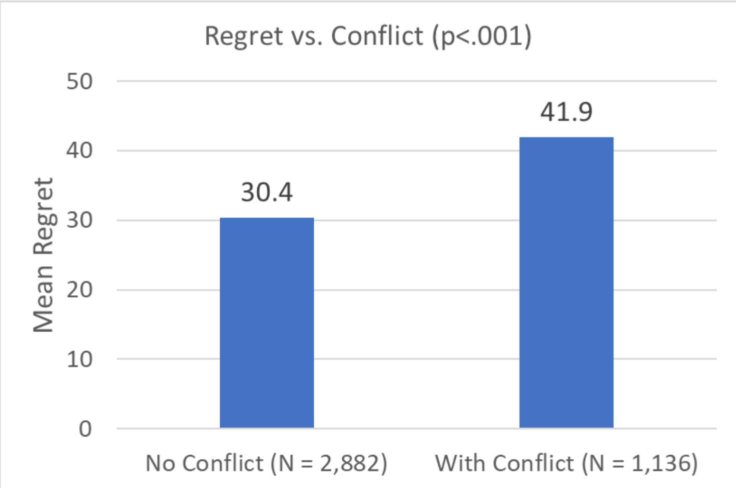

Figure 6: Higher levels of regret are expressed by those conflicted across the two behaviors.

Beyond the survey and driver analyses, this study also included a series of paired choices around shopping and protection preferences designed to get at differential levels of attitudinal conflict. This data was obtained with participants from the US market only. First, they were asked to indicate their basic preference between staying at home versus going out to shop. Subsequently, they were presented with 12 pairs of the choice behaviors, with different constraints added to each option (e.g., stay at home and protect healthcare workers versus go out to shop and help local businesses). According to DDMM, participants who take longer in deciding between the simple staying at home vs. going to shop options demonstrate the greatest conflict in their preference. Consistent with this prediction, individuals who were faster in selecting staying home in the base question were more likely to select the protection option across the additional pairs compared to those who were slower ($r=-.12$, $p=0.01$). Conversely, those faster in selecting the shopping option were more consistent in selecting shopping options across the choices compared to those who were slower ($r=-.10$, $p=.06$).

Thus, similar to the advertising study, we again found that response time can identify differences in the level of conflict involved in making the decision. The increased degree of conflict translates to choice behaviors that are less consistent across trials. In other words, individuals who experience greater conflict about their choice are slower in making their choices, and are the ones who are more likely to be influenced by contextual factors. In both cases, our proposed model argues for a more complex relationship between response time and attitudes with slower times not necessarily being normatively better or worse but identifying distinctions in the adaptive processing that individuals are experiencing. This challenges the popular notion that fast is always better and instead posits a more nuanced relationship between time taking and the *nature of the processing desired*. Sometimes it is helpful to slow people down and other times it is useful to encourage faster responses, it all depends on the behavior in question and outcomes being sought.

Conclusions and Implications

Human decision making is governed by a much more complex and nuanced process than a simple binary switch between two modes of thinking. We are flexible and dynamic in the way our decision processes unfold such that we can adapt our behaviors and outcomes to fit the environment or context we are in. Multiple processes ranging from more mindless and automatic to more mindful and controlled cascade in any given problem or focal choice situation. And all of this is influenced by our context, goals, sensations, emotions and prior experience and memory.

What does this mean for managers seeking to influence consumer choice or policymakers, governments or cultural leaders looking to influence human behavior? The marketing and public policy zeitgeist of the past 15 years has been dominated by a fascination with processes that are thought to be automatic and unconscious and not under human control. The latest research summarized by our new model shows that human decision making is adaptive in nature. Likewise, the strategies and methods used by marketers and policy makers to influence people must also be adaptive. Sometimes the goal is to reinforce existing behaviors and facilitate automatic responding. In other instances, marketers may want to disrupt current thinking and spark a change in behavior and then implement approaches that will help sustain that behavior, perhaps even making it more and more automatic over time. Managing the structure of the decision process or choice architecture can be helpful in this endeavor, but a more effective approach to influencing human decisions and behavior will look to the broader array of factors including the person’s goals, personal and social motivations, emotions, and knowledge and memory of prior experiences, and how all these forces are balanced by adaptive or executive control. Marketing, government and other public policy strategies should therefore be based on the context and desired outcomes, seeking in some instances to speed mindless non-adaptive processing to support already automated decisions/behaviors, but in other instances to trigger inhibitory control by activating goals, motivations, emotions or associations that will bring to the fore a more mindful, deliberative and adaptive process.

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