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INTRODUCTION

Leveling Up Applied Behavioral Economics

DANIEL G. GOLDSTEIN

Microsoft Research

If you are applying behavioral economics concepts in the field, high on your list of undesirable outcomes is witnessing an intervention that had an effect in the lab fail to have an effect in the real world.

In the wake of the replication crisis in behavioral science, many improved research practices have been recommended, from pre-registering studies, to placing materials in open archives, to collecting more data. Collecting more data, however, can refer to a variety of things. The typical interpretation of the advice is to run lab studies with greater numbers of participants, which in turn leads to more precise estimates of treatment effects, which then leads to better decisions about what interventions to transfer from the lab to the field.[1] In this introduction, I would like to focus on yet another aspect of collecting more data: collecting data over more levels of a treatment variable, both in lab studies and in field pilot studies. Hence the title. After presenting examples of the insights gained by leveling up, I'll talk about why it matters for applied behavioral economics. Let's kick it off with a vignette.

Perceiving Probabilities

You're sitting in a workshop in a hotel somewhere in the world. You know the kind, with the U-shaped table and the dozen people and the bottle of sparkling water for every person. It's 10 in the morning, someone's presenting, and you're having productive daydreams. You're inspired, and you know because it's 10 AM you're about to have the best idea you'll have all day.

You hear something about probability weighting, that is, how people overweight small probabilities when they read them (as in the gamble studies on which prospect theory was built) but underweight small probabilities when they experience them (Hertwig et al., 2004). You start thinking about communicating probabilities with visual stimuli. You think that if people see visualizations of probabilities, it would be different than reading about them and different than experiencing them. Because frequency representations help people in other tasks (e.g., Walker et al., 2022), perhaps people seeing visualizations of probabilities as frequencies would cause them to neither overestimate nor underestimate the probabilities they represent.[2] You think that if you can find a way to visually display probabilities as frequency-based icon arrays, without language or simulated experience, it might have a lot of applied uses and improve decision-making in other tasks such as mortgage borrowing, gambling, or investment.

You think about doing a study in which you would show people a 10 x 10 grid with a number of randomly placed squares filled in, which represent the probability. You would display a grid, as in Figure 1.

Then, after a few seconds, it would disappear and people would guess how many dark squares they saw, as in Figure 2.

The relevant theory is prospect theory (Kahneman & Tversky, 1979), one of the foundations of behavioral economics. Its probability weighting function guides you to sample a low value, where probabilities are overweighted in prospect theory, and a high value, where probabilities are underweighted, as in Figure 3.

You come up with a random low grid and a random high grid. As a control condition, you just display numerals instead of grids for a few seconds. Figure 4 shows the two grids you presented and the results of your pilot.

1 A classic blunder of the past involved behavioral economists putting their bets on interventions that appeared large in very small lab studies, but not realizing that in small studies conventionally statistically significant effects are overestimated in magnitude (Vasishth et al., 2018; List, 2021).

2 You realize that you're drawing inspiration from research on over- and under-*weighting* probabilities (e.g., Prelec, 1998; Herwig et al., 2004) and you're thinking about over- and under-*estimating* visual probabilities, but they have been compared before (e.g., Hollands & Dyre, 2000) and you don't get hung up on that; you'll take inspiration wherever you can find it.

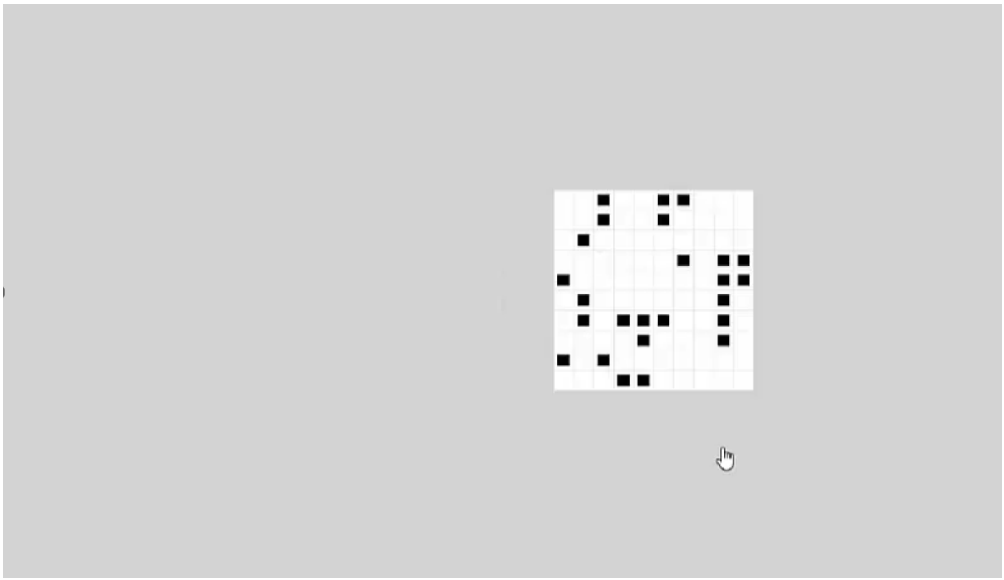

Figure 1: Randomly filled-in squares as a way of presenting probabilities.

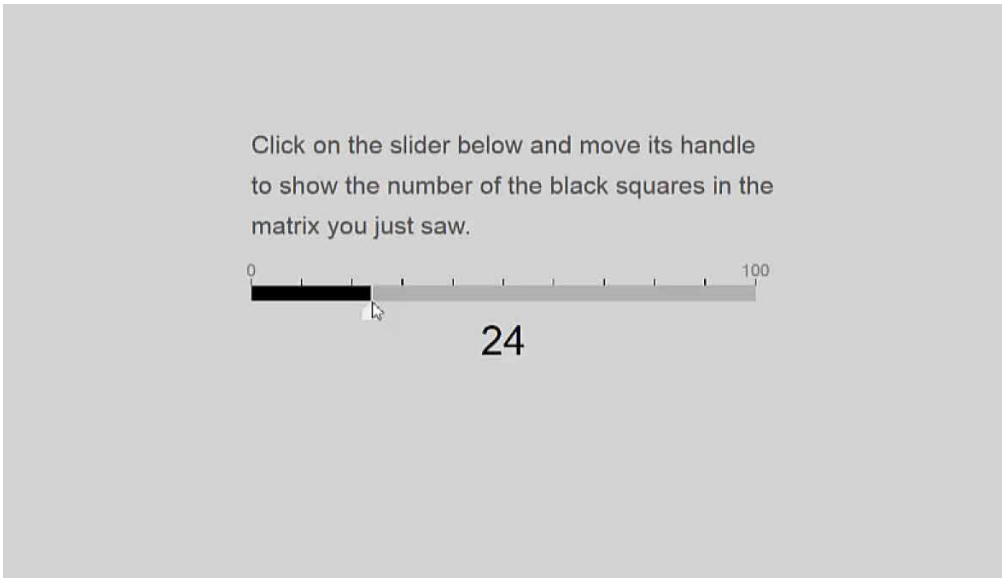

Figure 2: Interface for asking people to estimate the number of dark squares they saw.

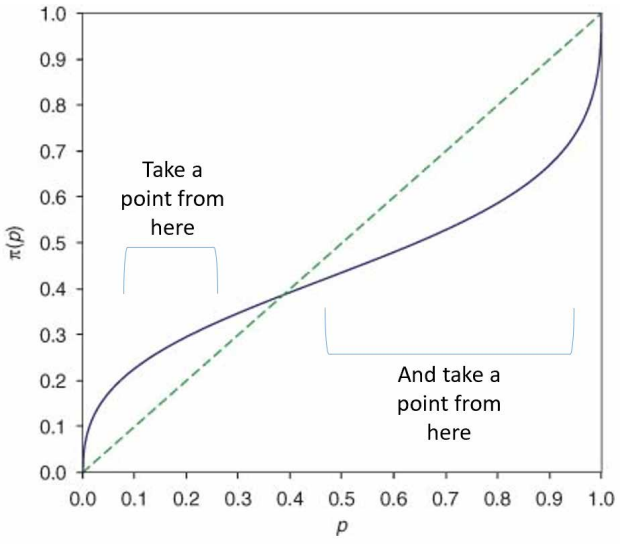

Figure 3: The probability weighting function from prospect theory.

People in the control condition who just read the numbers reproduced them perfectly on the slider. However, people overestimated the proportion after seeing the low value grid, and they then underestimated the proportion after seeing the high value grid.

This is not what you were expecting. You were expecting that this grid format might eliminate the bias. Instead, the results are somehow similar to the way prospect theory's probability weighting function overweights low probabilities and underweights high probabilities. So it's not what you were hypothesizing. Nonetheless, it is interesting because it shows that estimation of proportions in icon arrays works a bit like probability weighting in prospect theory!

Then you remember the lessons of the replication crisis. This is just one pilot with two grids—it might

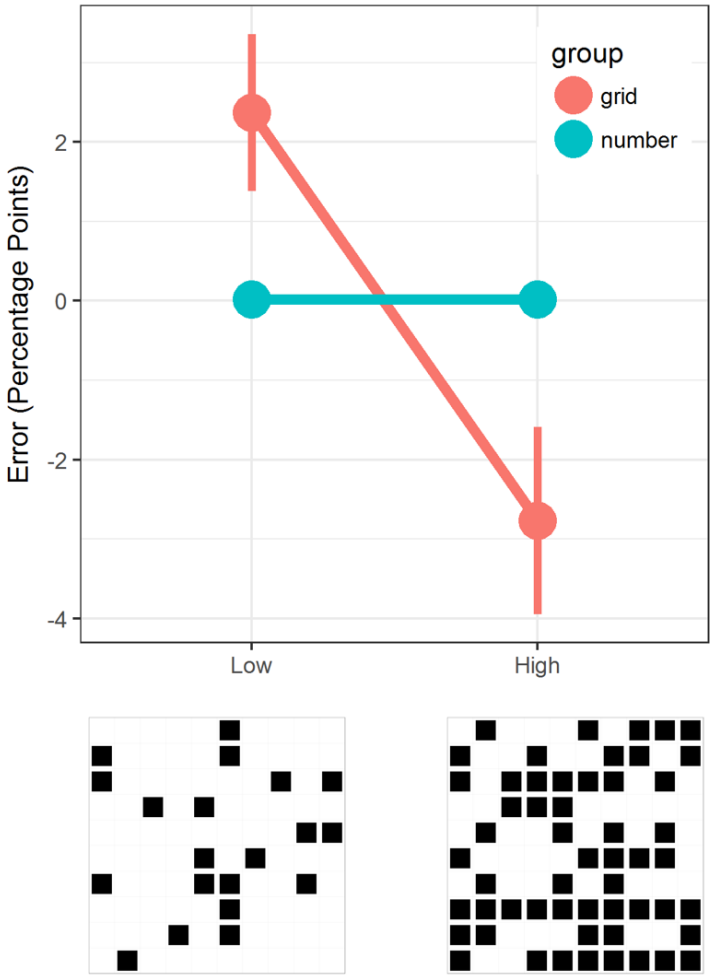

Figure 4: At the bottom, two grids that were presented to participants: one low (that would be overweighted in prospect theory) and one high (that would be underweighted in prospect theory). At the top, in red, the difference between the number of squares estimated and the actual number of squares presented. For the left grid, people overestimated the number of squares, while for the right grid, they underestimated it.

not replicate. So you choose some other low grid and another high grid (according to where prospect theory's probability weighting function suggests probabilities are overweighted and underweighted), and what do you know? It replicates. You choose two more grids. It replicates again. You choose two more grids. It replicates yet again. You've seen it in four pilots now, as shown in Figure 5. All with different stimuli!

Just to be safe, you run some more of these experiments, jittering the values around so that now you have 24 points on the horizontal axis. You fit Prelec's (1998) probability weighting function, which is a way to model probability weighting in prospect theory. Figure 6 shows that it looks like a probability weighting function, given that you take the classic plot (like in Figure 3) and change the vertical axis so that it shows the amount of overestimation or underestimation.

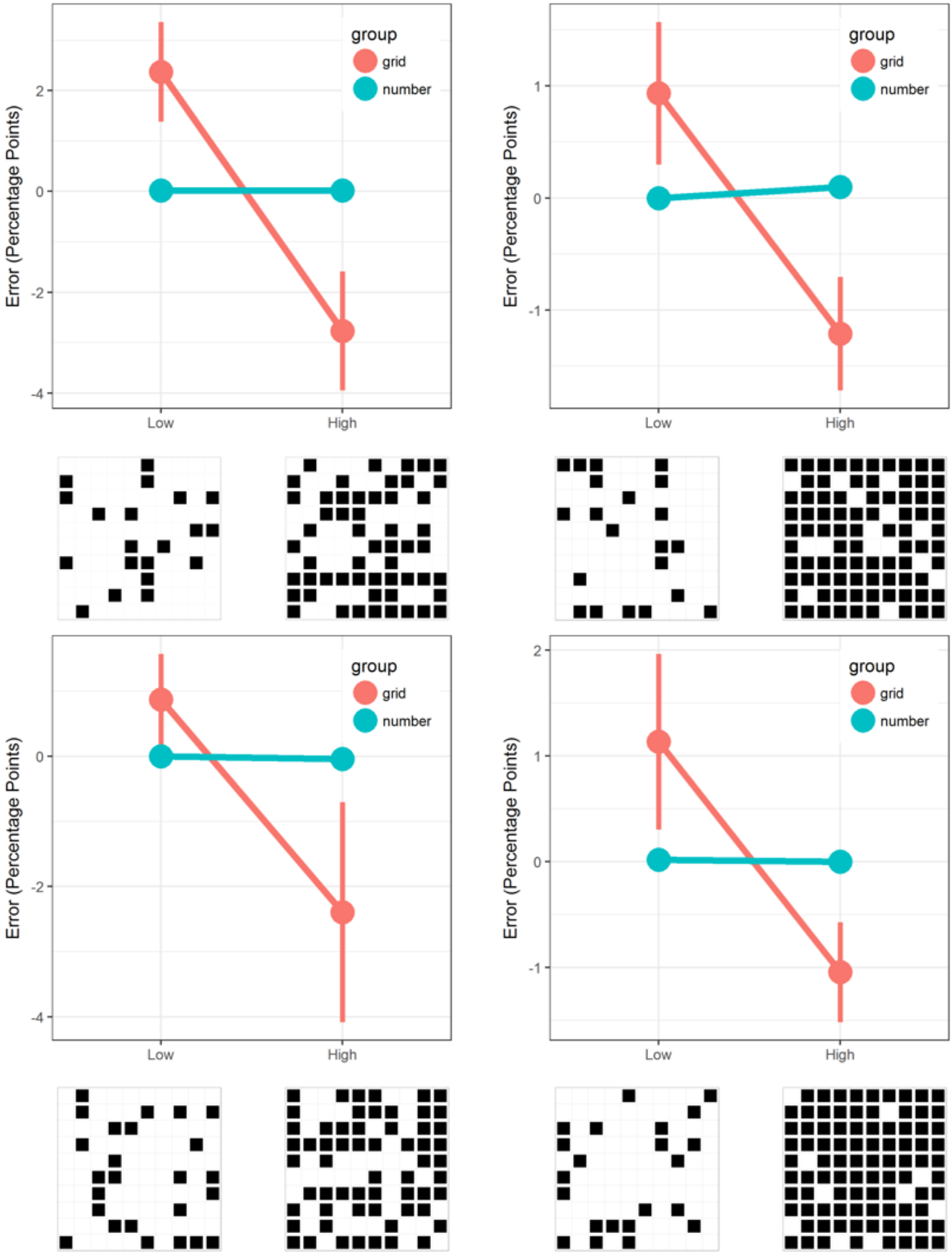

Figure 5: The same basic result appearing in four two-cell experiments, each involving a low value and a high value that would be predicted to be overestimated or underestimated according to the probability weighting function of prospect theory.

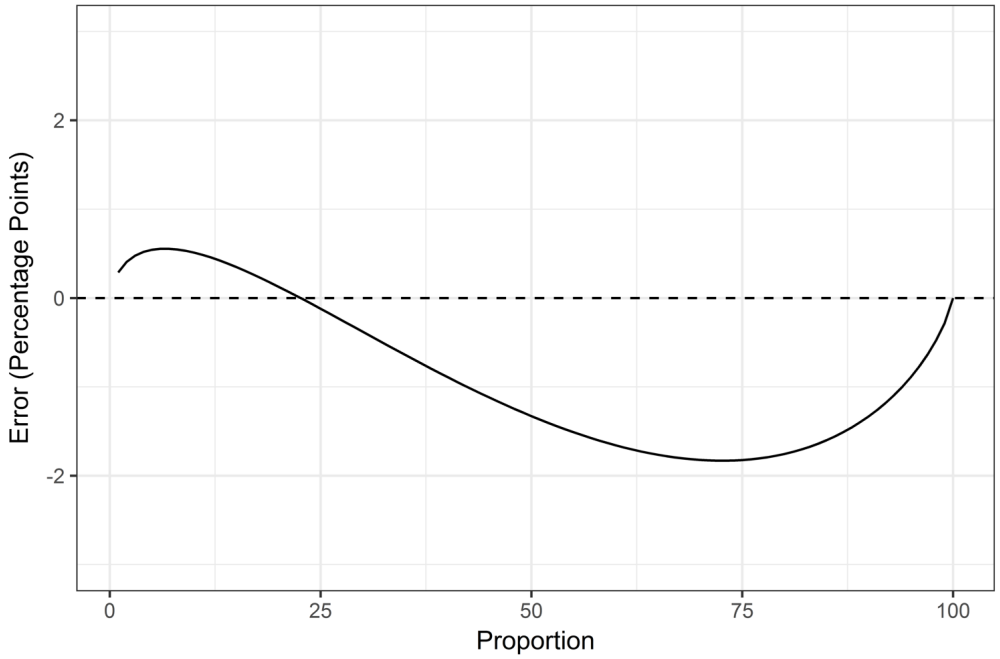

Figure 6: The result of fitting the probability weighting function to your results.

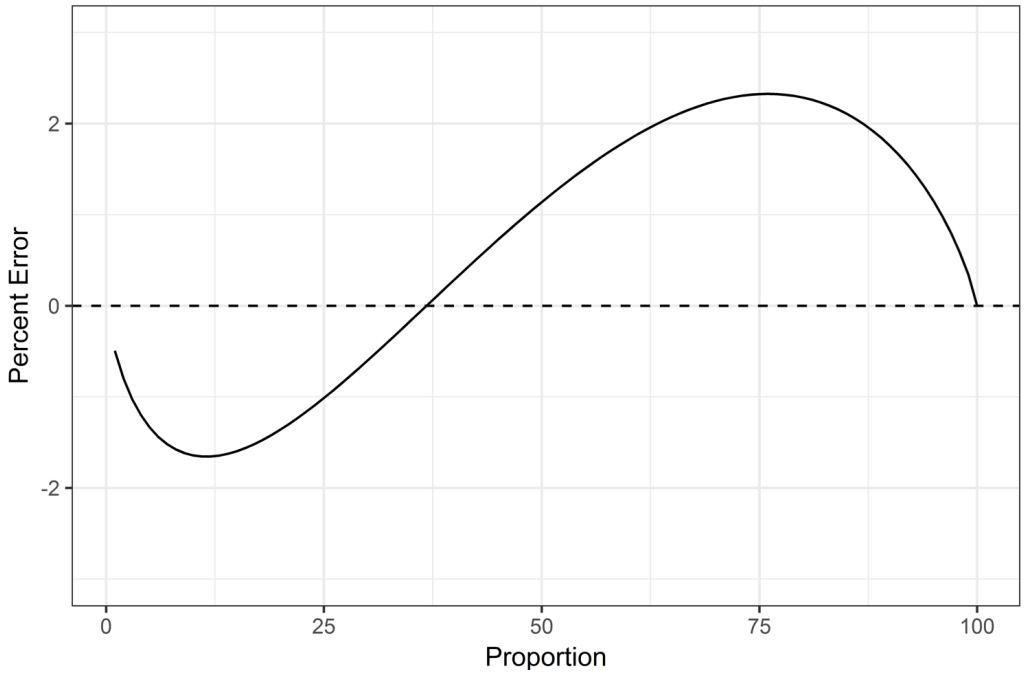

Figure 7: The result of your friend fitting the probability weighting function to their results.

Excited, you call your friend and explain what happened. Your friend agrees it's cool, but they say it is better if they try to replicate it. A chain of replication is the hot new thing.

You wait nervously. A few days later, your friend comes back to you with Figure 7 and says, "Good news, I also got it to fit the probability weighting function!"

You're dismayed. You tell your friend that their results look like your results flipped around the zero line. It's low where your graph is high, and high where your graph is low.

Your friend claims to have done what you did. They took some random low grids and high grids, in the places that prospect theory's probability weighting function suggested, and tested them.

To gain some insight, you ask to look at some of the underlying two-cell experiments. Figure 8 shows that even these simpler results are flipped, in that they're sloping up instead of down. You feel like you might be losing your mind.

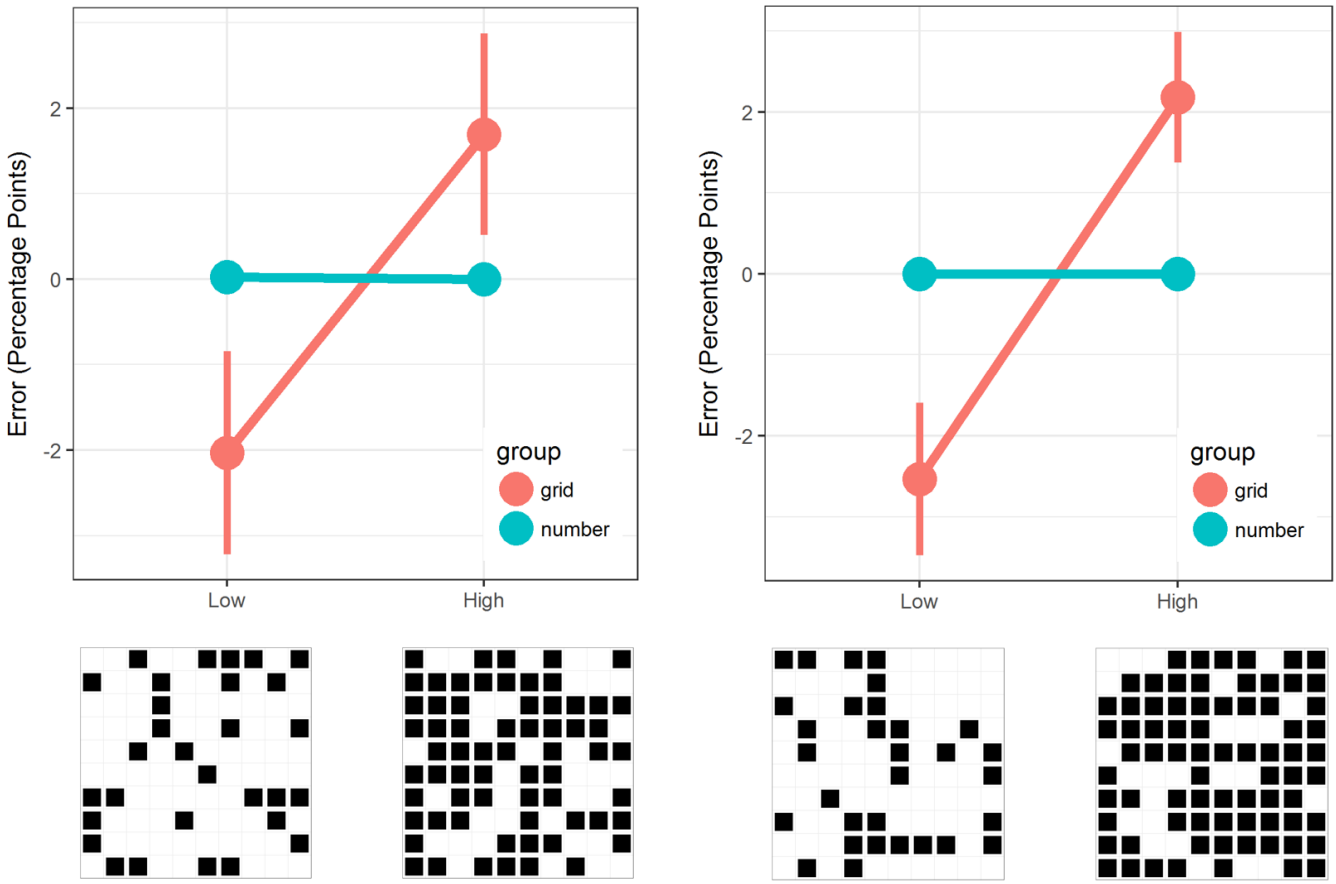

Figure 8: The results of two of your friend's two-cell experiments.

So what's going on?

Figure 9 shows the locations of the low (proportions around 0 to 35) and high (proportions around 35 to 100) grids you used as stimuli, along with your fit of the probability weighting function. In all your two-cell experiments, your low values were around 10 to 25. Nothing wrong with that, as it's in the zone of overweighting according to prospect theory. You did a bunch of runs where the high values were around 50 and then, to explore a bit, you did another

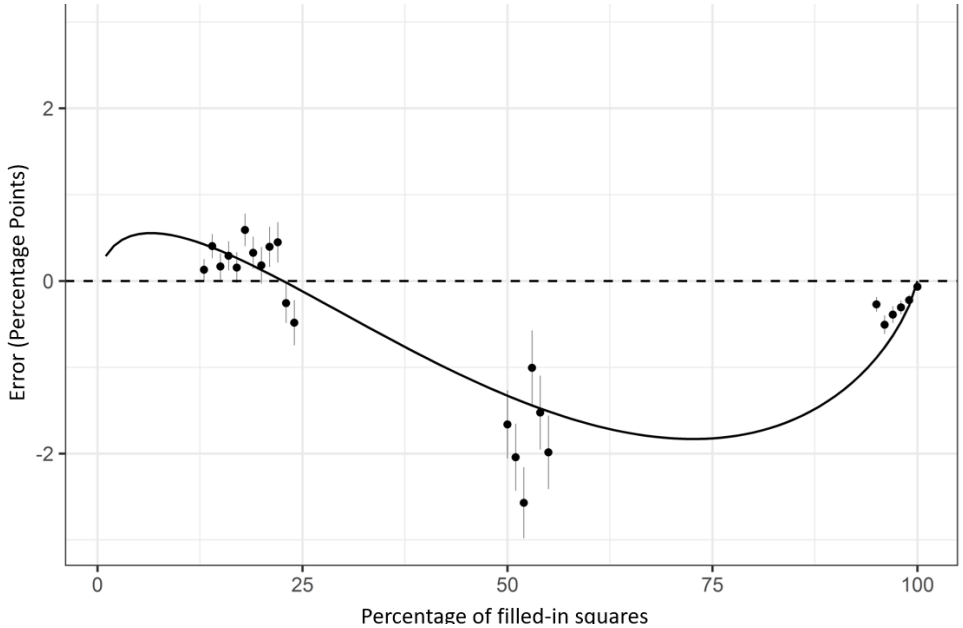

Figure 9: Your fit of the probability weighting function and the proportions (number of dark squares in the grids) you tested.

set where the high values were near 90. Seemed reasonable to you. Both zones are in the theoretical zone of underweighting. And it's good to explore a bit by looking at intermediate and extreme high values. You ran 12 two-cell studies, all with the same basic result.

Figure 10 illustrates the values your friend tested, as well as the function they fit. Your friend is also proud of having explored a bit, with one set of experiments using high values near 60 and one set with high values near 75. Your friend ran eight two-cell studies, each with the same (and opposite) result.

You and your friend both explored a lot of proportions. You both met the requirement of testing in the region where the probability weighting function predicts (around 0 to 35) and underweighting (around

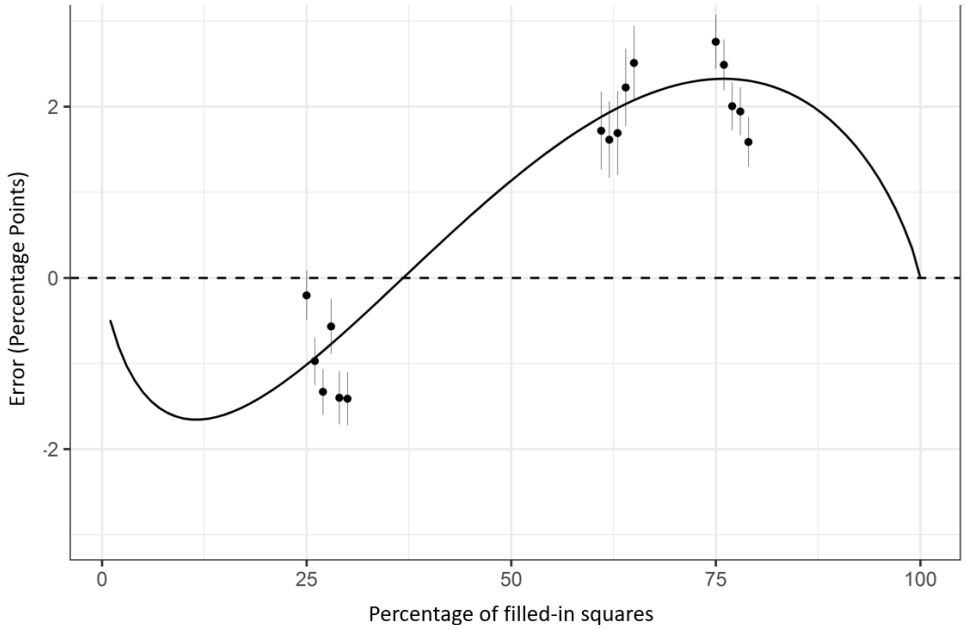

Figure 10: Your friend's fit of the probability weighting function and the proportions they tested.

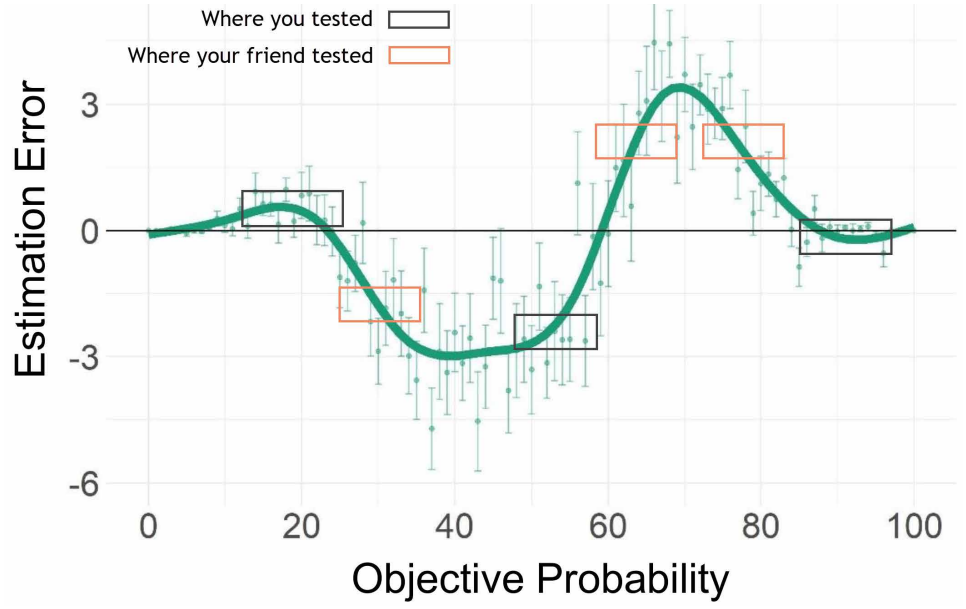

Figure 11: The pattern of estimation error when presenting random grids depicting proportions from 0 to 100. The black rectangles show the general areas your two-cell experiments covered (low values around 20, high values around either 50 or 90). The orange rectangles show general areas that your friend's two-cell experiments covered (low values around 30, high values around 60 to 80). Fitting the probability weighting function to your or your friend's studies would support either prospect theory or its opposite.

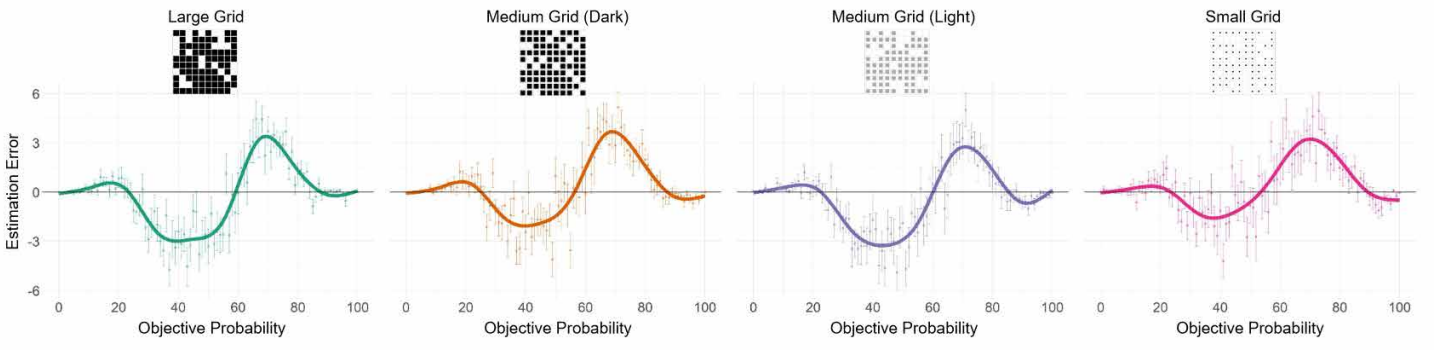

Figure 12: The pattern from Figure 11 replicates when manipulating various visual features of the display, such as the shading and size of the squares.

35 to 100). However, what you didn't realize is that the levels—the exact low and high values you tested—matter a lot! Neither of you was sufficiently leveled up to see the big picture.

What is the big picture? Leaving the vignette, my co-authors (Cindy Xiong, Ali Sarvghad, Çağatay Demiralp, Jake M. Hofman) and I have worked on this problem of getting icon array proportion estimates. The paper (Xiong et al., 2022) is linked to in the references. We tested every value from 0 to 100 and collected thousands of data points. Figure 11 shows what the response pattern looks like over the full range of levels. To allay concerns that I might be making too much of the results from one particular set of studies, we replicated this result many times, manipulating visual features of the display (for example, the size or shading of the squares), as shown in Figure 12.

You might notice the pattern is completely consistent with the results obtained by you and your friend in the vignette. When you test all the values from 0 to 100, you get this very weird—but very reliable—up, down, up, down, up pattern. I believe it was first discovered by Shuford in 1961 (see also Hollands & Dyre, 2000). Since you tested low values under 20 and high values around 50 and 90, you saw

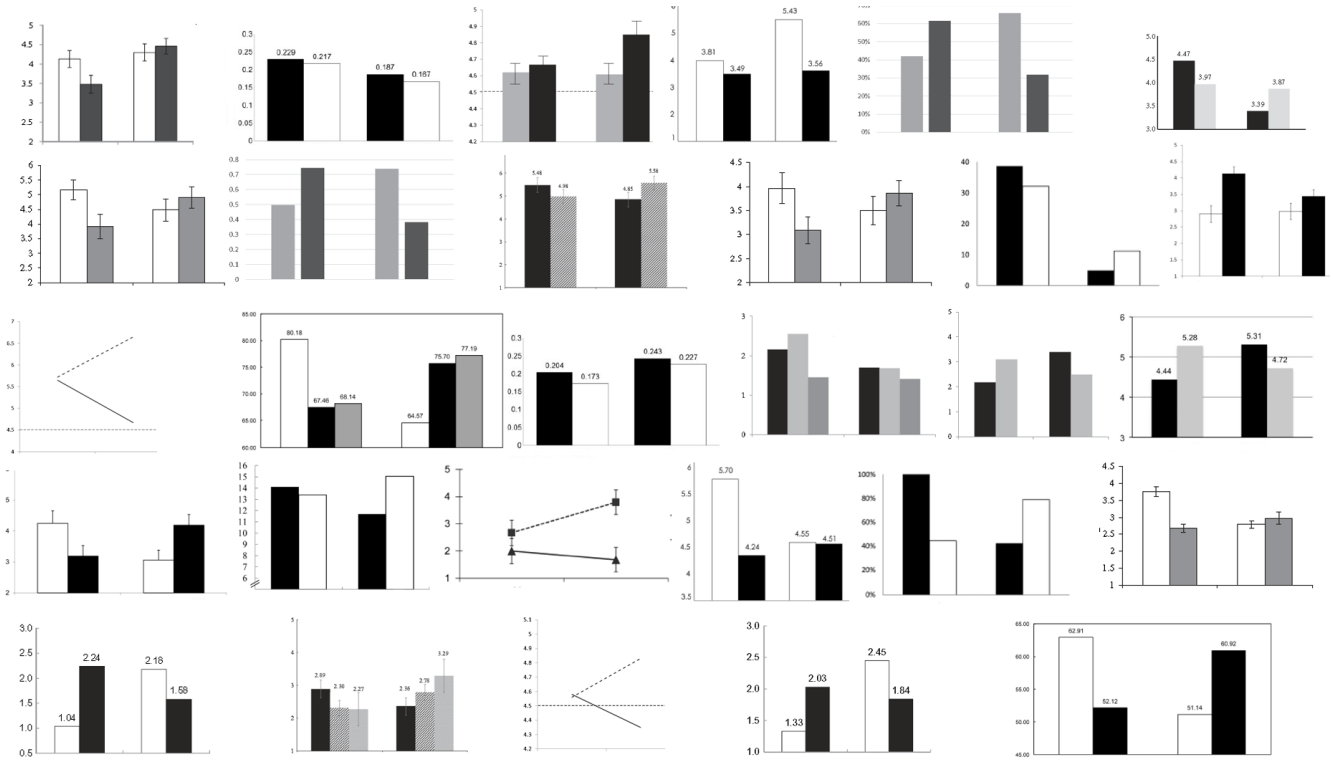

Figure 13: Graphs from published behavioral studies in which a continuous X variable has been split into two levels.

overestimation at low values and underestimation at high values. However, because your friend tested low values around 30 and high values around 70, they saw the opposite, namely, underestimation at low values and overestimation at high values. The moral of the story is that looking at the world through the keyholes of a two-level design can give you a very misleading picture.

Are few-level designs that prevalent? I asked our research assistant Joe Risi to take just two years of a particular "A" journal in our field and to look for graphs where a continuous X variable is split into two levels. He found all of these in Figure 13, where identifying information has been removed.

Many of these graphs have four or six bars, but they still only test two levels of a continuous variable on the horizontal axis. The similarity we see here is mostly the result of attempts to show a so-called "crossover" interaction in a 2 x 2 design, a kind of dress code for getting into particular journals. My experience is that few-level designs are the rule rather than the exception in large areas of behavioral science, and these few levels are often points on a continuous variable. If we don't spread out and test other values of that variable, we can be seriously misled—just like you and your friend were. Had you published, applied researchers might have designed interventions around your findings that would have failed in the field, where treatment levels typically exceed what can be tested in the lab.

Perceiving Wealth

Here's an example taken from my own research (Goldstein et al., 2016). If you ask people about which they find more satisfactory for retirement, a lump sum of money or an equivalent annuity, they often say the lump sum sounds more satisfactory. For example, people tend to say that a $100,000 lump sum seems more satisfactory than $500 / month for life, as shown in Figure 14.[3] Upon hearing this, people might say, "What's new there? Everybody knows that chopping up large amounts into monthly amounts makes them seem smaller. That's why companies advertise their monthly instead of their annual prices! That's why charities ask you to donate pennies per day!"

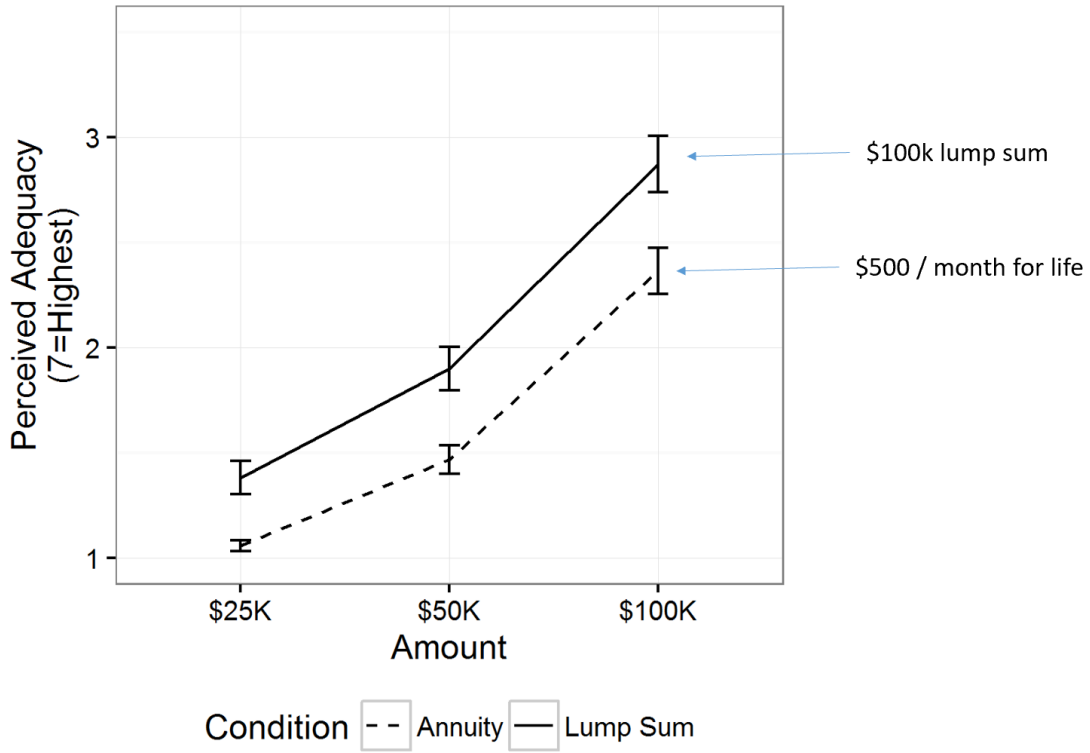

Figure 14: Perceived adequacy of lump sums versus roughly equivalent annuity payments. The horizontal axis represents the amount of the corresponding lump sums ($25K to $100K).

3 As shown in Goldstein, Hershfield and Benartzi (2016), these options have roughly equivalent values under basic assumptions. In Figure 13, the corresponding monthly amount for the $50k lump sum would be $250 / month for life. For the $25k lump sum, it would be $125 / month for life.

Figure 15: Perceived adequacy of lump sums versus roughly equivalent annuity payments across more a wider range of lump sums ($25K to $1.6M).

However, that finding flips if you explore more levels. Figure 15, which adds just four levels to the right of Figure 14, shows that when you ask about larger amounts of money, people find the lump sum less, not more, adequate. For example, $8,000 / month for life sounds more adequate than a $1.6 million lump sum. What happened to the conventional wisdom that monthly amounts seem like less? Where's the pennies per day effect everyone knows about?

Why Leveling Up Matters for Applied Behavioral Economics

The two lab studies discussed (perceiving icon array proportions and retirement wealth) would have painted a misleading picture if they didn't investigate enough levels. It is easy to think of scenarios in which applied behavioral economists could read published, few-cell lab studies and design field interventions that will backfire. For example, suppose a client wants to increase retirement saving by redesigning financial statements. If a lab study covering *only* the three right-most conditions in Figure 15 were published, an applied behavioral economics team might think that removing monthly equivalents from the front page of the statements would increase retirement saving. However, the rest of Figure 15 suggests that such a move could inadvertently decrease retirement saving by the more at-risk lower-income employees, jeopardizing their well-being in retirement. Such high-stakes consequences are not only hypothetical. Companies that auto-enrolled participants into 401k savings plans but set the default savings rate at a low level (e.g., 3% of income) found that the auto-enrollment increased participation but left people saving at a rate too low to be consistent with their retirement savings goals (Choi et al., 2006). Exploration of more default savings rate levels could have prevented this outcome.

Behavioral economics is full of common wisdom and adages such as "small probabilities are over-weighted" or "monthly amounts seem smaller." However, adages don't necessarily generalize or scale. It's not the fault of the lab studies that led to these adages; it's just that bits of common wisdom cannot live up to the unreasonable demands that the world places on them. We want them to apply in more contexts and over more levels than were tested in the studies that gave birth to them. In my leading example here, we see that the distinction between over- or under-*weighting* (based on gamble choice studies) and over- or under-*estimating* (based on visual perception studies) matters a lot, as do the particular levels (i.e., proportions). Even if one conducts deep research to find the most relevant papers and theories, it is still

quite difficult to predict in advance what will happen in new contexts and at new levels without running new experiments.[4]

A Three-Step Disappointment-Reduction Plan

The real world is rich in levels and full of situations that are only analogous to what has been studied in the lab. So what's an applied behavioral economist to do? I can't prescribe a one-size-fits-all solution, but I can share the three-step plan that my career in academia and industry has led me to. These are the things I try to do before bringing an intervention into practice.

Step one: Don't not run an experiment. Sometimes, I feel like not running an experiment, but then I remember step one. It's tempting to trust intuition or adages and just launch an intervention without testing. However, it's important to know that many ideas that should work simply do not work. My former Microsoft colleague Ron Kohavi found that 60-90% of A/B tests failed to improve the metrics they were built to improve (Kohavi et al., 2020). If the base rate of success for ideas were better, I might ease up on step one. But given that most good ideas don't move the needle, I try not to incur the expense of launching an intervention without some kind of lab or field testing.

Step two: Do some leveled-up, online, conceptual replications of published lab results. These quick, inexpensive studies typically make heavy use of hypothetical ("imagine that ...") questions and alter the context of published studies to make them relevant to the applied setting. This often requires getting creative. For instance, to get a handle on the degree to which annoying ads drove people from websites, we set up an experimental website that itself ran annoying ads in the sidebars, following which we measured how long it took people to quit the experiment (Goldstein et al., 2014). Failure to see an effect in these online studies can happen for a variety of reasons. While such failures do not always mean you should give up and try something else, I feel they are better than the original published lab studies for informing your decision. In addition, they are customized to the exact context and levels of treatment you are interested in.

Step three: Do a leveled-up pilot study in the field. If forging ahead seems prudent, I write up (and sometimes publish) the results and show them to stakeholders in the hope of getting them to bless some pilot studies in the field. In my tech world, these can take the form of tests that are run on a small percentage of total users. The ability to conduct—and ease of running—field tests varies from industry to industry and firm to firm. As a lot has been written about running field experiments (e.g. List, 2021; Kohavi et al., 2020) I will only emphasize that, as with the lab studies, it is vital to level them up to cover the full range of treatment levels that will be encountered in practice.

You might be irritated at me now, thinking yes, it's great to explore more levels, but how can we do that with limited funds? This is a valid concern, and it applies not only to exploring more levels, but also to other senses of collecting more data, such as recruiting more participants and running longer studies with more repeated measures. While there is no getting around the need to collect more data than we have done in the past, some good news is that recent innovations are making it less expensive. First, online subject pools make it possible to collect more data at a lower cost (Mason & Suri, 2012). This is accomplished *not* by paying participants less but by removing some of the overhead and transaction costs of in-person lab research. Efficient online tools provide the ability to speed up data collection and to obtain large numbers of repeated measurements from participants who are interested in earning more money by contributing them. Second, when researchers at several institutions collaborate, they can pool resources to conduct large, multilevel, and high-powered studies that can have more scientific and career impact than alternative uses of funds. Video conferencing and online collaboration software make it easier and much less expensive for researchers who are spread across the world to join forces. The results can shape history. Large-scale, cross-lab collaborations like the Many Labs projects have changed behavioral research for the better. They have also suggested ways to make the multi-lab

4 Despite good models for fitting and understanding how people perceive visual representations of proportions (e.g., Hollands & Dyre, 2000), it is still difficult to predict a priori, for a new visual format, what the bias patterns in perceiving proportions will be.

collaborations of the future even more efficient and informative (McShane et al., 2019). Third, the move towards digital experimentation has made it possible to create online experiences, services, interactive news stories, and games that themselves collect valuable data from volunteers. So-called "citizen science" projects have generated data on everything from economic behavior to ecology (e.g., Goldstein et al., 2020; Rubenstein, 2013; Silvertown, 2009).

In the wake of the replication crisis, the advice to collect more data was mostly meant to increase the rate at which lab studies replicate in other labs. I wish to emphasize that a replication of results across labs is far from an assurance that an intervention will have an effect in the field. The stimuli tested in published lab studies are rarely a close match to proposed field interventions, and the levels of treatment studied in the lab are often insufficient to generalize about where effects may disappear or invert in practice. Before launching field interventions, it is prudent to run your own experiments, tailor them to your setting, and to level them up. You'll be less often disappointed when you do.

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EDITORIAL

A Review of Emerging Trends in Self-Control and Goals: Introducing the FRESH Framework

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This year's Behavioral Economics Guide editorial reviews recent work in the areas of self-control and goals. To do so, we distilled the latest findings and advanced a set of guiding principles termed the FRESH framework: Fatigue, Reminders, Ease, Social influence, and Habits. Example findings reviewed include physicians giving out more prescriptions for opioids later in the workday compared to earlier (fatigue); the use of digital reminders to prompt people to re-engage with goals, such as for personal savings, from which they may have turned away (reminders); visual displays that give people data on their behavioral patterns so as to enable feedback and active monitoring (ease); the importance of geographically-local peers in changing behaviors such as residential water use (social influence); and digital and other tools that help people break the link between aspects of the environment and problematic behaviors (habits). We used the FRESH framework as a potential guide for thinking about the kinds of behaviors people can perform in achieving the goal of being environmental stewards of a more sustainable future.

Introduction

A central, unifying theme in much of behavioral economics concerns self-control and goal attainment. Pursuing goals in the face of temptations and short-term benefits is not easy. People frequently fall short of their goals or abandon them altogether. Whether trying to lose weight, avoiding distractions at work, or focusing on a demanding task, self-control is a key component to successful personal and professional pursuits. The need for self-control has never been more apparent than it the past 18 months. Before the pandemic, less than 10% of the global workforce spent their time working at home. By 2020, the figure was roughly 50% (Bick et al., 2020), and estimates for the U.S. workforce put the post-pandemic rate at about 22% (Barrero et al., 2021). With the push towards remote work, and as COVID-19 self-quarantine measures and country-level lockdowns were rolled out, the ability to stick to daily routines and habits was challenged, as many were quietly ushered into an era of 'self-management.'

For most individuals, the pandemic led to a greater reliance on technology. Many workplaces leaned heavily on virtual platforms with video call capabilities (e.g., Zoom, Microsoft Teams, Webex, Skype). Within a few weeks into the start of the pandemic, the term "Zoom fatigue" (Chawla, 2021; Fauville et al., 2021) started to gain momentum as a way to describe the physical and psychological toll of video calls. In turn, research has advocated for the use of mental resets, as well as structuring decision environments, in order to expect fatigue and make decisions as easy and as simple as possible.

The FRESH Framework for Self-Control

From mask-wearing to vaccines, to figuring out new hobbies or ways to exercise, the last two years have ushered in new domains and challenges associated with self-control. This year's Behavioral Economics Guide editorial dovetails with last year's editorial by Chilazi and Bohnet (2021), which focused on goals related to diversity and inclusion in the workplace. This year, we took a broader look at the latest work on goals and self-control, spanning fields as varied as economics, marketing, finance, psychology, health and medicine, computer science, and the environment. What emerged was five key factors influencing goals and self-control, which we have

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termed the FRESH framework: Fatigue, Reminders, Ease, Social Influence, and Habits. Heeding the call for more integrative thinking by one of our Behavioral Economics Guide editorial predecessors (Mažar, 2019), we review some of the most exciting and current findings in these areas and then use those insights to inform ideas on sustainability—an urgent problem raised by another Behavioral Economics Guide editorial author, Elke Weber (2020).

Fatigue

Estimates suggest that people make thousands of decisions every day. When to wake up, whether to look at the phone, what to wear, when to go to work, whether to listen to a podcast or audiobook on the way to work (not to mention which podcast or audiobook), or whether to attend a meeting – all of which are but a smattering of the myriad decisions people face on a daily basis. While the proliferation of choice has made life better in a number of ways, recent evidence finds that all of these decisions can take a toll.

At their core, human decision making and problem-solving are grounded in bounded rationality (Mullainathan & Thaler, 2001). The mental work of making choices can be cognitively demanding, eroding the ability to make subsequent choices—especially when those decisions pertain to people's goals or what they should be doing. First tested in the laboratory (Vohs et al., 2008), some of the most important advances in decision fatigue have identified and quantified its pernicious consequences in health, financial, and performance domains. Though the effects of decision fatigue at a broader level have been established across a broad set of domains, it is worth noting that the results have been more mixed when it comes to the related concept of ego depletion (for a recent mega replication attempt, see Vohs et al., 2021). Ego depletion refers to the idea that people have a limited supply of willpower that can hinder self-control efforts the more that people are faced with resisting temptations. When we use the term "decision fatigue," we refer to cognitively and mentally taxing efforts associated with making repeated decisions (versus exerting willpower or restraining impulses).

Over the past few years, studies have linked decision fatigue to an important area in healthcare: aggressive rates of drug prescriptions, whereby doctors are increasingly being criticized for overprescribing medications, with the opioid crisis being one striking example (Roland et al., 2020). A multi-year

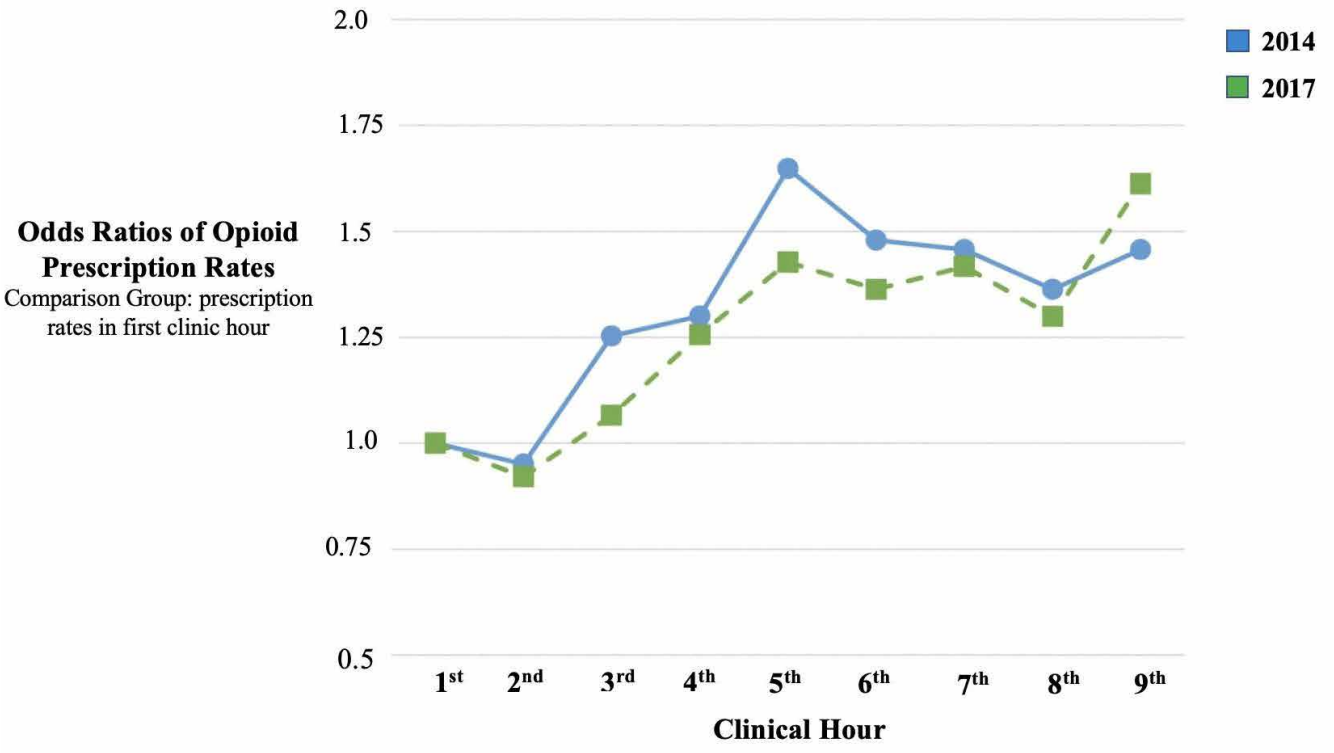

Figure 1: Odds ratios of opioid prescription rates in 2014 and 2017. Prescription rates during the first hour the clinic was open were given an odd ratio of 1.0. Adapted from Hughes et al. (2020).

investigation of opioid prescriptions decisions for 77,000 patients documented a troubling pattern, namely, that opioid prescriptions were more likely to be given out later in the day (Hughes et al., 2020, see Figure 1).[2]

Alarmingly, this is not an isolated finding. Another study reported that doctors were more likely to prescribe opioids for patients later in the day, even after controlling for average reported pain levels among other individual difference factors (Philpot et al., 2018). In a study of 642,00 patient appointments, those who were seen at the last appointments in the day were 1.3% more likely to be given an opioid prescription relative to those who were in the first slate of appointments (Neprash et al., 2019). As the authors put it, "[...] if the opioid prescribing rate for the first 3 visits had held constant throughout the day, there would have been 4459 fewer opioid prescriptions [that year]" (p. 6).

These results are consistent with findings for antibiotic prescriptions: the odds of leaving an outpatient appointment with a prescription for antibiotics increased for patients who were seen later in the day (Linder et al., 2014). Patients often believe that prescriptions for antibiotics or opioids are curative (even in cases when they are not), in which case they may come in asking for them. Doctors must refuse the request if they think the prescription is not the correct course of action. However, as doctors make more decisions throughout the day, it may be easier to forgo these conversations and offer the prescription. In these instances, choosing to make the easier choice in the present moment wins out instead of expending effort to say no to patients or weigh the costs and benefits of a drug prescription for a particular case. The consequences of clinicians' decision fatigue are not trivial.

Recently, research in the finance literature has examined the extent to which decision fatigue leads to worse outcomes. One study of financial analysts found that their forecasts worsened the more they made decisions (Hirshleifer et al., 2019). That is, the more forecasts they had issued already that day, the more likely they were to let heuristics guide their forecasts—for instance, defaulting to their own previous forecasts of a firm, or issuing a forecast ending in a 5 or 0—which contributed to overall less accurate forecasts. A last, notable aspect of this study concerned investors. Hirshleifer and colleagues (2019) found that the market underreacts to forecasts issued by analysts who have issued more forecasts already that day.

One study of 26,501 credit loan applications sought to quantify the cost associated with decision fatigue. It examined approval decisions and time of day for borrowers seeking to restructure the terms of their loans (Baer & Schnall, 2021). In these cases, rejecting the new loan is the default, making it the cognitively easier decision. Consistent with decision fatigue effects, the authors found that relative to earlier in the day, approval rates were significantly lower in the late morning (prior to a lunch break) and late afternoon hours (prior to leaving for the day). Yet many of those denials were in error, as borrowers ended up defaulting on their original loans and hence not paying back the bank. The monthly cost to the bank of those errors was estimated at more than $500,000.

Importantly, however, approval decisions that were made around midday (presumably after a lunch break had been taken) were not significantly different from those earlier in the day, i.e., a time when officers were less prone to decision fatigue. Taking breaks to mentally reset, and replenishing cognitive resources can have beneficial welfare effects for firms, employees, and applicants.

Recent work focusing on the decisions of Major League Baseball (MLB) home plate umpires shows that even short rest periods help combat decision fatigue (Archsmith et al., 2022). Using pitching technology that precisely locates the ball as it crosses the plate, the authors measured the quality of the umpire's decision by determining whether they were correct. The umpires seemed to apply greater effort to high-stakes calls insofar as those calls were more likely to be correct. At the same time, applying effort to those high-stakes calls was associated with more errors in the decisions that followed. These findings are consistent with umpires experiencing decision fatigue. The inning break, when teams transition

2 When we say that researchers found a certain effect that implies analyses that hold other factors constant. For this paper, for instance, this includes background variables such as patient demographics, insurance type, and type of provider.

from offense to defense, seemed to ameliorate the effect. Consequential decisions in previous innings had no discernible effects on decisions following the break, despite the break lasting for just a few minutes.

In summary, making decisions, especially those that are consequential or cognitively taxing, can be fatiguing in ways that can affect the quality of subsequent decisions. However, taking time to mentally reset and restore cognitive resources, even if only for a few minutes, can offset some of the pernicious effects of decision fatigue, thereby boosting self-control in the process.

Reminders

From reminders to meditate and drink water to automating online grocery orders, the design of the digital world can have a profound effect on the decisions people make and how they structure their lives. Digital aids, such as reminders, can serve to increase self-control efforts and help with habit formation (the *H* in our FRESH framework).

Reminders can aid self-control pursuits by providing feedback about goal progress or by prompting people to perform or withhold from a behavior. Reminders about health behaviors are a common example, with one recent study showing that mentally linking a reminder with the goal may be key. This six-month study found that presenting a visual reminder cue as helpful to dieting (i.e., a picture of a sculpture by the artist Alberto Giacometti depicting humans as very thin) did in fact lead them to lose more weight than other dieters (Stämpfli et al., 2020). Notably, dieters who were not told that the thin figure was helpful to dieting, but who came upon that idea themselves, also seemed to lose some weight.

While the importance of reminders has been previously documented (Rogers & Milkman, 2016), the breadth of their effectiveness has started to gain attention of late. Moshontz and Hoyle (2021) note that reminders can be particularly helpful when goal pursuit occurs over longer periods of time. When goals occur over longer time horizons, people may naturally disengage with the goal at some point to attend to other tasks. Reminders then operate as a cue prompting individuals to re-engage with their goal and goal-congruent behaviors.

This may help to explain the results of recent studies aimed at using SMS reminders to up savings rates and improving flu and COVID vaccination uptake (Dai et al., 2021; Milkman et al., 2021, 2022). In all three cases, i.e., savings, flu and COVID vaccines, there was limited evidence that the actual content of the message altered behavior. Rather, it was the reminder itself that significantly improved the target behavior.

As more data become available, behavioral economists are getting a fuller picture of when and how reminders can be used effectively. First, they are most effective for people who are motivated to achieve a specific goal. For instance, Karlan et al. (2016) showed that SMS texts reminding people to save because it would help them achieve specific financial savings goals were more effective in boosting contributions to an existing savings account relative to texts mentioning financial incentives alone.

Second, while emails and application notifications can be distracting and frustrating, reminders that are timely, personalized, and actionable may be less so.[3] One successful demonstration is with the popular language application Duolingo, which operates by encouraging users to set a daily goal to use the app for a set duration per day (usually between 5 and 20 minutes). Researchers experimented by sending push notifications at different points throughout the day, reminding people to complete their daily goal. They found that notifications sent a little less than 24 hours after the last lesson worked best at encouraging engagement on the app (Nushi, 2017).

Third, reminders can also be helpful sources of friction to curb impulsive behavior. For example, that pesky alert on Netflix prompting viewers to indicate whether they are still watching after multiple episodes in a row may prompt consumers to ask themselves whether they want to continue giving in to their lassitude. However, as Mažar (2019) noted, researchers, policymakers, and practitioners should be mindful of unintended side effects or heterogeneous treatment effects that may cause one population

3 While reminders and other nudges have been shown to be effective in many settings, recent meta-analyses indicate that their effects may vary as a function of the type of nudge and domain in which it is applied (Hummel & Maedche, 2019; Mertens et al., 2022). One possibility is that customization and personalization may improve their impact by enabling a tighter link between people's goals, settings, individual characteristics, and vulnerabilities.

group or subgroup to react differently than others.

Ease

While the idea of making things easy as a way to gain self-control may seem oxymoronic, behavioral economics research suggests otherwise. Rather, knowing that people are prone to making the easy, less effortful choice has been promising from a choice architecture perspective.

Automatic enrollment plans in programs such as Save More Tomorrow (Thaler & Benartzi, 2004) have successfully improved retirement savings by utilizing the status quo bias to overcome self-control failures. Opt-out forms of default interventions have also been useful in health settings to increase cancer screening rates (Huf et al., 2021) and the take-up of vaccines (Chapman et al., 2010).

Even healthy food and drinks choices have benefited from the use of defaults. Using a retrospective analysis from Walt Disney theme park restaurants, Peters and colleagues (2014) found that providing healthy choices as defaults for meal sides and beverages (e.g., carrots or low-fat milk versus French fries or regular soft drinks) were associated with an increase in demand for healthy food and beverage ordering by roughly 48% and 63%, respectively (see Figure 2).

Another aspect of contemporary life that has affected goal pursuit is digital technology. While, to be sure, being a source of distraction, digital innovations can facilitate goal pursuit as well. The last few years have seen an explosion in the number of people using sensor-rich smartphones and wearable devices (e.g., smartwatches, fitness trackers) to record, analyze, monitor, and obtain feedback on their behavior and activity. Wearable devices might be especially helpful for people seeking to understand their behavioral patterns for goals such as getting better sleep, tracking exercise and food intake, monitoring stress levels, and saving money.

Activity trackers, as well as online and mobile applications, offer several potential benefits to people seeking to boost their self-control. Data can be collected with little to no effort and processed into customized and visualized feedback displayed right on the device or application itself. Feedback and active monitoring can bring goals to the forefront of the mind, allowing users to make behavioral adjustments accordingly. Wearables can also provide just-in-time coaching for health-related activities such as meal planning, fitness workouts, and sleep hygiene, thereby making target behaviors easy to understand. Wearables also can help users set and track their goals, making it easier for them to self-monitor their progress and take actionable steps to reach those desired goals. Two recent meta-analyses (Dounavi & Tsoumani, 2019; Patel et al., 2021) concluded that mobile health apps facilitated weight loss by making it easier for users to self-monitor their progress and

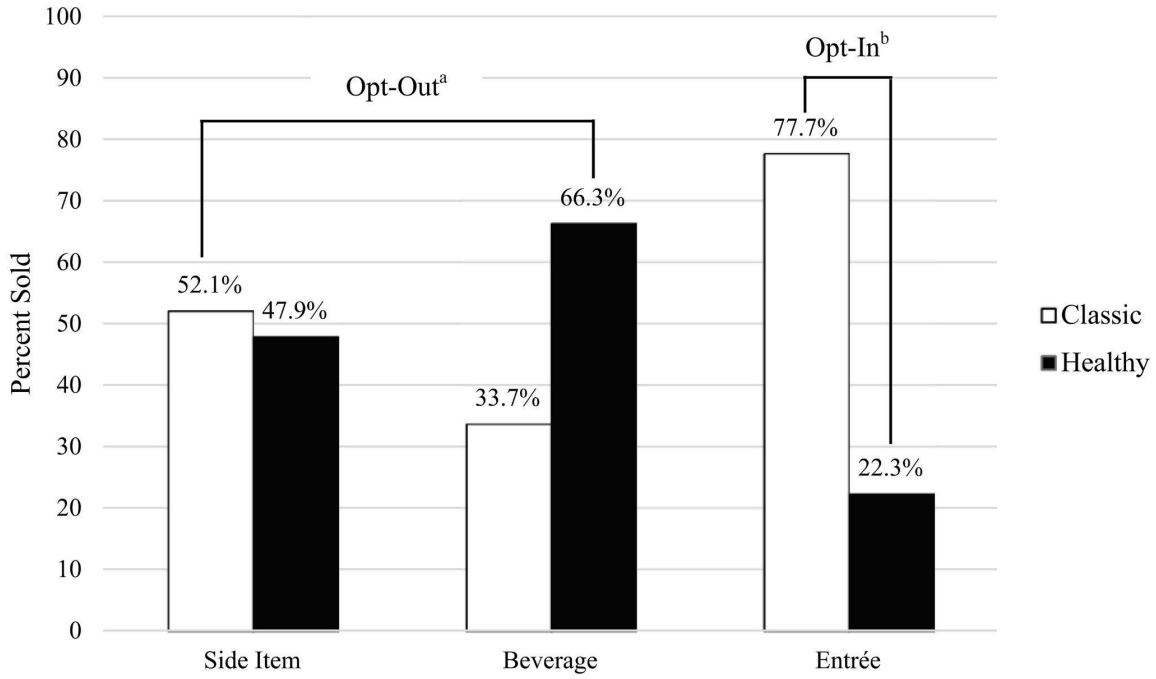

Figure 2: The impact of healthy defaults on food and beverage orders. Adapted from Peters et al. (2014).

in turn adhere to treatment regimes (Wang et al., 2012) such as exercise or nutrition programs (Du et al., 2016).

Social Influence

Behavioral economics has long recognized that individual behavior is susceptible to peer and social influence. In fact, it was one of the topics featured in Robert Metcalfe's (2018) excellent Behavioral Economics editorial in 2018. Research has consistently demonstrated the influence that peers play in changing financial choices (e.g., Bailey et al. 2018), energy consumption (e.g., Allcott & Mullainathan, 2010), and the likelihood to recycle (Goldstein et al., 2008; Meng & Trudel, 2017).

The recent shift to remote work, along with the popularization of neighborhood-based apps such as Nextdoor, the past couple of years also has sparked a surge of work highlighting the important role that geographic peers, such as one's neighbors, play in decision making. From residential water conservation during the summer (Bollinger et al., 2020; Burkhardt et al., 2021) to financial decisions such as refinancing a mortgage (McCartney & Shah, 2022) and adherence to social distancing guidelines (Holtz et al., 2020), evidence strongly suggests that proximate peers are an important source of influence.

Of note, recent evidence has found that the network position of individuals may influence how influential they are at changing behavior, particularly in self-control domains. Breza and Chandrasekar (2019) conducted an experiment to study whether people save more when information about how well they are progressing toward their savings goal is shared with a person in their community, termed a monitor. Those who were assigned a monitor increased their savings by 36% relative to those who did not have a monitor. Moreover, savers whose monitors were more socially connected to other community members had larger increases in savings. Having to share results with someone, and particularly someone who is popular or to whom one is accountable, is a powerful tool for behavioral change.

Technology has not only allowed for the ability to self-monitor and self-track various behaviors, but has also made it easier for peers to become part of the monitoring process. Websites such as StickK.com, Uloo, Aimtracker, and GoalsWon provide various ways that integrate social networking and public goal-setting to facilitate self-control efforts. While it may be too early to tell whether group-based interventions are successful at scale, there is reason to believe that interventions which factor in social elements will be persuasive for self-control pursuits.

Habits

COVID-19 has been especially difficult for managing routines. Lockdowns, self-quarantine measures, and changing guidelines have challenged people's ability to develop and stick to daily habits. One important question is, who is most likely to adapt and continue to pursue goals despite the major disruptions caused by the pandemic? In an online experiment, Kokkoris and Stavrova (2021) find that those with high trait self-control are not only more likely to continue their pre-pandemic goal-directed behaviors, they also have the flexibility to develop new habits to meet changing demands.

Simple modifications in choice environments can be used to help individuals control their immediate impulses and counteract procrastination, myopia, and impulsivity. In one early illustration, product researchers developed a locking timed container to build good habits and literally lock away temptation. The K-safe, once set, would not open until a specific amount of time had elapsed, preventing individuals from accessing tempting items such as unhealthy snacks, cigarettes, phones, remotes, or even cash and credit cards.

By design, digital technology and social media lend themselves to habit formation (Eyal, 2014). In fact, it is estimated that self-control problems cause 31% of social media use, as people are unaware of their habits and self-control issues (Allcot et al., 2021). Recent work in behavioral economics suggests that interventions can be more effective if they are implemented more deliberately and with the self-awareness of the decision maker (Bannerjee & John, 2021). Termed as "nudge plus" or "self-nudges," John and Stocker (2019), propose that people can nudge themselves by making use of self-imposed tools. The one precondition is that in order for people to engage in self-nudging, they would presumably need to have some awareness that certain aspects of the environment tend to elicit certain patterns of behavior in themselves. Conditional on having made

that mental link, there are multiple tools people can use to break (or modify) that behavior in a more lasting and deliberate manner. For example, apps like Stay Focused and Cold Turkey are serving as the K-safe for digital environments, allowing users to set limits on the amount of time spent browsing a particular website or interacting on a social media platform. On a more extreme level, Cold Turkey allows users to block off access to their desktop or device as well—a helpful tool for those who may struggle with self-control at particular times, such as the end of a workday, as reviewed in the section on fatigue.

Sustainability

The previous section unified insights from the goals and self-control literature over the past few years, distilling down the findings into a set of guiding principles that we termed the FRESH framework: Fatigue, Reminders, Ease, Social Influence, and Habits. The FRESH framework can be a helpful tool, not only to organize theory, but also as a potential way to design and develop effective policy and behavioral interventions. To demonstrate its impact, we apply the FRESH framework to one of the most important societal challenges in this lifetime: sustainability and environmental stewardship. Sustainability is an archetypal self-control dilemma, pitting short-term conveniences with long-term welfare. We are going to take it as a given that many people want to do better by the environment and hence view sustainable behaviors as part of their personal goal structure.

Like many of the most pressing policy issues globally (e.g., obesity, healthcare, financial access), sustainability is a massive problem that requires structural and system-level changes (Chater & Loewenstein, 2022: Loewenstein & Chater, 2016). At times, sustainability can seem beyond the realm of individual behaviors. Yet, research belies that belief. Reports estimate that 60% to 75% of worldwide greenhouse gas emissions can be attributed to households' consumption behaviors (Druckman & Jackson, 2016; Ivanova et al., 2016). We remain optimistic that behavioral interventions, when operating in conjunction with structural reinforcements and system-level change, can move the needle forward. Next, we leverage each of the five components of our FRESH framework to develop potential behavioral interventions designed to shift household consumption behaviors. We remain optimistic that behavioral interventions, when operating in conjunction with addressing structural concerns, can move the needle moving forward.

Fatigue

As reviewed above, predictable patterns of behavior emerge after people have made decisions. Namely, they tend to put off subsequent decisions, rely on heuristics, and stick with the status quo or defaults.

Those patterns may play a role in sustainability, leading people to make choices that are not in the best interest of the planet (or their own budgets, in many cases). Take, for instance, the issue of food waste. According to the USDA, around 35% of all food is wasted in the United States, and food waste comprises the biggest source of landfill space (Buzby, 2022). Marketing research shows that 85% of consumers do not have a plan for dinner just hours before mealtime (Crawford, 2018). At the end of the day, consumers may take the easy route when it comes to that decision and instead opt for convenience foods, such as prepared food at a grocery store, or to get takeout from a restaurant. While those behaviors may solve the problem of what to eat for dinner, they can also create the circumstances that lead to food waste, because what's in the refrigerator or pantry is not being consumed.

When it comes to deciding whether food is still good to eat or should be discarded, research indicates that people tend to rely on heuristics to make that judgment, namely, date labels on packages. One study found that consumers were 28% more likely to say they would throw out a carton of milk when it had a date label compared to the same carton without a date label (Roe et al., 2017). It is no surprise to students of behavioral economics that people are heavily reliant on heuristics to navigate the world, and those heuristics may be all the more potent at the end of the day when people are averse to making thoughtful decisions—with potential consequences for food waste.

Reminders

As described above, reminders—often in the form of visual cues—can be helpful in re-engaging with a goal from which people may have otherwise gotten distracted, or goals that are difficult to keep in mind.

Figure 3: Examples of recycling bins with lids that convey the intended material (left-hand panels) as well as framing non-recyclable waste as landfill (upper right-hand panel).

Sustainability research indicates that reminders that are pictorial as opposed to verbal can be especially effective (as reviewed in Mazar et al., 2021). Examples include signs with images of recyclable items placed in locations with recycling receptacles, or lids on top of recycling bins with shapes cut into them to indicate what goes where—and at the same time works to prevent unacceptable items from being deposited (Figure 3).

Framing, a common tactic used in behavioral economics, can be thought of as another type of reminder. One study sought to persuade people to choose foods produced with lower greenhouse emissions, using visual and verbal cues to make clear the foods' environmental impact. Color-coding (with green indicating more eco-friendly options, and red indicating less eco-friendly options) and framing the energy expenditure associated with a given food's production into light-bulb minutes (a product many consumers associate with energy use) resulted in people choosing foods with less environmental impact (Camilleri et al., 2018).

Ease

Making it easy to perform a desired behavior has long been a mainstay of behavioral economics, and in the arena of sustainability, making it easy often means setting out environmentally-friendly defaults. One impressive study of more than 200,000 households and 8,000 companies found that presenting customers with a new default, i.e., one that was more environmentally-friendly and also a little more expensive than the existing default, led to widespread acceptance. Namely, 80% of customers stayed with the new, green default, a rate that remained steady for 4 years (Liebe et al., 2021). Making it easy for customers to adopt a greener energy plan (insofar as they were defaulted into it and thus had to exert no effort to make it happen) led to more sustainable choices for a large swath of society. The power of using defaults, one of the most effective nudges, for green energy may be especially impactful given the current climate crisis and rising costs of energy.

Another way to engage in sustainable behavior is to make sustainable choices easier, while less sustainable choices are made a bit harder. A 2021 report from the Environment America Research and Policy Center detailed that the United States produced 12% of the world's trash despite being home to just 4% of the world's population (Pforzheimer & Truelove, 2021). One reason is because the nation has some of the lowest composting and recycling rates in the world, even though roughly 80% of all waste can easily be composted or recycled. However, many households

don't have an easy way to do either.

Federal and local governments could play a significant role in improving sustainability efforts. Providing households with recycling and green composting bins is one step in the right direction. In addition, providing small compost bins and biodegradable bags that could sit next to the sink or on a kitchen countertop, directly where produce and organics are primarily used, could allow for a more accessible, top-of-mind reminder for families relative to having just one main garbage bin. Also, making recycling and compost collection more frequent, such as once a week, while making garbage pickup less frequent, such as once every two weeks, would not only make sustainable choices easier, but also signal expectations about usage relative to options that are more damaging for the planet.

Social Influence

Some of the most promising findings in shifting individuals and households to more sustainable energy practices have been via social influence (see Wolske et al. 2020, for an excellent review). In the energy domain, neighborhood peers can significantly influence the adoption of energy-efficient technology, such as rooftop solar photovoltaic panels and hybrid cars, as well as use precious natural resources such as water consumption for residential lawn care (Bollinger & Gillingham 2012; Bollinger et al., 2020; Zhu & Liu, 2013).

Key to these findings is visual salience. People can see that a hybrid car is parked in their neighbor's driveway, whether a neighboring roof has solar panels, and even if a nearby lawn is lush and green or whether it is dry and arid. Indeed, peers' rooftop solar panels that are located near roadways and have less surrounding vegetation, thereby making them more visible from the road, are a stronger source of influence than when those choices are less visible (Bollinger et al., 2022). Yet, roughly half of all spending is private (BLS, 2017). For example, choosing an energy-efficient appliance or wearing an extra layer indoors instead of turning on the space heater are private choices that are less susceptible to social influence. How can the power of social influence be leveraged in a way to further sustainable actions for even those kinds of inconspicuous behaviors and consumption habits?

We offer a few solutions. First, make the private choices more public via technology. Neighborhood and community-based apps like Nextdoor could be one easy step to make these private choices more visually salient. According to internal company data, one in three households in the US are Nextdoor users, with more than 10 million active members checking the site weekly. If users were able to input their own green consumption habits, such as whether the appliances they use are energy-efficient or the temperature at which household thermostats are set in their local area, not only would this be a source of information, but it also could help guide sustainable and responsible practices.

Second, prior work suggests that green choices are motivating as a source of status, in that they provide a halo effect (Griskevicius et al., 2010; Mažar & Zhong, 2010). However, these choices go beyond the individual, sparking contagion effects that can be beneficial for sustainability. Energy companies could offer green sticker awards to the top 10% of users that could be displayed at the front of winning households, thereby reinforcing good habits while also serving as visually salient reminders to neighboring households. Third, enlisting the help of local influencers such as community leaders, or promoting neighborhood competitions, can leverage the power of social networks and foster community building.

Habits

As habits, by definition, are actions devoid of conscious deliberation (Wood et al., 2022), changing them can be harder than, say, behaviors for which people tend to weigh one course of action against another. We suggest perhaps acknowledging the power of habits and making choices for which the outcome largely doesn't depend on habits.

Consider the mismatch between what choices homeowners think save the most household energy versus what actually has the biggest impact. Consumers think that switching off the lights at home will have the greatest effect (Camilleri et al., 2018); however, buying energy-efficient appliances produces some of the biggest impacts in this regard (Attari et al., 2010). The pattern of mismatches between expectations and reality for energy savings can be understood as people believing that their everyday habits make a big difference, whereas they make

Figure 4: Nest Learning Thermostat. Retrieved from: https://www.zareview.com/how-much-does-nest-thermostat-save/.

only a modest difference; by contrast, they vastly underestimate the energy savings from switching to more efficient consumer products (such as washers, dryers, and lightbulbs).

The idea of set-it-and-forget-it also pertains to outsourcing energy savings to smart technologies. People's behavior is fairly regular, and thus predictable, which smart technology can detect and put to good use in saving energy. Popular brands (such as Nest Learning Thermostat, see Figure 4) train themselves on when homeowners are home versus away, so as to tailor temperature settings to when homeowners can experience the benefits of the system—and save energy and money when they are not (Dietz et al., 2009). Nest Labs (2015) measured energy bill usage pre- and post-installation of Nest Thermostats and found significant improvements in energy use compared to maintaining a constant temperature, i.e., the current standard of practice for many government and energy industry leaders. Using a smart device reduced natural gas use by roughly 10% and electricity use by roughly 18%, resulting in household energy bill savings of roughly 20% despite little to no extra effort exerted on the part of the user (NestLabs, 2015).

Conclusion

The past few years have challenged people's ability to stay on track toward their goals, exert self-control, and overcome (or avoid worsening) bad habits. By contrast—or maybe in response—behavioral economic research on goals and self-control is booming. We presented the FRESH framework as a way to convey some of the most exciting and inspiring findings over the past few years and as a potential guide for thinking about the kinds of behaviors individuals can perform toward the goal of a more sustainable future.

Work that we described, and indeed some of our own recent thinking (Vohs & Piquero, 2021), suggests that the good outcomes associated with self-control may result from setting up one's life so that fatigue, distraction, and reliance on heuristics do not make as much of a negative impact, due to the existence of smart technology, self-serving defaults, wise and helpful peers, and reminders that keep goals top-of-mind. While self-control isn't necessarily

easy (but can be made easier through suggestions of the kind we just mentioned), a bevy of research concludes that it is one of the most important traits to possess and cultivate in order to achieve a happy, healthy, wise, and wealthy life.

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APPLICATIONS

If We Build It Right, They Will Come: Driving Health Outcomes With "Precision Nudging"

SARAH DELANEY AND AMY BUCHER[1]

Lirio

Supporting individuals on their unique journeys toward improved health demands that we, as behavioral designers, leverage the tools in our arsenal while collaborating across fields to facilitate behavior change at scale. In this paper, we describe how Lirio uses behavioral economics tactics in tandem with behavior change techniques to develop comprehensive content libraries that address individuals' unique barriers to a target health behavior. We pair this process with intentional experience research to understand an individual's context. Then, we scale digital communication delivery using an artificial intelligence platform. This artificial intelligence platform applies reinforcement learning to optimize which behavioral science "ingredients" from our content libraries are included for a particular individual, thus maximizing the chances they will complete target behaviors. In the conclusion to this paper, we acknowledge areas of focus for implementing behavior change at scale.

Introduction

Counter to the "Field of Dreams" mantra of "If you build it, they will come," behavioral designers understand that people won't come, won't get vaccinated, won't exercise regularly, and will not take steps to improve their health unless they know the opportunity is there, the journey is smooth, and the destination is worth it. Furthermore, each person's starting point is unique and shifts over time. As behavioral designers, our work demands we craft interventions that address an individual's starting point, barriers, and motivations. We must also adapt our approach to meet each person where they are, at each moment on their health maintenance journey.

Behavioral economists and behavioral scientists have long highlighted the myriad contextual factors that influence individual decision-making. As the field matures, we have refined the tactics we use to influence decision-making so its results align with a person's goals and support their well-being. Additionally, as technology advances, we have identified ways to automate these tactics. The combination of refined tactics and technology automation allows us to connect with a person where they are on their journey, accommodate how this journey shifts over time, and support that person more effectively. We have also learned that different tactics are suited to different purposes: for our purposes, behavioral economics tactics direct attention, while behavior change techniques (BCTs) drive motivated behaviors. We have also learned that if we build our interventions *right,* individuals *will* come (or they will be far more likely to do so).

Our approach at Lirio is in the spirit of this evolution in behavior change. We combine the technology of artificial intelligence and machine learning with the evidence base of behavioral economics tactics and behavior change techniques to create personalized behavior change products. These interventions meet each individual where they are and support them where they want to go over time.

Combining Behavioral Economics Tactics and Behavior Change Techniques

Our team at Lirio designs digital communications that move people toward improved health. We have branded these interventions Precision Nudging™, recognizing that the mechanisms of action within interventions are not restricted to traditional nudges. In this article, we focus on one modality of these

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communications: email.

To design our email interventions, we divide messages into two main components: the "engage" element (which includes the subject line and pre-header of the email) and the "act" element (the body copy of an email or text message with a corresponding visual). The goal of the engage element is to grab the recipient's attention so they open and read the email. The goal of the act element is to inspire the recipient to act on the target health behavior. For any given behavior, behavioral and content designers compose a library (an organized and tagged repository of copy and images) of engage and act elements. Example library elements are illustrated in Table 1, and how they may appear in a real message is demonstrated in Figure 1.

Sample Engage Element (Email Subject Line)	Behavioral Economics Tactic	Sample Act Element (Excerpted Email Body Text)	Behavior Change Technique
Sam, did you forget to schedule?	Defaults	Women like you have this exam every day	Social comparison
You're due for your colonoscopy. Schedule before the end of the week	Deadlines	Let your provider know you're on track	Credible source
Your vaccine is waiting for you	Endowment effect	These appointments can help you stay in control of your diabetes and on top of your health	Information about health consequences

Table 1: Abbreviated example library items including engage elements and corresponding behavioral economics tactics, as well as act elements and the corresponding BCTs.

Our machine learning and artificial intelligence platform retrieves elements from a library to assemble a message, which is then delivered to a recipient. Across our libraries, we ensure each message aligns with the brand and voice of the client organization through which it is deployed. For example, we ensure that the color palette matches the client's brand guide, that we use the client's preferred vocabulary for common healthcare terms (e.g., "doctor" vs. "provider"), and that the call to action in the email accurately reflects the patient action path within the organization (e.g. phone numbers and links to scheduling portals are correct for the individual recipient's site of care). We also incorporate health literacy best practices to ensure our messages are accessible and actionable for as many people as possible.

Spark Engagement With Behavioral Economics Tactics

Former U.S. Surgeon General C. Everett Koop famously said, 'Drugs don't work in patients who don't take them'. Similarly, behavioral interventions cannot produce results if people do not engage with them. To support the goal of grabbing the recipient's attention and driving them to open the message, we apply select behavioral economics tactics, which are designed to work within the cognitively overloaded and shortcut-seeking environments of each recipient—that is, to rise to the top of a crowded inbox. This crafting of email subject lines and sub-heading text, to incorporate behavioral economics tactics, can yield the desired outcome of more people engaging with the intervention communications. In the health systems where these interventions have been implemented, we have attained engagement rates

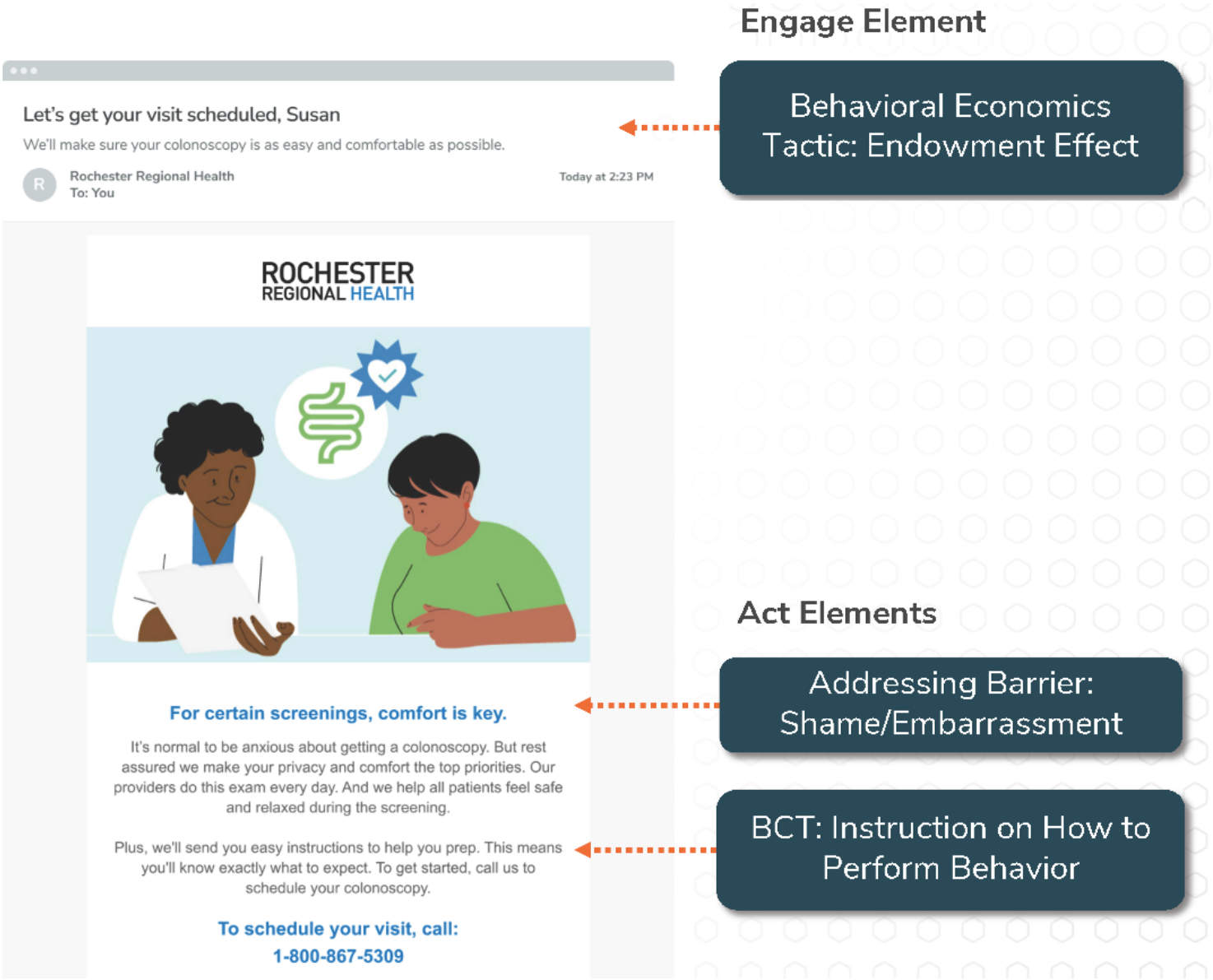

Figure 1: Example demonstrating how the engage element and act elements combine to compose a Precision Nudging message.

well above industry standards for email outreach. For example, a 2021 Gartner report finds average email engagement rates for healthcare emails of 28.1% (Bakker & Xu, 2021). Compare that benchmark to these examples from actual Precision Nudging intervention implementations:

- One Precision Nudging intervention that targeted engagement in an employee assistance program (EAP) resulted in an 80% engagement rate among employees, compared to with around 4% for the client's typical email outreach;
- Another intervention Lirio deployed at a healthcare organization resulted in an 80% engagement rate among patients due for mammograms; and
- In a different geographic market within the same healthcare organization, Lirio's messages elicited 81% engagement among patients with diabetes who were due for a primary care visit.

When emails go unopened, patients may miss important health communications that might otherwise spur them to action. The engage elements that leverage behavioral economics tactics serve as a first step to getting individuals through the door, so to speak. Once we accomplish this goal, people are more likely to benefit from the behavior change techniques used in the rest of the message, i.e., the body content of the email.

Inspire Action With Behavior Change Techniques

The body of an email message includes a hero visual and a section of copy that deliver a behavior change technique (Michie et al., 2013) intended to support the goal of inspiring the recipient to act on the target behavior. These techniques are designed to support complex behaviors, which, in health, may include diabetes management or getting a vaccination. We select which BCTs to include in a library based on a combination of literature reviews and experience research (described in more detail below) to identify barriers[2] to the target behavior. We compile the most common behavioral barriers and organize them using the COM-B taxonomy, which arranges barriers within the categories Capability, Opportunity, and Motivation. Then we use the Behaviour Change Wheel to identify appropriate intervention functions, or categories of solutions, to address the barriers (Michie et al., 2011). We then document specific BCTs that operationalize each intervention function and are appropriate for translation into an act element. Once we have compiled a complete list of likely barriers and corresponding BCTs, we prioritize BCTs through a ranking exercise that identifies: 1) the prevalence of each barrier, 2) the significance of its impact on the performance of the target behavior, and 3) the likelihood of the Precision Nudging intervention to effectively address the barrier (see Bucher, 2020 and Table 2).

Barrier or Benefit	Strength of Evidence	Ease of Implementation	Significance on Behavior	Prevalence	Frequency	Total
Perception of procedure as painful	3	3	3	2	1	12
Belief that procedure is necessary	2	2	3	3	2	12

Table 2: An example of the structured ranking exercise we use to prioritize barriers for inclusion in intervention design. Each barrier is assigned a numerical score for each category; barriers must have a total score above a pre-determined threshold in order to be included in intervention design.

Behavioral content and visual designers then operationalize or "translate" these top-ranking BCTs into copy and visuals that are ultimately assembled in our messages. Behavioral designers conduct a manipulation check of content to ensure the BCTs are operationalized accurately.

Paired together, these behavioral economics, tactics-based engage elements and BCT-based act elements comprise a content library that supports isolated behaviors, i.e., engage, then act, at key moments.

The Role of Experience Research

We identify key moments of an individual's health journey through experience research. This work examines the context of the journey within a specific health system environment, namely, everything with which a patient interacts when it comes to communication from their health system, from marketing outreach, to patient education, to the online patient portal experience. It also considers patient and stakeholder (e.g., healthcare professionals, call center representatives, or other employees) perceptions of this journey.

Mapping the context of the journey ensures we build intervention content that complements a series

2 We also identify facilitators for the target behavior and seek to amplify existing facilitators in our messaging. For the purposes of this article, we focus our discussion on designing ways to address barriers, as these tend to be more prevalent, and our interventions target people who are not successfully performing the target behavior at the clinically recommended frequency (i.e., who are likely experiencing more barriers than facilitators).

of interactions within a health system. "Good" patient experiences are likely to involve a single integrated experience (Collins et al., 2017) with many familiar elements (Downe, 2020). We map patient-health system interactions by gathering and examining the health system's existing communications a patient might receive at each touchpoint. This allows us to design an experience that feels integrated and familiar, rather than chaotic and unexpected. We also conduct stakeholder interviews to understand better when and how these communications are provided to patients, if at all. These interviews allow us to map the typical timeline of touchpoints between a patient and health system, pain points from the perspective of the stakeholder, and common questions posed by patients. At this stage, our mapping process looks similar to a service blueprint (see Figure 2).

Next, we integrate patient perspectives, gathered through patient interviews, to capture their perceptions of their experience. If available, we also capture patient insights through existing survey or behavioral data. By analyzing this timeline of interactions, and supporting communication artifacts, insights from stakeholders, and patient perspectives, we diagnose 'behavioral bottlenecks' likely affecting the patient experience (Datta & Mullainathan, 2014). We extend this diagnosis by incorporating findings from a literature review specific to the behavior.

Our experience research process connects our behavioral science content libraries—informed by psychological determinants likely affecting patient behavior—with the context of each unique health system and perspectives from patients' lived experiences. Often, our behavioral content and visual designers refer to the communication artifacts collected during the experience audit, along with supporting recommendations, during the content creation process. This ensures that content and visual design aligns with brand elements such as color palettes and organization-specific terminology, as well as existing action paths familiar to the patient.

The Role of Technology in Optimizing Communication

Including a broad set of behavioral economics tactics and BCTs in intervention design requires a mechanism to match the right tactic to each individual for a given target behavior and context. Implicit in the idea that context matters is the knowledge that not all BCTs are equally effective for all people at all times. Each person's context is unique and changes over time—there is no universal intervention. Therefore, a critical step in designing an intervention that produces reliable and scalable outcomes is to personalize the delivery of each behavioral economics tactic and BCT message element. Personalization is a powerful tool for behavioral intervention, as a personalized intervention is more likely to engage a person by connecting with their intrinsic sources of motivation. The self-determination theory of motivation suggesting that experiences that support the basic psychological needs of autonomy, competence,

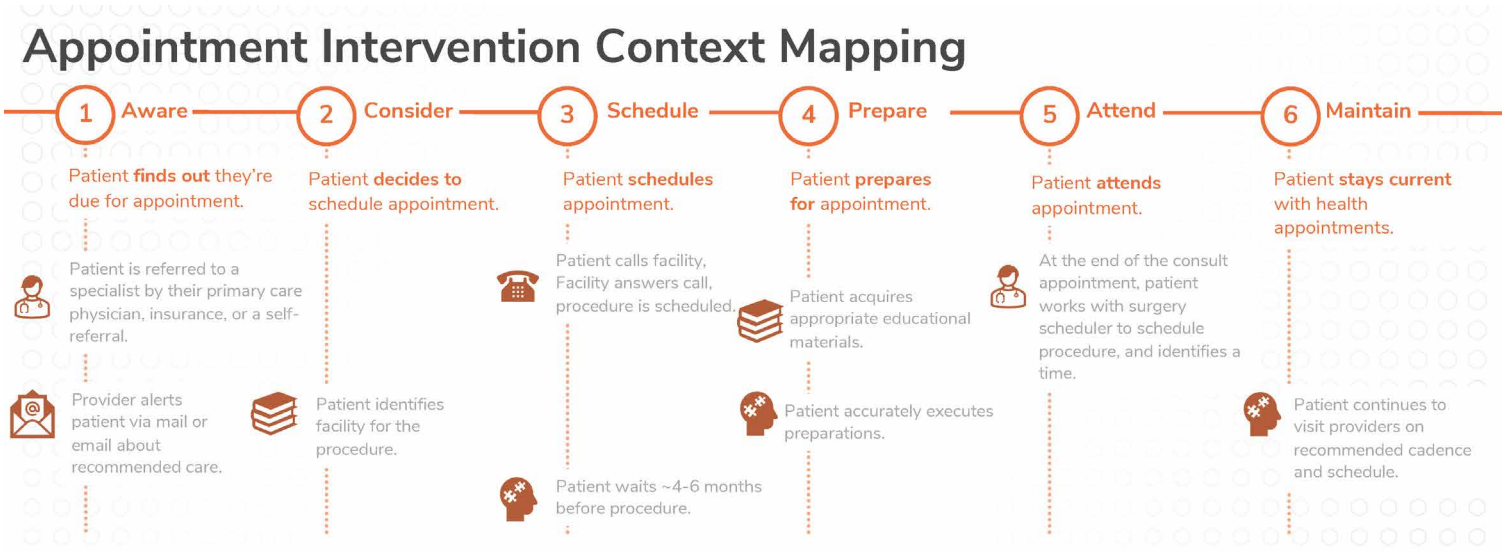

Figure 2: A genericized example of an intervention mapping that documents key touchpoints and communications as a patient schedules and completes a procedure.

and relatedness are more compelling (Vansteenkiste et al., 2020); personalization can help support all three of these needs (Peters et al., 2018; Ryan & Rigby, 2018). Personalization facilitates engagement of the individual with the intervention, which is a prerequisite to action (as Dr. Koop reminded us, 'Drugs don't work in patients who don't take them'.).

Evidence also supports the notion that personalization enhances an intervention's outcomes. Personalized interventions are more effective at changing behavior than generic or targeted ones (Revere & Dunbar, 2001) and lead to more sustained behavior change (Lustria et al., 2013). Furthermore, personalization may improve the uptake of intervention features like medication reminders (Burner et al., 2014). More personalization seems better than less, and when based on multiple data elements (e.g., channel preference, personal characteristics, etc.), it yields greater behavioral outcomes (Joyal-Desmarais et al., 2020; Strecher et al., 2008). Exposure to personalized content activates areas of the prefrontal cortex associated with self-relevance (Chua et al., 2009), and these neural responses are in turn associated with changes in behavior (Casado-Aranda et al., 2021). In short, personalization makes an intervention more appealing *and* more effective, but of course, it can be challenging to pull off, as it demands understanding an individual's unique barriers and context at the moment of intervention. Without technology to scale the process, this requires an enormous amount of data and decision architecture from intervention designers.

Fortunately, digital technology can help solve the challenge of personalization at scale. Outside of traditional healthcare organizations, companies like Amazon and Pandora are well-known for using recommender algorithms to personalize the options they present to consumers (Al-Ghuribi & Mohd Noah, 2019), and consumer data platforms (CDPs) offer increasingly personalized retail experiences. Within healthcare, context-aware interventions that use sensors, wearables, and other technology inputs are becoming more common for behavior change interventions (Michie et al., 2017; Thomas Craig et al., 2021). At Lirio, we use an artificial intelligence (AI) platform that employs a behavioral reinforcement learning algorithm (Dulac-Arnold et al., 2021; Dulac-Arnold et al., 2019; Mnih et al., 2015; Sutton et al., 1999). It selects the combination of behavioral economics tactics and BCTs to deliver to each person we message about recommended health behaviors. The recipient's message "recipe" is increasingly personalized over time, as AI uses the person's behavioral responses—such as opening messages, clicking calls to action, and completing health screenings—to identify the "ingredients" most effective for moving that individual to action. Additionally, we personalize content to reflect the recipient's name, place of care, best call to action, and more.

Regardless of the specific technology used, algorithm- or AI-based platforms present an opportunity to scale personalization beyond what was previously feasible. It also allows us to optimize the outcomes associated with behavioral science by applying those tactics in the most effective ways. Any technology that can personalize at scale will become a valuable tool in the behavioral science arsenal.

Reflections About the Future of the Field

While we are excited about the future of behavioral economics and behavioral science to support people in achieving their health and well-being goals, we also recognize the potential to misstep. As we look to the future of our field, we have several focus areas—ethics, preservation of autonomy, and awareness of our own design context—guiding our decisions and designs.

Our Responsibility as Ethical Behavioral Designers

This advancement in the application of behavioral economics tactics and BCTs can be applied to help or hinder well-being. The application of behavioral science to further business (instead of human) interests is well documented by organizations such as the Center for Humane Technology, among others. As the field grows, we must continue to hold ourselves to the idea that, by definition, a nudge 'influences choices in a way that will make the chooser better off, *as judged by the choosers themselves*' (Thaler & Sunstein, 2021). As designers working in healthcare, we recognize there is a spectrum of communication that can range from supportive to coercive. For example, dark patterns—features designed to trick users into an action they may not have chosen—may be effective in the short term but are ultimately

off-putting (Mathur et al., 2019; Nodder, 2013). As our capabilities to implement behavioral science interventions advance, we have a responsibility to hold ourselves to ethical standards, which include supporting individual well-being as defined by the individual, and not designing communications that manipulate or coerce.

Preservation of Autonomy

One challenge inherent in the behavioral design process is understanding and accommodating individual health goals. How a person thinks about and ultimately achieves a goal can be a dynamic process, since they might commit, waver, abandon, or readopt the goal over time. It can be tempting to focus on people achieving the target behavior as a goal worth any cost, but patient-centered design requires respecting a person's option to say no—what is known as 'volitional non-adherence' (Vansteenkiste et al., 2012)—even when that choice is detrimental to a person's health or the objective quality of their outcomes. Respect for autonomy is built into the very definition of a nudge. Thaler and Sunstein (2021), for instance, describe a nudge as 'any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives' (p. 8). We take this to heart in our application of behavioral science to our interventions. Recipients are always able to decline the call to action and/or unsubscribe from the intervention. Aside from the compelling moral and ethical reasons to preserve autonomy when it comes to healthcare behaviors, the science of motivation suggests that behaviors freely chosen are more likely to prevail over time (Deci & Ryan, 2000). Given that many of the health behaviors prompted by Precision Nudge messages should be repeated over time (e.g., cancer screenings, annual wellness examinations, or vaccinations), it behooves us to help people overcome their barriers rather than coerce their participation.

The Context of Our Design

As a U.S.-based company designing behavioral interventions within the American healthcare system, our entire behavioral design process is situated within the Western, Educated, Industrialized, Rich, and Democratic (WEIRD) context. Moreover, the evidence base built through research conducted within WEIRD contexts has enabled our work (Henrich et al., 2010). To further collective well-being, it is essential to build the behavioral science evidence base outside of the WEIRD context by applying, testing, and refining these techniques with more diverse populations, especially understanding that many of the people who seek healthcare in the United States are not from WEIRD contexts.

Looking Forward

When not applied coercively, behavioral science holds powerful potential to support well-being. Fueling much of behavioral design is the recognition that although we *intend* to act, the gap between intention and action absorbs many of us (Sheeran & Webb, 2016). Applied at scale, a supportive intervention bringing us all closer to well-being, as a person defines it for themself, could help reduce the volume of intentions that succumb to that gap. Over the course of the COVID-19 pandemic, we witnessed how a small reduction in the gap between intention and action enabled a critically positive outcome, namely, increased vaccination rates. Yet this gap persists across many important health behaviors. Nonadherence to actions recognized to improve health, such as smoking cessation (Mersha et al., 2021), regular exercise (World Health Organization, 2019), preventative screening attendance (Shani et al., 2021), and medication adherence (Piña et al., 2021), is common and well known.

Even the most well-intended interventions may have unanticipated drawbacks. While we strive to proactively identify and avoid introducing new obstacles to the patient experience, we also actively monitor intervention performance so that we can quickly detect and correct any unwanted patterns. For example, if Lirio's communications are the primary method of alerting patients to available care, it is critical to ensure messages are sent on the planned schedule and that they are successfully delivered. Similarly, we want to ensure that specific messages are not negatively associated with patients taking action on their health; such a pattern would suggest we inadvertently deter people from care. We use a combination of planned and ad hoc data monitoring, along with program audits, to protect against such unintended negative influences.

Our path to and maintenance of health is not frictionless. Individuals face barriers in recognizing opportunities to seek better health, getting started along an action path, and overcoming obstacles they encounter along the way. As behavioral designers, our purpose is to apply the tools we have at our disposal, so an individual's best efforts to quit smoking, exercise, seek preventative screenings, or otherwise pursue improved health are as frictionless as their lived context allows. For example, another tool we anticipate applying at Lirio is the delivery of a message at the moment a recipient is able to take action on it (a concept leveraged from Just In Time Adaptive Interventions; Nahum-Shani et al., 2018). We must balance the risk for coercive application with the potential of behavioral science applied at scale to support us in meeting our well-being goals. Lirio's 80% engagement rates among patients due for a mammogram or in need of a diabetes care visit are a preview of that potential, and it keeps us optimistic about the future of behavioral science interventions applied at scale.

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Partnership Between Data Science and Behavioural Economics

STEPHEN HEAL, PAULA PAPP[1] AND PRIYANKA ROYCHOUDHURY

Frontier Economics

How can organisations get more from their investments in data? We examine how the combination of behavioural and data sciences can improve risk models when behaviours need reassessing in new contexts. We cover two macroeconomic contexts challenging the value of traditional models. The first is the rapid and drastic economic and behavioural shock of COVID-19. Here, we use behavioural science to leverage near real-time data from point-of-sale transactions and observe how adaptive behaviours improved hotel and restaurant's chances of survival. The second, is the almost decade-long low – and sometimes negative – interest rate environment that prevailed in Europe until 2021. Through behavioural science we elaborated a new approach to evaluate the propensity of funds to migrate to alternative products. There is much to gain by bringing behavioural science to bear on problems linked to changed macroeconomic contexts – where data science investments can be leveraged to great effect.

Introduction – The Synergies Between Behavioural and Data Science

When we discuss potential Behavioural Economics (BE) projects with our commercial clients, the same questions keep cropping up. Can behavioural science help us get more from our investments in data? Can you show us examples where BE fundamentally changed traditional data science-based models? And what's the best way to integrate BE with our data science teams?

To answer these questions, we need to go back to the basics. Data science allows us to analyse the unseen – using techniques ranging from regression analysis to machine learning. It lets us look at large sets of data and surface patterns in past behaviour to inform business strategies by transforming those patterns into predictions (IBM, 2020). Data scientists, for example, can take information gathered from consumers' buying habits, product and channel usage to build models that describe patterns or propensities that are used in commercial decisions such as sales targeting or bank lending (Online, 2021).

One challenge is that while the patterns unearthed by data science models help in spotting relationships in the hope that they can point to future outcomes, they do not reveal *why* we see those patterns in the first place. Organisations need more – and this is where BE can prove to be valuable - by providing hypotheses (and evidence through testing) which explain the observed behaviours and thus offer stimulus for new and creative ways to change them. The BE toolkit[2] generates further value for the business by asking, '*What drives the customer behaviours that determine the economics of your business?*'

Additionally, the BE toolkit can determine the most effective ways of designing interventions that improve outcomes for customers and value for businesses, as well as evaluate the impact of such changes. Together, these disciplines can test and refine our understanding of a behaviour of interest and start to explore interventions that change it (see Figure 1).

In practice, we can start from either the observed patterns of behaviour or from a hypothesis. We illustrate this through the following two case studies.

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2 There are different definitions for the BE toolkit. At Frontier, we include in this toolkit not only behavioural traits or biases identified from the literature, but also the available frameworks (i.e. BASIC or COM-B) or techniques applied to market research.

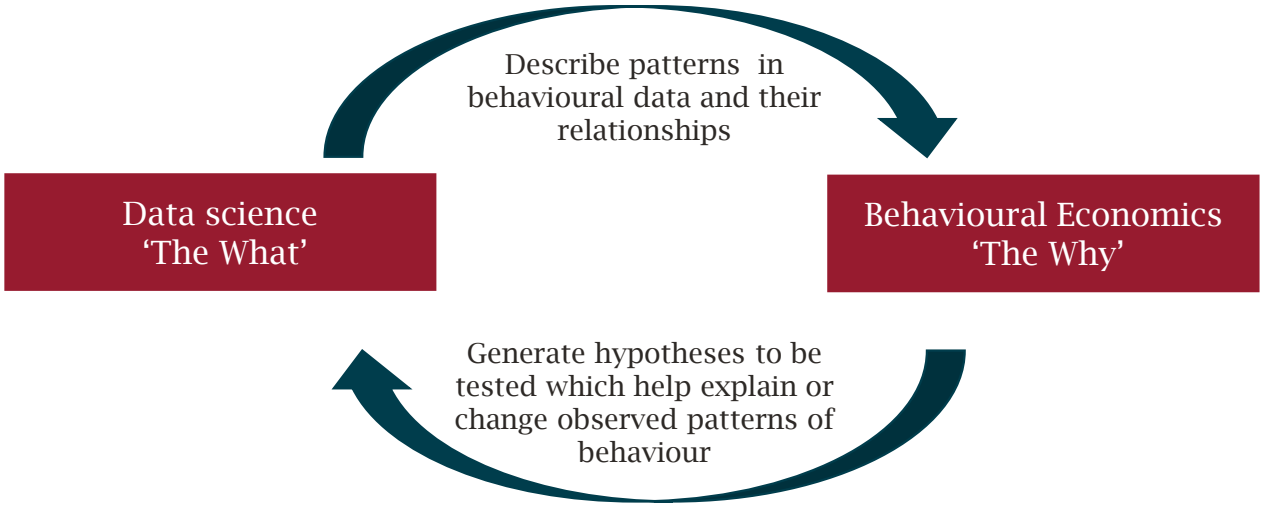

Figure 1: Complementarity between data science and behavioural economics.

Case Study 1: Adapt to Survive

How do small businesses react to a changing environment or a crisis? Does their behaviour predict their survival? This was a significant question for many lenders during COVID-19, particularly for banks lending to hotels and restaurants, which were hit very hard by the pandemic.

Tourism was responsible for 12.3% of Spain's overall GDP (OECD, 2022), and hotels and restaurants account for a big chunk of the value generated by the sector. Travel restrictions imposed in the early stages of the pandemic clearly signalled big challenges. One of our clients, a Spanish bank, has more than 1 million small-business clients, many of which are in the domestic hotel, restaurant and catering (HORECA) industries.

In this case study, we started from the hypothesis that *adaptive behaviours will improve the chances of survival in small businesses during the COVID-19 pandemic.* Data scientists looked for patterns in payment card data that describe the changing patterns of commercial activity, whilst behavioural scientists investigated adaptations made by the businesses. In doing so, we created new insights for the bank's risk modelling at a time of crisis.

The Initial Hypothesis

The rules of nature can be applied to businesses as well as to Darwin's finches[3]: at a time of rapid change, adaptive behaviours should improve the chances of survival.

Although not comparable to evolutionary timescales, COVID-19 has created one of the most extreme cases of altered human consumption patterns on recent record, and it is a great natural experiment in the study of how businesses behave. We can observe changes in both the habits of consumers during the crisis and the behaviour of firms serving them.

Individual small businesses can be strongly influenced by a few people who own and run them. As such, they may show more variation in their adaptive behaviours than large organisations. The core hypothesis was not only that adaptive behaviour aids business survival, but also that some adaptive behaviours are better predictors of survival than others[4]. Put another way, businesses which fail to adapt to the changing shape of demand will be less able to service their debts and be at greater risk of going under.[5]

Traditional financial risk yardsticks such as balance sheet, cash flow and past payment records

3 The Galápagos finches are a classic example of adaptive radiation. In 1835, Charles Darwin visited the Galapagos Islands and discovered this group of birds that would shape his ground-breaking theory of natural selection. Darwin's finches are now well-known as a textbook example of animal evolution.

4 Innovation is defined as the process by which firms actively change their business model to disrupt market conditions. Business model adaptation is the process by which firms align their business model with a changing environment.

5 Saebi (2017), Zahra & Sapienza (2006) and Kitching et al. (2009).

assessments are not granular, and they are also slow to reflect a sudden change in the business environment (Greuning & Bratanovic, 2020). The fast-moving conditions of the pandemic called for a quicker (almost real-time, given the regular changes in restrictions!) approach.

To address this idea, we relied on behavioural data. We used high-frequency information on consumer spending at hotels and restaurants across the country, captured by point of sale (PoS) terminals at each of the businesses that were clients of the bank.

This data painted a picture of how spending patterns evolved – day by day, hour by hour, town by town, business type by business type. For example, it showed us who was being hit hardest: was it pizza restaurants in the centre of Madrid or small hotels on the coast?

The Data Science

The data science challenges here were numerous, but having the behavioural hypotheses to guide the project enabled us to focus on a few critical tasks, including:

- Selecting the right samples from the mass of transaction data available – there were 4.3bn transactions using cards via PoS terminals in Spain in 2020 (ECB, 2020) – and our data from the client included a significant share of the overall transactions.
- Screening the data and matching it with comparable data from the previous year (pre-COVID-19). This was important, as the businesses are seasonal.
- Exploring the data through visualisations using R Shiny[6] to look at multiple variables at the same time and generate plots (including geographical) alongside tables.

We narrowed down a sample of 15,000 small businesses to a representative selection of about 2,500. Collectively, these clients generated 3.5 million linked PoS transactions during pairs of comparable[7] weeks in March and June in the years 2019 (pre-pandemic) and 2020 (during the pandemic).

Behavioural Assessment

To assess how the businesses adapted, we worked on subsequent hypotheses with a small sample of business owners and with people from the bank who know these clients. Drawing on their knowledge of the nature of these businesses and the challenges that Covid presented them with, we explored three sets of ways in which their behaviours may have changed as a result. Using these hypotheses, we then carefully constructed a survey for a selection of restaurants and hotels to explore what adaptations they made to different aspects of their businesses and how they viewed their chances of survival (as illustrated in Figure 2):

1. operational adaptions (changes in the use of space, working hours, staffing levels);
2. strategic adaptions (changes in product offering, suppliers, customer base or delivery channels) and
3. financial adaptions (use of COVID-19 support schemes[8], new sources of working capital, etc).

Results and Discussion

Naturally, the data science underlined the severe impact of the lockdown introduced to contain the pandemic. The effect of most people being confined to their homes[9] was broadly uniform across the HORECA sector. In March 2020, sales volumes at hotels and restaurants were down by more than 90%. However, the subsequent recovery observed showed considerable variation. After three months (by June 2020), sales in restaurants had rebounded by over 50 percentage points, outstripping a less than 10-point recovery in hotels.

6 The R Shiny framework is a package from RStudio that helps build interactive web applications with R. In essence, R Shiny helps to create highly effective data reports and visualisations through which the user can explore a dataset.

7 To make data comparable, we controlled for holiday seasons and extraordinary events.

8 Including ICO loans. As a state-owned bank, ICO provides loans to fund company investment operations inside and outside of Spain. In relation to the Covid-19 crisis, most loans were needed to cover short-term cash flow problems caused by a sharp drop in business income.

9 View State of Alarm Declaration

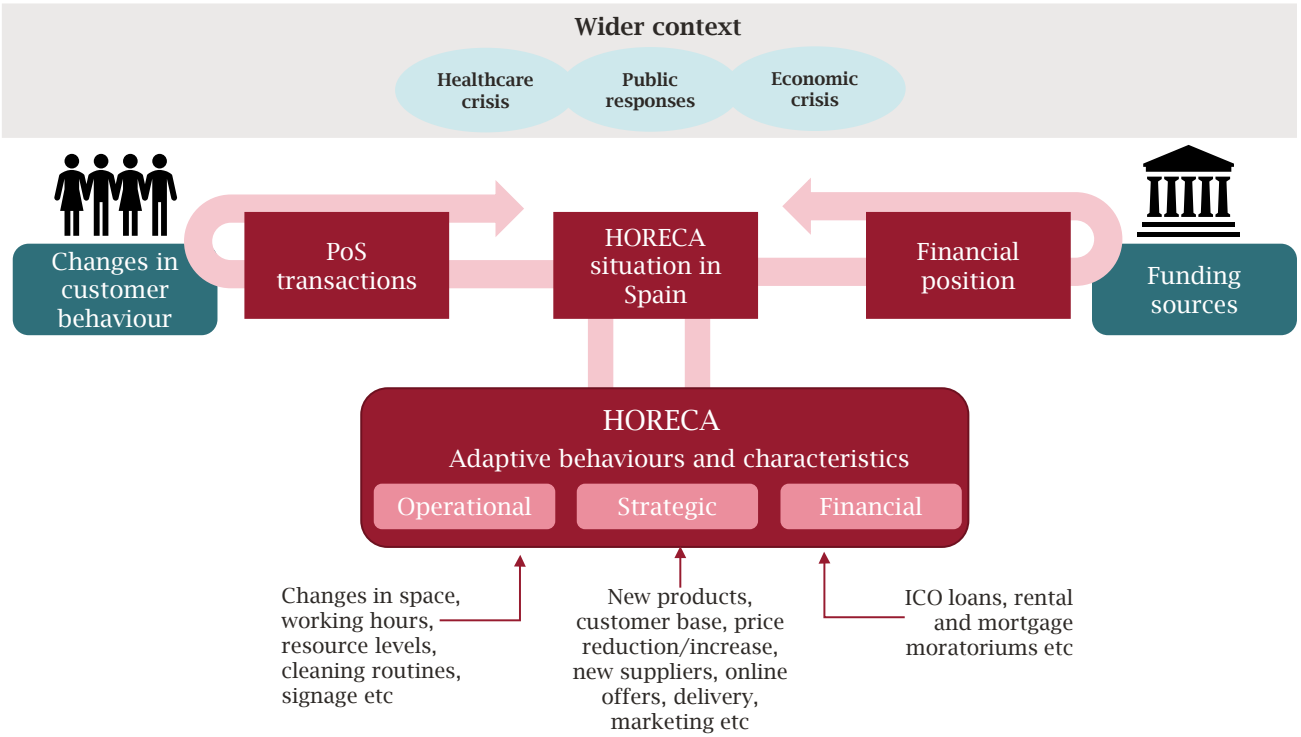

Figure 2: Using BE to understand how adaptative actions affect the survival of small businesses in a crisis.
Source: Frontier case approach 2020.
Note: Adapted from work with banking clients.

For our core behavioural hypothesis, our analysis revealed that businesses that actively adapted in the areas of strategy and operations did recover more strongly than those that took fewer, mainly financial, steps (as shown in Table 1).

The bank's clients that topped the recovery rankings made nearly twice as many strategic and operational adaptations as businesses at the bottom of the table[10]. These measures included altering prices or product offers, changing the use of space, turning to different suppliers and switching to online ordering and delivery. Tellingly, we found that financial actions – typically monitored by banks – were not a good predictor of recovery and ultimate survival.

Interestingly, restaurant customers were keener to come back for dinner than for lunch. They spent less on average than before the pandemic and almost completely stopped splashing out on very expensive items. We were able to track such behavioural details across sub-sectors and regions of the country in a granular, extensive and timely manner.

There was no guarantee of survival when the pandemic was raging. In June 2020, owners of hotels and restaurants in Spain estimated a one-in-three probability (32-36%) that their local competitors would go bankrupt over the coming 18 months (as shown in Table 2). Due to well-documented 'overconfidence bias' (Pallier, 2002)[11], those surveyed thought they were a lot less likely to go bust themselves. However, they put their chances slightly higher when the question was framed in terms of survival rather than bankruptcy, something which could reflect the anchoring point in their thinking (Kahneman & Tversky, 1974)[12].

In this case study we:

- started with a behavioural hypothesis with famous historical roots in evolutionary biology;
- which led data scientists to access non-traditional sources of behavioural data to improve their understanding and mitigate risks in a

10 This holds when measured for firms in both the 10th and 20th percentiles.

11 The overconfidence effect is observed when people's subjective confidence in their own ability is greater than their objective (actual) performance (Pallier et al., 2002).

12 Anchoring is a particular form of priming effect whereby initial exposure to a number serves as a reference point and influences subsequent judgments. The process usually occurs without our awareness (Tversky & Kahneman, 1974).

Share of the Adaptive Behaviours Shown by Firms	Top 10% of Firms by Recovery	Bottom 10% of Firms by Recovery
Strategic actions	18%	10%
Operational actions	16 %	10 %
Financial actions	11 %	11 %
TOTAL	**19 %**	**8 %**

Table 1: Contrasting adaptive behaviours and performance in the recovery. *Source:* Frontier case analysis 2020. *Note:* Recovery in sales measured March to June 2020 (in pandemic) compared with March to June 2019 (pre-pandemic). Figures disguised.

Probability of Bankruptcy When Question Framed as "Over 18 Months from June 2020"	Thinking of Your Local Competitors	Thinking of Your Own Business
'Bankruptcy'	**32%**	14%
'Survival'	**36%**	16%

Table 2: Assessing risks in a crisis: Overconfidence and anchoring. *Source:* Frontier case work with banking clients, 2020.
Note: If the question was framed as the probability of survival, the answers were converted to a bankruptcy equivalent measure (1-survival) for the comparison above. Figures disguised.

crisis (the analysis of high-frequency behavioural PoS data provided insights into w*hat* was happening – the behaviours of "clients-of-the-clients") and

- this in turn helped behavioural scientists explore (through a survey in which we included behavioural elements) *why* some businesses were rebounding better than others – the behavioural adaptations of the bank's clients.

This ultimately enabled the bank to support its portfolio of several thousands of hotels and restaurants through the crisis and to emerge with more than two-thirds of these businesses still trading.

Case Study 2: A Cluster of Savings Behaviours

A great deal has changed in the world of banking as a result of the ultra-low interest rates that have prevailed since the Global Financial Crisis. In response to the shifting landscape, our client (a major European bank) decided to re-assess the behaviour of its depositors and turned to a combination of behavioural and data science.

Since the 2008 recession, the Euro Interbank Offered Rate (EURIBOR), a benchmark interest rate, has remained close to zero – and even negative since 2014 (Claeys, 2021). Consequently, people's financial habits have changed considerably. One of the trends observed with savers is that they keep a smaller proportion of their cash savings in fixed-term deposits than in non-maturing deposits (NMDs)[13] that can be withdrawn at any time. Another is that some savers have also turned to alternative asset classes such as equity investments in search of higher returns (He, 2021).

At the same time, consumer habits have evolved to become increasingly digital, and in financial services, individuals can now move or invest their savings almost instantly – as long as they have an internet connection.

13 Examples of NMDs include savings accounts, demand deposits and current accounts.

On top of these trends, COVID-19 has affected people's financial situation in different ways. While some saw increased "involuntary" savings as a result of remote working and fewer spending opportunities, others lost their source of regular income (Dossche et al., 2021; Papp et al., 2021).

All of these elements challenge the capacity of traditional historic, statistic-based interest rate risk models to produce reliable results on the impact of interest rates on client behaviour.

As we did in the previous case study, we started from a hypothesis, which in this case was: *people keep a liquidity buffer to insure themselves against possible negative shocks* (Palenzuela & Dees, 2016). Our data scientists used a supervised machine learning (ML)[14] technique (a decision tree) to identify patterns of such behaviour that were not apparent in traditional models. We then explored the question further with a second round of behavioural hypotheses that involved additional data science analysis, thereby demonstrating the loop in practice. In this case, the insights provided a new way of driving their risk and propensity models that connected the dots taken from other drivers of behaviour beyond interest rates. Thus, this methodology was a cost effective, customer-driven and outcome-oriented way of analysing the potential evolution of deposits for the bank.

The First-Round Hypotheses

Based on a review of the literature (Kazarosian, 1997), we started from the hypothesis that people maintain balances in their NMD accounts for three broad purposes (see Figure 3):

- **Transactional**. Money for regular transactions (paying the rent, utilities and groceries etc), which fluctuates each month with some regularity.
- **Buffer**. Money for a rainy day – a buffer for the unexpected – that is relatively stable over longer periods.
- **Excess Savings**. The rest that may be moved between accounts and investments or used for irregular larger purchases – and may be unstable in the medium term.

Our goal was to understand the decision-making process regarding savings and deposits. To that end, we eschewed the traditional "portfolio" approach of analysing deposits in the aggregate and chose instead to focus on the behaviour of individual customers. This meant identifying all the funds each customer maintained across different accounts and generating a methodology that was able to sort the balances into these three categories.

Data Science and the 'Super-Optimisers'

Our objective was to identify the portion of customers' funds displaying a higher propensity to migrate if interest rates were to increase again. To do this, we first needed to separate, for each customer, their excess savings from their buffer. The rationale was that we would expect some level of mental accounting between money for a rainy day (the buffer) and excess savings. We would expect the buffer not to be influenced by the interest rate environment but by other elements in the customer's context.

We were unable to rely on traditional regressions due to the low and stable interest rate curve over the last few years. Therefore, to separate buffer from excess savings, we developed a novel approach that relied on machine learning and behavioural insight:

1. We started off by identifying a group of customers we called "super-optimisers," who actively made savings decisions and managed their savings. These were selected as active clients who had a high level of engagement with the bank and were observed to be actively managing their savings, i.e., showing a high share of financial wealth in products other than NMDs. Super-optimisers are thus the customers most likely to reveal their preferences for levels of savings, given they only held as NMDs the savings they did not want to invest, which would cover mainly the transactional and buffer functions.
2. The super-optimisers' buffer could then be approximated as the average minimum monthly

14 Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy.

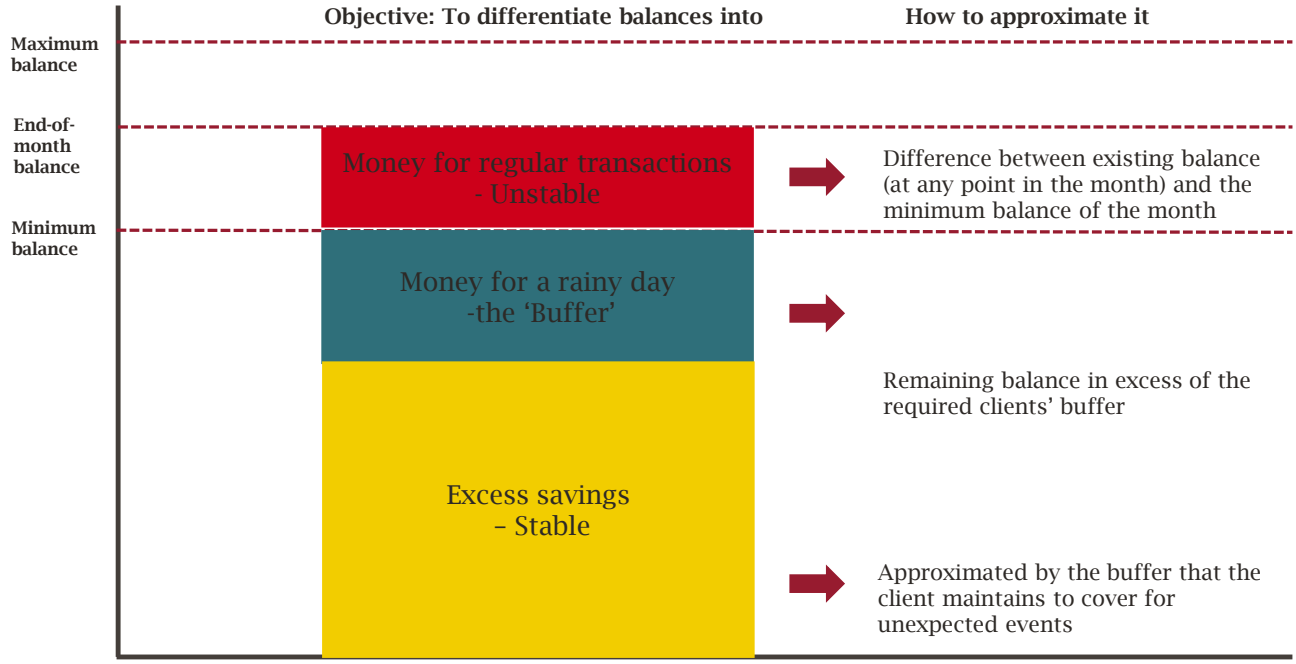

Figure 3: Behavioural categories of NMD funds. *Source:* Frontier case approach 2020.

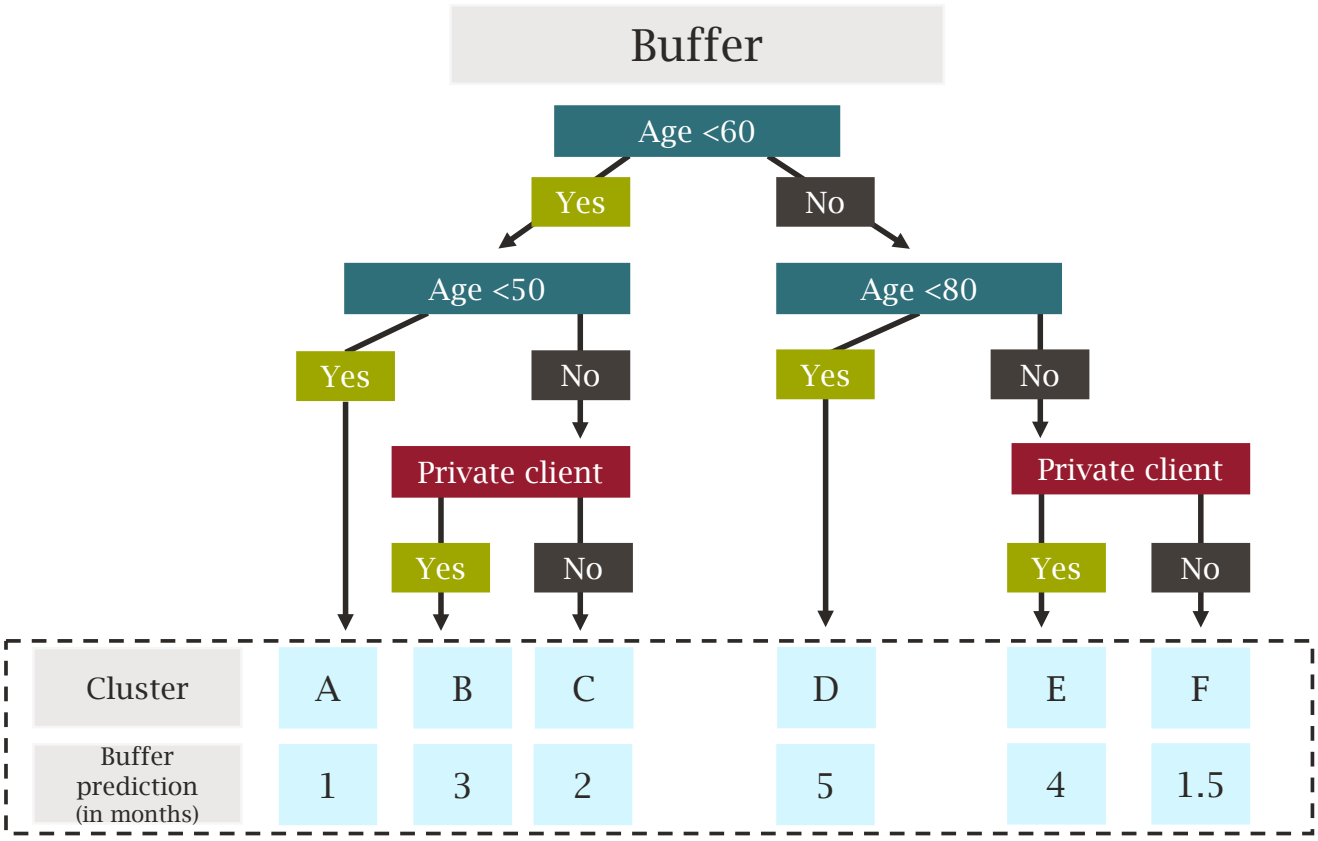

Figure 4: Illustrative example of a decision tree splitting "super optimisers" on age and client segment attributes to predict their buffer.

Note: Buffer variable is defined as the minimum balance in current accounts, relative to the sum of all transactions relating to daily expenditure and physical investment (in all accounts). Actual figures disguised.

balance held. We could express this as a ratio of their monthly expenses.

3. Once this ratio was obtained, we used an ML algorithm to assess how the buffer varied according to client characteristics, constructing a robust decision tree[15]. Our output was a set of six clusters (A, B, C, etc.) based on age and client characteristics (as illustrated in Figure 4).
4. We then applied the buffer rules obtained from super-optimisers to the rest of the clients in the sample.

The Second-Round Hypotheses: The Willing and the Able

Once excess savings were identified through data science, we turned to insights from BE to develop a framework to evaluate how much of the excess savings might actually move if interest rates were to increase. This framework was informed by a set of hypotheses to be tested by the data. These hypotheses were based on an economic and behavioural literature review of relevant evidence on savings behaviour in Spain and the UK[16]. It highlighted two key dimensions, namely i) willingness of people to actively manage their savings and ii) the actual capacity of people to save beyond their normal expenditure and buffers. These hypotheses (examples shown in Figure 5) were translated by data scientists into observable metrics to generate the behavioural segmentation (with quantification) illustrated in Figure 6.

For example, as part of willingness to manage (H3), we hypothesised that individuals who had previously

Main hypotheses	Sub-hypotheses
H1: Ability to save is constrained by financial liquidity which translates to the saving behaviour observed i.e. more free cash flow implies more savings	Higher average income of an individual will lead to higher savings
	Lower volatility of the difference between income and expenditure of an individual will lead to higher savings
	Ability to save changes through time for an individual wherein the average savings profile follows the lifecycle – rising from low in 20s to high in 50s and then falling after retirement
H2: The aggregate savings profiles hide important differences between groups of individuals with different ability to save profiles	Some characteristics (jobs/people/areas) will correlate with low ability to save throughout an individual's life. e.g. Persistent low income → lower educational attainment Persistent high expenditure → living in Madrid's city center
	Some individuals' ability to save can change dramatically with life events such as birth of children, children going off to college, divorce, retirement. On average we may be able to spot these common events.
H3: Willingness to manage savings can be seen in prior behaviours – especially ones that indicate stickiness and/or engagement with their finances	Individuals who now or previously had already invested in some saving product are more likely to do so again
	Individuals are more likely to manage their savings if they have: • Previously switched banks or accounts • An account in another bank i.e. they have multiple bank accounts • Searched or asked about conditions associated with savings products • Switched energy provider or mobile phone contract in last 18 months
H4: Different savings products will show different levels of willingness to manage savings	The more long term the saving product(and more perceived risk), the less frequent will be the amount of savings
	Diversification can be a source of willingness to manage

Figure 5: Hypotheses informing the data science. *Source:* Frontier case hypotheses informing the case framework.

Note: Adapted from work with the banking client.

15 A decision tree is similar to a classical linear regression in econometrics. The idea is to predict the dependent variable (buffer ratio) with the available information contained in the explanatory variables (age, sex, balance, etc.). However, unlike a linear regression, a regression tree allows for non-linear relationships and lets us produce a very clear visual segmentation of our sample.

16 See references by Banco de España (2008), Bover et al. (2016), Which? (2014) and Tonybee Hall and Building Societies Association (2019).

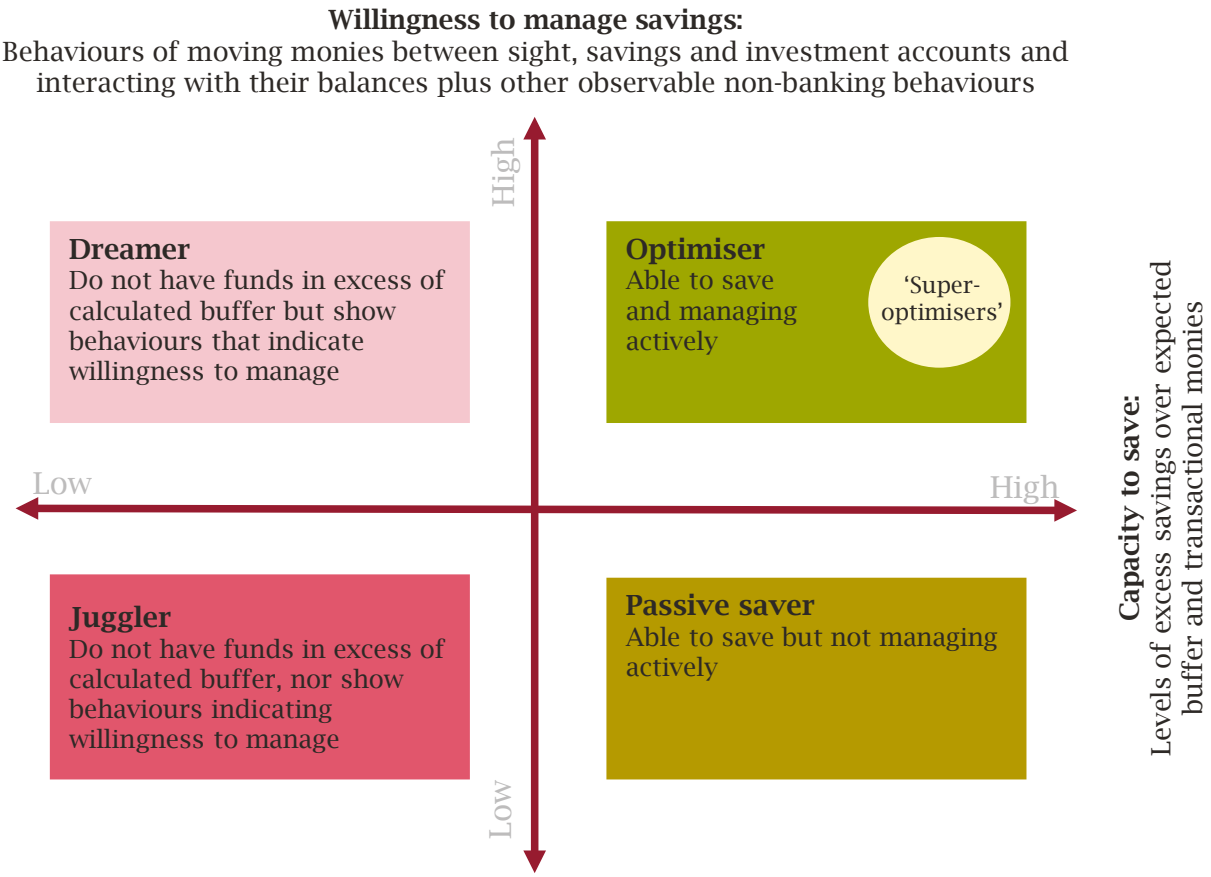

Figure 6: Overall behavioural segmentation. *Source:* Frontier case framework based on the case hypotheses. *Note:* Segmentation quantification results removed for confidentiality.

opened and used some saving products would face lower search and setup costs compared with people looking to actively manage their savings for the first time. We would expect to see people choosing to stick to a decision made previously – known as status quo bias (Samuelson & Zeckhauser, 1988).

Results and Discussion

The main findings from the analysis were:

- we can gain a better picture of behaviour by starting from understanding individual behaviour (relevant for the client) rather than by aggregating an individual's behaviours at a portfolio/account level (relevant for the bank);
- data science can provide useful new tools to identify and apply observed patterns in some groups of clients (such as super-optimisers) to other groups and
- behavioural hypotheses can help inform the data analyses and work as an instrument to enhance propensity models.

By segmenting clients based on their capacity to save and their propensity to put their savings to work, our findings increased the bank's understanding of its customers' decision-making processes. This approach further met the needs of interest rate risk analysis at the portfolio level by categorising and quantifying balances as either transactional (unstable), buffer (stable and insensitive) or excess savings (stable and sensitive).

The bank applied the methodology we created to its entire customer base, and it is now switching to a customer-led analysis for its interest rate risk models. This has ultimately allowed the bank to manage its risks better and to implement commercial campaigns in a more targeted fashion.

Conclusion

We have shown through our case studies that complementing data science with BE can provide businesses with better insights into how to design interventions that can improve outcomes for customers and value for businesses. Businesses that can harness the added value from BE research techniques

and toolkits, by embedding them into their data science processes, are able to make better use of their customer data by retargeting business value propositions, enhancing risk models, providing personalised experiences for specific users and – ultimately – improving overall business outcomes.

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Using a Behavioural Lens to Manage Risk in the Financial Industry

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ING

Triggered by the financial crisis in 2008, financial institutions have increasingly acknowledged that behaviour can be a root cause of problems affecting performance and integrity. Understanding behaviour and mitigating behavioural risks is complex and requires a thorough approach: from identification, to assessment and to intervention. This article offers insights into how the Dutch bank ING manages behavioural risk, helping others in – and outside the financial industry considering applying this new perspective, or "lens," on top of their traditional risk management framework.

Introduction

Banking is changing. In today's world – with more and more regulations to which banks must adhere, as well as emerging technologies such as artificial intelligence and blockchain – banking is much more than just handling cash and financial transactions; their social function has become increasingly more important. As gatekeepers of the financial system, banks need to keep their customers safe, secure and compliant.

For banks to take their role as a gatekeepers seriously, managing risks is a prerequisite. This exceeds looking through a traditional risk management lens with facts, figures and controls. One of the lessons that can be drawn from the financial crisis and major incidents in the financial sector is that employee behaviour and culture greatly affect the risk profile, performance and integrity of financial institutions. In fact, human factors make the difference: people can make a cumbersome process work, but at the same time, they can pose a risk – even in a solid process. This type of risk is referred to as "behavioural risk."

However, managing behavioural risk is challenging. For instance, how do you measure it, given that humans are complex creatures and do not always act rationally? And when behavioural risks have been uncovered, how do you mitigate them and change undesired behaviour? These types of questions require a multidisciplinary approach based on tools and insights from different disciplines.

This article offers insights into how ING manages behavioural risk, helping others in- and outside the financial industry considering applying this new perspective, or "lens," on top of their traditional risk management framework.

Understanding Behaviour

Behaviour is everything people do that *can* be perceived by others: it is about what we can see and hear, observe and express (Huczynski & Buchanan, 2001; Sarafino, 1996; Tiggelaar, 2010). Furthermore, it is a way of achieving a certain goal, in that it functions as a solution to a certain situation (Schein, 1992). Shaking hands (behaviour), for instance, is a way to greet someone (goal). Likewise, carefully communicating sensitive business information (behaviour) is a way of preventing reputational damage to an organisation (goal). Behaviours that are perceived to be effective in achieving their goal are used more often, leading to *patterns* of behaviour (Willcoxson & Milett, 2000; Straathof, 2009). These patterns are everyday habits that are performed automatically and unconsciously. Even more so, individuals and groups sometimes do not recognise their own behavioural patterns, because they seem so natural. These automatic, unconscious, implicit behavioural patterns can become a pitfall or even harmful to the performance of groups. Consider, for example, a CEO who is always very dominant

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in team meetings and does not listen to ideas or examples coming from others, while board members do not intervene but accept the leader's behaviour and thereby enable his dominance – time after time. This behavioural pattern stands in the way of making well-considered, weighted decisions.

What makes it even more complex is that behaviour does not arise in a vacuum; it is not solely based on someone's characteristics or intelligence (Bate, 1994; Wilber, 1996). Rather, people are social creatures who have a deep desire to be acknowledged and appreciated by others, and behaviour is strongly driven by the group a person connects to and identifies with (Scheepers & Ellemers, 2019) – for better or for worse.

Hence, managing behavioural risks is not about assessing individuals and finding the "bad apple." Instead, it's about understanding the habits of the group and investigating whether they lead to undesirable outcomes that need to be changed.

The Organisation as a Social System

Looking through a behavioural risk lens means understanding the organisational culture and looking at an organisation as a social system. Organisational culture is the 'social glue' that holds an organisation together by providing appropriate standards for how employees should behave (Robbins, 1996). It steers employees' behaviour towards what is desired and expected, while reducing unclarity or insecurity about what is inappropriate.

The well-known iceberg metaphor (Schein, 1992) can be used to understand and describe the levels at which organisational culture operates. At the top, there is observable *behaviour* (i.e. language used, activities practiced). This behaviour is influenced by directly assessable *group dynamics* and *behavioural patterns* (i.e. just below the surface). Lastly, deep under the water, is *mindset*, which is assessable only indirectly. Research on De Nederlandsche Bank (the Dutch Central Bank) (2015), carried out by Mirea Raaijmakers and colleagues, showed that understanding these different layers of culture is an important starting point in managing behavioural risks.

Managing Behavioural Risk

In order to manage behavioural risks and to change undesired behaviours, one must understand *how* and *why people behave the way they do*. To do this in a systematic way, ING's Behavioural Risk Management (BRM) team uses a tailormade BRM framework that guides them in understanding and mapping behaviours and drivers thereof that can contribute to the root causes of financial and non-financial risks in the organisation.

The framework used at ING is depicted below; it is composed of a set of informal and formal drivers that can trigger impeding patterns in the key behaviours, which, in turn, can result in financial and non-financial risks. Dysfunctional communications between departments, for example, can be influenced by distrust and an unsafe atmosphere, thereby discouraging healthy inter-departmental challenges and decision-making, which therefore might result in losses for the organisation. The key components of the BRM framework are explained in the sections below.

Key Behaviours

The framework includes four key behaviours (1-4) and one mediating driver (5), each of which is important for groups that work together and depend on each other to accomplish goals and results.

1. Decision-making

Decision-making refers to different behaviours that collectively constitute a balanced and effective decision-making process. For example, the degree to which the decision-making process is balanced and constructively challenged comprises the evaluation of different alternatives and the examination of all relevant information. An unbalanced and ineffective decision-making process might result in loss and can in turn impede the performance of the organisation (Finkelstein et al., 2009).

2. Ownership

Ownership refers to the willingness and ability of employees to take ownership, as well as the extent to which they are held accountable and feel responsible for work tasks. When people feel ownership and collective responsibility for their work, this promotes, *for instance*, cooperation and productivity. Conversely, insufficient ownership can result in tasks being delayed or insufficiently performed. Hence, a lack

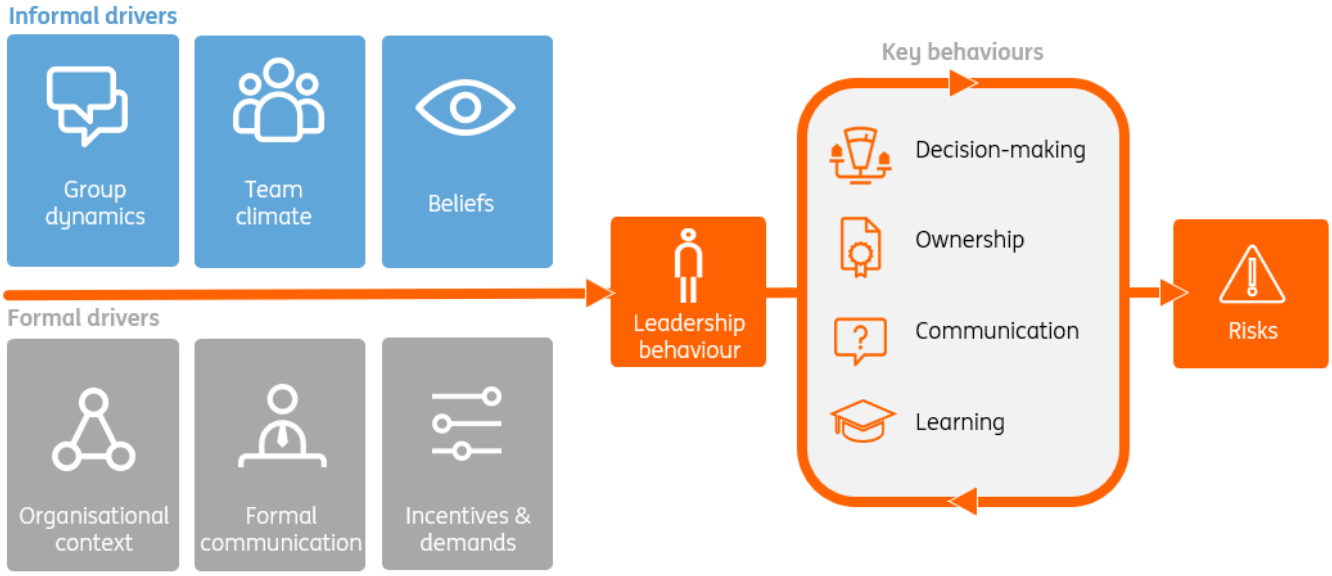

Figure 1: ING's Behavioural Risk Management framework.

of ownership negatively influences the quality of work and the performance of organisations (Van Dyne & Pierce, 2004).

3. Communication

Communication is crucial for groups to work effectively: between teams and within a team. Do people express their thoughts and feelings and speak up when necessary? Is exchange of information between employees clear and complete? Inadequate communication processes such as employees' reluctance to speak up about issues, or hesitation to share ideas or suggestions, directly affect the effectiveness of groups. This hinders performance, which subsequently has detrimental effects on the organisation in various ways (Greer et al., 2011; Losada & Heaphy, 2004).

4. Learning behaviour

The context in which financial organisations operate changes quickly. This requires employees to preserve and improve knowledge, create learning opportunities and continually reflect on their behaviour. It refers to organisational and individual learning and knowledge- sharing processes, the extent to which the company provides training programmes and the ways in which errors are managed and handled within the organisation. A lack of reflection and responsiveness to learning opportunities can impede the intellectual capital of organisations, resulting in risk (Van Dyck et al., 2005).

5. Leadership behaviour (mediating driver)

Leaders (i.e. managers across the organisation) steer employees to perform tasks willingly and competently, driving the performance of employees, teams and the organisation. The values and motives of leaders affect decision-making, and they communicate their preferences through role modelling, feedback, choices and using rewards and sanctions (Schein, 2010). Leaders (have to) create the conditions for change. Therefore, BRM considers leadership as a mediating driver. It is important that leaders are aware of their own leadership behaviour and adjust it when necessary (Yukl, 2012). Failure to create the right conditions (i.e. working environment) can constitute a risk.

Impeding behavioural patterns in these five categories have proven to lead to financial and non-financial risks, such as fraud or compliance risk, as well as people-related risks such as burnout or turnover. As such, these behavioural patterns are important not only in most organisational contexts, but also outside the financial industry. However, to effectively *change* these undesired behavioural patterns, one needs to dig deeper to be able to understand *why* people behave in a certain way, i.e. what *drives* them. BRM distinguishes between (1) informal drivers and (2) formal drivers.

1. Informal drivers

Informal drivers refer to the "intangible" side of an organisation, how people work together in practice. This intangible side is not written down on paper or voiced, and it is therefore often referred to as the unwritten, unspoken rules of an organisation. Informal drivers include, for example, social relationships, perceptions of the work climate and beliefs and values held by people. Moreover, they touch upon the ways in which people work together and share information, but is this based on a dynamic of competition or of cooperation? While informal drivers are often overlooked, most likely due to their intangible nature, understanding them is crucial in effectively changing behaviours and mitigating risks.

2. Formal drivers

Formal drivers refer to the "tangible" side of the organisation, i.e. "how it is set out on paper." They include the more structural side of the organisation, such as organisational charts, job descriptions, hierarchical lines, procedures and incentives. The structure of an organisation influences and interacts with its culture, in that processes and structures can either support or hamper activities, such as cooperation between teams or the extent to which individuals can learn and adapt. For example, think of the incentives and rewards system: when rewards are perceived as unfair, an employee's motivation and opportunity to perform well may decrease, which might then affect the extent to which they take ownership of their tasks.

Managing Behavioural Risks in Practice

With the BRM framework as a foundation for the approach, the team follows different steps in order to effectively manage behavioural risks in the organisation. What these different steps entail is explained below. Please note that the BRM team is always seeking to develop their ways of working.

1. Identification – what are our points of interest?

As a BRM team, you want to allocate your resources where these are needed most. This requires identifying areas that are prone to behavioural risks and/or could benefit from a better understanding of behavioural patterns and their drivers. To get an insight into potentially risky areas, BRM explores multiple sources of information, such as surveys, self-assessments, reviews and analyses of organisational reports or data from organisational systems such as HR or Compliance. A different route is by means of receiving explicit signals from individual employees, teams or managers, for instance about issues related to psychological safety, that indicate potential behavioural risks.

All information on potential behavioural risks is combined into a shortlist of potential "hotspots" that lead to conducting a behavioural risk assessment.

2. Assessment – what do we see?

Once a potential behavioural risk area has been identified, BRM initiates a thorough assessment process to examine which patterns of behaviour constitute a risk and, more importantly, what drives them. Different data collection methods are applied to support a conclusion from different angles (i.e. triangulation). In practice, this means that a mixture of qualitative and quantitative methods is used, such as desktop analysis, surveys, semi-structured group or individual interviews and work floor or meeting observations.

When all data have been collected, their analysis can start, in order to extract reliable and valid findings and *conclusions*. This is a thorough and iterative process consisting of several analysis rounds, in which patterns of behaviour and interrelationships are identified, and key overriding themes are highlighted. The ultimate goal of the analysis phase is to identify and prioritise behavioural patterns that need to be addressed to mitigate risks.

3. Intervention – what do we want to change?

After the behavioural risks in a specific area have been identified, assessed and analysed, only one question remains: what can you do about it? Or, in other words: how can these behavioural risks be mitigated and behavioural change be driven? To do this, BRM determines the intervention approach. The goal of the interventions is to change undesired behaviours and mitigate behavioural risks. BRM's intervention approach is based on scientific insights and supported theories that are relevant in the context of behavioural risk mitigation and guiding behavioural interventions, thereby contributing to effective and impactful change.

Interventions exist in all shapes and sizes, on employee as well as leadership levels. Going back to the example of the dominant CEO, for instance, replacing this leader may not be a solution if the social system (in this case, the board) itself carries risks through the – probably implicit – pattern of not speaking up and in turn allowing leaders to dominate. Tackling this group dynamic (informal driver), and in turn leadership behaviour, would require, for instance, an intervention with not just the CEO, but also the entire social system of which (s)he is part. It is most powerful to have smaller and larger interventions run synergistically, so that they consolidate and create a so-called "snowball effect," individually starting from a state of relatively small significance but then building on each other to drive systematic change. Which interventions are deployed is decided upon after the assessment. This can range from implementing simple nudges to doing a "World Café," or "Whole System in the Room", large-scale intervention methodologies focused on understanding and incorporating different perspectives on working towards solutions.

Regardless of which format is chosen, the team ensures it matches the needs of the organisation by following different steps: from creating the perception that change is needed, to moving towards the new, desired level, to solidifying the new level as the norm (Lewin, 1947). In this process, BRM fulfils the role of a "process consultant," helping the organisation or system take ownership themselves. This is based on the notions that problems will be solved more effectively and last longer if the organisation learns to solve the problems itself, as they are 'part of the problem' (Schein, 1969).

Case Study: Improving Decision-Making Hampered by Insufficient Collaboration Between Departments

The following case study, using real-life examples, describes what a BRM process may look like from beginning to end, bringing all of the insights discussed above to life.

1. Identification

Building up knowledge around customers and their activities is a key element in helping protect the financial system against serious economic crimes such as money laundering, tax evasion and financing terrorism. For this reason, the BRM team conducted a multiple Behavioural Risk Assessment (BRA) focused on Know Your Customer (KYC), i.e. the process by which bank employees verify the identity, suitability and risks involved in building or maintaining a business relationship with a customer.

2. Assessment

All assessments were performed in a carefully chosen location within ING and focused on the entire KYC value chain, including client-facing staff, operations and compliance. The assessments were designed to be an in-depth, detailed examination of a selected group of participants involved in parts of the KYC process. This focus helped local management understand the behavioural dynamics at play in their immediate work environment and to take action, where necessary.

The BRM team held interviews with several employees from different departments across the entire KYC value chain, following which they conducted a survey. To give an example, in one of the locations, analysis of the gathered data indicated that an undesired "us-against-them" dynamic had emerged, whereby different departments concentrated on their own tasks ("getting it their way") and had a challenging time understanding the needs of others (informal driver: group dynamics). As a consequence, inter-departmental cooperation was insufficient, which influenced the quality of decisions made around client files (key behaviour: decision-making).

3. Intervention

Based on the outcomes of the behavioural risk assessment, a Whole System in the Room intervention was organised: an effective large-scale intervention methodology that addresses group dynamics through evidence-based methods and insights. Having different perspectives in one room and managing inclusivity helps address the root causes of issues together and can lead to respect for potential solutions, as well as growing ownership and mutual understanding.

The session contributed to creating mutual understanding of (drivers of) behaviours that hinder and accelerate the desired change, in this case group dynamics and its impact on decision-making. Additionally, the session helped the participants to

create concrete actions to improve their behaviour with regard to group dynamics and decision-making.

Conclusion

Applying a behavioural risk lens means looking beyond the obvious to address deeply embedded behaviours. However difficult, implicit behavioural patterns can be changed through a profound understanding of behavioural drivers and a cooperative approach to implementing creative solutions, ranging from simple nudges to extensive leadership programmes. Using these insights and acknowledging their importance in understanding risk takes the risk management of financial institutions – and in fact any organisation – to the next level. Protecting organisations from major financial and non-financial risks requires thorough research and a profound understanding of an organisation's core, namely its people.

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Helping or Harming? How Behavioural Levers Can Influence People's Financial Outcomes

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As a financial regulator, the Australian Securities and Investments Commission (ASIC) has a long history of exposing consumer harm and poor outcomes. A recent review of over 100 ASIC reports identified five common "behavioural levers" that can be used to influence consumers (for better or worse), and five "situational vulnerabilities" that can amplify poor consumer outcomes. Illustrated with examples drawn from the review, this article unpacks how some financial firms have exploited or ignored behavioural vulnerabilities in the choice architecture of their products. Understanding these factors not only enhances regulators' ability to identify, describe, prove and prevent harm, but also reminds firms that they are in a uniquely powerful position to ensure their choice architecture helps – rather than harms – their customers.

Introduction

The Australian Securities and Investments Commission (ASIC) is a financial regulator with several responsibilities, including a consumer protection role. Like other regulators around the world, it employs a range of regulatory tools to prevent, prove and punish consumer harms.[2] Recently, its toolbox was enhanced by new outcome-oriented powers: powers that put greater emphasis on firms' uses of choice architecture (ASIC, 2020; ASIC, 2021c). These powers acknowledge the practical limitations of over-relying on disclosures to protect consumers, and they also recognise that good consumer outcomes are a fundamental part of a healthy financial system (ASIC & Dutch Authority for the Financial Markets, 2019).

Given the nature of its mandate, ASIC has exposed a considerable array of consumer harms and poor outcomes over many years. Here in ASIC's Behavioural Unit, we have contributed to that work by helping frontline teams apply behavioural science when identifying, describing, proving and preventing consumer harm. To enhance this case-by-case work, we recently undertook a comprehensive review of several decades' worth of relevant past ASIC reports (100+ reports), synthesising themes across different financial services contexts through a behavioural lens.[3] There are of course many ways to cut the data, but we have distilled it down to five particularly prominent behavioural "levers" and five associated "situational vulnerabilities" that can amplify poor consumer outcomes.

In this article, we offer only a brief overview of the themes we found. Our hope is to share further insights with regulators, researchers and firms over time. Together we all share an opportunity to use the lessons of the past and the insights from behavioural science to help – not harm – people's financial and everyday lives.[4]

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2 For more information about the range of regulatory tools and harms, visit www.asic.gov.au. Like other regulators, ASIC acknowledges that consumer harms are not necessarily limited to financial losses. See Susan Bell Research (2011) for examples of the emotional, physical and social costs associated with this issue in financial services.

3 Including a systematic qualitative content analysis followed by iterative stages of behavioural analysis and review to identify and assess the presence of behavioural techniques. All reviewed reports contained data about firm practices and financial consumers' experiences and/or outcomes.

4 To learn more about our review or the application of behavioural science at ASIC, please contact us at: behavioural.unit@asic.gov.au

Behavioural Techniques: Helping or Harming?

Persuasion techniques and behavioural biases are not innately good or bad; they can be deployed to help consumers or to take advantage of them.[5]

Unfortunately, our review uncovered many instances where firms created, amplified, exploited or ignored the harmful effects of behavioural and situational vulnerabilities in their product design, processes, communications and other choice architecture. Whether in the form of harmful frictions or harmful nudges, we repeatedly observed this "sludge" getting in the way of good outcomes.[6]

We Are All Only Human

Collectively, our review found that any financial consumer can find themselves vulnerable to poor outcomes. Even the most active, experienced and confident consumer could find themselves stuck in needless sludge or worried that their trust was misplaced. A consumer's defences appeared particularly weakened when:

- financial firms exploited/overlooked fundamental behavioural factors, such as biases and heuristics, that are part of being human
- inherent system complexity and situational factors exceeded the bounds of consumer capacity
- products, services and/or their providers failed to prioritise consumer needs and outcomes
- all or some of the above was hidden from or imperceptible to consumers.

Five Key Behavioural Levers

Our review scanned for the presence of behavioural techniques across 100+ descriptive reports. Frequently, we observed techniques and effects that were consistent with Robert Cialdini's seven 'weapons of influence' (Cialdini, 2021)[7] and the well-known Behavioural Insights Team resources EAST (The Behavioural Insights Team, 2014) and MINDSPACE (Institute for Government and Cabinet Office, 2010). Across many different financial services contexts, these techniques were sometimes applied subtly, and at other times they were overtly pressured.

Taken together, these practices naturally clustered around five key overlapping behavioural levers in our dataset: Social, Emotion, Ease/Difficulty, Timing and Framing.

1. Social

Trust is a gateway and is often formed through social factors. Social norms, proof, affinities and pressures were particularly powerful influencers across many of the reports we reviewed. See Table 1 for examples.

2. Emotion

How we feel can be manipulated to make us buy or do things that lead to harm. Our review uncovered many instances where emotions played a key role in directing what consumers did. Feelings and emotions also often worked alongside – but were not limited to – social dynamics. See Table 2 for examples.

3. Ease/Difficulty

Making something easy or difficult shapes what consumers do or do not do.

While making something easy can be a simple way to enhance a consumer's experience and drive good outcomes, it can be harmful when it is used against good outcomes – for example to make quick sales, speed up choices that need closer attention or deliberation or confuse consumers about what they are signing up for. Easy processes may be coupled

5 We acknowledge that behavioural techniques can be – and have been – used to improve consumer outcomes, for example Thaler & Benartzi's (2004) 'Save More Tomorrow' program.

6 Note: Thaler and Sunstein (2021) define a "nudge" as '*any aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives*' and "sludge" as '*any aspect of choice architecture consisting of friction that makes it harder for people to obtain an outcome that will make them better off*'. ASIC's Behavioural Research and Policy Unit builds on this definition with a practical focus on identifying consumer harm, defining "sludge" as: any aspect of the choice architecture that blocks consumers' access to a good outcome ***or*** pushes a consumer towards a poor outcome. This definition captures 'dark nudges', 'dark patterns', 'nudge-for-bad', and 'nudges for evil', which Thaler (2018) previously defined as sludge.

7 The seven weapons of influence include reciprocation, commitment and consistency, social proof, liking, authority, scarcity and unity (Cialdini, 2021).

with other emotional, social or timing levers that can increase the desire, motivation or urgency to make a purchase.

Making things difficult also has two sides: adding unnecessary obstacles to a process is harmful when it stops consumers achieving a good outcome – for example, when they are trying to complain or switch to a better provider or product. See Table 3 for examples.

4. Timing

Timing is used to direct what consumers notice, consider and do. It was a critical contextual factor in many of the financial scenarios in our review. See Table 4 for examples.

Behavioural Lever	Some of the Behavioural Biases, Traits and Persuasive Techniques Observed*	Three Indicative Examples*
Social	Social norms Social proof Rapport and liking Similarity or belonging (e.g. appearance, associations and affiliations, nationality, ethnicity) Authority (e.g. titles, clothing/ uniforms, status symbols) Familiarity Reciprocity Commitment/consistency (e.g. 'foot in the door') Concessions (e.g. 'door in the face')	• Social proofing (via referring to the common experience of like-placed others) was used to influence consumers to consolidate their different superannuation accounts (**retirement products**) into a specific superannuation product (ASIC, 2019a; ASIC, 2021b). • Cold calling **investment** scammers secured client trust via building rapport, simulating a 'chain of command' and offering convincing references (ASIC, 2002). More recently, we have seen scams leverage familiarity and authority (e.g. ASIC news articles (ASIC, 2021a; ASIC, 2021e; ASIC, 2021f; ASIC, 2021d). Beyond just financial services, our fellow regulator the Australian Competition and Consumer Commission has reported a variety of psychological tactics being used by scammers (ACCC, 2019). • Consumers with valid claims felt intimidated by the approaches used by claims investigators during **motor vehicle insurance claim investigations** (e.g. introducing themselves as former police officers, requiring the consumer to sit opposite them, using an accusatory tone of voice) (ASIC, 2019c).

Table 1: Social lever examples.

* *Note:* Often spanning several levers and reports.

Behavioural Lever	Some of the Behavioural Biases, Traits and Persuasive Techniques Observed*	Three Indicative Examples*
Emotion and feelings	Loss aversion Regret aversion (e.g. 'FOMO') Reciprocity Liking Positive feelings Consistency with (or projection of desired) self-identity Fatigue Fear Uncertainty Optimism bias Pressure	• An exhausting 'conveyor belt' of subtle and overt pressure tactics were used to sell **add-on insurance** in car yards (ASIC, 2016b). • The sales process for **time-sharing schemes** relied on an array of emotional and social levers (including liking and rapport, reciprocity, regret aversion, uncertainty, fatigue, norms, etc.) (ASIC, 2019h). • Financial **funeral products (insurance, bonds and prepaid funerals)** – which were sometimes poor value – used marketing that activated the feelings of guilt consumers had about the burden of their funeral and suggested that funeral preparation was the norm and the 'responsible' thing to do (ASIC, 2012b; ASIC, 2015).

Table 2: Emotion (and feelings) lever examples.
* *Note:* Often spanning several levers and reports.

Behavioural Lever	Some of the Behavioural Biases, Traits and Persuasive Techniques Observed*	Three Indicative Examples*
Easy or difficult	Sludge/"dark nudges" Frictions (absence or presence) "Roach motel" (i.e. easy to get in, but hard to get out) Hidden/unclear costs Defaults (Opt-in/Opt-out) Price comparison prevention Information overload Increased cognitive load Attractive offers Easy processes Forced continuity Inertia	• Already vulnerable consumers faced onerous hurdles while making **Total and Permanent Disability insurance** claims (ASIC, 2019g). • The smooth consumer experience of **buy now, pay later arrangements** made it easy to sign up and easy to spend money (ASIC, 2018b). • Consumers experienced numerous frictions when **making a complaint** to a financial service provider, with 81% experiencing at least one obstacle and many consumers withdrawing from the process (Nature, 2018).

Table 3: Easy or difficult lever examples.
* *Note:* Often spanning several levers and reports.

Behavioural Lever	Some of the Behavioural Biases, Traits and Persuasive Techniques Observed*	Three Indicative Examples*
Timing	Sunk costs Commitment/consistency Choice order Scarcity and urgency (e.g. limited time offers, limited availability, high value of limited information) Future discounting/present bias Defaults (strategic use of inertia)	• Timing was strategically used throughout the **time-sharing scheme sales** journey, from approaching some consumers on holiday through to same-day sign-up "exclusive" deals and withholding key information until after signup or login details until after the cooling-off period (ASIC, 2019h). • It was not unusual for some consumers purchasing **home insurance** to need to spend hours, or even a full day, getting online quotes and/or calling insurers (ASIC, 2014). • **Debt management firms** required further information or a face-to-face meeting before proceeding with a client, or in some cases before even providing any pricing information (ASIC, 2016a).

Table 4: Timing lever examples.

* *Note:* Often spanning several levers and reports.

5. Framing

Deliberate framing (curating the way something is presented) directs attention and can make a consumer do what the "choice architect" wants them to do. When firm and consumer interests are misaligned, this can sometimes lead to harm. Alternatively, neglecting to consider or monitor the possible – even accidental – effects of framing can also lead to harm.

In our review, framing tied all of the previous levers together (see Figure 1) – all the small details in the choice architecture that added up, for example product names and investment labels (ASIC, 2013), visual design features (ASIC, 2013; Bateman et al., 2016), messenger job titles (ASIC, 2002), descriptions of risks and benefits (ASIC, 2008; Westpac Securities Administration Ltd v ASIC, 2021; ASIC, 2010), process navigation and order (ASIC, 2019g), the emphasis in sales scripts (ASIC, 2002; ASIC, 2019h), the time frame to purchase (ASIC, 2019h) and so on.

Five Key Vulnerability Amplifiers

Some of the harm we identified was clearly caused by financial firms' deliberate strategies to exploit consumers, and some was the result of firms failing to prioritise consumers' real circumstances and needs.

Consumers and financial firms do not interact in a vacuum. Micro factors like specific life events, mental states or interpersonal interactions, as well as macro factors like an economic crash or even the economic system itself, all contribute to the situational context.

Our review suggested that consumers may be particularly vulnerable in financial settings when:

1. **There is complexity** (e.g. some products like reverse mortgages have features and dependencies that are hard to evaluate, including multiple complex options and costs, compounding interest and understanding trade-offs (either current or in an uncertain future). This complexity was often couched within broader life events such as divorce, retirement losses, poor health and the fact that some consumers saw

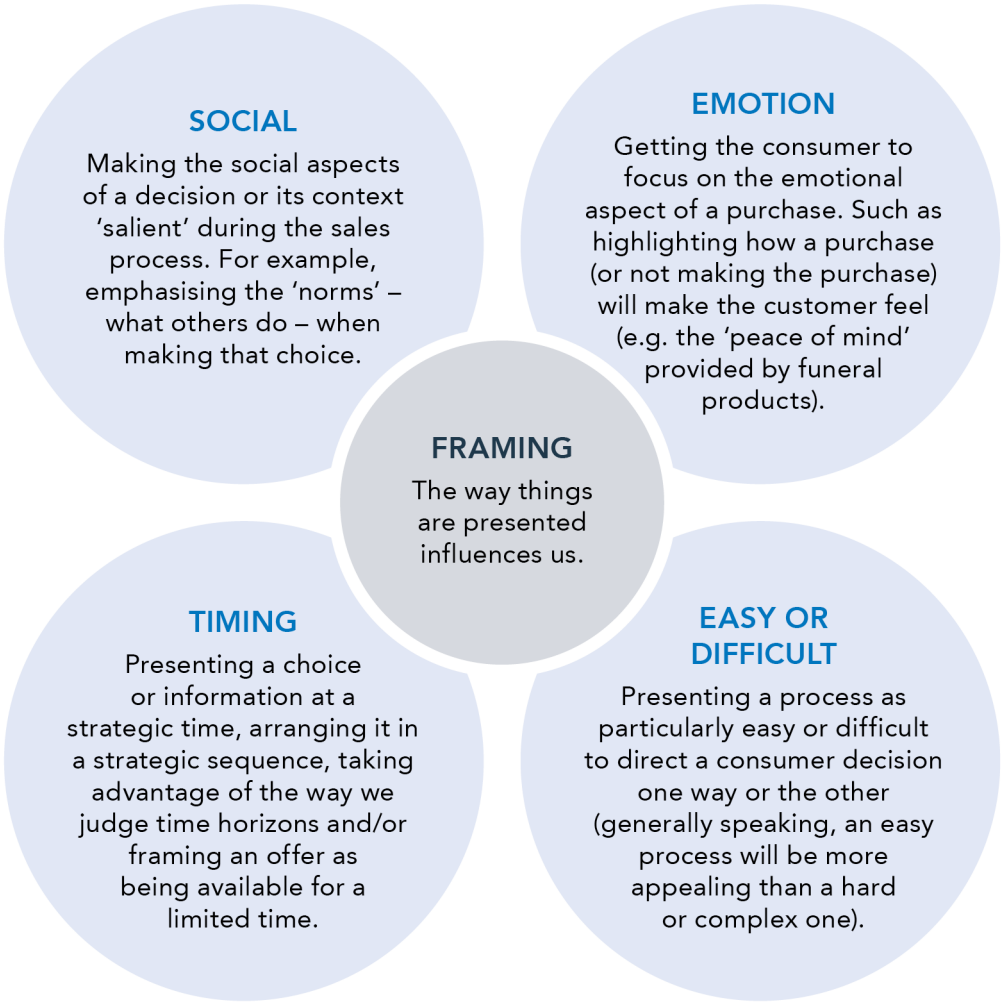

Figure 1: The framing lever tied the other levers together.

reverse mortgages as their only option (ASIC, 2018a).[8]

2. **Major life decisions and events coincide with financial ones** (e.g. marriage, job loss, the birth of a child, retirement, divorce, bereavement, illness, accident, natural disasters (ASIC, 2018a; Susan Bell Research, 2018; ASIC, 2019f) or even – as we are now experiencing first hand – a global pandemic. The impact of these situational vulnerabilities can be fleeting or lasting, and they can range from minor to catastrophic).
3. **Good, unbiased advice is needed but hard to get, recognise or follow** (e.g. when professional advisers are perceived as biased or too expensive (ASIC, 2019e), there is a disparity between perceived and actual advice quality (ASIC, 2012a), advice labels are confusing (ASIC, 2019b) and sophisticated scammers are gifted at building trust (ASIC, 2002)).
4. **We don't know where to turn, or processes are hard when things go wrong** (e.g. obstacles in making a complaint to a financial firm (Nature, 2018), hurdles when claiming on Total and Permanent Disability insurance (ASIC, 2019g) and the onerous information requests, intimidating interviews and inadequate support motor vehicle insurance claimants experienced when being investigated, despite over 70% of investigated claims being found to be valid (ASIC, 2019c)).

8 Note: The bar for what is "complex" is also lower than might be assumed. For example, Lunn et al. (2016) found that the human ability to distinguish between good and bad choices deteriorates rapidly once we have to consider more than two or three product features at a time. International studies also show that even standard features, elements and options in everyday products such as credit cards and insurance can be too complex for consumers (Lunn, McGowan, & Howard, 2018; ASIC & Dutch Authority for the Financial Markets, 2019).

5. **Hazards and levers are "in the dark"** (e.g. in many situations, consumers who were sold consumer credit insurance were not eligible or did not need the policy, and some were even unaware that they had purchased a policy (ASIC, 2019d; Susan Bell Research, 2013). Other elements that lie in the dark include "dark patterns" – carefully designed features on websites, apps or other digital interfaces that can influence consumer behaviours and cause them to act against their own interests or intentions (Norwegian Consumer Council, 2018; Norwegian Consumer Council, 2021; Mathur et al., 2019; Luguri & Strahilevitz, 2021)).

Small Details Matter

While improving people's financial outcomes is a shared responsibility and goal around the world for regulators, consumers and financial firms alike, firms are in a uniquely powerful position to help consumers navigate to good outcomes because they are in control of much of the choice architecture that guides consumers to – and through – financial products and processes. They create the product marketing, sales flows, web interfaces, claims processes, complaint forms and other features with which consumers interact. Whether noticed or unnoticed, each little design and distribution feature influences a consumer's perceptions, decisions, actions and outcomes. The small details matter, and they add up.

Financial firms also have direct access to consumers and consumer data. They have the earliest and clearest line of sight on the effect of choice architecture. Today, more than ever, they can record, monitor and influence many of the little things that get in the way of good outcomes.

Together, we can all find better ways to use behavioural levers to help more than harm.

> *'Let's continue to encourage everyone to nudge for good, but let's also urge those in both the public and private sectors to engage in sludge clean-up campaigns. Less sludge will make the world a better place'*
>
> Richard Thaler (2018).

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Behavioural Economics and Financial Services: A Focus on Insurance and Pensions

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Open Evidence

The European Insurance and Occupational Pension Authority (EIOPA) has realised the potential of behavioural sciences in explaining consumer behaviour regarding financial products. This article provides a review of how behavioural science can help to explain how consumers behave in relation to insurance and pensions. More specifically, there is a focus on the behavioural biases and heuristics that may influence consumers and lead to suboptimal decision-making. Based on this review, we summarise the findings of four behavioural research projects conducted by Open Evidence. Three of these experiments are in the field of insurance (insurance in the digital environment, travel insurance in the COVID-19 context and natural catastrophe insurance). One is in the pensions field and explores the impact of a behaviourally informed pension tracker. Through these examples, we demonstrate the value of employing a behavioural perspective in the evaluation and design of financial products, as well as the importance of conducting behavioural research.

Introduction

The influence of cognitive and behavioural biases on the demand for financial services is undeniable. Within the many behavioural theories and models explored, there are specific biases and heuristics which influence decision-making about financial services. This is proven by empirical findings in the literature as well as the findings of the experiments we conducted.

In this chapter, we explore the behavioural context and detail four of the behavioural experiments conducted in the domain of pensions and insurance for the European Insurance and Occupational Pension Authority (EIOPA). EIOPA decided to use behavioural tests and explorations in the context of the ongoing digital transformation, as well as specific and potentially disruptive events such as COVID-19 and natural catastrophes, both of which have affected Europe in the past two years, and pension tracking.

The added value of a behavioural experimental approach to these practical and applied policy issues consisted of identifying biases in decision-making and trying to redress them. Benefits also lie in testing the impact of different information architectures and graphic layouts on consumers' awareness, understanding and perceptions. Open Evidence integrates state-of-the-art experimental design with the use of experimental materials and artefacts for the due consideration of the human design factor.

Our first behavioural study on the digital distribution of insurance tested the extent to which the online environment would make consumers more prone to certain biases and impulsive decisions. Another experiment on travel insurance explored whether COVID-19 changed consumers' preferences and/or induced them to follow specific heuristics and biases. Our third insurance study is currently being developed and explores how consumers who experienced natural catastrophes understand the level of coverage they have from their insurance – and which attributes of an insurance package would increase their willingness to purchase it. The final experiment tested different versions of information documents related to a new pan-European pension product, to ascertain which communication and graphical design was most helpful in enhancing consumers' understanding of a pension product.

Section two first discusses the main heuristics and biases that apply more generally to financial services, focusing on pensions and insurance.

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The third section then further details the four studies mentioned above, discussing their main implications.

How Can Behavioural Science Help Explain Decision-Making Regarding Broadly Defined Financial Services?

Overconfidence and the Role of Affect

A large body of experimental literature finds that individuals are usually overconfident (see, for example, Fischhoff & MacGregor, 1982); that is, they believe their judgement is more precise than it actually is. Overconfidence can underlie consumer decisions regarding financial services. For instance, individuals may choose not to insure their property under the biased conviction that their probability of being affected is lower than the average (Pitthan & De Witte, 2021). Similarly, someone who is overconfident may under-weigh the chance that they will end up having an inadequate pension plan, and, as purported by the planning fallacy (Knoll, 2011), even overestimate their ability to make up for this in the future.

Such beliefs may stem from an individual's illusion of control, which involves a tendency to overestimate one's management of random events – as proven empirically by Fellner (2009), Qadri and Shabbir (2014) and Din et al. (2021) in the context of financial decision-making. These probability misperceptions in turn may be linked to the emotions triggered by these decisions, which may lead individuals to base their decisions on current emotions, a phenomenon popularised as the 'affect heuristic' (Slovic & Peters, 2006; Pachur et al., 2012).

Picturing oneself experiencing an adverse event involves a heavy emotional toll, which may thus render probability neglect (Sunstein, 2002), whereby individuals completely disregard the probability of such an event materialising. Consequently, they may be prone to directional motivated reasoning (Kunda, 1990), involving the dismissal of credible information which challenges this belief. For instance, evidence suggests that so-called "crisis-resistant" travellers may be engaging in "wishful thinking," choosing not to purchase travel insurance and disregarding the risks associated with the COVID-19 pandemic (Sembada & Kalantari, 2021).

Misperceptions and Social Norms

Individuals use other shortcuts that lead them to make misguided predictions. For example, people may rely on their previous experiences, overestimating the likelihood of an event salient in their mind, dubbed the "availability heuristic." Otherwise, they may rely on the representativeness heuristic, whereby they assess the probability of an event based on an existing prototype already present in their minds (Tversky & Kahneman, 1973). There is indeed abundant evidence from the insurance literature suggesting that past experiences and prior risk occurrences influence insurance choices (Papon, 2008; Michel-Kerjan & Kousky, 2010; Jaspersen & Aseervatham, 2017).

Similarly, the evidence seems to indicate that the saliency of the pandemic in people's minds may be increasing their willingness to book travel insurance (Uğur & Akbıyık, 2020; Chebli & Said, 2020). In addition, they might look at what others do (descriptive norms) or what most people approve or disapprove of (injunctive norms) when making financial decisions (Cialdini & Trost, 1998). For example, Lo (2013) conducted a survey analysing the adoption of flood insurance, finding that social norms mediated the relationship between risk perceptions and insuring decisions.

Intertemporal Decisions

It is also important to consider that choices regarding pension and insurance plans are intertemporal and as such influenced by the inconsistency of time preferences. Individuals tend to be present-biased, often delaying tasks that do not offer an immediate reward (Schouwenburg & Groenewoud, 2001). In fact, in the context of retirement planning, several studies have shown that this lack of self-control has consequences in terms of investment decisions (Riaz & Iqbal, 2015; Strömbäck et al., 2017). Lacking the ability to exert self-control, which refers to the ability to let our future selves control our current self, may thus affect retirement- and insurance-related behaviour. Construal-level theory, introduced by Trope and Liberman (2010), also explains the effect of distance on decision-making, in that mental representations of the future are often vague and abstract, while those of the present are concrete. Therefore, as imagining our future selves in retirement or experiencing an adverse event is more complex, decisions regarding the future

are often delayed, thereby leading to present bias.

Choice Architecture

Based on the notion that subconscious decision-making often drives behaviour, Thaler and Sunstein (2008) also highlighted the essential role of 'choice architecture' in decision-making. Choice architecture involves the number of choices that an individual is presented with and how they are presented. For instance, in the context of insurance decisions, having too many options can excessively complicate decision-making through cognitive overload, leading to sub-optimal decisions (Benartzi & Thaler, 2002). As implied by Agnew and Szykman (2005), even for individuals with different financial aptitudes, having a significant number of choices can push them towards choosing the default investment option. This tendency to choose the default may be explained by the status quo bias, which leads individuals to prefer choices that allow them to avoid change and/or cognitive efforts (Samuelson & Zeckhauser, 1988). This bias requires less cognitive resources and protects the individual from the potential regret of switching to a worse outcome.

Decision inertia, which involves the individual tendency to repeat a choice regardless of the outcome, has been recurrently identified in the context of insurance choices (Krieger & Felder, 2013; FCA, 2015; European Commission, 2017). Individual proneness to these behavioural biases may be further exacerbated by the employment of marketing practices. For example, the personalised ranking of offers may mean that the default is the most beneficial for the insurer but not necessarily for the consumer.

Information Processing

Similarly, rational ignorance (Downs, 1957), which occurs when information is long or presented in a cumbersome fashion, may lead consumers to consider the time costs of reading it greater than the benefits of being better informed, thereby encouraging them to make a less informed decision. Scholars have amply documented that contractual documentation such as "notice and consent" is fiction, since individuals face insuperable challenges when attempting to make informed choices (Acquisti et al., 2015).

In addition, information assessment may also be affected by the extent to which something is noticeable relative to its environment, or its salience. For example, if one insurance product is presented in a way that is comparatively more attention-grabbing, individuals may be more subconsciously drawn toward focusing on it and may overvalue its importance, as our study on the transparency of online platforms has documented (European Commission, 2018). This may be particularly problematic for consumers if the salient option has been personalised for them, using potentially unfair practices about which the consumer is unaware (e.g. the use of information from their social media accounts).

Overall, there are a plethora of behavioural biases which help understand how consumers make choices relating to insurance and pensions. Below, we discuss how this knowledge may be applied in different contexts. All of the experiments described below were conducted with nationally representative samples.

Areas of Application

Insurance in the Digital Environment

We conducted an online experiment for a study on insurance distribution and advertising via digital channels in five countries (Greece, Portugal, Estonia, Bulgaria and Germany), with 800 participants per country. We sought to analyse how online insurance marketing techniques affected consumer decisions, assessing the impact of different behavioural biases on consumer decision-making. Participants were asked to select a motor insurance contract, and one of these contracts presented one of the online marketing practices which we found to be more misleading for consumers, as well as the most used in insurance digital distribution, informed by both the literature review and mystery shopping exercises conducted. These practices, and the resulting experimental conditions, were social proof, disguised advertising, time-limited offers, drip pricing, hidden information and a control condition. Furthermore, all participants were randomly exposed to a risk factor, which could be either the automatic renewal of their insurance contract, the presence of additional coverage or the absence of the risk factor (i.e. the control condition). Participants were incentivised based on their ability to recall features of the insurance products with which they were presented, as well as the advertising

practices used.

Overall, the impact of commercial practices on the purchasing of the targeted contract produced unexpected results. Indeed, the presence of social proof decreased the likelihood of choosing the targeted contract in the full sample, in both the control condition and in the presence of risk factors. Similarly, time-limited offers produced the opposite result to the one expected, and the other four practices did not have a significant impact on the purchasing of the targeted contract.

Furthermore, we conducted a heterogeneity analysis on four variables (risk preferences, age, digital skill and financial literacy). The main factor that affected differences in the selection of the targeted contract was age, while the other factors did not have any significant impact on consumer behaviour. We found that older participants had a higher probability of selecting the targeted contract than younger participants when certain potentially misleading marketing practices were present (disguised advertising and drip pricing).

Thus, our results have important policy implications in the sense that they demonstrate how some consumers may be more vulnerable than others when buying online. As the digital transformation of insurance distribution advances, this is likely to translate into disadvantages for the older population, who are likely to be less digitally savvy and thereby more exposed to manipulation through digital advertising techniques.

Travel Insurance in the COVID-19 Context

In another behavioural study, we aimed to assess the impact of COVID-19 on consumer needs, the perceptions of these needs and attitudes to travel insurance products. As already shown by previous empirical evidence (Uğur & Akbıyık, 2020; Chebli & Said, 2020), we further investigated whether COVID-19 triggered an increase in consumer demand for more coverage to be provided by travel insurance policies. The study informed the supervisory activity of EIOPA. An online experiment was carried out in six countries (Italy, Germany, Romania, Finland, Hungary and Greece).

The primary objective was to understand whether consumers' preferences for different insurance types of coverage would vary between groups exposed to a COVID-19 prime. We experimented through a randomised control trial (RCT), by randomly dividing the full sample and using two experimental manipulations on the groups. The first group was exposed to a COVID-19 prime, the other to a joy prime or an image evoking a sense of happiness to mitigate the effect of COVID-19.

We used two images to prime the two groups and a very brief sentence reinforcing the emotions evoked by the images. This double manipulation allowed us to assess how the different mindsets produced changes in needs, perceptions, attitudes and behaviours. In addition, the participants were further randomised into two groups with two different trip scenarios: cheap and expensive travel packages. After this double randomisation, the participants were required to choose from among different insurance coverage types, and we elicited their willingness to pay for insurance products.

The results of the main task of the experiment confirmed our main hypothesis, showing that participants exposed to a COVID-19-related prime are more willing to include COVID-19-related coverage in their travel insurance products. In addition, we classified participants into different subgroups, based on socio-demographic characteristics, exposure to COVID-19, internal or external locus of control and tendency to be influenced by typical psychological biases. With this, we did not find any statistically significant differences in the likelihood to select COVID-19-related insurance coverage, meaning that the results are remarkably stable across subgroups. The results suggest that, regardless of individual characteristics, travel insurance is heavily shaped by the availability heuristic, as consumers are willing to pay more for risks that they can easily and vividly recall, such as the recent COVID-19 pandemic.

Natural Catastrophe Insurance

Currently, we are conducting a study on consumers' experiences and outcomes concerning natural catastrophe insurance protection products. One of the key objectives of this study is to explore factors that may influence decision-making behaviour when purchasing coverage for these types of events. We are currently developing the experimental design to test which features of an insurance policy may contribute to consumers purchasing this coverage.

However, the research activities we have conducted thus far (desk research, interviews with consumer associations and focus groups) have already helped us to understand better the singularity of natural catastrophe insurance – and what this implies for the application of behavioural science.

For instance, one distinctive feature of natural catastrophe risk perceptions is that they may often be affected by responsibility attribution (Han et al., 2021). That is, it may be the case that consumers choose not to insure because they perceive (often erroneously) that governments will bear the costs if a natural catastrophe materialises (Le Den et al., 2017).

Focusing on EU countries, several studies have empirically proven the issue that this so-called "charity hazard" poses to the functioning of the private insurance market. For instance, Tesselaar et al. (2022) explored the implications of the charity hazard on the flood insurance protection gap in the EU context, finding that the higher the certainty of government compensation, the higher the level of charity hazard.

The charity hazard has long been discussed as an important issue in insurance against natural catastrophes (Raschky & Weck-Hannemann, 2007), especially considering the growing insurance protection gap and the increasing threat posed by climate change. Evidence suggests that the advancement of climate change is increasing the frequency and severity of natural catastrophes. This may suggest that, if people attribute greater responsibility for natural catastrophes to climate change, they may causally link these two phenomena, which may then influence their subsequent behaviour.

Following this logic, Shreedhar and Mourato (2020) conducted an online experiment in which they tested different narratives linking the environmental crisis and COVID-19. They found that those narratives which reinforced this link encouraged greater support for pro-conservation policies. It is plausible to assume that consumers who understand the link between climate change and natural catastrophes will be more likely to realise the increased risk of exposure to natural catastrophes and may therefore be more prone to purchase natural catastrophe insurance products.

Through a vignette study and a discrete choice experiment, we will explore how the charity hazard, as well as other factors identified as relevant through the preliminary activities conducted (including risk-based premiums, bundling of perils and contract exclusions), influences consumer decisions to purchase natural catastrophe coverage.

Behaviourally Informed Pension Tracking

Another behavioural study was designed to support EIOPA in regulating the Pan European Pensions Product (PEPP). The empirical study aimed to identify the best way to present two information documents: a key information document (KID) and a benefit statement (BS). We employed behavioural principles in the design of different graphical versions of these two documents. We then tested consumers' reactions with a qualitative exploration followed by an experimental survey (n=300) in three countries (Spain, Ireland and Croatia) to determine whether consumers had a sufficient understanding of the attributes of pension products to make informed choices between different products.

The survey was divided into two parts. In the first part, respondents were shown different versions of the KID and BS for two different pension products, in order to assess the level of understanding of factual details relating to the different mock-ups, as well as their perceived attractiveness. In the second part, we aimed to assess the impact of different pension attributes on consumers' choices. This was investigated via a discrete choice experiment, which elicits individual preferences and in parallel identifies which attributes influence their choices. In choice experiments, participants are presented with sets of choice options made up of combinations of different attributes, and they are assumed to choose the utility-maximising option. A key objective of this part of the study was to determine if, when faced with such a multi-attribute decision, the average person can make an informed and rational decision between different pension plans.

The empirical results show that differences in attribute importance between the low- and higher-risk products fully resonate with risk aversion. When choosing a high-risk product, the guarantee becomes more important than the annual cost. However, when we explored the differences between respondents with different levels of financial literacy, our results suggest that those with low financial literacy tended to transform a multidimensional choice into a uni- or

bi-dimensional one. In contrast, individuals with high financial literacy tended to take more attributes into account in their choices.

Given that our behaviourally informed information document led to a reasonable level of understanding of pension terminology and prompted informed decisions among the more financially literate people, we conclude that applying behavioural design principles increases the likelihood that consumers can be empowered to make informed decisions when selecting a pension product. Similar principles may also benefit individuals with a lower level of financial literacy, who should be presented with information in a step-by-step manner to evaluate each attribute separately rather than presenting all of them at once.

Conclusion and Implications

Overall, our applications of behavioural science in financial services demonstrate the high value that this field presents, in terms of both achieving evidence-based policymaking and ensuring that consumers are adequately protected in changing environments (whether due to adverse events such as COVID-19 or the digital transformation of financial services).

Conducting randomised control trials in this area has allowed us to make important, policy-relevant inferences about how consumers perceive and act about features of insurance and pension products. RCTs have also helped to highlight the significant impact that the heuristics and biases described in Section 2 have on consumers, and the need to adapt the "choice architecture" to address these biases. Further research should use these insights to design experimental approaches to assess consumer behaviour with financial services. At Open Evidence, we will seek to continue applying behavioural sciences in this field, leveraging all the potential benefits of understanding the impact of consumer perceptions and behaviours on financial services.

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How Nudge Messaging Can Improve Product Take-Up: A Case Study on Funeral Insurance in South Africa

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In South Africa, funeral insurance is of extreme financial importance to millions of people, due to the cultural significance funerals have in the country. In this paper, we detail the process involved in a nudge messaging experiment that sought to help customers who chose to take out a funeral insurance policy follow through on their decision by paying for the first premium. Customers were sent one of four messages three days prior to their first debit order. Results indicated that using wording that leveraged commitment and consistency, aligned with social proofing principles, was successful in significantly increasing payment rates. Our findings demonstrate that making an initial commitment salient, as well as providing information on how other customers act in similar situations, is an effective way of nudging customers into paying their insurance premiums.

Introduction

Nudging, a concept introduced by Thaler and Sunstein (2008), is a technique that forms part of choice architecture whereby a decision-maker's behaviour is influenced toward a predictable outcome. The goal of nudging is to improve the decision-maker's outcomes. As part of their definition, nudges tend to have certain characteristics, which include being low-cost, easy to implement and cheap to avoid; thus, no restrictions on freedoms are imposed on the decision-maker by altering the properties of the decision (Thaler & Sunstein, 2008). Nudging has been used to encourage insurance take-up across a number of domains, including life insurance, flood insurance and agricultural insurance (Richler, 2019; Harris & Yelowitz, 2017; Davidson & Goodrich, 2021). Furthermore, it is seen as an attractive mechanism for insurance take-up, in part for the reasons stated above, but also because underinsurance can have devastating consequences for those affected. It is seen as a way to overcome the myriad of biases that prevent customers from choosing appropriate cover in the first place (Booth & Tranter, 2018; Chino et al., 2017; Collins et al., 2015). Insurance products are defined by a consumer paying a certain premium in order to protect themselves from a potential future negative event which may or may not come to pass, depending on the type of insurance. Even if the negative event happens, the timing of it is unknown, meaning that it could occur soon after the policy has been taken, or not for many years. This uncertainty places inherent strain on the purchasing decision and the consumer's present bias (Laibson, 1997), meaning that we myopically focus on the present at the expense of our future utility. The present study sought to determine how nudge messaging could increase insurance take-up. This was done by understanding how certain bottlenecks may be preventing customers from following through with decisions they have made with regards to funeral insurance policies.

Research

The cost of funerals in South Africa is driven not by wealth but rather by cultural expectations, due to the cultural and religious significance of the way in which someone is laid to rest. If not done correctly or respectfully, it is seen to cause spiritual misfortune

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for the living (Bank et al., 2022). There is also a belief that a person's final send-off is a sign of the family's social standing within the community, which is why families of the deceased invest in expensive rituals and opulent ceremonies.

South Africa is the fourth most expensive country when it comes to the cost of funerals, with the average service costing about 13% of the average yearly salary (SunLife Limited, 2022). In a country with half of its adult population living below the poverty line, funeral insurance in South Africa is a cultural and financial imperative (Maluleke, 2018).

In 2021, during the COVID-19 pandemic, the unemployment rate reached a record high of 34.9% – the highest unemployment rate in the world at the time (Naidoo, 2021). In the same year, death rates rose by over 33% to an estimated 700,000 people (Statistics South Africa, 2021), which created a huge focus on funeral insurance during the pandemic.

Standard Bank launched a new funeral insurance product in 2019 called the Flexible Funeral Plan, which is very different to traditional funeral insurance within South Africa, in that it offers an affordable and customisable funeral insurance option that does not cancel as soon as a customer is unable to pay a premium. Each of these features is relevant to the South African context, because it has made funeral insurance more accessible. In a country experiencing the highest unemployment rate in the world, while also being one of the nations with the most expensive funerals, more accessible funeral insurance benefits the population significantly.

In a short period of time, the Flexible Funeral Plan became the fastest-selling insurance product offered at Standard Bank. In 2021, activation rates began to hit a plateau, which meant there was room for improvement for the business. Activation rates are the number of funeral policies activated as a percentage of policies sold. A funeral policy is activated once the payment for the first premium has been received, but if this premium cannot be collected successfully, the policy is not activated, and the customer is not covered.

From a customer perspective, those who have intended to set up protection for themselves and their families are not covered until the first payment is received, and they are therefore at risk. For the business, the activation rate is an important metric as part of the sales process that can be improved.

To increase activation rates effectively, the team undertook the following actions:

1. Mapped out the customer decision-making pathway from point of sale to the first premium payment.
2. Reviewed existing collateral aimed at overcoming the activation rate plateau.
3. Conducted interviews with stakeholders familiar with the product and the activation rate plateau.
4. Analysed existing data to understand the activation rate plateau.
5. Identified a sample to test a nudge-based intervention.

Research into the problem revealed some significant bottlenecks that were preventing customers from activating their policies. Our research pointed to four key obstacles that were potentially causing the lower than desired activation rate, as illustrated in Table 1

Experiment Design

To increase the funeral insurance activation rate, we conducted a randomised controlled trial with three experimental conditions and a control. Each condition consisted of nudge messaging in the form of an SMS. Throughout the research process, an SMS was identified as the most appropriate channel to use because of its low cost and the fact that most customers had a cell phone number on which they could be reached. This was not the case for other communication channels, namely email and post.

Bottleneck	Description
Cognitive overload during sales process	During the sales process, there is a lot of information discussed about the policy's mechanics and features. This means that some information can be missed – such as the importance of paying the first premium and the implications of not doing so. People may be unaware that the policy is not activated without this first premium, leading to it having less importance than is actually the case.
Timing	In some cases, 20 to 30 days would go by between purchase intention and payment of the first premium, due to the nature of the product and a debit order needing to be set up to collect premiums from customers. A customer may choose to purchase funeral insurance, but their preferred debit date could be a significant number of days from when they agreed to take on the policy. With such a large gap between the two milestones, people may forget when their first premium is due to be debited or forget some of the reasons why they chose to take out the new policy in the first place. Consequently, the intention-action behavioural gap (Gollwitzer, 1999) could also manifest here, whereby people do not follow through with decisions or actions despite their initial intention to do so.
Change of routine	The funeral plan customer base consists mostly of people who are price-sensitive and generally hold a large amount of their money in cash. This means that a significant amount of money is withdrawn from the account in the form of cash, and debit orders are provisioned for with the remaining balance. Therefore, adding a new product places a burden on customers to remember to provision for the additional policy, which may be at odds with their existing behavioural habits.
Current SMS	The existing SMS that was being sent out was very transactional. It included irrelevant information, such as the customer's policy number, which most customers don't know off-hand, meaning it lacked relevancy. It also lacked any call to action, since most of the content was based on compliance/legislative requirements.

Table 1: Bottlenecks identified during the research process.

Experimental Conditions

Each SMS used different behavioural science principles that were relevant to funeral insurance and based on the bottlenecks identified during the research process. The experimental conditions were compared to the existing SMS that was used as the control. The details of each condition can be found in Table 2.

Behavioural Science Principle	Behavioural Science Description	Relevancy to Funeral Insurance
Loss aversion	Loss aversion is an important concept in behavioural science and is encapsulated in the expression 'losses loom larger than gains' (Kahneman & Tversky, 1979). In other words, customers would be more motivated to avoid a loss compared to receiving a gain of equivalent value.	This message highlighted that if customers did not pay for their first premium, they would lose out on the benefits that their funeral plan provides. In this way, we framed the level of cover and the benefits the customer had chosen as something that could be lost as a result of non-payment. We then focused on creating saliency by clearly instructing the customer on the steps they needed to take in order to avoid this loss by activating their policy. During the sales process, this potential loss is highlighted, and by re-emphasising it here, we hypothesised (H1) that it would lead to increased policy activations.
Commitment & consistency	The commitment and consistency principle is one of the six principles of persuasion introduced by Robert Cialdini (1984). It describes the way in which people want their beliefs and behaviours to be consistent with their values and self-image. In terms of decision-making, people tend to believe strongly in the decisions they have previously made, in order to avoid cognitive dissonance.	This message emphasised the initial commitment the customer made to purchase and pay for their funeral plan. Therefore, in this condition we wanted to highlight the customer's initial choice to purchase their funeral insurance policy. After highlighting the commitment, we provided customers with clear steps as to how they could be consistent with that commitment by making sure their first debit order was paid successfully. We hypothesised (H2) that this message would help customers to act in line with their initial purchase intention and lead to increased policy activations.
Social proofing	Under conditions of uncertainty, people look to the actions of those around them, and this influences their decisions and actions (Cialdini, 1984).	This message provided customers with information about how similar others acted in order to successfully activate their funeral policies. We provided customers with clear steps as to how other customers in the same situation as themselves, ensured that their first debit order was paid successfully. We hypothesised (H3) that customers would be influenced by the behaviour of similar others and would lead to increased policy activations.

Table 2: Experimental conditions and principles used in nudge messages.

Experimental Method and Results

The initial experiment involved selecting a specific debit date on which a significant number of policies would be put through the collection process. The 15th of the month was selected, as it offered sufficient numbers for a robust test (N=6970). Customers were randomly allocated into one of four conditions. No significant differences were found between groups in terms of key categorical variables, including age, gender, province, origination date, premium or sales channel.

All messages were sent out to customers three days prior to their debit date, and all received the messages at exactly the same time. Thus, we only manipulated message content and the not timing of the SMS being sent, which gave people enough time to act on the message by depositing the correct amount of money in their bank accounts or leaving sufficient money in their accounts, while also being close enough to avoid them forgetting to do so.

In order to test effectiveness, we looked at the first-time collection rate for insurance premiums. The collection rate is the percentage of policies for which premiums have been successfully collected on a defined date.

A one-way ANOVA was run to discern whether the nudge messaging had an impact on collections. The results of the analysis showed a significant difference between groups [$F(3,6966)=7.46$, $p < .001$]. Independent t-tests were run relevant to the control condition to determine the extent of each message's significance.

Loss Aversion. Results of the independent t-test showed no significant difference between the loss aversion condition and the control wording, and thus H1 was not supported.

Commitment & Consistency. Results of an independent t-test showed a significant difference between the Commitment & Consistency condition and the control [$t(3362)=-3.75$, $p<.001$]. Thus, H2 was supported.

Social Proof. Results of an independent t-test showed a significant difference between the social proof message and the control message [$t(3337)=4.03$, $p<.001$]. Thus, H3 was supported.

From the analysis, it was clear that the commitment & consistency and social proof messages were effective in driving an increase in collections. The table below indicates that 87% of customers who received these messages paid their premiums on time when they were supposed to. The implications of this seem to suggest a few things from a behavioural perspective, as discussed below.

Group	Principle	Sample Size	First-Time Collection Rate
1	Control	1719	83%
2	Loss Aversion	1755	84%
3	Commitment & Consistency	1760	87%
4	Social Proof	1736	87%

Table 3: First-time collection rates for each condition.

Discussion

First, H1 was not supported, meaning that customers were not persuaded by the fear of losing their cover due to not paying their premium. This fear may not have had relevancy, due to the policy not being activated at that stage. The endowment effect (Kahneman et al., 1990) states that individuals place a heightened sense of importance on an item they own, thereby making its loss more painful as opposed to something not in the individual's possession. It is possible that this wording may be more effective when it is delivered to customers whose policies are already active and have missed premiums as opposed to a policy that has not technically been paid for.

H2 was supported and, as suggested, this speaks to the nature of commitment and consistency. Given that there was a time delay between choosing to take out the policy and actually having to pay for it, there was a need to re-emphasise the reasons as to why the customer had chosen to take the policy

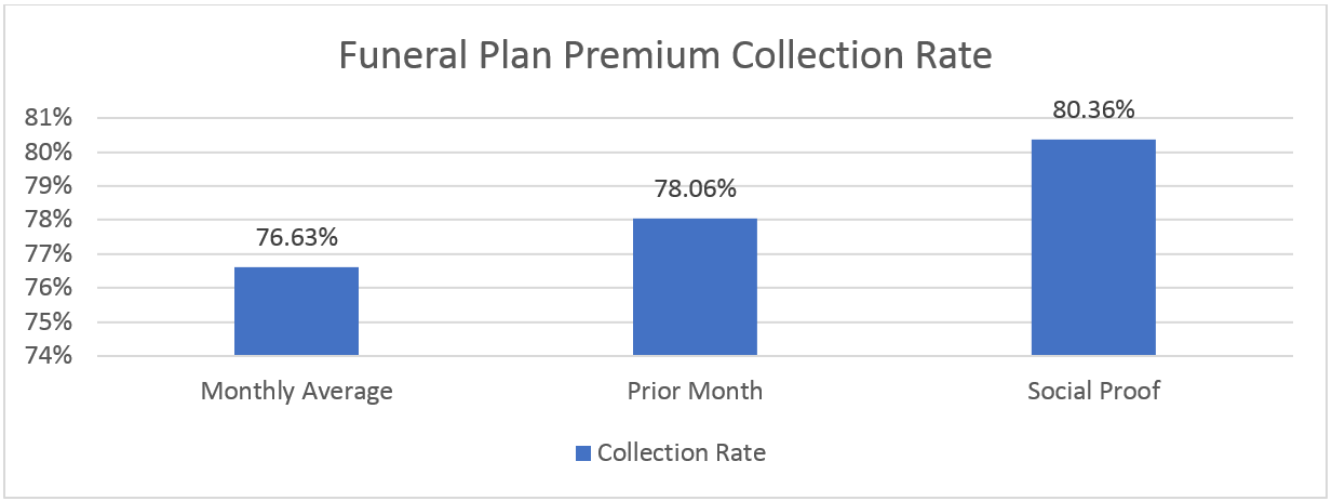

Figure 1: Funeral plan premium collection rate comparison.

in the first place. We believe that this is one of the means via which to overcome the intention-action behavioural gap (Gollwitzer, 1999) whereby people intend to perform a certain action but may be constrained from doing so because of procrastination, failing to act in time or deciding against acting at a critical moment. Making the reasoning for choosing to pay for their cover salient again was an effective way of encouraging more customers to pay for their premiums when they committed to doing so in the first place.

Finally, H3 was supported, and this again speaks to the overcoming of potential uncertainty with regards to making funds available prior to the selected debit date. The social proof (Cialdini, 1984) phenomenon states that people look towards others' behaviour to guide their own decision-making strategies, especially under conditions of uncertainty. By reminding the customer of their upcoming debit order, and also telling them how other similar customers provision for their debit order, more were able to pay successfully for their policy on the agreed upon date. We believe this also went some way to closing the intention-action behavioural gap (Gollwitzer, 1999), as it detailed steps that could be taken to ensure sufficient funds were in their stipulated account.

Overall, our results show that two of the three nudge messages were effective in increasing collections on stipulated debit order dates. To determine whether this impact would be seen on a larger scale, we scaled the social proof wording to the entire customer base for a full month of collections. The aim here was to assess if there were any differences in collection rates.

As evidenced in the graph below, scaling the social proof wording to the entire customer base for a full month had a very positive impact. The collection rate for the month in question was the highest it had been since inception of the product (80.36%), which was an improvement compared to average new policy collections (76.63%). In addition, the non-payment rate on the first premium attempt of 19.6% saw a 16% improvement compared to the prior 12-month average of 23.4%.

The implications in this regard are significant. First, by using nudge messaging to help people follow through with their choices, we are able to ensure that they receive the protection they chose in the first place. This is critical in terms of customers' financial well-being. Second, it has positive financial implications, as it means that more policies' premiums are collected every month. In terms of further opportunities for research in this field, there are a number of areas that can still be explored. We are exploring using machine learning (ML) in this type of approach, such that we can personalise messages to customers based on a number of different categories and factors. It is possible that ML will be able to detect better what type of message, sent on what channel and how many days prior would lead to an even higher collection rate, due to the increasing level of personalisation that would become available. Due to the process of implementation that occurred during our experiment, we were unable to use a hold-out group who did not receive a message, but this also presents an area of further study worthy of examination. The current intervention highlights the importance of making the sales decision salient

prior to collection whilst also demonstrating how socially framed information can assist customers in following through with their decisions. These insights could have significant positive impacts for customers as well as insurers.

THE AUTHORS

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A Behavioral Science-Led Understanding of COVID-19 Vaccine Hesitancy

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Final Mile

Developing a safe vaccine against COVID-19 in record time has been a success, but its comprehensive rollout has been challenging. While regulatory and supply challenges have received ample attention, the demand side challenge of vaccine hesitancy and refusal is often underestimated. Low confidence in COVID-19 vaccines, and low willingness to receive them, poses significant risk to the success of the global pandemic response. This chapter builds on the learnings from our studies in Pakistan, Burkina Faso, Côte d'Ivoire, and Kenya to highlight the importance of exploring psycho-behavioral factors in aiding segmentation and behaviorally informed human-centered design (HCD) to adequately address vaccine hesitancy.

A psycho-behavioral approach to segmentation captures clear, discrete, and relevant differences within the population, based on perceptions, motivations and affective cognition driving individual behaviors and decisions. The HCD approach makes these insights actionable and empowers a broad set of stakeholders to design, implement, and refine localized, segment-targeted interventions.

Introduction

The COVID-19 pandemic has had devastating effects and continues to be a cause for global concern. Amid the pandemic, efforts to develop a safe and efficacious vaccine for COVID-19 in record time have been a huge undertaking for the world. However, its rollout and delivery have been fraught with challenges. A year and a half after vaccine rollouts, only about 59 percent of the world population is fully vaccinated (Our World In Data, 2022). The supply and delivery of vaccines has been identified as one of the major obstacles that has marred their rollout. Dr. Tedros Adhanom Ghebreyesus, Director-General of the World Health Organization, has said that 'Vaccine inequity is the world's biggest obstacle to ending this pandemic and recovering from COVID-19'. This vaccine inequity is certainly visible, with 80 percent of the population in high and middle-income countries having received at least one dose while low-income countries continue to lag behind with only 15 percent of the population having being vaccinated at least once (Our World In Data, 2022). As of December 2021, the WHO target for achieving vaccination rates of 40 percent in every country by the end of December 2021 was missed across most of Africa. The next target, namely, to vaccinate 70 percent of the world's population against COVID-19 by mid-2022, might be achieved with the given rate; however, the rates might be skewed due to higher vaccination ratios in some countries (WHO, 2021).

Despite over a year of vaccines being available, there is limited uptake in African countries like Côte d'Ivoire, Burkina Faso, Nigeria, Kenya, Ethiopia, and Zambia, with less than 20 percent of the population fully vaccinated (Our World In Data, 2022)—a figure insufficient to reach the commonly stipulated threshold for herd immunity. Achieving vaccine equity requires both the availability of the vaccine and its uptake. Hence, a more holistic action to tackle the "biggest obstacle" may require efforts to address both supply-side as well as demand-side barriers.

The demand for vaccination is seen in the scenario whereby the vaccine is trusted, valued and actively sought by the target population. According to WHO's behavioral and social drivers model (WHO, 2019), vaccination is influenced by practical issues, motivation, social norms, and perceived disease risk. Any shortcoming in any or all these four elements

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can act as a potential demand-side barrier and lead to low confidence in COVID-19 vaccines—and low willingness to receive vaccines—thereby resulting in hesitancy. This in turn impedes positive COVID-19 vaccine action. According to WHO, vaccine hesitancy involves a delay in the acceptance of—or the refusal to partake in—a vaccination program despite the availability of relevant services. Hesitancy is complex and contextual, and it varies across time, place and vaccine type. Moreover, it is not driven solely by those who are anti-vaccination or sceptical towards vaccines; rather, hesitancy is a continuum. While vaccine hesitancy was a growing concern in the world even before the COVID-19 pandemic (MacDonald, 2015), the context of COVID-19 has added another layer of complexity. A good number of research studies have sought to understand vaccine uptake behavior with respect to other vaccines, such as DPT, MMR, and polio, which have seen less than optimal levels of uptake in recent years, including the role of incentives, social norms, risk perception (Piltch-Loeb & DiClemente, 2020; Olive et al., 2018; Dube et al., 2013), etc. The COVID-19 context is new and unique. While individuals with anti-vaccination attitudes refuse the vaccine, those harboring favorable vaccination attitudes also display doubts about getting vaccinated. Despite the historical precedence of vaccination programs in the world, whereby individuals trust their doctors and accept other immunizations, they are motivated uniquely within the COVID-19 context and the common desire for safety for self and family to arrive at their own conclusion, rather than defer the decision to medical and public health experts. Though this desire to make an informed decision around health needs not necessarily be bad by itself, within the context of the COVID-19 "infodemic" the pursuit leads to vaccine-hesitant pathways.

A demand-side focus brings to the forefront the need to understand micro-behaviors surrounding COVID-19 vaccination. Individual decision-making and actions in relation to vaccine uptake are more complex than commonly appreciated. Despite vaccine availability, social security support and better health delivery systems, the United States (66%) and the European Union (73%) have not been able to vaccinate the desirable percentage of their populations (Our World In Data, 2022). The problem is hence not only that vaccines are unavailable, but there is also inconsistent uptake behavior within the population. For Africa, the percentage of the population fully vaccinated is just 16 percent. Surveys (Yannick et al., 2021) from the pre-dissemination phase have suggested some hesitancy in the uptake of vaccines; however, the uptake rates have been poorer. There is a significant divergence between self-reported willingness to receive the COVID-19 vaccine and actual acceptance when it is available. While high approval of COVID-19 vaccines was reported in Ethiopia (97.9%), Nigeria (86.2%), Uganda (84.5%), Malawi (82.7%), and Burkina Faso (79.5%), actual uptake has been low (Our World In Data, 2022). Overcoming this gap requires identifying and targeting a range of barriers and drivers that underlie vaccine hesitancy within different populations, such as environmental, psycho-social, etc. One type of barrier and enabler that has garnered less attention relates to psycho-behavioral drivers. For example, even when environmental barriers such as accessibility are resolved, some people might still be hesitant, as their concerns about side effects increase their immediate available risk, while some others might resist getting vaccinated as a result of a low perceived risk of COVID-19 itself, due to discounting mental models, and yet others because of their mistrust of experts and institutions.

Demand-side barriers exist in the realm of human behavior, and they are affected by internal factors rooted in psychological underpinnings, as well as external factors present in the environmental landscape. Psycho-behavioral research brings together the social, structural, economic, and psychological factors surrounding COVID-19 vaccine confidence and uptake and identifies how unobservable psychological factors interact with observable social, structural, and economic factors to create differing vaccine beliefs and behaviors. Understanding vaccine decisions at a behavioral level can help direct interventions towards different parts of the population by addressing their unique psycho-behavioral barriers and enablers. A psycho-behavioral approach to targeted COVID-19 vaccine uptake thus explores the behaviors, attitudes, and beliefs supporting hesitancy and influencing the demand for COVID-19 vaccination and enables a more nuanced understanding needed for policymakers and governments for demand mobilization and improving vaccination numbers. Such an approach can also enable researchers to unearth psychological elements

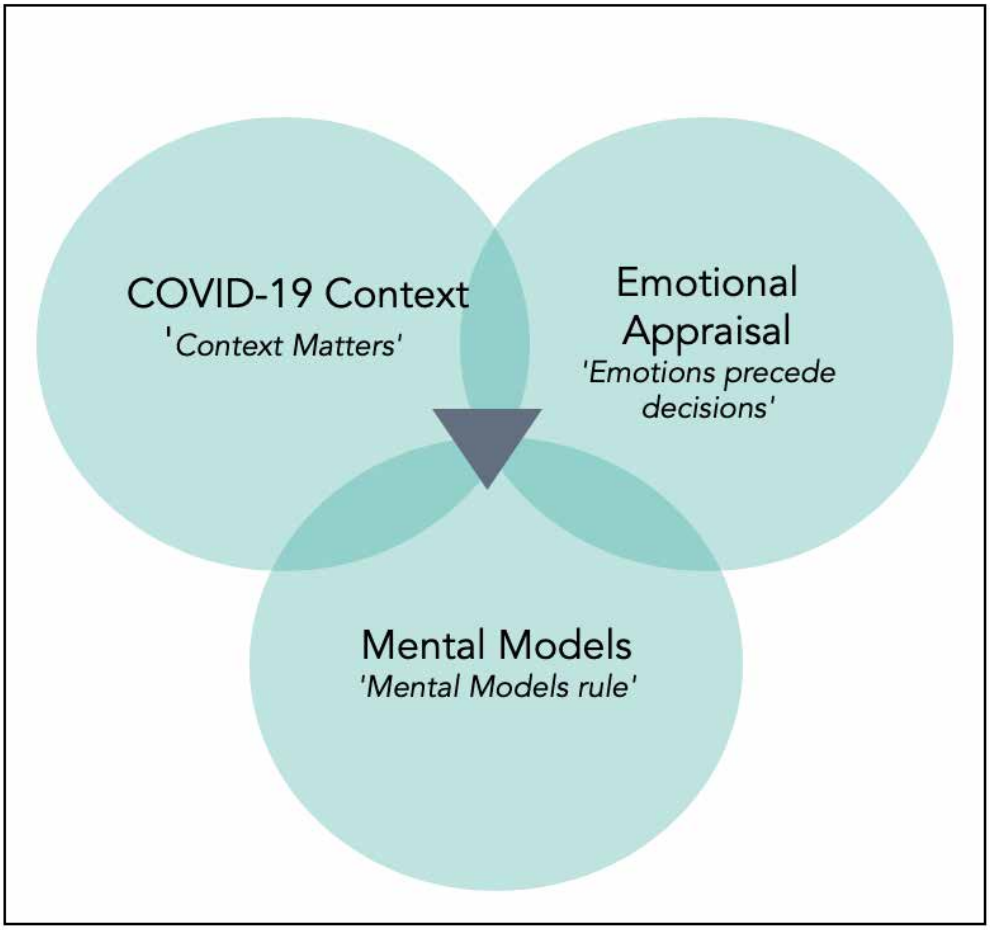

Figure 1: Psycho-behavioral factors affecting COVID-19 vaccine decisions.

influencing vaccine decisions, identify segments over time, and characterize their key drivers for future years as the context evolves.

Psycho-Behavioral Approach for Targeted Demand Generation for COVID-19 Vaccines

Why Do We Need a Psycho-Behavioral Understanding?

A psycho-behavioral analysis can assist in defining target population segments that are understood at a non-conscious level based on the type of emotional appraisal, certain dominant mental models, and contextual influences. Decisions lie at the intersection of these three factors.

Emotions Precede Decisions

How does one feel about a decision? How does one anticipate and evaluate consequences following a decision? How does one explore the stressors and enablers preceding a decision? Similar and even greater numbers of questions accompany any action or decision akin to one where individuals decide on COVID-19 vaccination. Behaviors surrounding a decision can act as mirrors reflecting the underlying motivations, beliefs, and emotions that are generated. Emotion appraisal-based decision-mapping can help determine a range of behavioral discriminants. Appraisal theory (Arnold, 1960; Roseman, 1984; Smith & Ellsworth, 1985; Scherer & Ekman, 2014; Frijda, 1986) informs us about the cognitive processes individuals adopt to assess external stimuli that are relevant to an individual's internal goals (e.g., '*I need to remain protected from COVID-19*'). The process helps trigger appropriate responses to the situations in which they occur. Furthermore, appraisals and subsequent emotions help individuals navigate through their social lives and accompanying conundrums.

Components of emotion appraisal involve the following: relevance ('*Is COVID-19 relevant to me? Does it affect me or my social group directly?*'), implications ('*What are the implications or consequences of taking the COVID-19 vaccine, and how does it affect my well-being and my immediate or long-term goals?*'),

coping potential (*'Can I cope with or adjust to these consequences of taking the COVID-19 vaccine?'*), and norms (*'What is the significance of the COVID-19 vaccine with respect to my self-concept and to my community/social group?'*)—all of which play out differently within the population, thus influencing COVID-19 vaccine decisions in a diverse way. For instance, cohorts with low COVID-19 disease relevance exclude the vaccine as part of the possible mitigation strategy and instead over-rely on CABs (COVID-19 appropriate behavior) compared to those who think COVID-19 is relevant and hence actively consider the vaccine's risks and benefits.

Context Matters

The context in which an individual finds him- or herself is a critical influencer, and it is dictated by external actors and conditions. Individuals decide their actions within a context. COVID-19 is experienced in the context of not only health concerns, but also economic hardships and social disruption. The COVID-19 pandemic has been experienced not as a single context but as multiple contexts (waves, lockdowns, lowered restrictions, vaccines, etc.) and has often been highly dynamic. The way decisions were made during the context of the second wave was very different to how they were made in the subsequent waves. Additionally, vaccine decisions in the context of a travel mandate are different from those made when restrictions have been lifted.

Mental Models Rule

At the core of behavioral decision theories lie biases and heuristics (Kahneman et al., 1982), i.e., the systematic deviations that prevail during judgment and decision-making. Together they create mental models that are used by individuals in their decisions and assessment preceding actions. Furthermore, these mental models can explain the reasoning, inferences, and decision-making processes of an individual that influence anticipated outcomes, and they affect risk perception, trust priors, and outcome evaluation.

What Is Psycho-Behavioral Approach in Relation to Segmentation?

Segmentation is defined as a statistical method of classifying people into groups based on their characteristics, and it is used to tailor products and services to subsections of targeted populations (Wedel & Kamakura, 2000). Over the years, segmentation has been used in the private sector to understand online habits and user preferences, as well as to market environmentally friendly products and attitudes to animal welfare (Bhatnagar & Ghose, 2004; Lutz & Newlands, 2018; Pomarici et al., 2016; Hölker et al., 2019). With a psycho-behavioral approach to segmentation, emphasis is placed on capturing clear, discrete, and relevant differences within the population, based on perceptions, motivations, and affective cognition driving individual behaviors and decisions. Identifying these segments requires defining groups in the population according to their differences in relation to one or several characteristics inferred through insights derived from a qualitative research, a literature review, or analyses of secondary quantitative data and then further clustering the data across a multidimensional set of quantitative data-measuring variables, which can be predictive. These clusters can be derived using surveys or machine learning cluster algorithms. They are robust, nuanced, and highly predictable of needs, wants, and behaviors in the population, and therefore they are used to develop targeted communication and intervention to drive uptake. A psycho-behavioral approach tries to augment the "how" aspect of decisions/actions (how did an individual decide) alongside the "what" aspects of decisions (what choice/action has one taken or is expected to take).

In the public health space, psycho-behavioral segmentation has been applied to understand HIV-related risk perceptions in Malawi, barriers to voluntary medical male circumcision in Zambia and Zimbabwe, and family planning in technology in Niger (Rimal et al., 2009; Sgaier et al., 2017; Collective, 2015). More recently, this approach has been used for targeting health interventions in relation to HIV testing and treatment of young men in South Africa (Bell et al., 2021). A study (Charles et al., 2022) published in 2022 used a mixed method approach, including psycho-behavioral segmentation, to suggest segment-specific interventions to increase the uptake of social distancing during COVID-19. Even though there is difficulty in measuring the impact of these approaches, evidence suggests that psycho-behavioral segmentation, which incorporates findings on the motivations, behaviors, and beliefs

of individuals, results in more homogeneous (and therefore recognisable and useful) segments than a purely demographic analysis (Matz et al., 2017; Boslaugh et al., 2005; Gomez et al., 2018).

We used psycho-behavioral segmentation to segment adolescent girls and young women (AGYW) for HIV prevention. The study identified three psycho-behavioral segments based on different relationship goals. We also conducted psycho-behavioral segmentation to segment a target population for voluntary medical male circumcision (VMMC) and found six segments based on different behavioral barriers.

The Study

Objective

Considering the varied and complex nature of the factors driving attitudes, beliefs, and decisions with respect to the COVID-19 vaccine, programmatic solutions need to be behaviorally nuanced, relevant to the needs of population segments, and localized to context, with a particular need to focus on vulnerable populations. To tackle the problem of COVID-19 vaccine hesitancy in Pakistan, Kenya, Burkina Faso, and Côte d'Ivoire, we adopted a psycho-behavioral approach with the aim of uncovering the different attitudes and mental models prevalent within the population with respect to the COVID-19 vaccine and to facilitate design strategies and interventions to drive confidence in and the uptake of the vaccine. The aim was to also aid in the future psycho-behavioral segmentation of more hesitant members of the population in the target geographies.

Method

A qualitative formative research study was conducted to explore the emerging themes within vaccine uptake behaviors, including the conscious and non-conscious drivers of hesitancy and vaccine confidence, with an end-user sample. The emphasis was to have an in-depth understanding of the decision-making process of individuals by capturing the COVID-19 context, attitudes towards the vaccine, COVID-19 mitigation behaviors, general immunisation behaviors, information channels, and influencers.

An in-depth interview (IDI) method, using a discussion guide, explored both individual beliefs as well as community narratives around COVID-19 vaccines. Along with the perceptions and beliefs around general and COVID-19 vaccines, their experiences of making health-related decisions in the past were explored in order to decode the elements of and processes behind decision-making.

A diversity sample (n=55, N=220), representative of demographics (age, gender, income, location), vulnerability (health risk, information access, socioeconomics, historical, and inclusion), and COVID-19 vaccine attitudes, was recruited.

Findings

The COVID-19 Vaccination Decision Is a Journey

The study showed that vaccine decisions involve a journey involving micro-decisions. This decision journey consists of six stages through which an individual progresses to make an informed decision regarding the COVID-19 vaccine. The decision stages involve assessments that are emotionally appraised for the given stage-specific decision, and each one is then characterised by a desired outcome/goal that helps the decision-maker move forward. Furthermore, collectively, the desired outcomes create a positive pathway for vaccine uptake action, but as individuals navigate through the decision stages, an evaluation that leads to an unfavorable assessment of the COVID-19 vaccine can direct them away from the positive pathway and lead them to drop off the decision stage. This journey framework exists within the larger dynamic COVID-19 context. There are triggers, arising within the context, which can result in non-linear and iterative movements within the journey, and they can:

- Push an individual forward towards uptaking the COVID-19 vaccine (e.g., during a pandemic peak, the high case load leads to higher risk perception and a more favorable vaccine appraisal).
- Move an individual back towards avoiding the COVID-19 vaccine (e.g., a lower case load leads to lower risk perception, or a high "viral" vaccine adverse event leads to a higher vaccine risk) and
- Lead an individual to skip some stages and move directly to uptake (e.g., extreme symptoms).

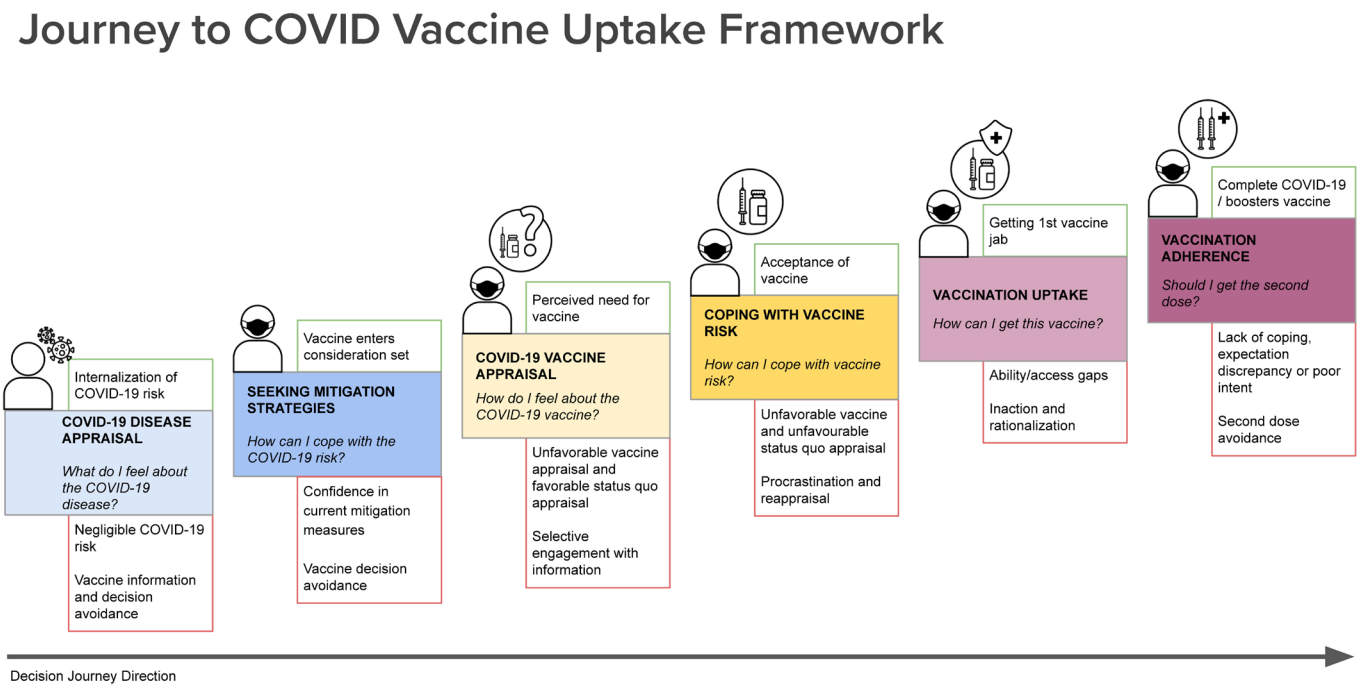

Figure 2: COVID-19 vaccine decision journey from qualitative research.

Two non-linear and iterative movements appear to occur in the COVID-19 vaccination decision journey. These movements probably unearth the key reasons why we see differences in reported willingness to have the vaccine and actual uptake. Individuals appear to be willing to embark on the COVID-19 vaccine decision journey but do not abandon it; instead, they appear to continuously be on it, without any forward progress into vaccine uptake. These movements are as follows:

- Procrastination loop: Despite understanding the perceived rewards of vaccination, the inability to cope with the perceived risks of vaccines leads to people procrastinating and delaying the decision to vaccinate. This delay in action results from ambiguity aversion, whereby individuals bet in favor of known risks rather than unknown risks, and the hot-cold empathy gap, where in the context of a decision (hot state) individuals use an emotional rather than a rational mode of evaluation. New information or contextual changes exacerbating uncertainty trigger a reconsideration of the decision to get vaccinated, and this repeated procrastination and reconsideration constitutes a loop, which involves regression to disease-coping resulting from an inability to cope with vaccine risk.
- Rationalise inaction loop: Ability and access gaps result in prolonged inaction. Individuals rationalise their inaction, often leading to updating vaccine beliefs and regressing on the journey to the vaccine appraisal stage. Updating of vaccine beliefs is done in a way to reduce cognitive dissonance. So, if one has favorable vaccine beliefs, prolonged inaction may lead them to update these beliefs and move away from the vaccine and more towards favoring their inaction, due to self-consistency bias. Reappraising the vaccine with these now unfavorable updated vaccine beliefs may lead them to completely drop off the journey to vaccination.

Biases and Heuristics

An array of mental models influence beliefs around COVID-19 and the vaccine—and thereby their risk assessment. The dominant mental models include:

- *Availability heuristics* to retrieve known COVID-19 cases and fatalities and judge if COVID-19 is still relevant or dangerous.
- *Private optimism* bias to assess the risk of infection and attribute any risk to specific demographics and geographies.
- *Status quo* bias to avoid the vaccine and maintain the current "healthy" state one finds himself/herself in. This also helps cope with the

ambiguity around the virus and its vaccine.
- *False consensus* in projecting their vaccine viewpoint and miscalculating actual vaccination rates in their community, which in turn distorts social proof.
- *Confirmation bias* to structure their engagement with information channels that support their beliefs and vaccine action, in-group out-group yardsticks to characterise vaccines as methods of population control, etc.

Behavioral Enablers

- *Novelty of COVID-19:* COVID-19 and its unprecedented fallouts are able to create necessary relevance for vaccines.
- *Adult and child vaccine precedents:* Communities with a rich and favorable child and adult vaccine history harbor positive associations around vaccines and manage anticipated side-effects optimally.
- *Desire to conform to social proof:* Visual cues such as queues and vaccination cards serve as signals of social proof.

Behavioral Barriers

- *Hot-state hesitancy:* There exist hot state barriers which influence individual decisions just before the required action is to take place. Such barriers can be seen to exist only when an individual is at the cusp of vaccine action and succeeding in his/her initial vaccine intent. During this hot state, i.e., the time of action, evaluations take a more emotional route than the rational belief or attitude route. Emotions are much more volatile and context-dependent.
- *Affective coping:* COVID-19 has been experienced in terms of social and economic constraints and not necessarily health risks. As one navigates through the COVID-19 decision, individuals are susceptible to cues such as low masking and the removal of travel mandates, all of which create positive mental imagery and produce a sense of control over the pandemic. In some cases, individuals forego their sense of control and resign to a state of learned helplessness, wherein they believe that nothing they do will protect them from COVID risk, so they might as well stop trying.
- *Reference dependence:* Individuals and communities use points of reference such as proximate COVID-19 cases, malaria/meningitis/HIV symptoms, fatalities from other diseases, etc. to judge the degree of danger from COVID-19.
- *Historical priors and group mentality:* Distrust breeds from historical priors such as colonial persecution, racism, covert military operations, etc. These historical priors lead to an "Us" vs "Them" frame of evaluating COVID-19 and the vaccine, such as 'COVID-19 is White man's disease', 'The COVID-19 vaccine [was sent] to kill Africans', etc.

Discussion

Demand generation for COVID-19 is as much a demand-side problem to address as it is a supply-side problem. A demand-side perspective to vaccination engenders micro-behaviors—steeped in behavioral underpinnings—involved in individual decision-making. The COVID-19 vaccination decision is influenced by an elaborate emotional appraisal, contextual dynamism, and systematic cognitive deviations signaling the importance of defining and exploring populations at the psycho-behavioral level. The findings from this study reinforce the need for a nuanced behavioral understanding of the population. Our understanding of the COVID-19 vaccine decision's journey stages, and mental models accompanied by cognitive deviations, can further inform segmentation efforts as policymakers and governments ramp up their efforts to achieve optimal vaccination rates. Thus, psycho-behavioral segmentation and behaviorally informed, human-centered design approaches can help in adequately addressing COVID-19 vaccine hesitancy. The human-centered design approach can also help in making these insights actionable and empower a broad set of stakeholders to design, implement, and refine localized, segment-targeted interventions. The findings of this research should be further augmented with quantitative and behavioral design (rapid testing and co-creation) research studies involving stakeholders, and help in identifying and profiling psycho-behavioral segments within the populations and building localized, relevant, and targeted interventions.

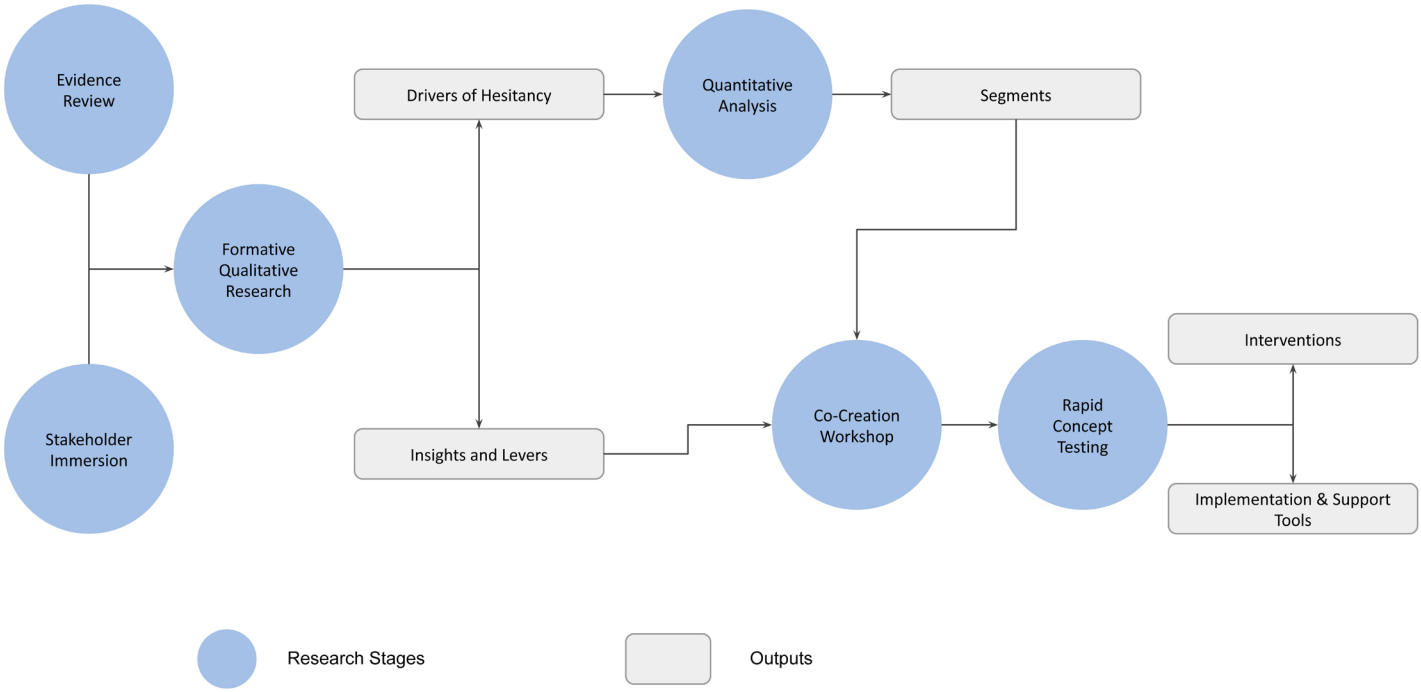

Figure 3: Ideal research pathway to psycho-behavioral segmentation.

THE AUTHORS

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How to Introduce Behavioral Science Into Organizations and Not Perish While Trying

GUSTAVO CABALLERO[1], ASHLY CÁCERES, SILVIA COTTONE, CAMILA DELGADO, DANIELA ESPITIA AND ANA STEIN

BeWay

Behavioral science is at the core of the fast-growing success of your competitors. Perhaps you have seen it at a conference or on social media, and now you are interested in introducing it into your organization. How do you begin? Based on our experience at BeWay, we have designed a roadmap to implement behavioral science in an organization, beginning with internal sales, professional development, and ultimately how to lead a behavioral organization.

Introduction

If you are reading this article, it is likely that you already have an interest in behavioral science (BeSci) and you would like to apply it to your business or workplace. Applied behavioral science has recently grown worldwide (Action Design, 2022), as leading 500 Fortune companies such as Google, Meta, and Amazon acknowledge its value and are using it extensively. Likewise, governments and public organizations have had the opportunity to experience the impact of BeSci firsthand (Lindemann, 2019).

BeSci is an interdisciplinary field that explores how people make decisions and behave. Through a cognitive and psychological approach, it considers relevant features of human behavior (e.g., heuristics and biases) not considered in the standard economic framework (Diamond et al., 2007). So, what does it mean to become a behavioral organization? It means implementing a scientific approach and generally entails a three-step framework:

1. An in-depth analysis of behavioral factors affecting decision-making processes.
2. The design of solutions based on analysis.
3. Experimentation with solutions to measure impact.

A broad body of literature has been developed on the discipline, but there are still considerable challenges when transitioning from simply being curious about BeSci to fully applying a scientific approach in an organization. Let us consider some main challenges.

Challenge #1: Tradition vs. Innovation

Traditional organizations are product or service oriented. In the past few decades, there has been an increased demand for human-centered design, with roles such as UX and Service Design to unveil user pain points and design solutions catering to those needs. Despite this shift, how organizations work and develop communication strategies is still not rooted deeply enough in psychology. By understanding how people decide, and how to achieve behavior change, we can open new doors for innovation.

Opportunity: Thinking Outside the Behavioral Box

When adding BeSci to disciplines such as UX and marketing, not only will products and services be designed based on psychological principles, but it is also a recipe for innovation.

One example in this regard is the global success of the Spotify Wrapped campaign. In December 2020, 90 million users engaged with the campaign by reviewing their music preferences throughout the year and sharing it on social media (Jain, 2022). This campaign implemented multiple elements of BeSci, such as emotional and psychological elements, but it also calculated theorems of rational choice, which

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led to a more comprehensive design and ultimately a 21% increase in downloads. BeSci is more than just theory and experimentation. It involves observing and continually learning about how people behave, and ultimately designing for improving their welbeing.

Challenge #2: People in Organizations Are Also Prone to Behavioral Biases

When designing a strategy for a product or service, biases that affect your customers' decisions might be considered, but how biases affect the choices made by your teams has most likely not been considered. Status quo bias, a term BeSci uses to define people's resistance to change, plays an essential role in traditional organizations, in that it keeps people from embracing change (Griffin & Moorhead, 2009). This notion is also related to loss aversion, which refers to people's tendency to prefer avoiding losses to acquiring equivalent gains. Introducing BeSci to organizations entails an inside-out transformation, and biases such as status-quo and loss aversion may become a substantial barrier on the path towards innovation.

Opportunity: Experimentation to Avoid Initiative Shipwreck

A key element to BeSci is testing. You have an idea, you pilot it, collect data, learn about it, and either scale it or set up a new round of ideation. Without proper evaluation, interventions become anecdotes, and their potential impact can be swayed by biases that affect our decision-making. Hindsight and information-processing biases (e.g., confirmation bias), in addition to political considerations, can lead to poor innovations being scaled and top-notch ideas being cast aside. The introduction of BeSci helps managers and stakeholders move from decisions based on biases and subjective assessments to data-driven decisions.

With so many reasons to adopt BeSci in organizations, one may wonder why we do not see it applied more broadly. Despite its proven effectiveness and growth, not all organizations know how to successfully leverage BeSci.

While some succeed in incorporating BeSci through consultancy, others may opt to install the discipline permanently. Slowly, but surely, more companies are seeking full-time behavioral scientists. As one recruiter for a Fortune 500 company wrote, '[BeSci], especially applied in a corporate environment, is very new to our company. Before I started recruiting in this space, honestly, I had no idea roles and individuals with backgrounds like this existed. After networking and learning more about the "why" and how it can add value, it makes sense. I foresee a lot of companies building up this function, which will make the market extremely competitive and challenging' (Habif, 2016).

With these main challenges in mind, when starting to apply BeSci, the question is how do you persuade your colleagues to get on board? We have designed a brief guide for practitioners and organization leaders (see Figure 1) to (i) better convince your team to start using BeSci with an initial sale, (ii) prepare the first trials, (iii) experiment, (iv) consolidate and expand to other areas, and (iii) ultimately become a behavioral organization.

Stage 1: The Initial Sale

First impressions matter (Willis & Todorov 2006). This is also true when considering the first contact with a new client (who in this case may be your own boss). From our experience, it is possible to pinpoint two main types of clients:

Type 1: Companies that already know what BeSci is and are therefore interested.

Type 2: Companies that do not know about BeSci and therefore do not know that are interested (yet).[2]

When companies already recognize the value of BeSci, they most likely see the value in your proposal and will probably give the green light for experimentation; however, when they do not know about it, there might be higher resistance to change.

Explaining BeSci

Ideally, one would start with training, in the form of workshops, followed by a clear communication strategy.

However, if you anticipate that your client has no prior knowledge regarding BeSci (type 2 client), it is important to establish common ground to express ideas and behavioral principles in a manner that is easy to follow. A formal explanation of biases and other BeSci principles might seem too abstract and,

2 One could argue there is a third type: companies that know about BeSci but are not interested now.

Figure 1: The roadmap to becoming a behavioral organization.

frankly, even boring. If one can ease into these concepts through relatable stories or situations, where your client can see themselves making the same "mistakes," instead of giving them a lecture, receptiveness increases.

One way to help someone become aware of their own biases and heuristics is through case studies. In the early stages of the process, resistance is often found, so a few examples on how biases work is a great conversation starter. There are many, but we

like using two in particular.

The first one is an intervention designed by Hubbub in London. Two transparent cigarette bins were placed next to each other. One was labeled "Cristiano Ronaldo" and the other "Lionel Messi," encouraging smokers to vote for the greatest player (Restorick, 2015). This is a great example of gamification for environmental protection and a fun conversation starter.

The second example is the Selective Attention Test by Simons and Chabris (1999), better known as the "Gorilla Video", which is a fantastic example of inattention bias. The video shows how something so obvious will not be perceived if our brain is not focused. This video is a great way of exposing the limited resources our brain has and how this leads to human mistakes. A simple conversation in this direction will increase interest in BeSci and hopefully encourage further learning.

BeSci Training

Training should be provided by someone with a deep understanding of BeSci. For this crucial step, a consultancy firm of BeSci experts is best.

Training should always be designed to focus more on practice than on theory. This means providing teams with an understanding, not only of the most common biases and heuristics, but also those that best match the product or service being designed, whilst also training them to understand and implement behavioral models such as COM-B (Michie et al., 2011) and EAST (Behavioural Insights Team, 2014). Additionally, providing case studies and designing a quick pilot test could accelerate the learning curve by giving trainees hands-on experience.

Finally, training should not be a one-time event but rather a continual cornerstone of the company´s culture. Applying BeSci is easier said than done, but coaching is a great way to ensure that participants can apply their new skills.

Coaching and working together, instead of having experts coming to the organization and leaving after designing and implementing a solution, is key. Oftentimes, this approach fails due to a lack of understanding about the organization and their client's needs. This approach will not create momentum, and even if successful, it could result in the termination of BeSci once the relationship ends.

Find a Champion as Soon as Possible

In the process of training, and even at the first moment of sale, it is important to identify a potential "champion" within the organization. Make that person your ally to boost BeSci interest between your colleagues in the early stages of the transformation.

The champion is:

1. Typically, a person in a position of some power with a genuine interest in the subject (i.e., reads independently about the subject in articles and books).
2. Passionate about BeSci and is motivated.

Champions know the organization inside and out: they understand the business goals, are proficient in the corporate lingo, and are experts in navigating the bureaucracy of the organization. Champions will help you open doors with skeptical members, as they are deemed trustworthy. As a result, they can help by participating in training and the first trials.

Stage 2: Preparing for the First Trials

After the first sessions of training, the BeSci team can start putting into practice their newly acquired tools. Yet, as the first formal training sessions will likely be introductory, teams should be accompanied for a while. Not only will this help increase the chances of early success, but it will also provide teammates with the opportunity to share potential issues with the BeSci experts. Providing instant feedback will empower teammates to apply BeSci to their upcoming projects. The challenge here is that the team will encounter colleagues who are unfamiliar with the BeSci framework, in which case this could be an opportunity to promote "BeSci ambassadors", or people who know about BeSci and are able to answer questions that arise.

A number of psychological and organizational barriers influence the environment and the decision-making process for BeSci ambassadors. A few of the main ones are outlined in Table 1.

Psychological Barriers	Organizational Barriers
Status quo bias	Knowledge and ability gaps
Loss aversion	Misperceptions regarding potential gains
Cognitive dissonance	Misperceptions regarding possible gains
Group thinking	
Sunk cost bias	
System justification with Semmelweis reflection	

Table 1: List of psychological and organizational barriers.

When facing these barriers, what leverage can be used?

Reach Out to Relevant Stakeholders

Alignment with the organization's goals is key from the outset, because any influences on the organization's main KPIs will always catch the attention of upper management. For example, managers are always impressed if you can increase customer satisfaction or brand engagement, and they will focus their attention on innovation if it helps to achieve the goals used to measure success.

To ensure you are aligned, identify and invite all relevant stakeholders (including design, marketing, legal, HR, etc.). Some proposals will face barriers if (i) they affect other segments of the organization in ways that may not be evident from an outside viewer, and (ii) if some colleagues may feel left out of the project. Avoid difficult situations by considering people's feelings; sometimes it is difficult to notice scenarios like this, but it is all worth it when you can work and reach out to colleagues without them second-guessing your intentions. This is also related to the IKEA effect, i.e., the more involved team leaders and participants feel within the proposal, the more likely they are to value it.

Having all relevant stakeholders does not mean having a working team of an unmanageable size. Usually, you will only require their input at specific moments, but they should be informed from the beginning and after reaching key milestones. Also, keep in mind that, even if they are highly motivated, there are risks associated with trying to include team members with a very heavy workload.

Additionally, it is important to consider how interventions can affect end-users. BeSci is a powerful discipline and should be used to create a positive impact. There are no neutral designs, and therefore it is important to align BeSci with an ethics framework to ensure that not only are we reaching the same goal, but we are also considering the ideal means.

Teammates System

We suggest building a support system (AKA "teammates") whereby trainees, BeSci coaches, and organization leaders can design and develop the organization's main products and policies. By positioning teammates as figures of authority regarding BeSci, employees feel confident in the solutions being implemented.

Quick Wins

Aim for low-hanging fruits. The literature has identified several low-cost interventions, many of which are specific to how to communicate ideas to final users, with great impact. The first aim is to improve existing communication materials (websites, e-mails, printed materials) by applying BeSci. Identify how to simplify communication materials to achieve cognitive ease and create a clear hierarchy of information. Also, if possible, aim for products or services with a high return per unit. Numbers speak louder than words, and BeSci skeptics could become interested in jumping aboard with the right numbers.

Stage 3: Measuring the Contribution of BeSci

Measuring the results of all behavioral interventions, specifically during the first trials, is crucial for the successful introduction of BeSci into the

organization. Some colleagues might initially be reluctant about adopting it, even in the face of its previous successes, possibly due to questions regarding the circumstances in which these other tests were conducted and how the geographical, cultural, and economic frames might be different. Additionally, there could be some limiting beliefs within the organization to accomplish similar results. Yet, when presented with results from within the organization, this apprehension will dissipate, thus reducing the aspirational gap and making possibilities more tangible.

Experimentation

Experiments are the best tool to measure the impact of behavioral interventions, because the results generated in the first run of experiments are scalable to a full product or service rollout. Nevertheless, this depends greatly on how the methodology is applied.

Special attention must be placed on the usual proposals that put rigor at risk. For instance, testing only with "the best" will provide no insight on what can be achieved when scaling the innovation to others in the same organization—just like running an "experiment" with only six to eight participants will provide no accurate estimate of any effect.[3]

Thus, it is necessary that clarity must be achieved early in the process around what it means to experiment in BeSci. The focus must fall on how to achieve accurate measurements of the effect (sample size and internal validity) as well as how representative the finding is deemed (external validity). It is also important to emphasize that a proper experiment measures the average effect expected when scaled.

Additionally, there are ways to learn about the organization's ability to run experiments, with minimal risk and before conducting any actual experiment. Experiments require the deployment of competing interventions to randomly selected clients or users, aligned with procedures to ensure proper randomization. Depending on the case, this may mean programming, if intervention is online, or new procedures when done in a physical setting. To deploy an intervention with minimal risk, one option is A/A testing (Kohavi et al., 2008), whereby randomization is in place but the information is the same except for an identifier that lets us learn whether proper randomization was possible.

Document Every Lesson Learned

Document your work and share it with colleagues. Use the language of the organization and create a library of best practices identified in the first interventions.

Disseminating results, especially the effects on KPIs of early experiments, helps to arouse the curiosity of other departments. For instance, if a copy on a sales landing page was rewritten using BeSci principles, it would be possible to not only highlight the effectiveness of the new copy, but sales percentages would also have increased due to the intervention. On a day-to-day basis, many leaders feel highly engaged with KPIs, so this helps capture their attention.

However, documenting failure is also important. Not every project is successful, and so the best we can do is document what was done and then try our best to understand what went wrong and rebuild from there. If an idea reached the experimentation stage, it is because it seemed promising, so learning about past failures will help adjust expectations and improve implementation.

Disseminating findings and continuing work in more areas leads to establishing the discipline as a fundamental element in the design of solutions. When different departments have worked with BeSci, successful interventions are talked about, and stakeholders start requesting the support of BeSci.

Stage 4: Consolidation and Expansion to Other Areas

Once the first successful interventions and experiments have been achieved and communicated to the teams and stakeholders, the next step is to grow within the organization. Expansion to other areas of the company may seem difficult, but by following the guidelines used for the first interventions from Stage 2, the probability of success increases. In fact, we must always remember to build bridges, be empathetic, constantly train, maintain order in the

3 It is noteworthy that areas such as marketing and SEO routinely conduct tests labeled "experiments," so most organizations are familiar with the concept. The problem is that—just like they can be A/B tests—they can also refer to research of another non-conclusive nature.

methodology, and spread knowledge to apply BeSci across different areas.

Identify Where to Expand Next

The first step necessary to expand is to identify areas of the organization in which to replicate best practices. For example, teams such as Marketing & Communications, Customer Experience (CX) Design, HR, and Transformation, among others, could improve performance with the help of BeSci. An additional point here is to consider whether these departments' leaders have already had contact other teams that have successfully applied BeSci in their projects. The social factor plays a primary role in this instance, because the recommendation of someone who has measured the impact of applying behavioral insights generates authority and reduces the uncertainty and risk of embracing a new, innovative framework.

Become an Ally

Once we have identified the other areas into which we can expand, the second step is to establish a relationship between leaders and departmental teams. It is important to keep in mind that we must become an ally to our clients in order to maintain constant, open, and empathic communication. By building a relationship, teammates will see us as allies and share both failures and successes. Allies are always promoted, especially when they help us succeed.

Finally, keep promoting BeSci, documenting, and disseminating. The initial sale you made when starting will have to be done continuously. Expanding means reaching areas unfamiliar with your work, collaborating with new employees, and eventually sharing your experience beyond the organization. In addition, learning does not stop at the first trials—a body of evidence can be created that strengthens future ideas.

Stage 5: The Goal: Structure a Behavioral Organization

Once a foundation of trust has been built around the discipline and the teams' capacity to apply it, BeSci can be practiced in different departments. It can be applied to improve gender parity and environmental awareness in organizations, the work environment, team productivity, and compliance, among others. Depending on the case, the consolidation of BeSci can mean that everyone in the organization becomes a Behavioral Scientist, but more often than not it will consist of a system of specialized teams established to be part of projects throughout the company, with each one formed by BeSci specialists.

In enjoying the benefits of BeSci, appreciate how far you have come, and always remember to continue being rigorous and always willing to learn.

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Applying Behavioural Economics to Firms

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It is widely accepted that consumers are boundedly rational, due to their cognitive limitations and behavioural biases. However, less is known about why firms may not be fully "rational" in an economic sense. In this article, we focus on firm behaviour, exploring (i) the reasons why we should care about it, (ii) the current status of knowledge on the subject and (iii) the models and technical tools that can be used to analyse it. Behavioural economists talk a lot about the design of "choice architecture" – and this article takes us into the realm of "market architecture." We draw out its implications for policymakers and nudge practitioners, using applied behavioural industrial organisation (Behavioural IO) case studies. Last, we explore the how firms may not 'rationally' pursue their environmental objectives; and why tackling this is important for society.

Why Should We Care About the Behaviour of Firms?

Over the past 20 years, much of the behavioural economics literature that has been applied to firms has explored the 'rational firm-irrational consumer' framework, under which profit-maximising firms may seek to exploit and magnify consumers' behavioural biases (such as consumer inattention or impulsivity) (Gabaix & Laibson, 2006; Heidhues et al., 2012).

In this article, we instead focus on how markets function when *firms* have behavioural biases, in terms of how they make decisions and what we can say about the consequences in the context of industrial organisation (IO).

Ultimately, non-profit-maximising behaviour may be positive or negative for consumer welfare, depending on whether the behavioural decision-making nudges firms towards maximising consumer welfare or away from it.

By better understanding firm behaviour, policymakers and those shaping the market architecture (including platforms and regulators) will be better placed to understand the impact (and unintended consequences) of their interventions on consumer welfare and competition.

The emphasis of this article is on policymaking and market architecture, illustrated through case studies, and it is structured as follows.

- What do we know about the behaviour of firms?
- How can we assess the behaviour of firms?
- What next for policymakers and nudge practitioners?

What Do We Know About the Behaviour of Firms?

Economists often work under the *Econ 101* assumption that firms are profit-maximising. Whether by chance or deliberate corporate strategy – so the traditional argument goes – a firm must be profit-maximising to exist in the long term. Short-term losses can be sustained (e.g. a start-up gaining scale) as long as profits are maximised in the long term; otherwise, another firm that is more adept at profit-maximising will take its place (Friedman, 1953). Within firms we would also expect management and employee biases to be scrutinised and challenged, i.e. we would not expect managers or employees who systematically make sub-optimal decisions (for the firm) to be retained or promoted.

However, the behavioural IO literature highlights situations in which firms are not profit-maximising (Heidhues et al., 2012; Armstrong & Huck, 2010). For example, the labour market for the National Football League (NFL) in the USA fails to profit-maximise: we know each NFL team's budget constraints, and we know the ex-ante and ex-post quality of each player, so we can say with confidence whether teams

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are profit-maximising. This is a competitive market with ample opportunity for learning, aligned with high financial stakes. Nevertheless, NFL teams systematically overvalue the (ex-ante) highest-ranked players, thereby undervaluing other players (Massey & Thaler, 2013). Explanations such as "superstar quality" or increased ticket sales fail to explain the phenomenon.

We therefore seek explanations for what causes non-profit-maximising behaviour and why that behaviour is sustainable in competitive markets. These two issues are investigated and discussed below.

> 'Just like consumers, managers can be subject to mistakes or limited attention, and therefore they do not always make optimal decisions.'
>
> (Heidhues & Kőszegi, 2018, p. 521)

What Causes Non-Profit-Maximising Behaviour?

The assumption that firms are fully rational comes down to some intuitive observations. Firms have a corporate governance structure, with boards and managers who are held to account for their decisions, as well as resources and budgets to figure out the best strategy and course of action. In competitive markets, firms that deviate from this path may fail.

However, at a fundamental level, we know that firms are collections of individuals. Therefore, the bounded rationality of individual employees, managers and owners may affect the decisions made by these firms.

Non-profit-maximising behaviour may be due to rational (rather than behavioural) causes, such as asymmetric information and the principal-agent problem. For example, in the case of (perverse) incentives, an unbiased manager might still choose to follow a sub-optimal market-wide strategy. Deviating from the market norm might result in the manager facing additional criticism (or impaired career prospects) if the alternative strategy fails (Armstrong & Huck, 2010, p. 13). In the words of John Maynard Keynes, 'worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally' (Keynes, 1936, pp. 157–158).

Further, non-profit-maximising behaviour can be a deliberate decision by a firm's ownership, for example to respond to environmental, social and governance (ESG) reporting requirements (Oxera, 2022). Similarly, some firms explicitly state that their corporate purpose is wider than just profit maximisation – such as B-corps, social enterprises and charities (Franks, 2019). Later, we return to the idea that, due to behavioural biases, firms may not optimally pursue explicit environmental aims.

In the context of firms that have not made explicit decisions to avoid profit-maximising, we now explore the three most common underlying behavioural causes of non-profit-maximising behaviour:

- complex optimisation;
- mistaken beliefs;
- group dynamics

We would also note that, while beyond the scope of this article, anti-competitive (but not profit-maximising) behaviour – such as collusion – may be sustained due to behavioural (social) preferences.

Complex Optimisation

Behavioural economics teaches us that our cognitive limitations make us boundedly rational, and that this makes optimisation difficult. Complex optimisation problems can also cause firms to be non-profit-maximising, either because they do not have a complete understanding of the problem or due to computational mistakes (Abreu & Rubinstein, 1988). For example, many firms did not exhibit optimal bidding behaviour in the (complex) Texas electricity markets 2002-03 (Hortaçsu, et al., 2019).

When facing a complex optimisation problem, firms might reduce complexity by aiming for a "satisficing" outcome rather than an optimal one (Simon, 1955; Cyert & March, 1956). Instead of aiming for the maximum profit, for instance, a firm might set a volume-of-sales or profit-per-sale target.

Similarly, they might reduce the complexity of the problem by using decision-making heuristics (i.e. rules of thumb). For example, they might imitate the strategy of a successful competitor or target relative profit (i.e. their profit compared with that of a competitor). The welfare effects of these strategies have been shown to depend on the market structure, and in some cases they may not lead to a significant deviation from profit-maximising behaviour (Armstrong & Huck, 2010).

However, satisficing behaviour could be considered profit-maximising when firms know that the cost of complex optimisation would exceed the benefits.

Mistaken Beliefs

Like consumers, firms may have incorrect beliefs about uncertain or unknown outcomes, which can lead to sub-optimal decision-making (even where optimisation would be possible). For example, they might make incorrect predictions about market conditions (e.g. demand or costs), the probability of success arising from investment in R&D or about the skills of their managers or employees (Aguirregabiria & Jeon, 2020).

Furthermore, managers may misjudge the likelihood of low probability events occurring due to the availability bias (i.e., when people assess the frequency of a particular event occurring, they are more likely to think that the event is frequent if they can easily recall the event occurring in the past).

One widely prevalent mistaken belief is that of overconfidence in one's own efforts, i.e. being over-optimistic about which future states of the world are likely to occur.

In large firms, overconfidence has been shown to result in more mergers and acquisitions, leading to poor results (Malmendier & Tate, 2008); indeed, it has been estimated that 70–90 per cent of mergers fail to add investor value (Kenny, 2020).

Among entrepreneurs, the nature of overconfidence has been shown to have different implications for markets (Astebro et al., 2014). Not only are entrepreneurs drawn from a population of people who are subject to behavioural biases and mistaken beliefs, but selection effects also mean that entrepreneurs are likely to be overconfident (Artinger & Powell, 2016; Landier & Thesmar, 2019). When a CEO's selection process is biased towards a particular set of features, it can ultimately affect the firm's investment policy and the efficacy of any corporate governance mechanism (Goel & Thakor, 2008).

In small firms, decisions are more likely to be taken by individuals, with less opportunity for challenge and scrutiny of any individual's beliefs.

In the EU, there are over 20 million businesses with nine or fewer employees (European Commission, 2021). Therefore, an individual's biases and beliefs could more directly affect the behaviour of a small firm. It has also been argued that, because firms are more likely to be small in developing countries, they are less likely to be profit-maximising in these locations (Kremer et al., 2019). However, the evidence suggests that it is not only small firms that deviate from profit-maximisation; indeed, the pitfalls of group decision-making dynamics (see below) may be less relevant to them. Furthermore, small firms may find it easier to adapt more quickly to changing circumstances (i.e. update their beliefs).

Group Dynamics

Group decision-making dynamics are not always conducive to the elimination of behavioural biases or mistaken beliefs, and from a behavioural perspective, there is no reason to assume that groups make more "rational" decisions than individuals.

The "wisdom of crowds" theory assumes that groups, in which people combine their expertise and work together, are better at decision-making than individuals. The theory can explain why the median average of many individuals' best estimates is often correct (e.g. guessing the weight of an animal at an agricultural fayre, which is the seminal example given by Francis Galton in 1906). However, it does not apply in many corporate settings.

The wisdom of crowds can be harnessed only when individuals make their best estimates independently of one another. Collective group decisions (e.g. a decision taken in a meeting) do not ensure that individual mistaken beliefs "average out" (instead, individual mistaken beliefs may be compounded due to herding and confirmation biases).

In addition, behavioural biases are at play in group decision-making. For example, as confirmation bias leads people to seek evidence that confirms rather than falsifies existing hypotheses, it can also contribute to 'groupthink' (where a group reaches consensus without having sufficiently challenged or scrutinised its decision) (Schuldz-Hardt et al., 2000).

It is possible to mitigate the effects of these biases in corporate settings, for instance by increasing diversity in the group or by appointing a decision observer to challenge potential flaws in decision-making (Kahneman et al., 2021). However, these steps may be perceived as costly, and, ironically, firms may be of the mistaken belief that their group decisions are optimal.

Why Is Non-Profit-Maximising Behaviour Sustainable?

There are several reasons why certain types of non-profit-maximising behaviour appear to be sustainable.

First, market structures may perpetuate (rather than discipline) mistaken beliefs. For example, auctions for offshore oil leases have been shown to be subject to the "winner's curse," whereby the most over-optimistic firm wins the auction (and subsequently makes underwhelming profits) (Thaler, 1988, as cited in Heidhues & Kőszegi, 2018). In the presence of over-optimistic firms, unbiased firms are unlikely to win the auction (and therefore exit the market in the short term).

Second, not all markets are competitive. In the absence of competitive pressure, firms with market power may have less incentive to be efficient and profit-maximising (as there is less of a penalty on inefficiency). Put another way, smaller firms who do not have market power, and who face intensive competition in the market, may be punished more if they deviate from profit-maximising behaviour.

Third, there may not be a market-disciplining mechanism from firms that do maximise profit, because they may not actually exist in a market. Within a market, optimisation may be too complex for all firms, or some degree of mistaken beliefs and unhelpful group decision-making dynamics may be prevalent in all firms.

In addition, regulators and policymakers may be behaviourally biased, unable to detect potentially harmful behaviour or erroneously prevent potentially beneficial outcomes (Cooper & Kovacic, 2012). Nonetheless, sophisticated economic models and tools might allow for an enhanced understanding of firm dynamics, reducing biases and enhancing economic decisions at all levels.

How Can We Assess the Behaviour of Firms?

Decision-making is context-dependent, and so it is important to assess how firms behave in different situations. For instance, to evaluate the likely impact of an intervention in a particular market, a policymaker will need to consider how firms in that market behave.

This is a two-step process, as shown in Figure 1.

The first step is to collect evidence on firms' behaviour in a particular market, which can be procured either through assessing secondary data or by conducting new research. The latter can be done via:

a. **Natural experiments or field experiments.** There may have been previous exogenous shocks to the market that allow for robust econometric analysis of firm behaviour (a 'natural experiment'). However, finding a directly relevant natural experiment may prove difficult, and even when natural experiments

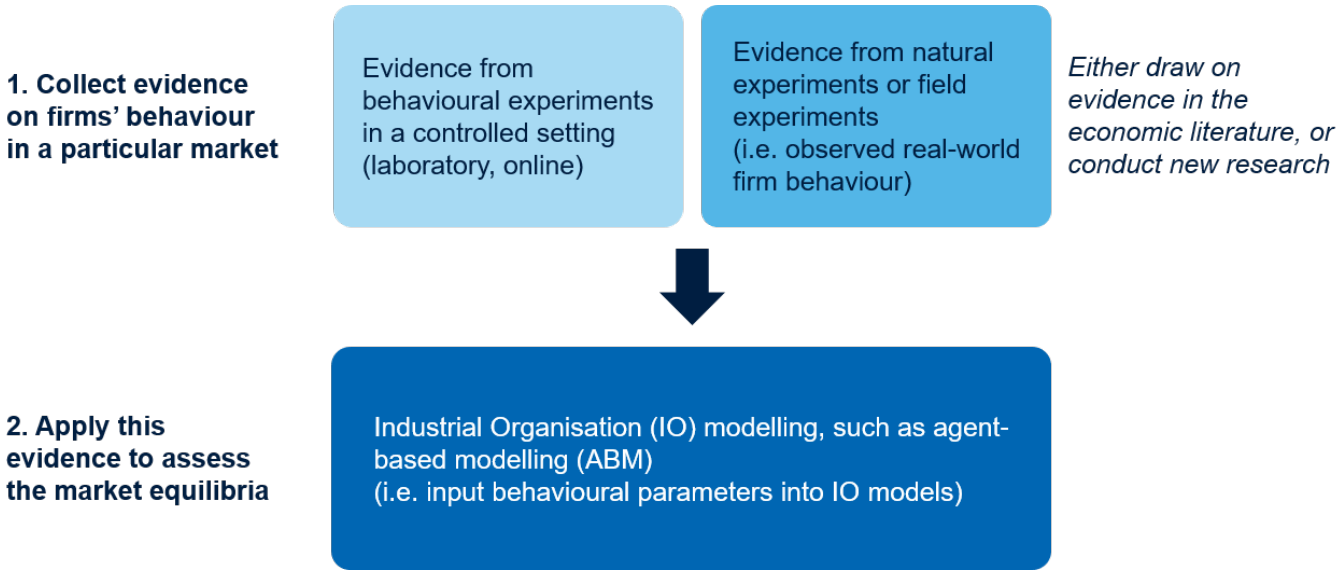

Figure 1: Assessing firm behaviour and market outcomes. *Source*: Oxera.

are analysed, they are not necessarily designed to answer policy questions and often face limitations. There may also be opportunities to run field experiments (also known as randomised control trials, or RCTs, such as A|B testing) on firms and markets, although this carries the risk of causing real-world adverse outcomes.

b. **Behavioural experiments in a controlled setting.** When new public policies are designed, businesses and policymakers do not always have readily available datasets to inform their decision-making – the policymakers may, for example, propose policies that have never been tried before. Behavioural experiments in controlled environments (e.g. the laboratory, online) offer a unique tool to build robust datasets tailored to answer economic questions, thereby allowing researchers to isolate different factors and identify causal effects. Well-designed behavioural experiments offer a good degree of external validity, but the results must be carefully interpreted (Oxera, 2021).

The second step is applying this evidence to assess the resulting market equilibria through *IO modelling*, which seeks to describe outcomes in markets given the market environment, the objectives and decision-making of firms and consumers and the interaction between firms. The outputs from stage 1 can be entered into the models as parameters.

Various well-understood IO models compute market equilibria under different assumptions and market structures. One form of IO modelling is *agent-based modelling* (ABM), which allows for greater heterogeneity between agents (i.e. firms, consumers). ABM is useful for identifying equilibria where solving the problem is mathematically complex; for example, the method has been used to understand the impact of using auctions to allocate airport "slots" to airlines (Herranz et al., 2016). ABM could be used to model markets with both (a) heterogeneous and boundedly rational consumers and (b) heterogeneous and boundedly rational firms.

Depending on the required level of accuracy from the research, the process can be fairly rapid (e.g. utilising evidence in the economic literature, analysing tractable IO models).

Case Study: Mobile Data Bill Shock

A telecoms regulator wanted to understand the reason for the occurrence of bill shock – when customers exceed their mobile data caps – and the reactions of firms to the resulting customer behaviour. It was clear from customer data that a well-defined group of customers were either naïve about the cost of exceeding the data caps or overconfident about not exceeding them.

Oxera's assessment of the market, which incorporated consumer heterogeneity, illustrated the commercial incentives facing firms, whose pricing strategies demonstrated price discrimination between customer groups, thus exploiting certain customers' bounded rationality (Gabaix & Laibson, 2006; Armstrong, 2015; Ellison, 2005; Grubb, 2009). This analysis informed the regulator's interventions to mitigate the effects of bill shock on naïve (or overconfident) customers.

This case study illustrates how a regulator can use behavioural IO to better understand market dynamics and alter the market architecture with the reduced risk of unintended consequences.

Case Study: Airport Slots

A European government wanted to understand how best to allocate "slots" at a busy airport, given bounded rationality on the part of airlines. There has been significant debate about whether an administrative slot allocation procedure or a market-based mechanism would be the most appropriate mechanism for achieving this goal.

Oxera's experiment tested the impact of different policies around slot allocation mechanisms on efficiency, competition and connectivity. The results quantified the trade-offs between the different objectives, meaning that policymakers could make informed decisions about which policy to adopt. As the experiment was conducted in a controlled environment, there was no risk of adverse outcomes as a result.

This case study demonstrates how policymakers can use behavioural IO experiments to empirically test major changes to the market architecture, without detrimental risk to consumers.

Case Study: Incentives to Innovate

Motivation

Empirical analysis of the link between regulation and innovation in an economy is challenging, because both concepts are difficult to quantify. Hence, experimental evidence is useful in generating data from a "game" in which participants face real incentives based on their choices. This method allows us to observe the effects of changing the rules of the game (i.e. introducing regulation). In this context, Oxera conducted an experiment for Amazon to test the impact of regulatory interventions, such as the proposal for the EU Digital Markets Act (DMA), on innovation in the EU (Oxera, 2021).

Design

The online experiment was conducted on business students at Universität Wien. Each round randomly matched the participants into pairs, with one student in the role of a "global" firm and the other playing a "local" firm, with each one differing in terms of their R&D costs. This captures the idea that global firms have an advantage in investment in R&D through economies of scale or funding advantages. Each participant was randomly assigned to one of three groups – as shown in Figure 2.

Results

Innovation requires not only an idea, but also a degree of risk-taking to invest in the idea and bring it to market. On examining participants who were willing to invest in innovating, both the global players and the local players invested less (8.6 per cent and 3.9 per cent, respectively) when faced with the additional risk of having to share the benefits of doing so.

In the treatment in which local players were favoured, a smaller treatment effect was found, with the local innovators decreasing their innovation efforts by 2 per cent (a statistically significant difference), while the global players did not change their behaviour at all. This suggests that if regulation holds back global competitors in order to give local competitors space to innovate, it could actually reduce competitive pressure on local players and lead to them innovate less.

Implications for Policymakers

The results from the first treatment indicate that an ex-ante regulation which reduces the size of the prize is likely to lead to substantially less innovation output by firms that want to innovate, be they local or global players. The results from the second treatment indicate that policies aiming to favour local firms may actually be counterproductive.

Wider Lessons

The experiment demonstrates that it is possible to test the assumptions and theory behind how firms will react to a proposed policy. They may not behave in a straightforward profit-maximising manner, which can be assessed and quantified to inform the expected costs and benefits of a proposed policy.

However, it is unclear to what extent the findings can be extrapolated to other policy contexts – the

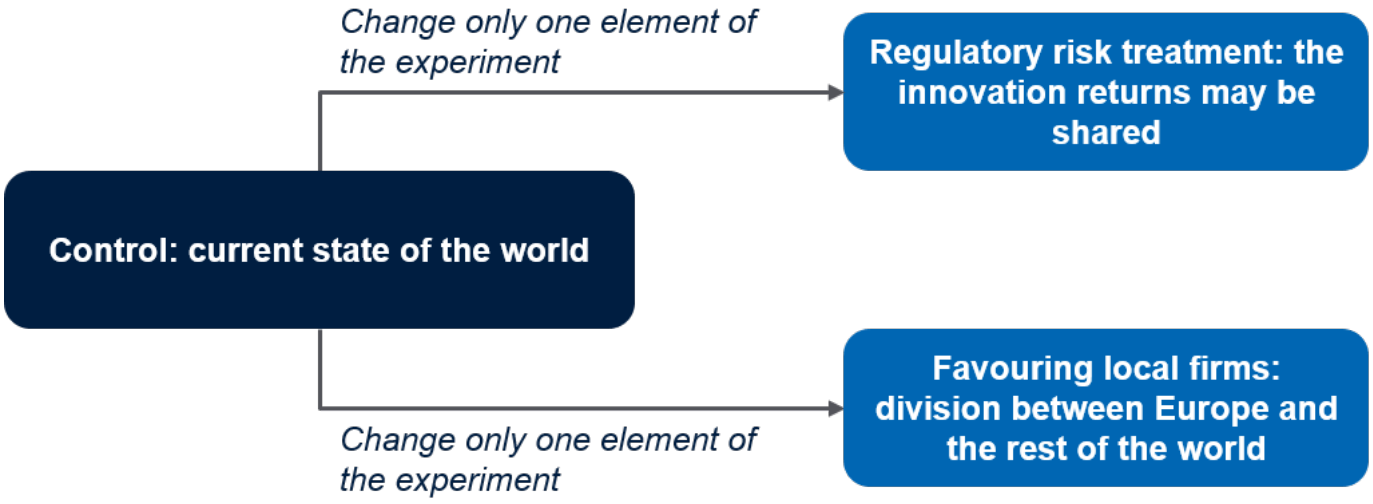

Figure 2: The control and two treatments. *Source*: Oxera, 2021.

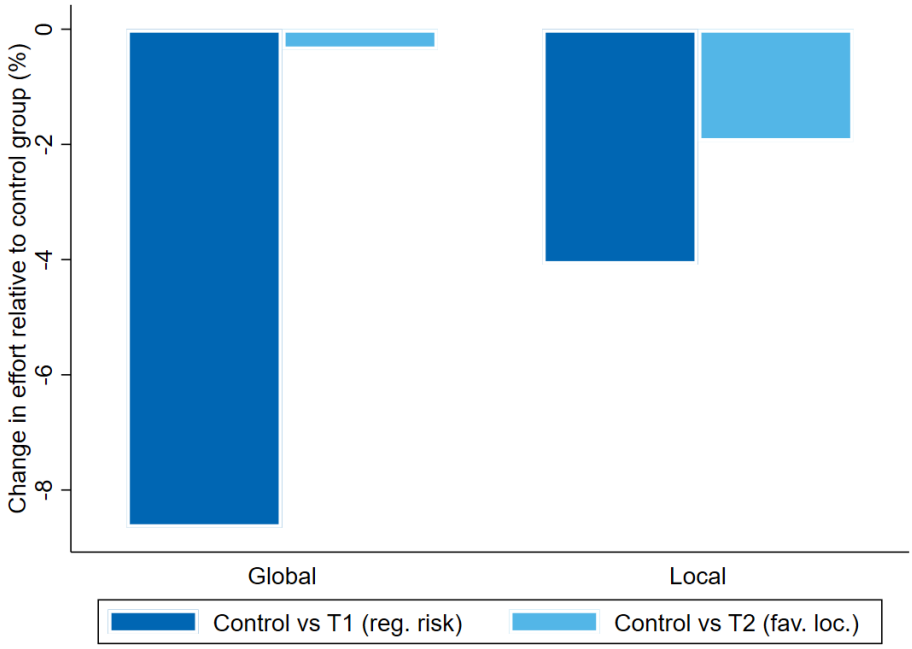

Figure 3: Treatment effect for each player type expressed as a percentage. *Source*: Oxera, 2021.

impact of a different policy cannot necessarily be extrapolated from these results.

What Next for Policymakers and Nudge Practitioners?

Nudging Firms

Ultimately, non-profit-maximising behaviour may be positive or negative for consumer welfare, depending on whether the behavioural decision-making nudges firms towards maximising consumer welfare or away from it.

As evidence on behavioural biases at the firm level is collected and it is concluded that a loss has been suffered, social and economic tools can be applied by policymakers and those influencing the design of the market architecture. Nudges and other interventions can be deployed to either counteract or harness firms' biases in order to enhance welfare.

Agent-Based Modelling

Focusing on either heterogeneous boundedly rational firms or heterogeneous boundedly rational consumers in isolation ignores the interactions between supply and demand. Solving such problems mathematically may not be possible, but it would be possible to use ABM to discover the more likely equilibria (using inputs gathered from behavioural experiments). We anticipate new research using ABM to analyse the impact of bounded rationality on both the supply and demand sides of the market.

Corporate Environmental Objectives

Thus far, the literature has mainly concentrated on the role of behavioural biases in hindering firms from achieving profit maximisation. However, this paradigm is limited. As noted above, many firms are choosing to explicitly set themselves alternative objectives regarding their environmental impact.

So how do behavioural biases hinder firms from achieving their environmental objectives? This is a new question for behavioural economists, and we can identify at least three dimensions.

- **Complex optimisation.** Optimising for multiple goals, or optimising profit with an additional constraint (environmental impact), may be more complex than pure profit maximisation. The likelihood of sub-optimal satisficing behaviour is presumably greater.
- **Mistaken beliefs.** Just like individuals, firms may not realise the gravity or urgency of the climate crisis, and therefore they may not act accordingly. Alternatively, firms may be overconfident in their ability to manage their environmental impact.
- **Group biases.** Given the breadth of the climate crisis, diversity of thought and a variety of

approaches are likely to be important factors for firms; however, there is the potential for groupthink to constrain their decision-making.

Tackling these behavioural biases would have a direct positive effect on our ability to reduce and mitigate climate change. We look forward to seeing the new wave of research into the topic.

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The Influence of Influencers: Inspiring More Cost-Efficient Marketing

HENRY STOTT, ABBIE LETHERBY AND ALICE PEARCE[1]

Dectech

In 2020, brands spent $98bn on social media advertising worldwide. Over the past four years, that spend has been growing at 20% per year, making it the highest-growth digital marketing category. This growth rate has tracked the number of active Instagram users, and we are witnessing the birth of a powerful new media format, with both the disorder and opportunity that generates. In this report, we examine the role that sponsored social media posts should play in a wider marketing strategy. Specifically, we use our immersive randomised controlled trial approach, Behaviourlab, to explore some key questions on how businesses negotiate and capitalise on this changing landscape

Executive Summary

Herein, we explore the role that sponsored social media posts can play in a wider marketing strategy. Utilising our immersive randomised controlled trial approach, Behaviourlab, we gain robust insights into the sphere of Influencer advertising. Behaviourlab is a bespoke online test platform via which we put participants through a realistic simulation of seeing a sponsored advert from an Influencer on Instagram. Analysis then involves statistically modelling different levers across a range of industries to assess their impact on purchase likelihood.

Using the Behaviourlab methodology, we explore some key commercial questions. Which Influencers should a brand recruit? What sponsored content has the greatest impact? How will Advertising Standards Authority (ASA) transparency rules change the market? How does social media effectiveness compare to traditional print advertising? Some of the headline findings of our research are:

- **Massive Reach and Big Headaches**: Across the three main platforms (Facebook, Instagram and YouTube) there are more than 4bn active users, accounting for 72% of the world's adult population. At the same time, there are 3.5m Influencers (defined as >10k followers) to navigate.
- **More Followers ≠ More Persuasive**: Having a larger following or greater follower engagement does not make an Influencer more persuasive per se. This indicates that Instagram's recent removal of likes will not undermine social media effectiveness.
- **Authenticity is Crucial**: Posts with the greatest sales impact are by Influencers who are familiar to their followers. Likewise, the most powerful posts are eye-catching, authentic and within the Influencer's area of expertise.
- **ASA Rules have No Effect**: The ASA's new rules, requiring greater transparency when posts are incentivised, do not noticeably diminish their effectiveness. Followers expect their Influencers to be sponsored and trust them to only engage with the "right" brands.
- **Influencers are 30% Cheaper**: In a head-to-head comparison with print media, Influencers generate 10% fewer sales but are 40% cheaper per impression. As such, overall, Influencer CPA (cost per acquisition) is 30% cheaper than traditional media.

Based on these insights, we make a series of recommendations summarised here – and described in more detail later – to help brands remain competitive and increase their marketing spend efficiency. As

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JFK once said, 'Change is the law of life, and those who look only to the past or present are certain to miss the future'.

Chapter One: Reach of the Stars

By any measure, social media has an extraordinary reach. Cristiano Ronaldo has 277m Instagram followers, with Ariana Grande and Dwayne Johnson not far behind with 232m and 229m, respectively. These figures contrast sharply with traditional TV. Sky has 24m subscribers in Europe (Sky Group, 2021), Comcast has 20m in North America (Statista, 2021a) and Disney+ has 95m globally (Statista, 2021c).

Whilst appreciating the merits of TV advertising, given the above figures, it would be foolish for any brand to ignore the effect that social media exerts on its market. As Figure 1 shows, there are around 4.2bn unique and active social media users worldwide (CIA.gov, 2021).

That's 72% of the world's population aged 15 and over (Statista, 2021d; Dectech, 2021). In the UK, 90% of people have used at least one of their 3.4 accounts in the past six months.

Engagement with social media is very high, and consequently it shapes people's purchasing behaviour. In the UK, 75% of users spend more than an hour per day across the three main platforms, and 54% have posted within the past week. For purchases made within the past year, 37% of Instagram's 1.2bn users, some 450m consumers, bought a product that they'd first seen on Instagram. Moreover, 82% of those transactions were new-to-brand, which equates to 360m Instagram-driven customer acquisitions per year.

However, if you're going to negotiate this remarkable new channel successfully, you'll necessarily need to identify, contact and manage a legion of Influencers. Figure 2 describes the sheer scale of that task. Planning a TV campaign across 100s of channels is one thing, but on Instagram alone there are 110k "Celebrities" (defined as >1m followers) and 623k "Midfluencers" (10k-1m followers), which is a total of 733k Instagram Influencers to navigate.

As detailed in Figure 1, there are around 3.7m Influencer accounts operated by 1.6m Influencers worldwide across Instagram, YouTube and Facebook. These figures are both daunting and motivating. History has repeatedly taught us that it is important to embrace and master new media channels. In 1969, the UK's first colour TV ad was for Birds Eye peas, then

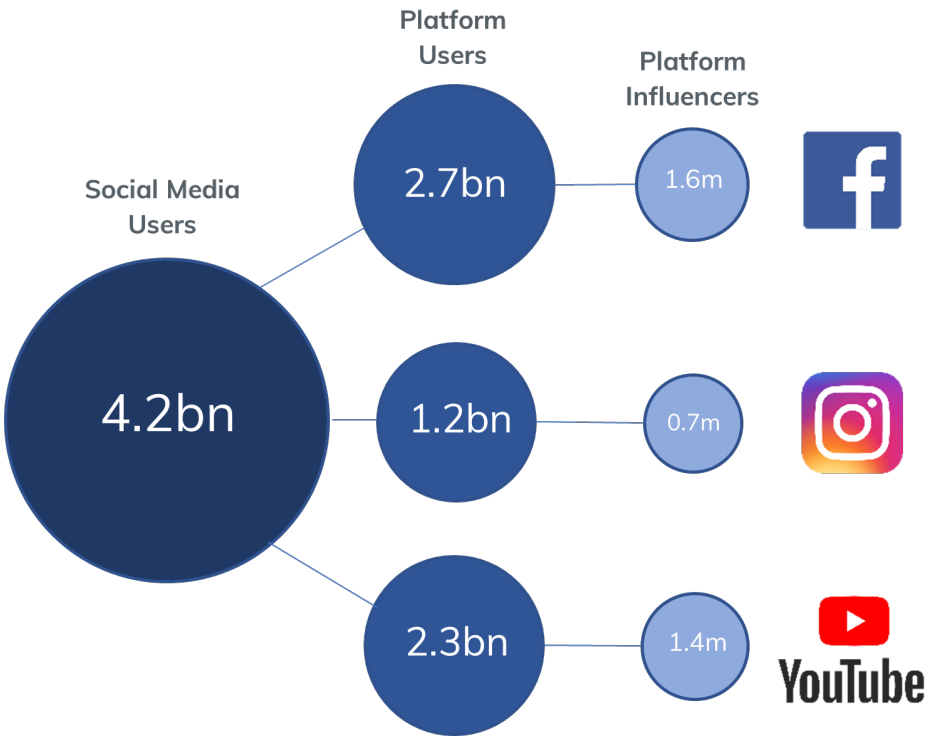

Figure 1: Reach of the big three (DataReportal, 2021).

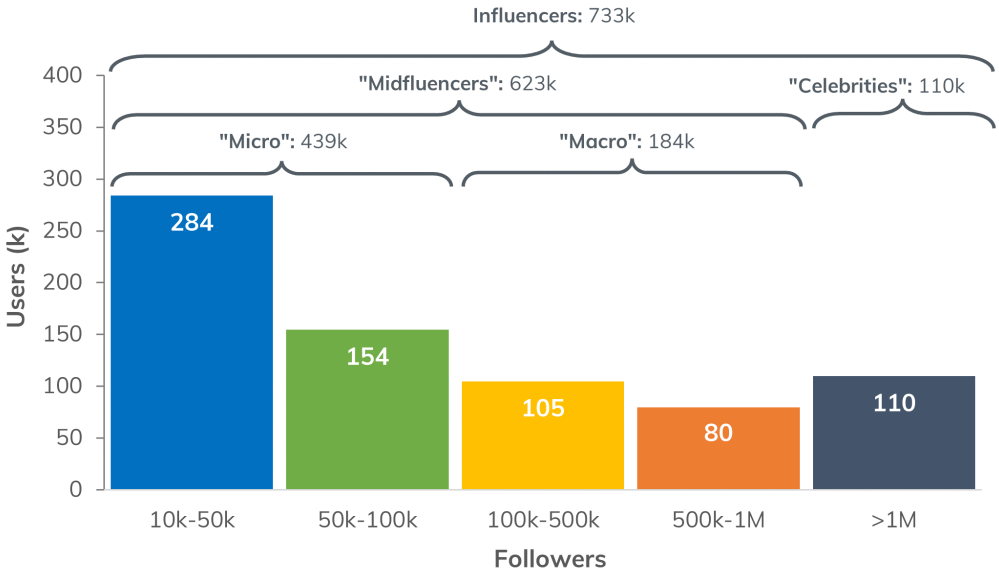

Figure 2: Instagram Influencers.

owned by Unilever. Today's equivalent challenge is to develop and industrialise the technologies needed to run impactful Influencer campaigns.

Arguably, this challenge could be shirked by just pursuing a Celebrity-only strategy. Sure, calling Ronaldo's agent simplifies the problem, but there are still hundreds of thousands of Celebrities and their aggregate reach is no larger than Midfluencers'. Meanwhile, by definition, Midfluencers are the only way to run a more targeted and tailored campaign. The social media brand battle will likely be won or lost in midfluence. In essence, Midfluencers are the new "Avon ladies" or Tupperware party hosts.

Chapter Two: The Brand Reaction

The emerging effects of social media on consumer behaviour is not news to the marketing vanguard. As Figure 3 documents, digital marketing spend is growing at around 13.2% per year. However, within that digital spend, social media advertising is growing at about 20.1% per year. In 2020, brands collectively invested $97.7bn globally in social media, including Influencer incentives and performance monitoring. The internet is migrating away from a pure paid-advertising model and recognising the potential to detect and activate consumer advocates.

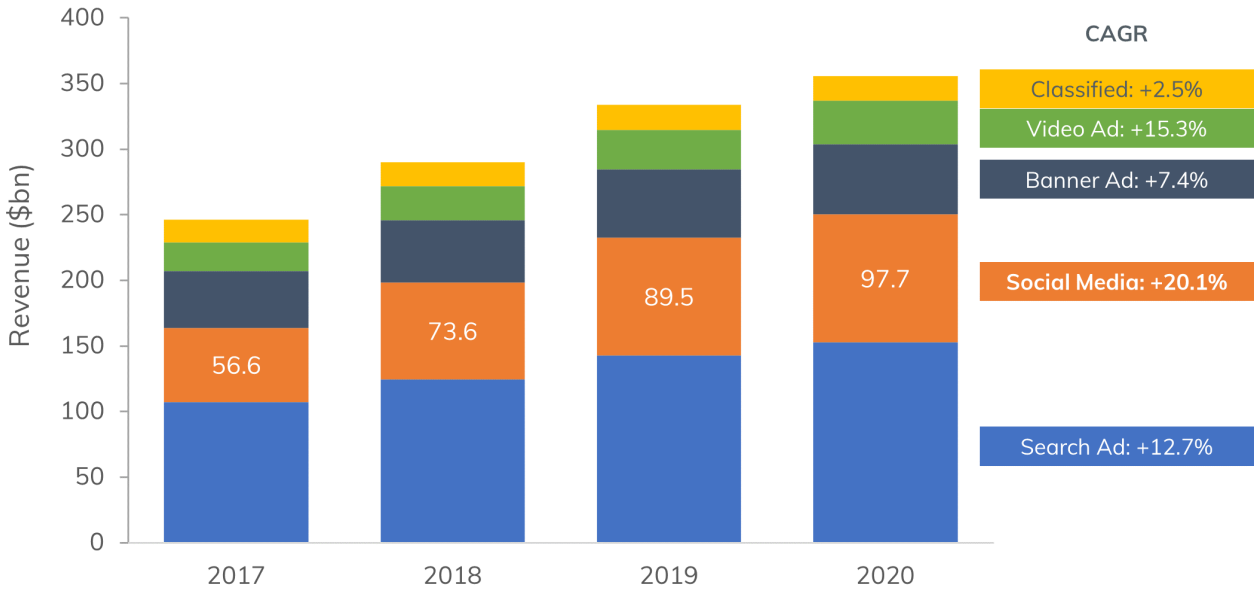

Figure 3: Worldwide digital marketing spend (Statista, 2021b).

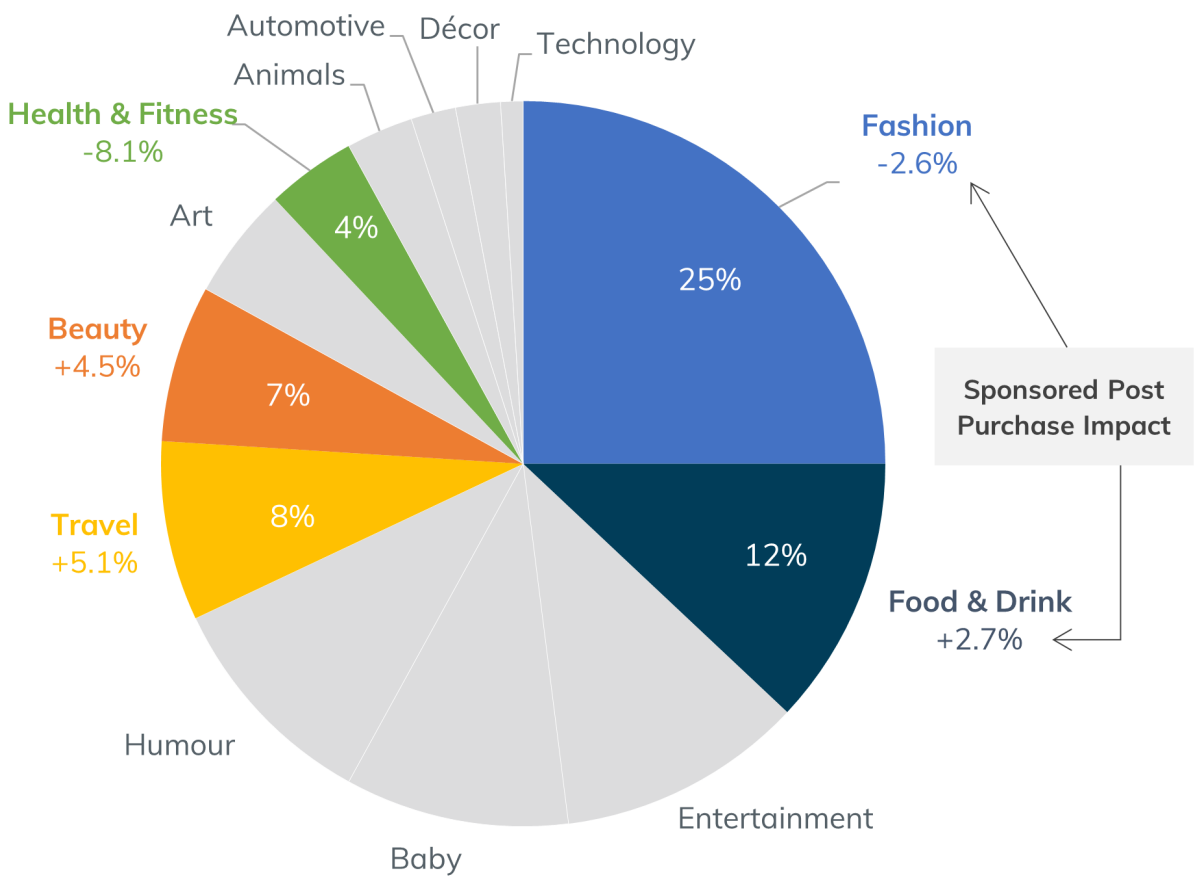

Figure 4: Instagram sponsored posts 2019 (influencerdb.com, 2019).

Influencer expenditure is currently dominated by Instagram; for example, in 2019, over two-thirds of US sponsorship spend was on that platform. Figure 4 itemises where the money is going. The topics of Fashion, Food & Drink and Entertainment account for nearly half of the marketing activity. But what return will brands achieve on that investment? Which sectors have most to gain from Influencer advertising? How should brands select their Influencers? What should they ask them to post?

These are all good questions. To answer some of them, we ran a Behaviourlab experiment. Behaviourlab is our immersive randomised controlled trial approach to understanding what is driving – and how to change – consumer behaviour. In practice, this meant showing paid participants sponsored Instagram posts and observing their impact on subsequent purchase intention. We used a between-subject design, in which we altered the posts and the Influencers posting them, to test the impact of different levers. Example stimuli and more details can be found in the appendix.

Sponsored posts were tested for the five sectors shown in Figure 4. The observed purchase propensity in the experiment was calibrated to the 37.2% real-world prevalence cited earlier. By this measure, being exposed to a sponsored Food & Drink post raises the product purchase propensity of the gin brand involved from 37.2% to 39.9%, the +2.7% in Figure 4. The relatively large real-world marketing spend on that sector resonates with this above-average effect. Conversely, we find sponsored posts for a Fitness sports watch are less impactful, aligned with that sector's lower Instagram spend.

Chapter Three: Optimal Influencer Strategy

Our experiment tested the effects of Influencer characteristics and post perceptions on propensity to purchase. For Influencers, we independently varied their following, likes and comment volumes to see if these measures of Influencer solidity change post effectiveness. To our surprise, none of the attributes materially altered the outcome. Figure 5 plots the data for followers. Influencers with more followers

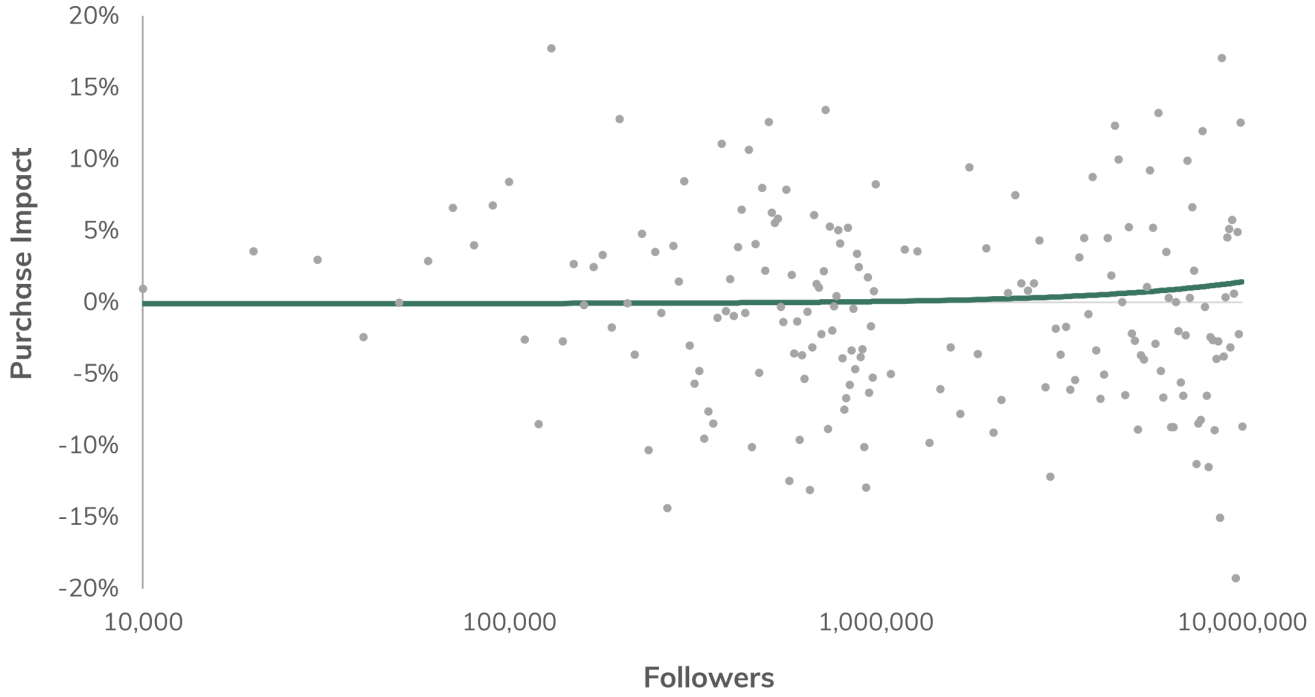

Figure 5: Example of following's effect on Influencer persuasiveness.

are only marginally more influential. Beyond having additional reach, there is no halo.

Interestingly, the only observed statistically significant effect is in comment volumes. In that case, 'more comments' has a slightly negative impact. For the products we tested, people seem to value exclusivity, and perceived widespread popularity backfires against sales. As such, Instagram's announcement that it will make likes private, aligned with the wider mental health-motivated trend towards removing popularity markers on social media, seems likely to either not change Influencer effectiveness or, counter-intuitively, make them marginally *more* effective.

On content, there are two main insights across the tested variables. First, purchase propensity increases in line with Influencer familiarity – the more you feel you know and like someone, the more you will

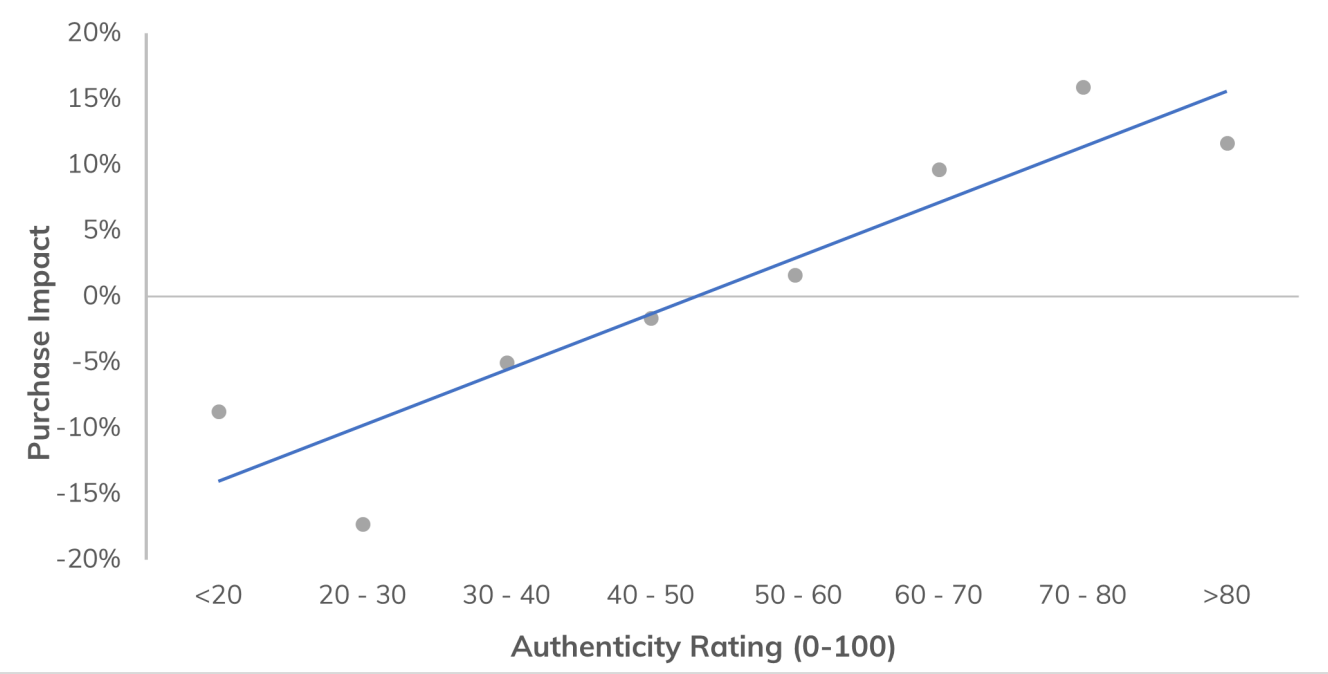

Figure 6: Perceived authenticity of a post.

act on their advice. This works against Celebrities, with their larger and more impersonal audiences. The only advantage Celebrities offer is reach and, since Influencers are paid by engagement, the cost of a Celebrity is the same – and often more – than several Midfluencers with an equivalent reach. Midfluencers are more hassle to recruit and manage but, via this familiarity effect, more persuasive and better value.

Second, as demonstrated by Figure 6, post authenticity matters. People are turned off by incongruent content generate by an Influencer who does not have the relevant domain expertise. It makes the post feel disingenuous and therefore less persuasive. Accordingly, brands should find Influencers who are well liked, rather than controversial, who produce quality content, are aligned with their brand values and who have the relevant knowledge to deliver genuine, authoritative opinions.

In the UK, the ASA recently introduced new regulations designed to increase the transparency of sponsored posts. The regulator wants people to know when an Influencer is making an incentivised endorsement. Since one key advantage of Influencers might be their seemingly independent advocacy of a product, could these regulations diminish Influencer effectiveness? To find out, we tested three scenarios – Undeclared, Declared and Denied. One participant group saw a post that did not mention any incentive, another saw a post that did so, and a third post actively denied any incentive.

The main finding is that disclosing the incentive has no impact on purchase propensity. Consumers understand that this is how the world works and trust their Influencers to act responsibly, only working with brands they can advocate in good faith. In the end, it is not in an Influencer's long-term interests to upset their followers. The other finding is that the denial of payment actively decreases people's purchase propensity, by 2.3% relative to the Declared and Undeclared conditions. When an Influencer protests their innocence, they are flagging up that there's something going on – and their followers are suitably suspicious. This resonates with our other findings on authenticity. Disavowal damages authenticity, and therefore credibility, and reduces sales effectiveness.

Chapter Four: Return on Investment

A central metric in advertising is Return on Investment (RoI) and the resultant media buying optimisation. Yet, marketing mix modelling involves so many complexities, unknowns and prejudices that there could be endless questions over RoI's authenticity – especially across media formats. This does not lessen the importance, however, in finding a way to optimise the media mix. Taking a scientific

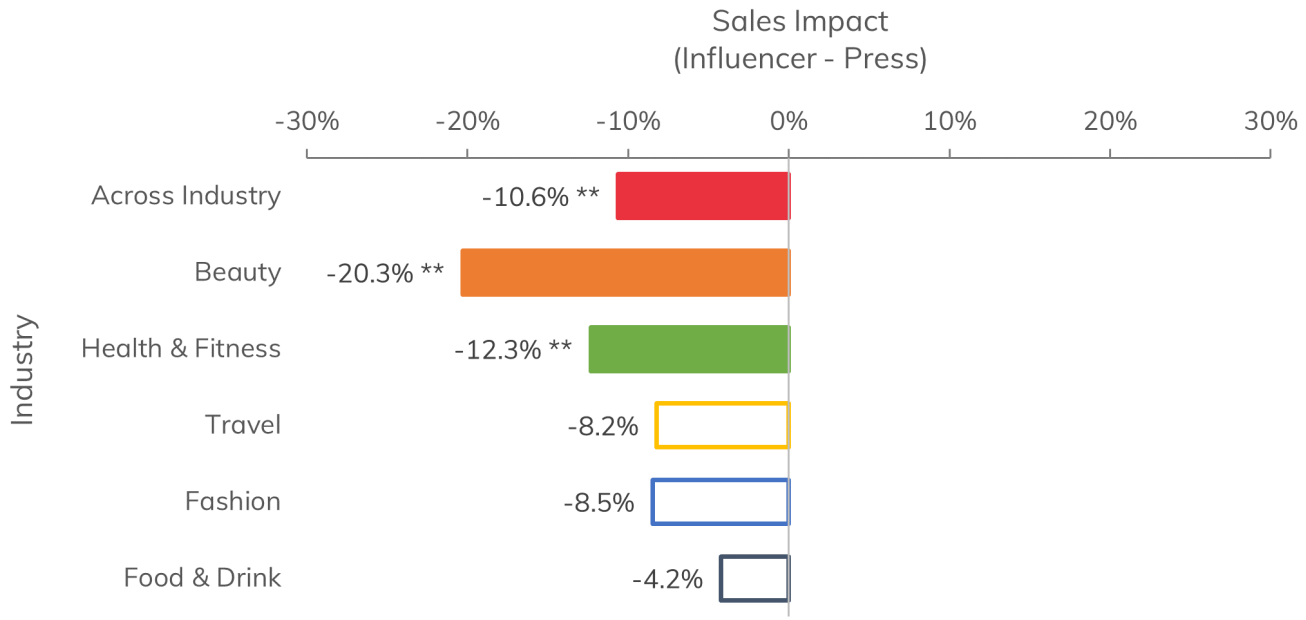

Figure 7: Head-to-head sales effectiveness.
Note: ** Significant at 95% Confidence.

approach, we aim to lend a voice to these kinds of decisions with the following analysis.

We ran a head-to-head trial to test the relative effectiveness of Influencers compared to press advertising. The first participant group saw an Influencer post and the second an equivalent press advert with identical imagery and branding. Both groups were then asked if they wanted to buy the product. The results in Figure 7 reveal that, under these noise-free lab conditions, the press advert is more persuasive, particularly for a Lancôme Mascara. Overall, the Influencer post generated 10.6% fewer sales: if the press ad drove 500 sales, the Influencer post would generate 447.

But wait: so much for the "R," what about the "I"? Table 1 examines that trade-off. We used the London Metro for a press advert cost benchmark of 1.88p per impression (the circulation is 2.4m (tmwi, 2021) and a full-page colour ad is £46k (Metro Media, 2021)). Meanwhile, an average Influencer is paid 28p per engagement. Since the average Influencer engagement rate is 4.3%, that works out at 1.19p per impression. Influencers are about 36.7% cheaper than press advertising, which more than offsets their marginally lower effectiveness; consequently, Influencer cost per acquisition (CPA) has a 29.2% advantage.

	Influencer	Press	Difference
Reach	1,000,000	1,000,000	
Ad Cost	£11,900	£18,800	
Cost per Impression	1.19p	1.88p	-36.7%
Incremental Acquisitions	447	500	-10.6%
Cost per Acquisition	£26.63	£37.60	-29.2%

Table 1: Return on investment.

Clearly, in practice, these numbers will be all over the place. Some newspapers are more expensive because they have larger circulations or are more effective. Likewise, costs per engagement rates for Influencers can range from 5p to 100p – and beyond, depending on the topic, whether there's an agent involved and so forth. Finally, outside Table 1 and the lab environment we used to run the test, there are other forces in play such as the ability to target customer segments, "in-field" impression attention, media context effects, various forms of advertising fraud and so on. In particular, due to the data volume limitation, we were not able to explore fully the heterogeneity in preference amongst target segments. This represents a focal point for any future research in this area despite the fact that our results remain convincing at an aggregated level.

Whilst there remains plenty of scope for a savvy media buyer to add value by trading-off all these considerations, the central case in Table 1 will tend to prevail. Influencers are an important new media development. They have incredible reach. They are already influencing consumer behaviour. They can offer better RoIs. Moreover, they represent a tremendous opportunity to create a diversified, targeted, nuanced and persuasive media campaign. However, globally, there are about 50k newspapers and 25k TV channels compared to the 1.6m Influencers on the three most popular social media platforms. There is therefore an enormous logistical challenge to identify, negotiate and monitor Influencers in that vastly higher dimensional ad space.

Recommendations

The very first Instagram post was an unassuming photo taken from the desk of co-founder Mike Krieger at 5:26 pm UTC on July 16, 2010 (see Figure 8 [Krieger, 2010]). Whilst Facebook significantly pre-dates Instagram, it is probably that date which should mark the beginning of Influencer marketing. Ten years later, brand managers are finally starting to grasp the rapidly expanding power of this new

Figure 8: The first Instagram post.

media and how to navigate its complexity. Based on this research, we offer the following advice:

- **Budget for Social in the Marketing Mix**: Brands should consider Influencers to diversify their marketing strategy and increase their ad-spend efficiency. Influencer marketing is low in cost but with an impact roughly comparable to traditional media. No brand should dismiss social media as irrelevant to their market. Everyone should budget for at least some investment. To not explore social media, given the evidence, would be unwise.
- **Instagram is a Good Entry Point**: Instagram is currently the leading platform for Influencer marketing. As such, it is the obvious place to start, since it is a more developed channel with a wider selection of experienced practitioners. Nevertheless, clearly the over-riding criterion is which platform your customers are using or will use in the near future. For example, you may want to explore TikTok, given its momentum.
- **Midfluencers are Better than Celebrities**: Don't blindly select ambassadors based on followers, likes or comment volumes, as they do not make an Influencer more persuasive per se. For the same reach, Midfluencers are cheaper and more impactful, since they are more familiar to their followers. Moreover, this diversified portfolio approach supports tighter targeting and de-risks the campaign against one idiosyncratic individual.
- **Your Influencer Portfolio needs Optimisation**: Although popularity measures such as follower volumes do not mean Influencers are more persuasive, there are other characteristics that do. Recruit likeable Influencers, rather than controversial or divisive ones, who are well known to their audience rather than remote. They should also have relevant domain knowledge and carry the authority to be a legitimate brand ambassador.
- **Do Not Let ASA Rules Deter You**: The current ASA regulations, and the general trend towards sponsorship transparency, do not undermine effectiveness. People expect Influencers to be incentivised and are not surprised or offended by such commercial links. Indeed, somewhat ironically, if an Influencer genuinely isn't being sponsored, they should not confirm it, since it goes against people's expectations and can be disruptive.
- **Content Should be Authentic**: Editorial policy should follow three main guidelines. First, posts should use an eye-catching creative that attracts attention. Second, the post should be interesting and appealing to the target audience. Third, and most importantly, the post must be authentic and "Influencer congruent." Posts that jar with the Influencer's style or lack credibility are less convincing.

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APPENDIX: METHODOLOGY

Sampling

The primary research undertaken for this report was conducted online from 1st October 2020 to 8th October 2020 with a nationally representative sample of 1,518 UK consumers aged 18 and over that had an active Instagram account.

Behaviourlab Paradigm

Behaviourlab is our bespoke online test platform that uses a randomised controlled trial to address key commercial questions more accurately and definitively. The method follows modern academic standards of eliciting consumer preferences and behaviours.

This research involved putting participants through a realistic simulation of seeing a sponsored advert from an Influencer on Instagram. Each participant was shown two adverts for two different products selected at random from the following five industries: Fashion, Beauty, Health & Fitness, Travel and Food & Drink.

We explored the impact of a number of different levers that might influence a consumer's likelihood to purchase the advertised product, including Influencer, brand, size of following, number of likes and comments and endorsement declaration. The products mirrored a brand's real-world pricing and proposition, with the product category fixed within industry to ensure comparability. For each industry, we included six brands and nine Influencers, which were found using the Wearisma platform.

To provide some context on the Influencer, respondents were shown a summary of their Instagram account page first (see Figure i) and were then asked how familiar they were with that Influencer. The accounts replicated the Influencers actual account, but the size of following was varied, personal contact details were removed and the six most recent images were handpicked to ensure they were representative of the types of content the Influencer typically posted.

Participants were then shown a sponsored advert from that Influencer (see Figure ii). The images used were manufactured to ensure there were no differences in creative quality between brands, so that they could be used for any of the Influencers included in the experiment. Participants were then required to indicate their likelihood to purchase the product in the advert and rate the post and the Influencer on a number of different perception statements. The analysis involved statistically modelling whether the different levers increased purchase likelihood.

AB Test

To compare Influencer marketing with more traditional marketing, we ran an AB test exploring the impact of an Influencer ad vs a press ad. Each respondent was shown three adverts from either an Influencer or press for three different industries. We used real press adverts, which were adapted for the Instagram posts to control for differences in quality between press and Influencer (see Figure iii and Figure iv). Any key details included in the press ad were also included in the Instagram comment. Participants were asked to indicate their likelihood to purchase the product included in the advert. The analysis involved statistically modelling whether purchase likelihood was significantly different between press and Influencer channels.

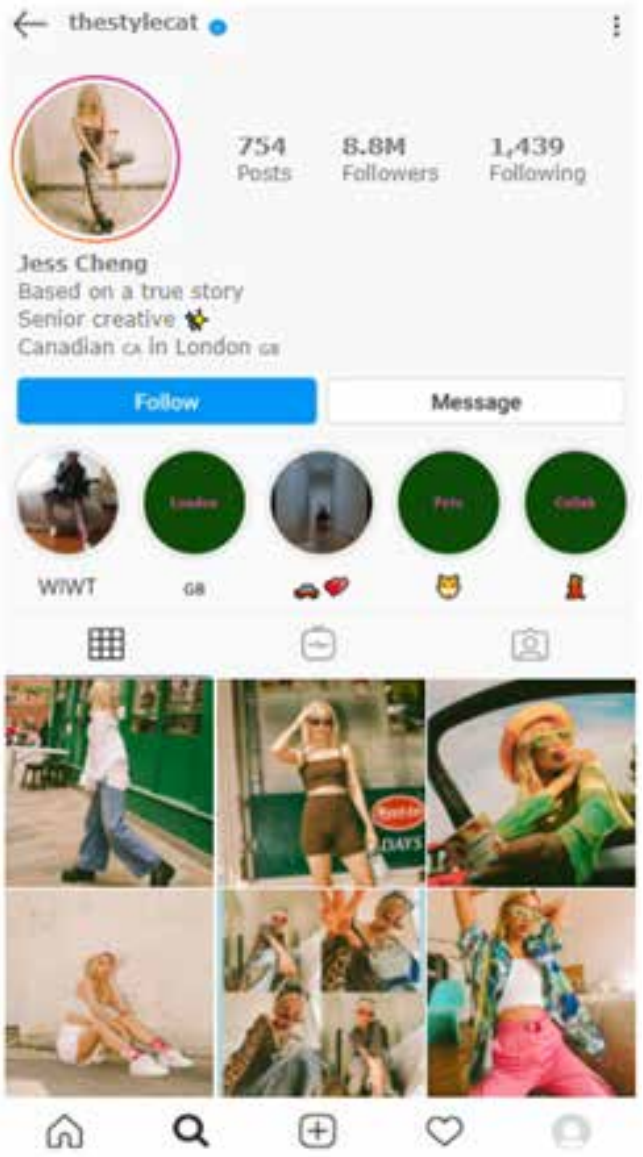

Figure i: Example screenshot of a Fashion Influencers Instagram account.

Figure ii: Example screenshot of a sponsored Influencer advert for Fashion.

Modelling

For the Behaviourlab experiment and the AB test, an ordinal logistic regression was used to model purchase likelihood. Choices were modelled across all industries as well as separately for each industry.

The purpose of modelling is to determine the impact of other information (such as consumers' age) and to control for these factors, thereby isolating and estimating the impact of different benefits on the probability of purchase. The controlling factors were:

- Personality traits
- Financial literacy
- Age
- Gender
- Marital status
- Employment status
- Income
- Education level
- UK region
- Social media usage
- Past purchase behaviour on Instagram
- Interest in a specific industry

Figure iii: Example screenshot of an Influencer Instagram ad for Travel.

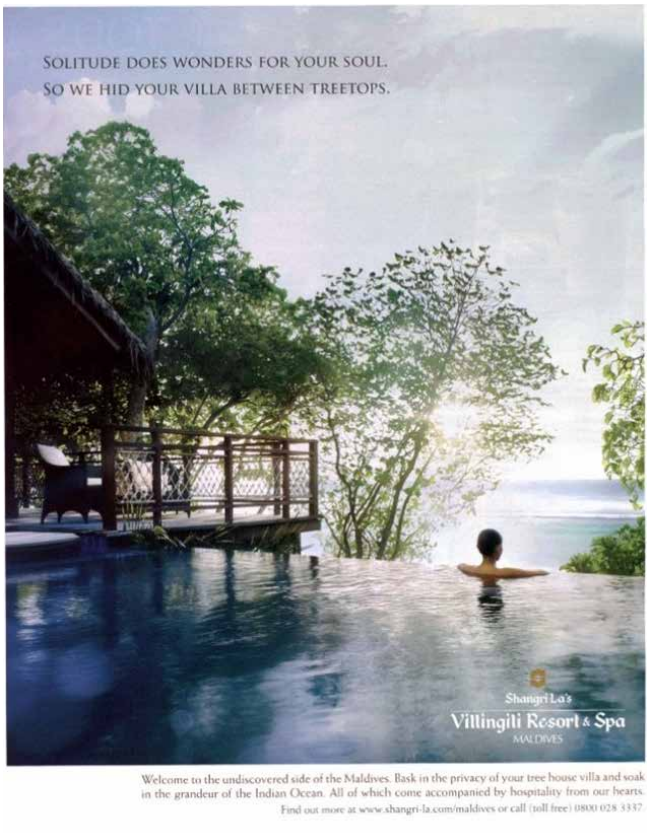

Figure iv: Example screenshot of a press ad for Travel.

Behavioral Incentives and Their Influence on Employee Performance

JUAN DE RUS[1]

Neovantas

A 2020 Gallup report states that almost 85% of employees globally are not engaged. Companies tend to reward behavior outside of individuals' control and without considering their core psychological needs, such as a feeling of belonging at work. Many jobs include monotonous tasks and can benefit from an incentive system to support employee motivation. For this purpose, we designed an experiment in an organization in Spain. Our interventions included a calculator, a piggy bank, and a ranking system among employees, using behavioral science principles of loss aversion, endowment effect, framing effect, social norms, and money priming. Our research suggested that a modification in the incentive architecture has the potential to improve employee performance without increasing costs for the company.

Introduction

Despite a fast-changing world, many organizations are applying old performance management strategies (e.g., many just give feedback to their employees one or two times per year, and the employee's performance goals are often not well defined or individualized). These outdated management strategies reportedly only motivate two out of ten employees to do extraordinary work (Gallup, 2021). Moreover, companies often consider purely monetary rewards for performance, i.e., a total reward approach, which includes monetary and immaterial components, is not yet widely used. However, "if an organization embraces a total rewards strategy, they can reinforce the desired behaviors that contribute to organizational success. A total rewards strategy that addresses employee needs enhances productivity, since satisfied employees tend to be more productive. Additionally, there is a direct correlation between employee satisfaction and customer satisfaction, which should enhance company performance" (Kaplan, 2005, p. 34).

In this article, we will explain a case study in a Spanish organization in which we tested whether employees' performance could be improved by minor modifications to the incentive architecture, based on behavioral science principles.

Theoretical Foundation

The classic economic approach considers incentives fundamental, with their strength deriving from their ability to predict how individuals modify their behavior (Fehr & Falk, 2002). According to this notion, the individual responds directly to any increase in incentives with an increase in effort at work or in the activity carried out (Grant, 1999).

However, this traditional approach is not complex enough to capture behavior in relation to incentives among other factors that may influence motivation and the nature of tasks.

The Theory of the Self

The theory of the self (Ryan & Deci, 2000) establishes that there are three psychological needs (competence, autonomy, and relationships with others) which, when satisfied, positively influence intrinsic motivation and well-being. In addition, it determines that individuals will be intrinsically motivated by the activities that interest them.

Goal Setting Theory

Goal setting theory (Locke & Latham, 2002) looks at how establishing the importance of task commitment improves performance. This commitment is influenced by three factors: external influences (authority, peer influence, and incentives), interactive

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factors (participation and competition), and internal factors (internal expectations and rewards) (Locke et al., 1988).

It was important to consider these theories of social psychology as inputs into the design of the new incentive scheme. Additionally, we must not ignore two fundamental factors, namely, the intrinsic motivation of individuals and the nature of tasks.

To motivate people to perform well, it is important to gain insights into their motives. What motives play a role in the work situation? We can identify two types of motives: intrinsic and extrinsic.

Intrinsic Motivation

Regarding intrinsic motivation, some authors have shown that—in certain circumstances—standard incentives (money) can be counterproductive. For example, assuming that the task is inherently interesting, and the employee's behavior is altruistic, incentives that are too large or stressful to attain substantially reduce intrinsic motivations, thereby leading to reduced productivity. This is also known as either the 'crowding out' effect or an 'over-justification' effect (Ariely et al., 2009; Frey, 1997; Goette & Stutzer, 2008). Therefore, we can conclude that, for some tasks with high intrinsic motivation, economic incentives are not always necessary, and sometimes they can be counterproductive.

However, in the workforce, it is not uncommon for individual employees to face tasks that do not motivate them. For example, in the call center industry, there are many monotonous and routine tasks that are traditional to that industry. For example, agents must deal daily with hundreds of calls, most of which are often very similar to each other. It is a job that, due to its nature, is sometimes valued as unrewarding and stressful, which in some situations leads employees to fail to achieve the objectives set for them (Deloitte, 2021). Furthermore, the turnover of sales representatives in a call center is around 37% during the first six months, and it costs $8,800 to re-recruit and train a new agent (liveops, 2018). General dissatisfaction and high employee turnover in this sector represent a major challenge, as sales representatives have close contact with the end customer, which is likely to correlate with customer service quality (Randstad, 2015).

Considering the above, our hypothesis is that, by investing in a better behavioral approach in terms of incentives in this kind of organization, employees will be able to handle their work more efficiently, effectively, and happily. However, it is essential to understand the specific context in which this new incentive's system will be applied (Kamenica, 2012).

Applying Behavioral Science to Create an Impact

After a series of interviews and focus groups with employees, it was concluded that current incentives not only demotivated them, but they were also counterproductive to achieving objectives, since the sales representatives considered them confusing and unattainable, which in turn increased their daily frustration. For this reason, we considered it essential to adapt the incentives' architecture so that they would once more act as a tool for managers to use in order to improve their sales representatives' performance. For this purpose, the incentive system that existed at that time was analyzed to evaluate if it was in line with some fundamental aspects of behavioral science that could influence employee perception.

We implemented three features in consideration of some biases, and these are explained as follows.

Incentive Calculator

The experiment was designed in such a way that the calculator already showed the total amount that an employee could earn every month and depending on their performance on each day, this amount could be reduced if the set objectives were not achieved. This is termed *loss aversion*, and it highlights that the pain of losing something is psychologically equivalent to twice the pleasure of gaining it; therefore, individuals try harder not to lose it than to gain it (Kahneman & Tversky, 1979). Furthermore, the *framing effect* was considered. All choices can be formulated in a way that highlights their positive or negative aspects (Kahneman & Tversky, 1979). Therefore, a measure was designed to use positive vocabulary to motivate agents (e.g., 'If I continue at this rate, what incentive will I get?', 'This is what I have to date', etc.)

Figure 1: Piggy bank and calculator.

Piggy Bank

People in the experimental group were given a piggy bank containing the maximum incentive they could receive every month, and depending on daily performance, the team leaders withdrew or included token money in the piggy bank. This was intended to strengthen the *loss aversion* principle and the *endowment effect*, whereby people assign a higher value to things when they establish ownership over them (Kahneman et al., 1991). Moreover, it considered the *priming effect*, which demonstrate that information, and patterns stored in memory become more accessible through the presentation of certain stimuli. By activating certain schemes, behavior can be influenced to a certain extent. Thus, *money priming* shows that people reminded about money shift into a professional, business, and work mentality, and they expend effort on challenging tasks, demonstrate good performance, and feel efficacious (Vohs, 2015). Research shows that the largest money-priming effect occurs when people actively handle money (Lodder et al., 2019).

Comparative Ranking With Peers

Every week, a ranking was published along with the incentives achieved by the agents. In this case, it was necessary to take care of the possible lack of motivation on the part of those with lower incentives and who did not reach the levels attained by the top agents, which is why, every month, the greatest positive variations were highlighted (i.e., sales representatives who occupied the lowest positions in the ranking and who had improved). This helped maintain the motivation of the whole team, because motivation tends to be a process of *social comparison* in which effort and results, or rewards received by a person, are considered, and compared with the results of, and efforts made by others (Festinger, 1954). In behavioral science, different authors mention the importance of social comparison in establishing adequate incentives. Recent empirical studies argue that the comparison of income and perceived incentives affects the assessment of life satisfaction (Clark & Oswald, 1996; Luttmer, 2005; Clark et al., 2008; Clark et al., 2010). Moreover, as stated previously, goal-setting theory emphasizes the importance of peer influences, participation, and competition in relation to improving performance.

Implementation of the Intervention and Results

Our experiment tested the effectiveness of this new incentive architecture by selecting a group of sales representatives for our experimental group. Along with the standard information the company distributed to all employees, the treatment group also received the incentive calculator, a comparative ranking with the rest of their peers and the piggy banks with some fictitious money. The control group, on the other hand, only received the standard information. It is important to note that the potential amount of the incentive was similar in both groups.

The experiment consisted of 360 sales representatives and 16 team leaders in the control group, and 60 sales representatives and three team leaders in the experimental group. By reviewing the previous performance on the sales ratio of sales representatives, we ensured that the experimental group and

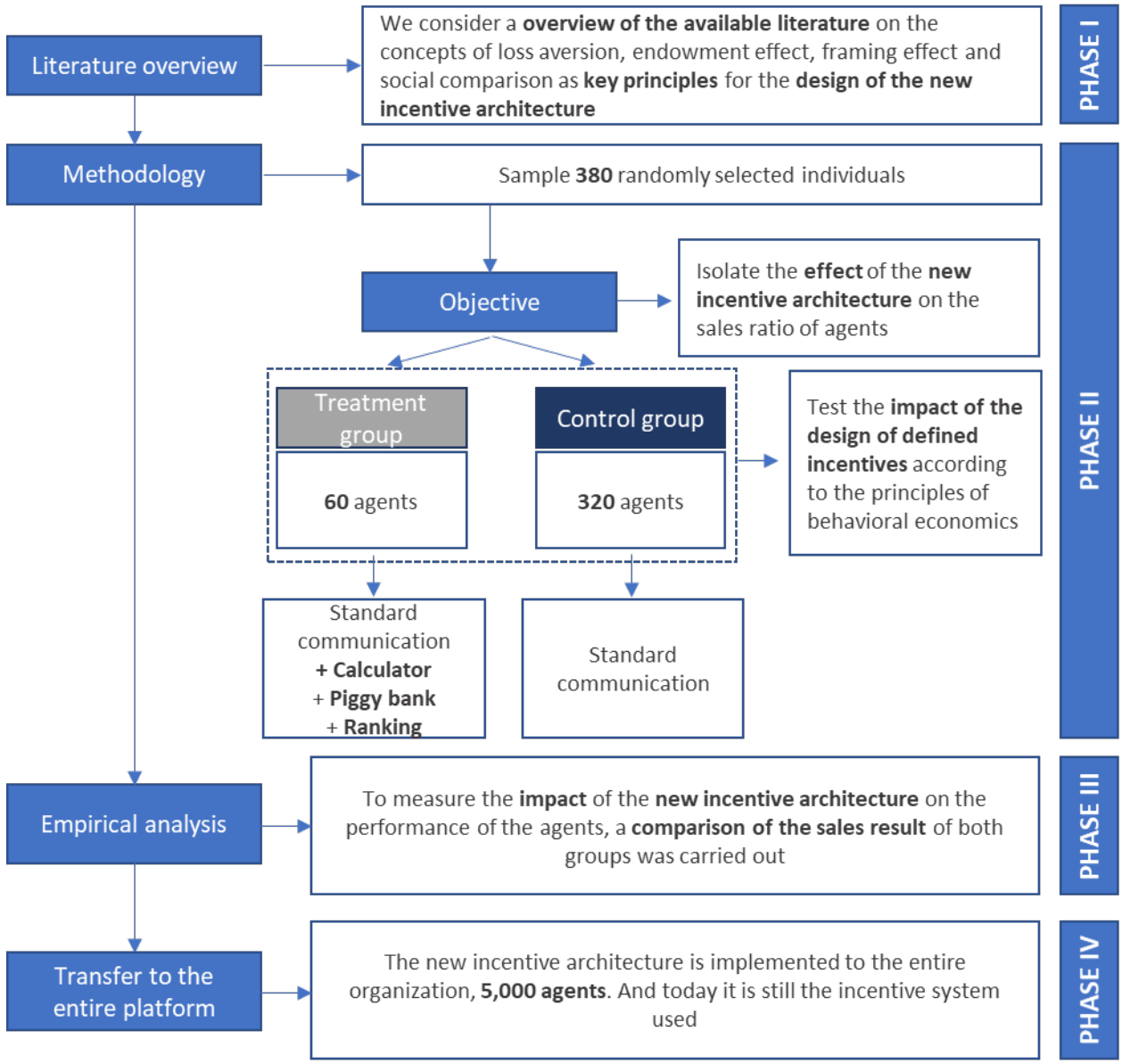

Figure 2: Experiment overview.

the control group were similar before the experiment. The sales ratio was calculated as the number of sales divided by the total amount of incoming calls handled by the sales representative in that period.

The experiment was successfully carried out for a full month. During that time, individuals in the experimental group achieved a sales ratio of 3.56% of total incoming calls, while the sales ratio for the control group was 3.26% of total incoming calls. Hence, the new incentive architecture improved the sales representatives' performance by 10%[2]. After these initial results, the company decided to implement the new incentives architecture to the whole team (more than 4.000 employees) obtaining an overall improvement in the sales ratio of around 16% compared to the previous period.[3]

Ethics and Further Considerations

Our work resulted in a transparent win-win situation for both the company and the employee, since

2 We were unable to establish statistical significance for these results due to the circumstances of the project. The top management of the company did not allow a greater sample size for the experiment to avoid distractions and they preferred to see an initial business impact before rolling out to the whole team. Sometimes, operating in the real world, we must decide on a particular course of action based on limited or suboptimal evidence.

3 Once the new system was implemented for the whole team, we were not able to isolate how much of this improvement was due to the new incentive's architecture and how much was coming from other initiatives and external factors.

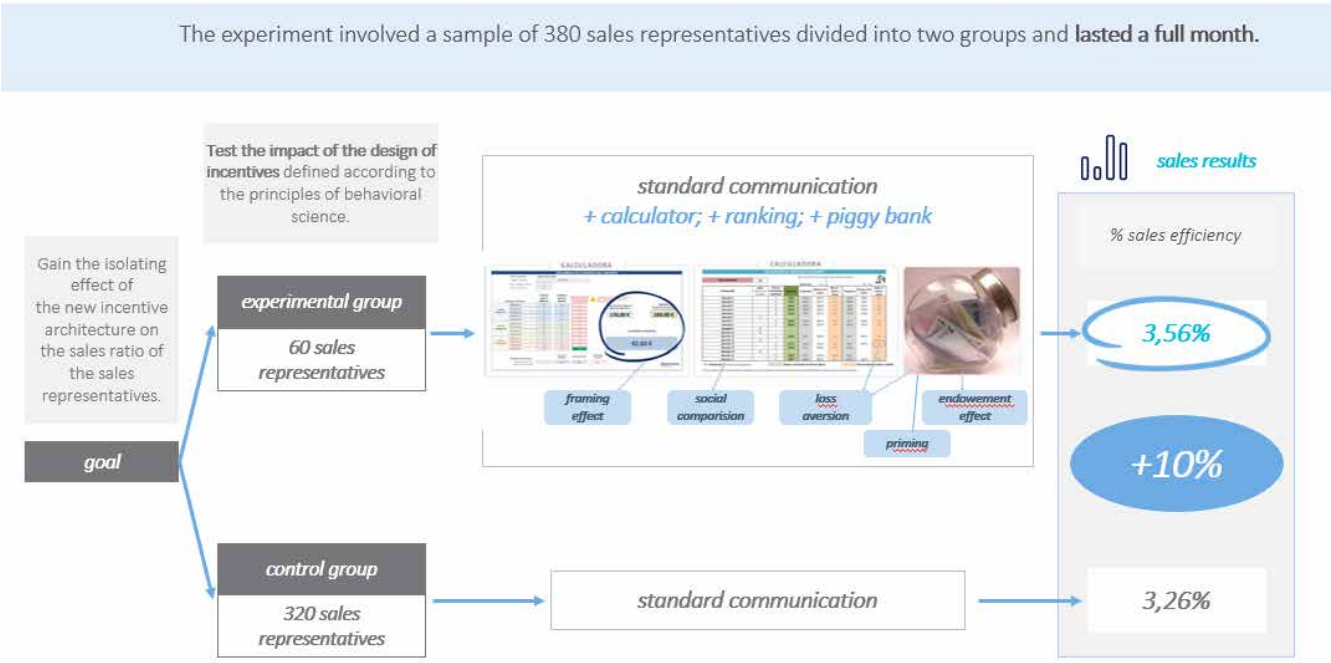

Figure 3: Results overview.

we experienced an improvement in the company's bottom line and in sales representatives' salaries. Moreover, information was fully transparent since all sales representatives and supervisors were fully informed about the experiment.

As stated in the introduction, companies often focus on pay-for-performance, which exclusively applies to monetary rewards and often considers material components. We tested and implemented a new incentive architecture that relied on multiple behavioral science principles. Future research would have an opportunity to look at the separate rather than combined impact of these nudges. There are also several other non-material reward components that could be tested in further experiments. One example, which combines material and non-material components, is the 'cafeteria system' (Beke et al., 2014).

In this system, employees can opt for rewards that are most attractive to them, according to their needs. Some options in this regard include:

- Money for time: unused or saved vacation time is paid out.
- Time for money: employees can retire early or "purchase" extra days off.
- Work arrangement: employees arrange their own working hours.
- Monetary arrangement: employees receive part of their pay in savings schemes or shares.
- Additional arrangement: employees receive a meal plan or a grant towards their children's education.

A modern reward system must appeal to a person through material and non-material components. This also supports the idea of a total reward strategy, which includes individual growth, a bright future, total pay, and a positive work environment (Jiang et al., 2009).

Remote Work: A Threat or an Opportunity?

The pandemic has accelerated the trend for increased remote working—with many companies forced to adapt faster than they expected to do (one out of four companies said they experienced lower agent performance and longer hiring and onboarding cycles as a result). Despite these challenges, contact center leaders are realizing that the benefits of remote working are worth the effort. By embracing the work-from-home model, companies can often find both better qualified and less expensive employees while offering the flexibility that workers require. In total, 77% of service organizations are either adopting or accelerating their work-from-home programs. Before the pandemic, only 6% of agents, on average, worked from home (Deloitte, 2021).

Further studies, taking remote working into account, will need to be undertaken. However, our work is an excellent initial step toward handling new work challenges, as we have shown how aspects of behavioral science, such as loss aversion, endowment effect, framing effect, priming, or social comparison could have an impact on employees' performance—and therefore on the company's bottom line. Also, we explained how incentives can influence employees' internal and external motivations.

All tangible factors that were included in the intervention, such as the piggy bank or the printed rankings, should be adapted to the remote working environment through the use of digital tools. However, it would be important to test the effectiveness of this digital version of the intervention.

Maintaining Motivation in the Long Term

One of the future challenges of this type of intervention is to maintain the impact over time. In our case, for further research endeavors, we suggested periodic reminders or slight modifications that would allow the impact to not be substantially reduced (Karlan et al., 2016; Cialdini, 2016).

Moreover, we are aware of the priming effect, and we suggest that the effects of money-priming should be considered, i.e., people reminded of money may shift into an independent work mentality; they may exert effort on challenging tasks, demonstrate good performance, and feel efficacious. Also, they are less interpersonally interested and less willing to help. People primed with money work independently, even when they are given the option of turning to someone else for assistance. They are not perceived as prosocial, caring, or warm (Vohs, 2015). Research shows that there is a large money-priming effect when participants actively handle money (Lodder et al., 2019). As we did not test the effect of our intervention in the long term, it is important that companies pay attention to the potential spillover effects of this new reward system.

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RESOURCES

WARWICK
THE UNIVERSITY OF WARWICK

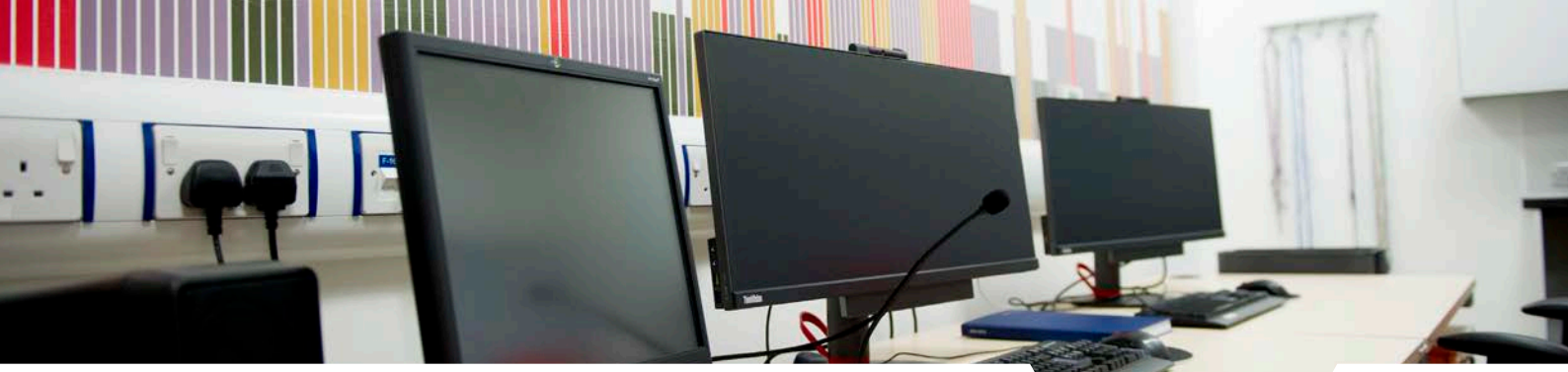
MSc in Behavioural and Economic Science

The Departments of Psychology and Economics at the University of Warwick offer innovative new courses in the growing area of decision science and behavioural economics. The MSc draws on the excellent, ground-breaking research being undertaken in the departments of Psychology, Economics and the Warwick Business School.

The MSc will suit those with a quantitive background (e.g. maths, sciences, economics, psychology).

Further Details:
Email: **PsychologyPG@warwick.ac.uk** Tel: **+44 (0)24 7657 5527**

www.warwick.ac.uk/bes



WARWICK
THE UNIVERSITY OF WARWICK

MSc in Behavioural and Economic Science

Why should I take this course?

This inter-disciplinary course emphasises both theoretical foundations and real-world applications of Behavioural Science, and is aimed at those intending to work in business, public policy implementation or research.

Modules will include

- A thorough grounding covering both the theory and real-world application, in behavioural economics and the cognitive science of judgement and decision making.
- Modules on the design, conduction and analysis of behavioural experiments and the analysis of large-scale datasets.
- An empirical research project.

Our previous students have gone on to take positions at The Busara Center for Behavioral Economics, The UK Behavioural Insights Team, Google, Frontier Economics, Facebook, Ogilvy Change and more.

Further Details:

Email: **PsychologyPG@warwick.ac.uk** Tel: **+44 (0)24 7657 5527**

www.warwick.ac.uk/bes

WARWICK
THE UNIVERSITY OF WARWICK

Why Warwick?

You will be taught by leading researchers from the Departments of Psychology and Economics and Warwick Business School.

Three leading departments in this area of research.

Warwick has been ranked top of the specialist subject table for Economics in The Times and the Sunday Times University League Tables for 2020. Behavioural Science was identified as an area of significant academic achievement in the Research Excellence Framework.

Warwick is a global community. Our students come from all over the world, including South America, Asia, Europe, USA and the Middle East and from many backgrounds including undergraduate study, industry and the public sector.

Find out more about Postgraduate Study at Warwick
www.warwick.ac.uk/study/postgraduate

Further Details:
Email: **PsychologyPG@warwick.ac.uk** Tel: **+44 (0)24 7657 5527**

www.warwick.ac.uk/bes

Penn
Master of Behavioral and Decision Sciences

Learn the theory, apply the tools, and make a difference

Penn's **Master of Behavioral and Decision Sciences (MBDS)** program equips students with theoretical and practical tools to understand how individuals and groups make decisions, how to affect those decisions, and how social norms play a role in motivating and changing social behaviors. Led by world-renowned faculty, researchers, and practitioners, the MBDS program creates unique opportunities for students to engage with an exceptional advisory board, apply tools and knowledge in our annual Design Challenge, and pursue independent, cross-disciplinary research throughout Penn.

From our alumni:

"I facilitated a four-month behavioral consulting project for graduate students who delivered a top-notch final brief and research paper—as good as anything I've seen from professional consulting firms. The students superbly applied their knowledge of behavioral science to everyday situations and answered tough questions from national and regional leaders during the final presentation."

Alex Willard, MBDS '19
Marketing Strategist, US Army Enterprise Marketing Office

"One of the most rewarding aspects of the MBDS program is the design challenge. Not only does it provide the opportunity to apply theoretical concepts to solve industry challenges, but it also encourages you to proactively identify existing the behavioral biases driving these very challenges. In my current role as a data scientist, I find this to be a valuable skill that has enabled me to better interpret the end result of certain decisions."

Anu Raghuram, MBDS '19
Data Scientist, BlackRock

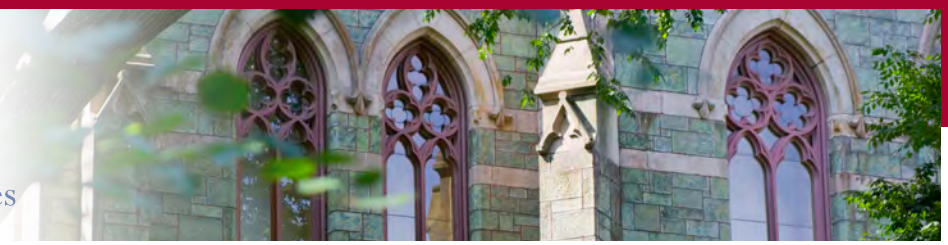
"The MBDS program has several key components bridging behavioral science concepts and practice, which were crucial for my experience as a student. The Design Challenge enabled me to apply learnings from my classes by working with a team of fellow students to find novel solutions to a real business challenge. The program and Design Challenge developed my knowledge and skills which have allowed me to make unique contributions at my company, and I've had the opportunity to remain involved with the program through ongoing initiatives."

Michael Hayden II, MBDS '19
SIP Associate Consultant, ZS Applied Behavioral Insights

Learn more about our engaged and well-connected alumni at

www.upenn.edu/mbds

Penn
Master of Behavioral and Decision Sciences



Meet the Master of Behavioral and Decision Sciences program's founding director

"Wherever there is a human group there are social norms."

-Cristina Bicchieri

Cristina Bicchieri

Founding Director, Master of Behavioral and Decision Sciences

S.J. Patterson Harvie Professor of Social Thought and Comparative Ethics, Departments of Philosophy and Psychology

Director, Center for Social Norms and Behavioral Dynamics

Cristina Bicchieri is a world authority on social norms and has consulted with UNICEF, the World Bank, the Gates Foundation, the United Kingdom's Department for International Development, and many other organizations. She is the founder of the Master of Behavioral and Decision Sciences program, the Penn Social Norms Group (PENN SoNG), and the Behavioral Ethics Lab. She is also the Director of the Center for Social Norms and Behavioral Dynamics, a newly formed research center at Penn that aims to support positive behaviors on a global scale.

The Center for Social Norms and Behavioral Dynamics

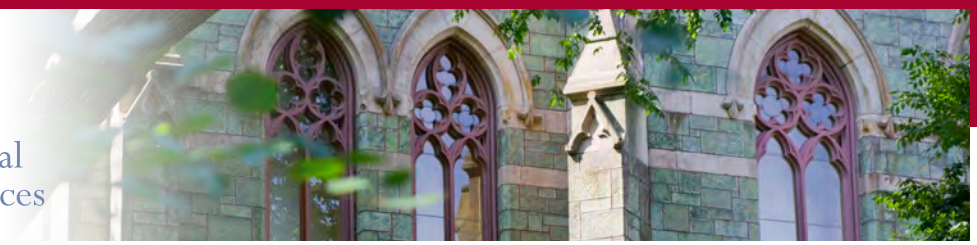
CENTER FOR
Social Norms and Behavioral Dynamics
University of Pennsylvania

The Center for Social Norms and Behavioral Dynamics at Penn, led by Director Cristina Bicchieri, aims to support positive behaviors on a global scale, across both informal and organizational settings. The Center has undertaken a range of projects with partner organizations around the world by leveraging their expertise in measuring behavior, analyzing behavioral data, and identifying systematic behavioral drivers. Master of Behavioral and Decision Sciences students can explore research and learning opportunities at the Center around social norms frameworks and theory. Through the Center, both students and professionals have access to the NoBeC (Norms and Behavioral Change) Talks, which showcase interdisciplinary early career and senior researchers working on norms and behavioral change around the world.

To learn more about the MBDS program's world-renowned faculty and researchers, visit:

www.upenn.edu/mbds

Penn
Master of Behavioral and Decision Sciences



Unparalleled connections, exceptional opportunities

A defining feature of the University of Pennsylvania's Master of Behavioral and Decision Sciences program (MBDS) is its network of outstanding industry and research partners who help bring students exceptional networking experiences, such as internships, our annual Design Challenge, and employer-driven projects.

Meet our advisory board

Charlotte Blank
Transformation & Analytics, Jaguar Land Rover North America

Claire Hobden
Specialist on Vulnerable Workers, Domestic Work, International Labour Organization

Jeff Kreisler
Head of Behavioral Science for JP Morgan Private Bank and Founding Editor of PeopleScience.com

Pavan Mamidi
PhD, Director of the Centre for Social and Behaviour Change (CSBC), Ashoka University

Namika Sagara
Co-Founder, Chief Behavioral Officer and Head of Consulting, Syntoniq

Greg Szwartz
Practice Lead – Healthcare Predictive Modeling, Deloitte Consulting

Piyush Tantia
Chief Innovation Officer, ideas42

Renos Vakis
Lead Economist, the Poverty and Equity Global Practice

Chiara Varazzani
PhD, Lead Behavioral Scientist, Organisation for Economic Cooperation and Development (OECD - OCDE)

Scott Young
Principal Advisor, Head of Private Sector, the Behavioural Insights Team (BIT) North America

Allison Zelkowitz
Founder and Director, Center for Utilizing Behavioral Insights for Children (CUBIC) at Save the Children International

About our Design Challenge

The MBDS program hosts a Design Challenge every spring to drive collaboration between student groups and industry partners who, together, apply cutting-edge knowledge and research to current organizational projects. For six weeks this spring, 62 students teamed up to tackle nine challenges in health and wellness, cryptocurrency, governance, and business management.

Learn more about how MBDS connects students and industry at

www.upenn.edu/mbds

University of East Anglia | SCHOOL OF ECONOMICS

HARNESS THE POWER OF BEHAVIOURAL ECONOMICS

Governments, businesses and non-profit organisations are increasingly looking to behavioural economists to help achieve their objectives. Unlock your future career by learning to harness the power of behavioural economics. Whether you'd like to focus on experimentation or big data, the University of East Anglia (UEA)'s masters courses in Behavioural Economics will give you the skills you need.

WHY THE SCHOOL OF ECONOMICS AT UEA?

The University of East Anglia pioneered Behavioural and Experimental Economics in the UK and remains a leading centre in the use of experiments in economics. You'll be in the best place to benefit from interaction with world-leading researchers in the Centre for Behavioural and Experimental Social Science (CBESS), and get the opportunity to learn to conduct experiments in our state-of-the-art Laboratory for Economic and Decision Research (LEDR).

https://www.uea.ac.uk/course/postgraduate/msc-behavioural-and-experimental-economics
https://www.uea.ac.uk/course/postgraduate/msc-behavioural-economics-and-data-science

University of East Anglia | SCHOOL OF ECONOMICS

MSc BEHAVIOURAL ECONOMICS AND DATA SCIENCE

COURSE HIGHLIGHTS

- Prior economics background unnecessary – we'll get you up to speed
- Learn programming – an increasingly valuable skill in the job market
- Alumni network in behavioural science and data science to facilitate job search.

One of the biggest upcoming changes in the world of work is the huge increase in demand for data scientists. This MSc will prepare you for a career as a data scientist so that you can meet this change in demand.

Behavioural Economics is an ideal framework in which to carry out big data research. The MSc focuses on the methodology for testing predictions of behavioural economics using big data sources (e.g. testing auction theory using data from online auctions).

Research-led training includes core Economics and Econometrics modules, as well as specialised modules in Programming and Behavioural Economics and a dissertation. By combining Data Science with Behavioural Economics your employment prospects will be strong. Governments and private sector organisations need expertise in both areas to achieve their objectives.

MSc BEHAVIOURAL AND EXPERIMENTAL ECONOMICS

Policymakers in government and decision-makers in industry are increasingly looking to behavioural economics for insights into decision-making behaviour. Whether the objective is how to encourage firms to use green energy or how to ensure consumers buy the most suitable products, behavioural economists can help.

If you have already studied economics, this MSc course will give you the specialist, research-training you need. You'll blend economic and psychological modelling with controlled experiments inside and outside the laboratory.

Research-led training includes: Behavioural and Experimental Economics, Advanced Economic Theory and Econometrics and a dissertation (where you can design and run your own experiment).

COURSE HIGHLIGHTS

- A research budget and logistical support to design and run your own experiment
- Guest lectures from behavioural science practitioners to inform your career choice
- Alumni network working in behavioural science to facilitate job search.

This Master's is ideal if you aim to work as a professional economist in government, industry, international agencies or other similar organisations. It's also an excellent step towards progressing onto PhD study in this area.

https://www.uea.ac.uk/course/postgraduate/msc-behavioural-and-experimental-economics
https://www.uea.ac.uk/course/postgraduate/msc-behavioural-economics-and-data-science

University of East Anglia | SCHOOL OF ECONOMICS

WHAT OUR STUDENTS SAY:

"The MSc in Behavioural and Experimental Economics has been incredibly useful. This course gave me the opportunity to conduct my own lab experiment and get feedback on my research design from a room full of experts. Such an experience is rare in other masters courses and has therefore given me additional credentials that I will take into my post-university job search."

Joshua
MSc Behavioural and Experimental Economics (Current Student; Graduating 2022)

"Studying behavioural and experimental economics at UEA was a critical platform for my career in applying behavioural economics to public policy. Several years on, I still find myself referring back to concepts introduced to me during my studies on a daily basis. In addition to high-quality and engaging teaching, the course exposed me to cutting edge behavioural research and gave me the opportunity to use the state-of-the-art laboratory facilities for my own research. These opportunities fostered in me a curiosity to use experimental research to learn what works and to test interventions in public policy that sticks with me today."

Cameron
MSc Behavioural and Experimental Economics Alumnus (Graduated 2014)

"I found the course especially useful for the work that I now do as a PhD student. It did an excellent job of overviewing research done in the field and provided detailed training on how an experiment should be designed/run, both theoretically and practically. Most importantly, it did a phenomenal job of taking all the concepts and training provided and teaching students how to write a high-level research paper on a topic of their own choice."

Vincent
MSc Behavioural and Experimental Economics Alumnus (Graduated 2020)

"All the lecturers I encountered were extremely enthusiastic about the field, friendly and supportive. This created a vibrant and welcoming atmosphere with lots of opportunities. They encouraged free-flowing discussions on each topic and had guest lectures from behavioural scientists from industry and government, providing invaluable insights on turning behavioural economics into a successful career."

Alastair
MSc Behavioural and Experimental Economics Alumnus (Graduated 2021)

FACEBOOK - *@ueaeconomics*
TWITTER - *@UEA_Economics*
LINKEDIN - *@School of Economics UEA*

FIND OUT MORE:
https://www.uea.ac.uk/about/school-of-economics
CONTACT US:
Professor Peter Moffatt, PGT Admissions Director
p.moffatt@uea.ac.uk or ***admissions@uea.ac.uk***

https://www.uea.ac.uk/course/postgraduate/msc-behavioural-and-experimental-economics
https://www.uea.ac.uk/course/postgraduate/msc-behavioural-economics-and-data-science

Department of
Psychological and Behavioural Science

EXECUTIVE MSc BEHAVIOURAL SCIENCE

UNCOVER THE SCIENCE BEHIND BEHAVIOUR

An increasing number of organisations now engage with the idea of applying behavioural insights to their organisational challenges.

The Executive MSc Behavioural Science, based in LSE's Department of Psychological and Behavioural Science, is taught by experts at the forefront of international research in behavioural science.

Our programme provides rigorous training for professionals who are seeking to expand their knowledge in this emerging and exciting field. Many of our alumni are now prominent behavioural science leaders and experts in a range of organisations around the world.

CONTACT US
pbs.emsc@lse.ac.uk

For more information, please visit **lse.ac.uk/EMScBehaviouralScience**

LSE Department of Psychological and Behavioural Science

EXECUTIVE MSc BEHAVIOURAL SCIENCE

A UNIQUE AND DYNAMIC PROGRAMME FOR PROFESSIONALS

LSE's Executive MSc Behavioural Science is taught by specialists at the forefront of international research in behavioural science. Our programme provides the opportunity for full-time professionals working in any sector to obtain a graduate qualification in behavioural science, allowing you to pursue new and expanded opportunities within this emerging and exciting field.

The programme starts in September each year with teaching being delivered during three two-week intensive teaching blocks at the LSE campus in London. You are not required to be in attendance on campus outside of these weeks and can therefore continue to live and work outside of London and the UK. Between teaching sessions you work independently on various assignments. After the final teaching session you complete a dissertation on a topic of your choice with support from your supervisor.

The programme includes unique and innovative modules such as:

- Behavioural Science and Policy
- Behavioural Decision Science
- Research Methods for Behavioural Science
- Frontiers in Behavioural Science Methods
- Policy Appraisal and Ethics
- Behavioural Science in an Age of New Technology
- Corporate Behaviour and Decision Making
- Organisational Culture

Please note that while this information is correct at the time of publication, the School may on occasion need to change, suspend or withdraw a course.

OUR STUDENTS

Our students come from a wide range of academic and professional backgrounds from all over the world, but one thing binds them together: a passion for behavioural science and a desire to better understand how principles from behavioural science can be applied in their professional (and personal) lives.

CONTACT US

pbs.emsc@lse.ac.uk

For more information, please visit **lse.ac.uk/EMScBehaviouralScience**

Department of
Psychological and Behavioural Science

WHAT OUR ALUMNI HAVE TO SAY ABOUT THE PROGRAMME

LSE's Executive MSc Behavioural Science is second to none in providing a complete insight into contemporary behavioural science debate and methodology, delivered by world-class experts.

Ana, 2021 graduate

The EMSc was a rigorous, but perfectly balanced, compliment to my work obligations.

Joshua, 2019 graduate

The Executive MSc Behavioural Science has equipped me with tools to address some of the most pressing challenges with strong behavioural roots in the MENA region and the Global South.

Nabil, 2020 graduate

The network built during the EMSc is unmatched by any past professional or educational experience I've had, through faculty support, alumni connections, and lifelong professional and personal relationships.

Madeline, 2019 graduate

CONTACT US

pbs.emsc@lse.ac.uk

For more information, please visit **lse.ac.uk/EMScBehaviouralScience**

TheChicagoSchool®
of Professional Psychology

Explore the mind of the consumer through The Chicago School's Behavioral Economics programs.

With foundations in advanced psychology, the Behavioral Economics programs at The Chicago School provide students with two pathways to building skills in understanding and influencing consumer behavior: the Certificate in Behavioral Economics, a customizable and abbreviated credential situated within the Behavioral Economics program, and the M.A. in Behavioral Economics, a traditional full master's degree with elective options.

Our M.A. in Behavioral Economics and Certificate in Behavioral Economics programs blend elements of consumer, social, and cognitive psychology to provide a psychological perspective to consumer behavior.

Those who earn their degree or certificate are prepared to deliver professional services, perform research, excel as leaders and policy advisers, and serve diverse populations in business, marketing, and politics with sensitivity and inclusion.

ABOUT THE CHICAGO SCHOOL

The Chicago School of Professional Psychology is a nonprofit, accredited institution with more than 5,700 students at campuses across the country (Chicago, Dallas, Southern California, Washington, D.C., and online). The Chicago School has been an innovator in the field of psychology and related behavioral sciences since 1979. The Chicago School offers more than 30 degree programs and several opportunities for international experiences.

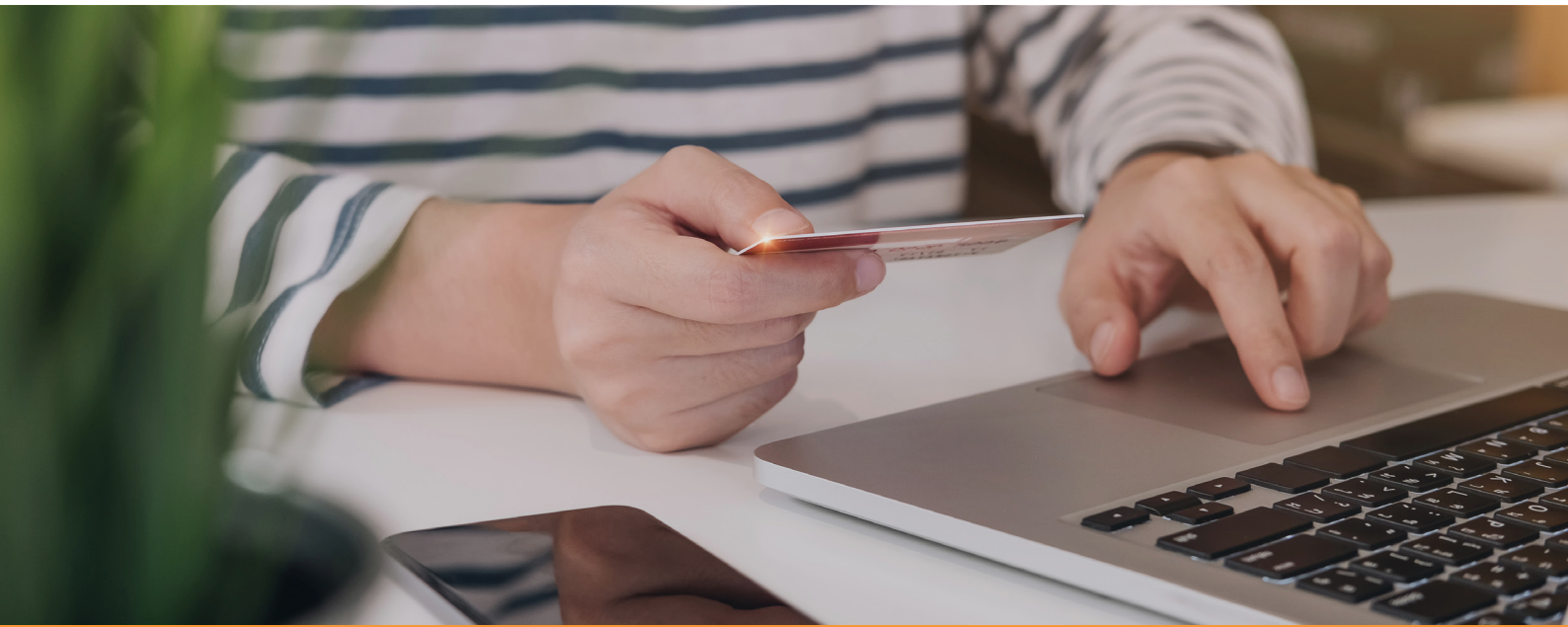
Program features

Dedicated, engaged faculty who are highly experienced professionals and leaders in their respective fields.

A student-faculty partnership model that encourages collaborative work between students and instructors, enhancing professional, academic, and community engagement.

Integrated learning that balances classroom instruction and "real work" research and application.

A curriculum that values exposure to a variety of strategies for understanding and researching diverse human experience and behaviors.



CONTACT US TODAY TO LEARN MORE: 800-721-8072 | www.thechicagoschool.edu

TheChicagoSchool®
of Professional Psychology

M.A. IN BEHAVIORAL ECONOMICS

The online M.A. Behavioral Economics non-licensure program is designed for working adults interested in psychological perspectives of human decision-making, risk assessment, and consumer behavior. This program provides students an alternative to the traditional MBA by offering a curriculum with a foundation in advanced psychology that addresses broader business applications to decision-making, negotiation, marketing, and consumer behavior.

The M.A. in Behavioral Economics utilizes a competency-based model grounded in consumer, social, cognitive and consulting psychology, as well as political science and infuses multicultural perspectives from diverse market audiences.The curriculum is interdisciplinary in approach and integrates theories of consumer decision-making, consulting, and financial literacy, including coursework in choice architecture, neuromarketing, and persuasive messaging to generate a richer understanding of human behavior.

Graduates are prepared to deliver professional services, perform research, excel as leaders and policy advisers, and to sensitively and inclusively serve diverse populations in business, marketing, and politics.

WHAT DISTINGUISHES THIS PROGRAM?

• The online Behavioral Economics M.A. program provides students with an alternative to the traditional MBA by combining social psychological theory with a practical application toward decision-making and consumer behavior within the context of a psychology degree.

• The program is distinct from those of competing institutions both in its flexible online delivery model and its curriculum, which blends elements of consumer, social, and cognitive psychology while providing a psychological perspective to behavioral economics.

• Upon successful completion of the online M.A. in Behavioral Economics program, students who meet admissions requirements will be prepared to enter The Chicago School's Business Psychology Ph.D. program, allowing them to pursue additional postgraduate and career opportunities.

CAREER POSSIBILITIES

Graduates can consider careers in the following fields:

- **Consulting**
- **Public service**
- **Marketing**
- **Public relations**
- **Health care**
- **Higher education**
- **Human resources**
- **Nonprofit**
- **Government**

TheChicagoSchool®
of Professional Psychology

M.A. STUDENT EXPERIENCE

The M.A. in Behavioral Economics program is designed to support interaction and learning among students and faculty by incorporating cohort membership, small groupings, a blended delivery system, active learning, and pedagogical "best practices" within the design.

Cohort model: Students in the Behavioral Economics M.A. program move through a sequence of courses collectively. The common goal of starting and completing the program together encourages students to work collectively, which promotes the development of personal relationships and the building of a professional network. Cohort membership enables students to support and learn from other students.

Small groupings: The program strategically allows for arrangement of students in small groups for online learning that is advantageous for active learning. As approximations, online courses have fewer than 20 students.

Diverse delivery system: This program utilizes both synchronous and asynchronous instructional modalities to provide students an accommodative learning environment that encourages interaction among students and faculty, supports active learning, and respects diverse talents and ways of learning. Asynchronous learning includes the use of online forums, as well as audio and video recordings. Synchronous learning includes the use of live chat sessions and virtual meetings.

Student services: Online students have access to a range of students support services including: access to Library Services, professional skill development through Career Services, opportunities to study abroad, the chance to present original research at the Graduate Research Forum, and engagement opportunities through student groups and societies.

CERTIFICATE IN BEHAVIORAL ECONOMICS

Also available is our Certificate in Behavioral

Economics. This program requires fewer credit hours than the M.A. yet also blends behavioral economics and business psychology to provide a unique alternative to a traditional MBA. Curriculum begins with an introduction to the fundamentals of behavioral economics. Students then choose two electives that suit their professional goals.

Total program credits: 9-10 credit hours

Length of program: 3 terms

Delivery format: online

M.A. PROGRAM SPECIFICATIONS

The M.A. in Behavioral Economics is a non-licensure 40 credit hour program. The program includes:

- **18 credit hours of core course work**
- **16 credit hours of research course work**
- **6 credit hours of elective course work**

The program culminates in an Applied Research Project in which students will apply behavioral economics concepts to an approved topic. Students will complete classwork over the course of their studies that will guide them through the process of writing the Applied Research Project. A faculty member will approve and supervise the project through these courses.

Postgraduate Programs

(Taught in English)

University	School/Department	Program
United States		
Brown University	School of Public Health	Master of Public Health (Health Behavior concentration)
	Department of Economics	PhD in Economics
California Institute of Technology (Caltech)	Division of the Humanities and Social Science	PhD in Social and Decision Neuroscience
Carnegie Mellon University	Department of Social and Decision Sciences	PhD in Social and Decision Sciences
	Tepper School of Business	PhD in Behavioral Economics (see also Dynamic Decision Making Laboratory) (see also Center for Behavioral and Decision Research)
Chapman University	Economic Science Institute	MS in Behavioral and Computational Economics
The Chicago School of Professional Psychology		Masters in Behavioral Economics **See pp. 129-131**
Claremont Graduate University	School of Social Science, Policy, and Evaluation	PhD in Economics (see also Center for Neuroeconomics Studies)
Columbia University	Columbia Business School	MBA, MS, and PhD in Business (see also Center for Decision Sciences)
	Department of Economics	MA and PhD in Economics (see also Cognitive and Behavioral Economics Initiative) (see also Cognition & Decision Lab)
Cornell University	Charles H. Dyson School of Applied Economics and Management	PhD in Applied Economics and Management Master of Professional Studies (MPS) in Applied Behavioral Economics and Individual Choice (see also Lab for Experimental Economics & Decision Research)
Duke University	The Fuqua School of Business	MBA and PhD in Business Administration (Marketing or Decision Sciences track)

Franklin University	College of Arts, Sciences & Technology	Master's in Business Psychology
Georgia State University	Andrew Young School of Policy Studies	PhD in Economics MA in Economics (see also Experimental Economics Center)
Harvard University	Department of Economics School of Public Health	PhD in Economics MS and PhD in Social and Behavioral Sciences
Johns Hopkins University	Johns Hopkins Bloomberg School of Public Health	PhD in Social and Behavioral Sciences
Massachusetts Institute of Technology	Department of Brain and Cognitive Sciences MIT Sloan School of Management	PhD in Brain and Cognitive Sciences Masters in Management, Analytics, Applied Economics (see also MIT Sloan Neuroeconomics Laboratory)
New York University	Graduate School of Arts & Science	MAs and PhDs in Economics, Politics and Psychology (see also Center for Experimental Social Science) (see also Institute for the Study of Decision Making)
Ohio State University	Department of Psychology	PhD in Psychology (Decision Psychology) (see also Decision Sciences Collaborative)
Stanford University	Department of Economics	PhD in Economics (Behavioral & Experimental specialization) (see also Institute for Economic Policy Research)
Texas A&M University	Department of Economics	PhD in Economics (see also Economic Research Laboratory)
University of Arizona	Eller College of Management	PhD in Economics (see also Institute for Behavioral Economics)
University of California, Berkeley	Haas School of Business Department of Psychology Department of Economics	PhDs in Marketing, Psychology and Economics (see also Initiative for Behavioral Economics & Finance) (see also Berkeley Decision Science Research Group)
University of California, Los Angeles	Anderson School of Management	PhD Behavioral Decision Making

University of California, San Diego	Rady School of Management	MBA and PhD in Management (see also Atkinson Behavioral Research Lab)
University of California, Santa Barbara	College of Letters & Science	PhD in Economics (see also Experimental and Behavioral Economics Laboratory)
University of Chicago	Booth School of Business	MBA PhD in Behavioral Science (see also Center for Decision Research)
University of Kansas	College of Liberal Arts and Sciences	MA in Applied Behavioral Science PhD in Behavioral Psychology (see also KU Applied Behavioral Economics Laboratory)
University of Maryland	College of Behavioral & Social Sciences	PhD in Social, Decision, and Organizational Sciences
University of Oregon	College of Arts and Science	MA and PhD in Psychology PhD in Economics
	Lundquist College of Business	PhD in Marketing (see also Institute of Cognitive and Decision Sciences)
University of Pennsylvania	School of Arts & Sciences	Master of Behavioral and Decision Sciences **See pp. 120-122** (see also Behavioral Ethics Lab) (see also Social Norms Group)
University of Pittsburgh	Katz Graduate School of Business	PhD in Marketing
	Dietrich School of Arts & Sciences	PhD in Economics
University of Southern California	Dana and David Dornsife College of Letters, Arts, and Sciences	PhD in Economics (see also Los Angeles Behavioral Economics Laboratory)
University of Wisconsin	School of Human Ecology	MS and PhD in Human Ecology: Consumer Behavior and Family Economics (see also Behavioral Research Insights Through Experiments Lab)

Washington University in St. Louis	School of Arts and Sciences	PhD in Behavior, Brain and Cognition (see also Behavioral Economics Laboratory)
Yale University	Yale School of Management	Doctoral Programs in Financial Economics, Marketing, and Organizations and Management (See also Yale-Ipsos Consumer Marketing & Behavioral Economics Think Tank)

United Kingdom

City University London	Interdisciplinary School of Arts and Social Sciences	MSc in Behavioural Economics PhDs in Economics and Psychology (see also Decision Making and Behavioural Economics Research Group)
Durham University	Department of Psychology Durham Business School	MSc in Behavioural Science MSc in Experimental Economics
Kingston University	Faculty of Arts and Social Sciences	MSc in Behavioural Decision Science
Lancaster University	Management School	PhD Behavioural and Experimental Economics
London School of Economics and Political Science	Department of Psychological and Behavioural Science	MSc in Behavioural Science Executive MSc in Behavioural Science **See pp. 126-128**
	Departments of Management, Social Policy, Economics and Psychological and Behavioural Science	PhDs in Management (Marketing), Social Policy, Economics and Psychological and Behavioural Science (see also LSE Behavioural Lab for Teaching and Research)
Middlesex University	Business School	MSc in Applied Behavioural Economics
Queen Mary University of London	School of Economics and Finance	MSc in Behavioural Finance
University College London	Division of Psychology And Language Sciences Division of Psychology And Language Sciences School of Management and the Behavioural Insights Team	Executive Programme in Behavioural Science MSc in Cognitive and Decision Sciences MSc in Behaviour Change PhD in Experimental Psychology PhDs in Management with Behavioural Science and Policy

University of Bath		MSc Applied Psychology and Economic Behaviour
University of Cambridge	Judge Business School	MBA, Executive MBA and PhDs in Business Economics, Marketing, etc.
	Faculty of Economics	PhD in Economics (see also Cambridge Experimental and Behavioural Economics Group)
University of East Anglia	Department of Economics	MSc in Behavioural and Experimental Economics MSc in Behavioural Economics and Data Science **See pp. 123-125**
		PhD in Economics (see also Behavioural Economics Group) (see also Centre for Behavioural and Experimental Social Science)
University of Essex	Department of Economics	MSc in Behavioural Economics
University of Huddersfield		MSc in Behavioural Economics and Decision Science
University of Leeds	Leeds University Business School	MSc in Business Analytics and Decision Sciences (see also Centre for Decision Research)
University of Nottingham	School of Economics	MSc in Behavioural Economics PhD in Economics (see also Centre for Decision Research and Experimental Economics)
University of Oxford	Department of Economics	DPhil in Economics (see also Behavioural Economics Research Group) (see also Nuffield Centre for Experimental Social Sciences)
University of Reading	Henley Business School	MSc Behavioural Finance
	Graduate Institute of International Development, Agriculture and Economics	MSc in Consumer Behaviour
University of Stirling	Stirling Management School and Behavioural Science Centre	MSc in Behavioural Science for Management (see also Behavioural Science Centre)

University of Warwick	Interdisciplinary	MSc in Behavioural and Economic Science **See pp. 117-119**
	Department of Psychology	PhD in Psychology (see also Behavioural Science Group)
	Department of Psychology & Department of Computer Science	MSc Behavioural and Data Science

The Netherlands

Erasmus University Rotterdam	Erasmus School of Economics	Master in Economics and Business (Behavioural Economics specialization) PhD in Applied Economics (Behavioural Economics group)
Leiden University	Institute of Psychology	Master in Psychology (Economic and Consumer Psychology specialization)
Maastricht University	School of Business and Economics	Master in Human Decision Science
Radboud University Nijmegen	Department of Social Science	Master in Behavioural Science Master in Economics (Economics, Behaviour and Policy specialization)
Tilburg University	Department of Social Psychology School of Social and Behavioral Sciences Tilburg University Graduate Schools	Master in Social Psychology (Economic Psychology track) Research Master in Social and Behavioral Sciences Research Master and PhDs in Economics, Business (Marketing track) and Social & Behavioural Sciences (see also Tilburg Institute for Behavioural Economics Research)
University of Amsterdam (Amsterdam Business School / School of Economics)	School of Economics	MSc in Economics (Behavioural Economics and Game Theory track) PhD in Economics (Behavioural Economics research priority area)
University of Groningen	Faculty of Behavioural and Social Sciences	Research Master in Behavioural and Social Sciences
Utrecht University	Graduate School of Social and Behavioural Sciences	PhD in Social and Behavioural Sciences (see also Behaviour in Social Context)

Wageningen University & Research		MSc in Statistical Science for the Life and Behavioural Sciences

Germany

Friedrich-Schiller University Jena	Jena Graduate School	PhD in Human Behaviour in Social and Economic Change
Applied University at Hamm-Lippstadt		Intercultural Business Psychology Masters (Economic Psychology concentration)
Ludwig-Maximilians University Munich	Munich Graduate School of Economics	PhD in Economics (see also Munich Experimental Laboratory for Economic and Social Sciences)
TH Köln		MA in Behavioral Ethics, Economics and Psychology
University of Bonn	Bonn Graduate School of Economics	PhD in Economics (see also Center for Economics and Neuroscience) (see also Bonn Laboratory for Experimental Economics)
University of Kassel		MSc in Economic Behaviour and Governance
University of Konstanz	Graduate School of Decision Sciences	PhDs at the Graduate School of Decision Sciences (interdisciplinary)

Other Countries

Australia

Monash University	Faculty of Business and Economics	Master of Applied Economics and Econometrics
	School of Business, Monash University Malaysia.	PhDs in Business and Economics (see also Monash Laboratory for Experimental Economics) (see also Monash Business Behavioural Laboratory)

RMIT University		Master of Business (Behavioural Economics specialization) PhD in Economics, Finance & Marketing (Behavioural Economics specialization) (see also Behavioural Business Lab)
University of Melbourne	School of Psychological Sciences	Master of Applied Psychology
University of Queensland	School of Economics	Master and PhD in Economics (see also Risk and Sustainable Management Group)
University of Technology Sydney (UTS)	UTS Business School	PhD in Economics (Behavioural or Experimental Economics research field) (See also UTS Behavioural Laboratory)

Austria

University of Vienna	Faculty of Business, Economics, and Statistics	PhD in Economics MSc in Economics (see also Vienna Center for Experimental Economics)
Sigmund Freud University		Master in Psychology (Business & Economic Psychology specialization)

Canada

University of British Columbia	UBC Sauder School of Business	PhD in Marketing and Behavioural Science
University of Saskatchewan	Interdisciplinary	PhD in Applied Economics (Research area in Behavioural and Experimental Economics) (See also Experimental Decision Laboratory)
University of Toronto	Rotman School of Management	MBAs and PhDs in Marketing and Business Economics (see also Behavioural Economics in Action)

Cyprus

University of Cyprus	Department of Economics and Department of Psychology	MSc in Behavioural Economics

Denmark

University of Copenhagen	Department of Economics	MSc and PhD in Economics (See also Centre for Experimental Economics)

Finland

Oulu University in Finland	Business School	Master's program in Economics

France

Burgundy School of Business		Msc in Data Science and Organizational Behavior
Paris School of Economics	School of Economics	Masters and PhDs in Economics (see also Parisian Experimental Economics Laboratory)
Toulouse School of Economics		PhD in Economics (Behavioral and Experimental Economics specialization)

Italy

Bocconi University in Milan		Bocconi Experimental Laboratory for the Social Sciences
Catholic University of the Sacred Heart, Milan	PhD School in Economics and Finance	PhD Economics and Finance
University of Chieti-Pescara	School of Advanced Studies	PhD in Business and Behavioural Sciences Master in Behavioral Economics & Neuromarketing
University of Trento	Department of Economics and Management	Master in Behavioural and Applied Economics
	Doctoral School of Sciences	PhD in Economics and Management (Behavioural Economics)

Norway

Norwegian School of Economics		PhD in Business and Management Science (see also the Choice Lab)

Portugal

Universidade Catolica Portuguesa		Master in Psychology in Business and Economics
IDC Herzliya	Raphael Recanati International School	MA Behavioral Economics

Romania

University of Bucharest	Faculty of Business and Administration & Faculty of Psychology	Master in Behavioural Economics

Russia

National Research University Higher School of Economics		Master in Applied Social Psychology

Singapore

National University of Singapore	NUS Business School	MBA and PhDs in Management, Decision Sciences and Economics (see also Centre for Behavioural Economics)

South Africa

University of Cape Town	School of Economics	Masters and PhD in Economics (see also Research Unit in Behavioural Economics and Neuroeconomics)

Spain

University of Barcelona	Faculty of Psychology	Master's in Research in Behaviour and Cognition

Sweden

University of Gothenburg	School of Business, Economics, and Law	PhD in Economics (Behavioural Economics concentration) (see also Behavioural and Experimental Economics Group)

Switzerland

Conférence Universitaire de Suisse Occidentale		PhD in Behavioral Economics and Experimental Research
University of Zurich (Zurich Graduate School of Economics)	Department of Economics	PhD in Economics and Neuroeconomics (see also Laboratory for Experimental and Behavioral Economics)

Behavioral Science Concepts*

A

Action bias

Some core ideas in behavioral economics focus on people's propensity to do nothing, as evident in **default bias** and **status quo bias**. Inaction may be due to a number of factors, including **inertia** or anticipated **regret**. However, sometimes people have an impulse to act in order to gain a sense of control over a situation and eliminate a problem. This has been termed the action bias (Patt & Zeckhauser, 2000). For example, a person may opt for a medical treatment rather than a no-treatment alternative, even though clinical trials have not supported the treatment's effectiveness.

Action bias is particularly likely to occur if we do something for others or others expect us to act (see **social norm**), as illustrated by the tendency for soccer goal keepers to jump to left or right on penalty kicks, even though statistically they would be better off if they just stayed in the middle of the goal (Bar-Eli et al., 2007). Action bias may also be more likely among **overconfident** individuals or if a person has experienced prior negative outcomes (Zeelenberg et al., 2002), where subsequent inaction would be a failure to do something to improve the situation.

Affect heuristic

The affect heuristic represents a reliance on good or bad feelings experienced in relation to a stimulus. Affect-based evaluations are quick, automatic, and rooted in experiential thought that is activated prior to reflective judgments (see **dual-system theory**) (Slovic et al., 2002). For example, experiential judgments are evident when people are influenced by risks framed in terms of counts (e.g. "of every 100 patients similar to Mr. Jones, 10 are estimated to commit an act of violence") more than an abstract but equivalent probability frame (e.g. "Patients similar to Mr. Jones are estimated to have a 10% chance of committing an act of violence to others") (Slovic et al., 2000).

Affect-based judgments are more pronounced when people do not have the resources or time to reflect. For example, instead of considering risks and benefits independently, individuals with a negative attitude towards nuclear power may consider its benefits as low and risks as high under conditions of time pressure. This leads to a more negative risk-benefit correlation than would be evident without time pressure (Finucane et al., 2000).

The affect heuristic has been used as a possible explanation for a range of consumer judgments, including product innovations (King & Slovic, 2014), brand image (e.g. Ravaja et al., 2015), and product pricing (e.g. the **zero price effect**; see Samson & Voyer, 2012). It is considered another general purpose heuristic similar to **availability heuristic** and **representativeness heuristic** in the sense that affect serves as an orienting mechanism akin to similarity and memorability (Kahneman & Frederick, 2002).

Altruism

According to neoclassical economics, rational beings do whatever they need to in order to maximize their own wealth. However, when people make sacrifices to benefit others without expecting a personal reward, they are thought to behave altruistically (Rushton, 1984). Common applications of this pro-social behavior include volunteering, philanthropy, and helping others in emergencies (Piliavin & Charng, 1990).

Altruism is evident in a number of research findings, such as **dictator games**. In this game, one participant proposes how to split a reward between himself and another random participant. While some proposers (dictators) keep the entire reward for themselves, many will also voluntarily share some portion of the reward (Fehr & Schmidt, 1999).

While altruism focuses on sacrifices made to benefit others, similar concepts explore making sacrifices to ensure **fairness** (see **inequity aversion** and **social preferences**).

* **Acknowledgements:** The editor would like to thank Andreas Haberl, Chelsea Hulse, and Roger Miles for their contributions to this encyclopedia.

Ambiguity (uncertainty) aversion

Ambiguity aversion, or uncertainty aversion, is the tendency to favor the known over the unknown, including known risks over unknown risks. For example, when choosing between two bets, we are more likely to choose the bet for which we know the odds, even if the odds are poor, than the one for which we don't know the odds.

This aversion has gained attention through the Ellsberg Paradox (Ellsberg, 1961). Suppose there are two bags each with a mixture of 100 red and black balls. A decision-maker is asked to draw a ball from one of two bags with the chance to win $100 if red is drawn. In one bag, the decision-maker knows that exactly half of the pieces are red and half are black. The color mixture of pieces in the second bag is unknown. Due to ambiguity aversion, decision-makers would favor drawing from the bag with the known mixture than the one with the unknown mixture (Ellsberg, 1961). This occurs despite the fact that people would, on average, bet on red or black equally if they were presented with just one bag containing either the known 50-50 mixture or a bag with the unknown mixture.

Ambiguity aversion has also been documented in real-life situations. For example, it leads people to avoid participating in the stock market, which has unknown risks (Easley & O'Hara, 2009), and to avoid certain medical treatments when the risks are less known (Berger, et al., 2013).

Anchoring (heuristic)

Anchoring is a particular form of **priming** effect whereby initial exposure to a number serves as a reference point and influences subsequent judgments. The process usually occurs without our awareness (Tversky & Kahneman, 1974) and has been researched in many contexts, including probability estimates, legal judgments, forecasting and purchasing decisions (Furnham & Boo, 2011).

One experiment asked participants to write down the last three digits of their phone number multiplied by one thousand (e.g. 678 = 678,000). Results showed that people's subsequent estimate of house prices were significantly influenced by the arbitrary anchor, even though they were given a 10 minute presentation on facts and figures from the housing market at the beginning of the study. In practice, anchoring effects are often less arbitrary, as evident the price of the first house shown to us by a real estate agent may serve as an anchor and influence perceptions of houses subsequently presented to us (as relatively cheap or expensive). Anchoring effects have also been shown in the consumer packaged goods category, whereby not only explicit slogans to buy more (e.g. "Buy 18 Snickers bars for your freezer"), but also purchase quantity limits (e.g. "limit of 12 per person") or 'expansion anchors' (e.g. "101 uses!") can increase purchase quantities (Wansink et al., 1998).

Asymmetrically dominated choice

See **Decoy effect**

Availability heuristic

Availability is a heuristic whereby people make judgments about the likelihood of an event based on how easily an example, instance, or case comes to mind. For example, investors may judge the quality of an investment based on information that was recently in the news, ignoring other relevant facts (Tversky & Kahneman, 1974). In the domain of health, it has been shown that drug advertising recall affects the perceived prevalence of illnesses (An, 2008), while physicians' recent experience of a condition increases the likelihood of subsequently diagnosing the condition (Poses & Anthony, 1991). In consumer research, availability can play a role in various estimates, such as store prices (Ofir et al., 2008) or product failure (Folkes, 1988). The availability of information in memory also underlies the **representativeness heuristic**.

B

Behavioral economics

The field of behavioral economics studies and describes economic decision-making. According to its theories, actual human behavior is less rational, stable, and selfish than traditional normative theory suggests (see also *homo economicus*), due to **bounded rationality**, limited **self-control**, and **social preferences**.

Bias

See **Cognitive bias**

Bounded rationality

Bounded rationality is a concept proposed by Herbert Simon that challenges the notion of human rationality as implied by the concept of *homo economicus*. Rationality is bounded because there are limits to our thinking capacity, available information, and time (Simon, 1982). Bounded rationality is a core assumption of the "natural assessments" view of **heuristics** and **dual-system models** of thinking (Gilovich et al., 2002), and it is one of the psychological foundations of behavioral economics. (See also **satisficing** and **fast and frugal**.)

(Economic) Bubble

Economic (or asset) bubbles form when prices are driven much higher than their intrinsic value (see also **efficient market hypothesis**). Well-known examples of bubbles include the US Dot-com stock market bubble of the late 1990s and housing bubble of the mid-2000s. According to Robert Shiller (2015), who warned of both of these events, speculative bubbles are fueled by contagious investor enthusiasm (see also **herd behavior**) and stories that justify price increases. Doubts about the real value of investment are overpowered by strong emotions, such as envy and excitement.

Other biases that promote bubbles include **overconfidence**, anchoring, and **representativeness**, which lead investors to interpret increasing prices as a trend that will continue, causing them to chase the market (Fisher, 2014). Economic bubbles are usually followed a sudden and sharp decrease in prices, also known as a crash.

C

Certainty/possibility effects

Changes in the probability of gains or losses do not affect people's subjective evaluations in linear terms (see also **prospect theory** and **"Zero price effect"**) (Tversky & Kahneman, 1981). For example, a move from a 50% to a 60% chance of winning a prize has a smaller emotional impact than a move from a 95% chance to a 100% chance (certainty). Conversely, the move from a 0% chance to a 5% possibility of winning a prize is more attractive than a change from 5% to 10%. People over-weight small probabilities, which explains the attractiveness of gambling. Research suggests that problem gamblers' probability perception of losing is not distorted and that their **loss aversion** is not significantly different from other people. However, they are much more risk-taking and strongly overweight small to medium probabilities of winning (Ring et al., 2018).

Choice architecture

This term coined by Thaler and Sunstein (2008) refers to the practice of influencing choice by "organizing the context in which people make decisions" (Thaler et al., 2013, p. 428; see also **nudge**). A frequently mentioned example is how food is displayed in cafeterias, where offering healthy food at the beginning of the line or at eye level can contribute to healthier choices. Choice architecture includes many other behavioral tools that affect de-

cisions, such as **defaults**, **framing**, or **decoy** options.

Choice overload

Also referred to as 'overchoice', the phenomenon of choice overload occurs as a result of too many choices being available to consumers. Overchoice has been associated with unhappiness (Schwartz, 2004), **decision fatigue**, going with the **default** option, as well as choice deferral—avoiding making a decision altogether, such as not buying a product (Iyengar & Lepper, 2000). Many different factors may contribute to perceived choice overload, including the number of options and attributes, time constraints, decision accountability, alignability and complementarity of options, consumers' preference uncertainty, among other factors (Chernev et al., 2015).

Choice overload can be counteracted by simplifying choice attributes or the number of available options (Johnson et al., 2012). However, some studies on consumer products suggest that, paradoxically, greater choice should be offered in product domains in which people tend to feel ignorant (e.g. wine), whereas less choice should be provided in domains in which people tend to feel knowledgeable (e.g. soft drinks) (Hadar & Sood, 2014).

Chunking

When the same information is presented in a different form that is easier to process, our ability to receive and remember it is greater. People often reorganize, regroup or compress information to aid in its understanding or recall. The resulting subgroups are 'chunks', which can be defined as a set of information or items that are treated collectively as a single unit (Mathy & Feldman, 2012). Chunking may be done through strategic reorganization based on familiarity, prior knowledge, proximity or other means to structure the information at hand. For example, a phone number may be split up into three subgroups of area code, prefix and number or one might recognize a meaningful date in it, and so can organize it more easily into different chunks.

In relation to the ideal amount of chunks, Miller (1956) found that humans best recall seven plus or minus two units when processing information. More recently, various studies have shown that chunking is, in fact, most effective when four to six chunks are created (Mathy & Feldman, 2012). Although this seems to be a 'magic number', it is also possible to learn to increase the size of those chunks over time (Sullivan, 2009).

In behavioral science, chunking has also been used to refer to breaking up processes or tasks into more manageable pieces (see for example Eşanu, 2019, on chunking in UX design or Wijland & Hansen, 2016, on mobile nudging in the banking sector).

Cognitive bias

A cognitive bias (e.g. Ariely, 2008) is a systematic (non-random) error in thinking, in the sense that a judgment deviates from what would be considered desirable from the perspective of accepted norms or correct in terms of formal logic. The application of **heuristics** is often associated with cognitive biases. Some biases, such as those arising from **availability** or **representativeness**, are 'cold' in the sense that they do not reflect a person's motivation and are instead the result of errors in information processing. Other cognitive biases, especially those that have a self-serving function (e.g. **overconfidence**), are more motivated. Finally, there are also biases that can be motivated or unmotivated, such as **confirmation bias** (Nickerson, 1998).

As the study of heuristics and biases is a core element of behavioral economics, the psychologist Gerd Gigerenzer has cautioned against the trap of a "bias bias" – the tendency to see biases even when there are none (Gigerenzer, 2018).

Cognitive dissonance

Cognitive dissonance, an important concept in social psychology (Festinger, 1957), refers to the uncomfortable tension that can exist between two simultaneous and conflicting ideas or feelings—often as a person realizes that s/he has engaged in a behavior inconsistent with the type of person s/he would like to be, or be seen publicly to be. According to the theory, people are motivated to reduce this tension by changing their attitudes, beliefs, or actions. For example, smokers may rationalize their behavior by holding 'self-exempting beliefs', such as "The medical evidence that smoking causes cancer is not convincing" or "Many people who smoke all their lives live to a ripe old age, so smoking is not all that bad for you" (Chapman et al., 1993).

Arousing dissonance can be used to achieve behavioral change; one study (Dickerson et al., 1992), for instance, made people mindful of their wasteful water consumption and then made them urge others (publicly **commit**) to take shorter showers. Subjects in this 'hypocrisy condition' subsequently took significantly shorter showers than those who were only reminded that they had wasted water or merely made the public commitment.

Commitment

Commitments (see also **precommitment**) are often used as a tool to counteract people's lack of willpower and to achieve behavior change, such as in the areas of dieting or saving. The greater the cost of breaking a commitment, the more effective it is (Dolan et al., 2010). From the perspective of social psychology, individuals are motivated to maintain a consistent and positive self-image (Cialdini, 2008), and they are likely to keep commitments to avoid reputational damage (if done publicly) and/or **cognitive dissonance** (Festinger, 1957). A field experiment in a hotel, for example, found 25% greater towel reuse among guests who made a commitment to reuse towels at check-in and wore a "Friend of the Earth" lapel pin to signal their commitment during their stay (Baca-Motes et al., 2012). The behavior change technique of 'goal setting' is related to making commitments (Strecher et al., 1995), while **reciprocity** involves an implicit commitment.

Confirmation bias

Confirmation bias (Wason, 1960) occurs when people seek out or evaluate information in a way that fits with their existing thinking and preconceptions. The domain of science, where theories should advance based on both falsifying and supporting evidence, has not been immune to bias, which is often associated with people processing hypotheses in ways that end up confirming them (Oswald & Grosjean, 2004). Similarly, a consumer who likes a particular brand and researches a new purchase may be motivated to seek out customer reviews on the internet that favor that brand. Confirmation bias has also been related to unmotivated processes, including primacy effects and **anchoring**, evident in a reliance on information that is encountered early in a process (Nickerson, 1998).

Control premium

In behavioral economics, the control premium refers to people's willingness to forego potential rewards in order to control (avoid delegation) of their own payoffs. In an experiment, participants were asked to choose whether to bet on another person or themselves answering a quiz question correctly. Although individuals' maximizing their rewards would bet on themselves in 56% of the decisions (based on their beliefs), they actually bet on themselves 65% of the time, suggesting an aggregate control premium of almost 10%. The average study participant was willing to sacrifice between 8 and 15% of expected earnings to retain control (Owens et al., 2014). (See also **overconfidence**.)

Curse of knowledge

Economists commonly assume that having more information allows us to make better decisions. However, the information asymmetry that exists when one economic agent has more information than another can also have negative effects for the better-informed agent. This is known as the curse of knowledge (Camerer et al., 1989), which occurs because better-informed agents are unable to ignore their own knowledge.

The curse of knowledge can manifest itself in many domains of economic life, such as setting prices or estimating productivity. With respect to the latter, one study found that experts consistently underestimate the amount of time required by novices to perform a task (Hinds, 1999).

A fun way to show the curse of knowledge in action is through a musical game in which participants are either the "tapper" or a "listener." In the game, the tapper selects a simple, well-known song, such a "Happy Birthday," and taps out the rhythm on a table. The listeners then try to guess the song. In an early experiment, tappers expected the listeners to correctly guess the song 50% of the time, yet, in reality, listeners were only correct 2.5% of the time (Newton, 1990).

D

Decision fatigue

There are psychological costs to making decisions. Since choosing can be difficult and requires effort, just like any other activity, long sessions of decision making can lead to poor choices. Similar to other activities that consume resources required for executive functions, decision fatigue is reflected in self-regulation, such as a diminished ability to exercise self-control (Vohs et al., 2008). (See also **choice overload** and **ego depletion**.)

Decision staging

When people make complex or long decisions, such as buying a car, they tend to explore their options successively. This involves deciding what information to focus on, as well as choices between attributes and alternatives. For example, when people narrow down their options, they often tend to screen alternatives on the basis of a subset of attributes, and then they compare alternatives. **Choice architects** may not only break down complex decisions into multiple stages, to make the process easier, but they can also work with an understanding of sequential decision making by facilitating certain comparisons at different stages of the choice process (Johnson et al., 2012).

Decoy effect

Choices often occur relative to what is on offer rather than based on absolute **preferences**. The decoy effect is technically known as an 'asymmetrically dominated choice' and occurs when people's preference for one option over another changes as a result of adding a third (similar but less attractive) option. For example, people are more likely to choose an elegant pen over $6 in cash if there is a third option in the form of a less elegant pen (Bateman et al., 2008). While this effect has been extensively studied in relation to consumer products, it has also been found in employee selection (e.g. Slaughter et al., 2006), apartment choices (Simonson, 1989), or as a nudge to increase cancer screening (Stoffel et al., 2019).

Default (option)

Default options are pre-set courses of action that take effect if nothing is specified by the decision maker (Thaler & Sunstein, 2008), and setting defaults is an effective **nudge** when there is **inertia** or uncertainty in decision making (Samson, 2014). Since defaults do not require any effort by the decision maker, defaults can be a simple but powerful tool when there is inaction (Samson & Ramani, 2018). When choices are difficult, defaults may also be perceived as a recommended course of action (McKenzie et al., 2006). Requiring people to opt out if they do not wish to donate their organs, for example, has been associated with higher donation rates (Johnson & Goldstein, 2003). Similarly, making contributions to retirement savings accounts has become automatic in some countries, such as the United Kingdom and the United States.

Delusion of competence (Dunning-Kruger effect)

This is the case whereby, either socially or pathologically, a person lacks reflexive acknowledgement that they are not equipped to make a decision or to act appropriately in relation to the demands of a situation. Kruger and Dunning (1999) observed a divergence between perceived and actual competence which explains a range of unsound decision-making. The effect explains why, among other real-world difficulties, management boards decide to promote products whose working they don't understand, and why talent show contestants are unaware of their inability to sing, until ejected by the judges. (The prevalence of this bias has made the producers of certain talent shows very wealthy.)

Dictator game

The dictator game is an experimental game (see **behavioral game theory**) designed to elicit **altruistic** aspects of behavior. In the **ultimatum game**, a proposing player is endowed with a sum of money and asked to split it with another (responding) player. The responder may either accept the proposer's offer or reject it, in which case neither of the players

will receive anything. Since expressed preferences in the ultimatum game may be due to factors other than altruism (e.g. fear of envy), the dictator game is played without the responder being able to decide whether to accept the offer or not (Camerer, 2003). As a result, it only involves one actual player and is not strictly a game. Whether or not these games really better measure altruism, or something else, forms part of an interesting debate (e.g. Bardsley, 2008) (See also **trust game**.)

Discounting

See **Time discounting**

Disposition effect

The disposition effect refers to investors' reluctance to sell assets that have lost value and greater likelihood of selling assets that have made gains (Shefrin & Statman, 1985). This phenomenon can be explained by **prospect theory** (**loss aversion**), **regret avoidance** and **mental accounting**.

Diversification bias

People seek more variety when they choose multiple items for future consumption simultaneously than when they make choices sequentially, i.e. on an 'in the moment' basis. Diversification is non-optimal when people overestimate their need for diversity (Read & Loewenstein, 1995). In other words, sequential choices lead to greater experienced **utility**. For example, before going on vacation I may upload classical, rock and pop music to my MP3 player, but on the actual trip I may mostly end up listening to my favorite rock music. When people make simultaneous choices among things that can be classified as virtues (e.g. high-brow movies or healthy deserts) or vices (e.g. low-brow movies or hedonic deserts), their diversification strategy usually involves a greater selection of virtues (Read et al., 1999). (See also **projection bias**.)

Dual-self model

In economics, dual-self models deal with the inconsistency between the patient long-run self and myopic short-run self. With respect to savings behavior, Thaler and Shefrin (1981) introduced the concepts of the farsighted planner and myopic doer. At any point in time, there is a conflict between those selves with two sets of **preferences**. The approach helps economic theorists overcome the paradox created by self-control in standard views of **utility**. The more recent dual-self model of impulse control (Fudenberg & Levine, 2006) explains findings from the areas of time discounting, risk aversion, and self-control (see also **intertemporal choice**). More practically-oriented research on savings behavior has attempted to make people feel more connected to their future selves, making them appreciate that they are the future recipients of current savings. In an experiment, participants who were exposed to their future (as opposed to present) self in the form of an age-progressed avatar in virtual reality environments allocated twice as much money to a retirement account (Hershfield et al., 2011).

Dual-system theory

Dual-system models of the human mind contrast automatic, fast, and non-conscious (System 1) with controlled, slow, and conscious (System 2) thinking (see Strack & Deutsch, 2015, for an extensive review). Many **heuristics** and **cognitive biases** studied by behavioral economists are the result of intuitions, impressions, or automatic thoughts generated by System 1 (Kahneman, 2011). Factors that make System 1's processes more dominant in decision making include cognitive busyness, distraction, time pressure, and positive mood, while System 2's processes tend to be enhanced when the decision involves an important object, has heightened personal relevance, and when the decision maker is held accountable by others (Samson & Voyer, 2012; Samson & Voyer, 2014).

E

Efficient market hypothesis

According to the efficient market hypothesis, the price (market value) of a security reflects its true worth (intrinsic value). In a market with perfectly rational agents, "prices are right". Findings in behavioral finance, by contrast, suggests that asset prices also reflect the trading behavior of individuals who are not fully rational (Barberis & Thaler, 2003), leading to anomalies such as asset **bubbles**.

Ego depletion

Ego depletion is a concept emanating from self-regulation (or self-control) theory in psychology. According to the theory, willpower operates like a muscle that can be exercised or exerted. Studies have found that tasks requiring self-control can weaken this muscle, leading to ego depletion and a subsequently diminished ability to exercise self-control. In the lab, ego depletion has been induced in many different ways, such as having to suppress emotions or thoughts, or having to make a range of difficult decisions. The resulting ego depletion leads people to make less restrained decisions; consumers, for example, may be more likely to choose candy over 'healthy' granola bars (Baumeister et al., 2008). Some studies now suggest that the evidence for this resource depletion model of self-control has been overestimated (e.g. Hagger & Chatzisarantis, 2016).

Elimination-by-aspects

Decision makers have a variety of **heuristics** at their disposal when they make choices. One of these effort-reducing heuristics is referred to as 'elimination-by-aspects'. When it is applied, decision makers gradually reduce the number of alternatives in a choice set, starting with the aspect that they see as most significant. One cue is evaluated at a time until fewer and fewer alternatives remain in the set of available options (Tversky, 1972). For example, a traveler may first compare a selection of hotels at a target destination on the basis of classification, eliminating all hotels with fewer than three stars. The person may then reduce the choice set further by walking distance from the beach, followed by guest reviews, etc., until only one option remains.

(Hot-cold) Empathy gap

It is difficult for humans to predict how they will behave in the future. A hot-cold empathy gap occurs when people underestimate the influence of visceral states (e.g. being angry, in pain, or hungry) on their behavior or preferences (Loewenstein, 2005). In medical decision making, for example, a hot-to-cold empathy gap may lead to undesirable treatment choices when cancer patients are asked to choose between treatment options right after being told about their diagnosis.

In a study on the reverse, a cold-to-hot empathy gap, smokers were assigned to different experimental conditions (Sayette et al., 2008). Some smokers in a hot (craving) state were asked to make predictions about a high-craving state in a second session. Others made the same prediction while they were in a cold state. In contrast to those in the hot group, smokers in the cold group underpredicted how much they would value smoking during the second session. This empathy gap can explain poor decisions among smokers attempting to quit that place them in high-risk situations (e.g. socializing over a drink) and why people underestimate their risk of becoming addicted in the first place.

Endowment effect

This bias occurs when we overvalue a good that we own, regardless of its objective market value (Kahneman et al., 1991). It is evident when people become relatively reluctant to part with a good they own for its cash equivalent, or if the amount that people are **willing to pay** for the good is lower than what they are **willing to accept** when selling the good. Put more simply, people place a greater value on things once they have established ownership. This is especially true for goods that wouldn't normally be bought or sold on the market, usually items with symbolic, experiential, or emotional significance. Endowment effect research has been conducted with goods ranging from coffee mugs

(Kahneman et al., 1990) to sports cards (List, 2011). While researchers have proposed different reasons for the effect, it may be best explained by psychological factors related to **loss aversion** (Ericson & Fuster, 2014).

Extrapolation bias

See **Representativeness heuristic**

F

Fairness

In behavioral science, fairness refers to our **social preference** for equitable outcomes. This can present itself as **inequity aversion**, people's tendency to dislike unequal payoffs in their own or someone else's favor. This tendency has been documented through experimental games, such as the **ultimatum**, **dictator**, and **trust games** (Fehr & Schmidt, 1999).

A large part of fairness research in economics has focused on prices and wages. With respect to prices, for example, consumers are generally less accepting of price increases as result of a short term growth in demand than rise in costs (Kahneman et al., 1986). With respect to wages, employers often agree to pay more than the minimum the employees would accept in the hope that this fairness will be **reciprocated** (e.g. Jolls, 2002). On the flip side, perceived unfairness, such as excessive CEO compensation, has been behaviorally associated with reduced work morale among employees (Cornelissen et al., 2011).

Fast and frugal

Fast and frugal decision-making refers to the application of ecologically rational **heuristics**, such as the recognition heuristic, which are rooted in the psychological capacities that we have evolved as human animals (e.g. memory and perceptual systems). They are 'fast and frugal' because they are effective under conditions of **bounded rationality**—when knowledge, time, and computational power are limited (Goldstein & Gigerenzer, 2002).

Fear of missing out

Social media has enabled us to connect and interact with others, but the number of options offered to us through these channels is far greater than what we can realistically take up, due to limited time and practical constraints. The popular concept of FoMO, or Fear of Missing Out, refers to "a pervasive apprehension that others might be having rewarding experiences from which one is absent" (Przybylski et al., 2013). People suffering from FoMO have a strong desire to stay continually informed about what others are doing (see also **scarcity heuristic**, **regret aversion**, and **loss aversion**).

Framing effect

Choices can be presented in a way that highlights the positive or negative aspects of the same decision, leading to changes in their relative attractiveness. This technique was part of Tversky and Kahneman's development of **prospect theory**, which framed gambles in terms of losses or gains (Kahneman & Tversky, 1979a). Different types of framing approaches have been identified, including risky choice framing (e.g. the risk of losing 10 out of 100 lives vs. the opportunity to save 90 out of 100 lives), attribute framing (e.g. beef that is described as 95% lean vs. 5% fat), and goal framing (e.g. motivating people by offering a $5 reward vs. imposing a $5 penalty) (Levin et al., 1998).

The concept of framing also has a long history in political communication, where it refers to the informational emphasis a communicator chooses to place in a particular message. In this domain, research has considered how framing affects public opinions of political candidates, policies, or broader issues (Busby et al., 2018).

G

Gambler's fallacy

The term 'gambler's fallacy' refers to the mistaken belief held by some people that independent events are interrelated; for example, a roulette or lottery player may choose not to bet on a number that came up in the previous round. Even though people are usually aware that successive draws of numbers are unrelated, their gut feeling may tell them otherwise (Rogers, 1998).

(Behavioral) Game theory

Game theory is a mathematical approach to modeling behavior by analyzing the strategic decisions made by interacting players (Nash, 1950). In standard experimental economics, the theory assumes *homo economicus* – a self-interested, rational maximizer. Behavioral game theory extends standard (analytical) game theory by taking into account how players feel about the payoffs other players receive, limits in strategic thinking, the influence of context, as well as the effects of learning (Camerer, 2003). Games are usually about cooperation or **fairness**. Well-known examples include the **ultimatum game**, **dictator game** and **trust game**.

H

Habit

Habit is an automatic and rigid pattern of behavior in specific situations, which is usually acquired through repetition and develops through associative learning (see also System 1 in **dual-system theory**), when actions become paired repeatedly with a context or an event (Dolan et al., 2010). 'Habit loops' involve a cue that triggers an action, the actual behavior, and a reward. For example, habitual drinkers may come home after work (the cue), drink a beer (the behavior), and feel relaxed (the reward) (Duhigg, 2012). Behaviors may initially serve to attain a particular goal, but once the action is automatic and habitual, the goal loses its importance. For example, popcorn may habitually be eaten in the cinema despite the fact that it is stale (Wood & Neal, 2009). Habits can also be associated with **status quo bias**.

Halo effect

This concept has been developed in social psychology and refers to the finding that a global evaluation of a person sometimes influences people's perception of that person's other unrelated attributes. For example, a friendly person may be considered to have a nice physical appearance, whereas a cold person may be evaluated as less appealing (Nisbett & Wilson, 1977). Halo effects have also been applied in other domains of psychology. For example, a study on the 'health halo' found that consumers tend to choose drinks, side dishes and desserts with higher calorific content at fast-food restaurants that claim to be healthy (e.g. Subway) compared to others (e.g. McDonald's) (Chandon & Wansink, 2007).

Hedonic adaptation

People get used to changes in life experiences, a process which is referred to as 'hedonic adaptation' or the 'hedonic treadmill'. Just as the happiness that comes with the ownership of a new gadget or salary raise will wane over time, even the negative effect of life events such as bereavement or disability on subjective wellbeing tends to level off, to some extent (Frederick & Loewenstein, 1999). When this happens, people return to a relatively stable baseline of happiness. It has been suggested that the repetition of smaller positive experiences ('hedonic boosts'), such as exercise or religious practices, has a more lasting effect on our wellbeing than major

life events (Mochon et al., 2008).

Herd behavior

This effect is evident when people do what others are doing instead of using their own information or making independent decisions. The idea of herding has a long history in philosophy and crowd psychology. It is particularly relevant in the domain of finance, where it has been discussed in relation to the collective irrationality of investors, including stock market **bubbles** (Banerjee, 1992). In other areas of decision-making, such as politics, science, and popular culture, herd behavior is sometimes referred to as 'information cascades' (Bikhchandi et al., 1992). Herding behavior can be increased by various factors, such as fear (e.g. Economou et al., 2018), uncertainty (e.g. Lin, 2018), or a shared identity of decision makers (e.g. Berger et al., 2018).

Heuristic

Heuristics are commonly defined as cognitive shortcuts or rules of thumb that simplify decisions, especially under conditions of uncertainty. They represent a process of substituting a difficult question with an easier one (Kahneman, 2003). Heuristics can also lead to **cognitive biases**. There are disagreements regarding heuristics with respect to bias and rationality. In the **fast and frugal** view, the application of heuristics (e.g. the recognition heuristic) is an "ecologically rational" strategy that makes best use of the limited information available to individuals (Goldstein & Gigerenzer, 2002).

There are generally different classes of heuristics, depending on their scope. Some heuristics, such as **affect**, **"Availability heuristic"**and **representativeness** have a general purpose character; others developed in social and consumer psychology are more domain-specific, examples of which include brand name, price, and **scarcity** heuristics (Shah & Oppenheimer, 2008).

Hindsight bias

This bias, also referred to as the 'knew-it-all-along effect', is a frequently encountered judgment bias that is partly rooted in **availability** and **representativeness** heuristics. It happens when being given new information changes our recollection from an original thought to something different (Mazzoni & Vannucci, 2007). This bias can lead to distorted judgments about the probability of an event's occurrence, because the outcome of an event is perceived as if it had been predictable. It may also lead to distorted memory for judgments of factual knowledge. Hindsight bias can be a problem in legal decision-making. In medical malpractice suits, for example, jurors' hindsight bias tends to increase with the severity of the outcome (e.g. injury or death) (Harley, 2007).

Homo economicus

The term *homo economicus*, or 'economic man', denotes a view of humans in the social sciences, particularly economics, as self-interested agents who seek optimal, utility-maximizing outcomes. Behavioral economists and most psychologists, sociologists, and anthropologists are critical of the concept. People are not always self-interested (see **social preferences**), nor are they mainly concerned about maximizing benefits and minimizing costs. We often make decisions under uncertainty with insufficient knowledge, feedback, and processing capability (**bounded rationality**); we sometimes lack **self-control**; and our preferences change, often in response to changes in decision contexts.

Honesty

Honesty is an important part of our everyday life. In both business and our private lives, relationships are made and broken based on our **trust** in the other party's honesty and **reciprocity**.

A 2016 study investigated honesty, beliefs about honesty and economic growth in 15 countries and revealed large cross-national differences. Results showed that average honesty was positively associated with GDP per capita, suggesting a relationship between honesty and economic development. However, expectations about countries' levels of honesty were not correlated with reality (the actual honesty in reporting the results of a coin flip experiment), but rather driven by **cognitive biases** (Hugh-Jones, 2016).

People typically value honesty, tend to have strong beliefs in their morality and want to maintain this aspect of their self-concept (Mazar et al., 2008). Self-interest may conflict with people's honesty as an internalized **social norm**, but the resulting

cognitive dissonance can be overcome by engaging in self-deception, creating moral "wiggle room" that enables people to act in a self-serving manner. When moral reminders are used, however, this self-deception can be reduced, as demonstrated in laboratory experiments conducted by Mazar and colleagues (2008). It is not surprising, then, that a lack of social norms is a general driver of dishonest behavior, along with high benefits and low costs of external deception, a lack of self-awareness, as well as self-deception (Mazar & Ariely, 2006).

Honesty must also be understood in the context of group membership. Employees of a large international bank, for example, behaved honestly on average in an experiment's control condition, but when their professional identity as bankers was rendered salient, a significant proportion of them became dishonest. This suggests that the prevailing business culture in the banking industry weakens and undermines the honesty norm (Cohn et al., 2014) (see also identity economics).

Hot and cold states

See Empathy gap

Hyperbolic discounting

See Time discounting

I

Identity economics

Identity economics describes the idea that we make economic choices based on monetary incentives and our identity. A person's sense of self or identity affects economic outcomes. This was outlined in Akerlof and Kranton's (2000) seminal paper which expanded the standard utility function to include pecuniary payoffs and identity economics in a simple game-theoretic model of behavior, further integrating psychology and sociology into economic thinking.

When economic (or other extrinsic) incentives are ineffective in organizations, identity may be the answer: A worker's self-image as jobholder and her ideal as to how his job should be done, can be a major incentive in itself (Akerlof & Kranton, 2005). Organizational identification was found to be directly related to employee performance and even indirectly related with customer evaluations and store performance in a study on 306 retail stores, for example (Lichtenstein et al., 2010). Also, when employees were encouraged to create their own job titles such that they better reflected the unique value they bring to the job, identification increased, and emotional exhaustion was reduced (Grant et al., 2014). In some cases, identity can also have negative implications. Bankers whose professional identity was made salient, for example, displayed more dishonest behavior (see honesty).

IKEA effect

While the endowment effect suggests that mere ownership of a product increases its value to individuals, the IKEA effect is evident when invested labor leads to inflated product valuation (Norton et al., 2012). For example, experiments show that the monetary value assigned to the amateur creations of self-made goods is on a par with the value assigned to expert creations. Both experienced and novice do-it-yourselfers are susceptible to the IKEA effect. Research also demonstrates that the effect is not simply due to the amount of time spent on the creations, as dismantling a previously built product will make the effect disappear.

The IKEA effect is particularly relevant today, given the shift from mass production to increasing customization and co-production of value. The effect has a range of possible explanations, such as positive feelings (including feelings of competence) that come with the successful completion of a task, a focus on the product's positive attributes, and the relationship between effort and liking (Norton et al., 2012), a link between our creations and our self-concept (Marsh et al., 2018), as well as a psychological sense of ownership (Sarstedt et al., 2017. The effort heuristic is another concept that pro-

poses a link between perceived effort and valuation (Kruger et al., 2004).

Incentives

An incentive is something that motivates an individual to perform an action. It is therefore essential to the study of any economic activity. Incentives, whether they are intrinsic or extrinsic (traditional), can be effective in encouraging behavior change, such as ceasing to smoke, doing more exercise, complying with tax laws or increasing public good contributions. Traditional incentives can effectively encourage behavior change, as they can help to both create desirable and break undesirable **habits**. Providing upfront incentives can help the problem of **present bias** – people's focus on immediate gratification. Finally, incentives can help people overcome barriers to behavior change (Gneezy et al., 2019).

Traditionally, the importance of intrinsic incentives was underestimated, and the focus was put on monetary ones. Monetary incentives may backfire and reduce the performance of agents or their compliance with rules (see also **over-justification effect**), especially when motives such as the desire to **reciprocate** or the desire to avoid social disapproval (see **social norms**) are neglected. These intrinsic motives often help to understand changes in behavior (Fehr & Falk, 2002).

In the context of prosocial behavior, extrinsic incentives may spoil the reputational value of good deeds, as people may be perceived to have performed the task for the incentives rather than for themselves (Bénabou & Tirole, 2006). Similarly, performance incentives offered by an informed principal (manager, teacher or parent) can adversely impact an agent's (worker, student or child) perception of a task or of his own abilities, serving as only weak reinforcers in the short run and negative reinforcers in the long run (Bénabou & Tirole, 2003). (For an interesting summary of when extrinsic incentives work and when they don't in nonemployment contexts, see Gneezy et al., 2011).

Inequity aversion

Human resistance to "unfair" outcomes is known as 'inequity aversion', which occurs when people prefer **fairness** and resist inequalities (Fehr & Schmidt, 1999). In some instances, inequity aversion is disadvantageous, as people are willing to forego a gain in order to prevent another person from receiving a superior reward. Inequity aversion has been studied through **experimental games**, particularly **dictator**, **ultimatum**, and **trust games**. The concept has been applied in various domains, including business and marketing, such as research on customer responses to exclusive price promotions (Barone & Tirthankar, 2010) and "pay what you want" pricing (e.g. Regner, 2015).

Inertia

In behavioral economics, inertia is the endurance of a stable state associated with inaction and the concept of **status quo bias** (Madrian & Shea 2001). Behavioral **nudges** can either work *with* people's decision inertia (e.g. by setting **defaults**) or *against* it (e.g. by giving warnings) (Jung, 2019). In social psychology the term is sometimes also used in relation to persistence in (or **commitments** to) attitudes and relationships.

Information avoidance

Information avoidance in behavioral economics (Golman et al., 2017) refers to situations in which people choose not to obtain knowledge that is freely available. Active information avoidance includes physical avoidance, inattention, the biased interpretation of information (see also **confirmation bias**) and even some forms of forgetting. In behavioral finance, for example, research has shown that investors are less likely to check their portfolio online when the stock market is down than when it is up, which has been termed the ostrich effect (Karlsson et al., 2009). More serious cases of avoidance happen when people fail to return to clinics to get medical test results, for instance (Sullivan et al., 2004).

While information avoidance is sometimes strategic, it usually has immediate hedonic benefits for people if it prevents the negative (usually psychological) consequences of knowing the information. It usually carries negative utility in the long term, because it deprives people of potentially useful information for decision making and feedback for future behavior. Furthermore, information avoidance can contribute to a polarization of political opinions and media bias.

Intertemporal choice

Intertemporal choice is a field of research concerned with the relative value people assign to payoffs at different points in time. It generally finds that people are biased towards the present (see **present bias**) and tend to discount the future (see **time discounting** and **dual-self model**).

L

Less-is-better effect

When objects are evaluated separately rather than jointly, decision makers focus less on attributes that are important and are influenced more by attributes that are easy to evaluate. The less-is-better effect suggests a preference reversal when objects are considered together instead of separately. One study presented participants with two dinner set options. Option A included 40 pieces, nine of which were broken. Option B included 24 pieces, all of which were intact. Option A was superior, as it included 31 intact pieces, but when evaluated separately, individuals were willing to pay a higher price for set B. In a joint evaluation of both options, on the other hand, Option A resulted in higher willingness to pay (Hsee, 1998).

Licensing effect

Also known as 'self-licensing' or 'moral licensing', the licensing effect is evident when people allow themselves to do something bad (e.g. immoral) after doing something good (e.g. moral) first (Merritt et al., 2010). The effect of licencing has been studied for different behavioral outcomes, including donations, cooperation, racial discrimination, and cheating (Blanken et al., 2015). Well-publicized research in Canada asked participants to shop either in a green or a conventional online store. In one experiment, people who shopped in a green store shared less money in a **dictator game**. Another experiment allowed participants to lie (about their performance on a task) and cheat (take more money out of an envelope than they actually earned) and showed more **dishonesty** among green shoppers (Mazar & Zhong, 2010).

Loss aversion

Loss aversion is an important concept associated with **prospect theory** and is encapsulated in the expression "losses loom larger than gains" (Kahneman & Tversky, 1979a). It is thought that the pain of losing is psychologically about twice as powerful as the pleasure of gaining. People are more willing to take risks (or behave **dishonestly**, e.g. Schindler & Pfattheicher, 2016) to avoid a loss than to make a gain. Loss aversion has been used to explain the **endowment effect** and **sunk cost fallacy**, and it may also play a role in the **status quo bias**.

The basic principle of loss aversion can explain why penalty **frames** are sometimes more effective than reward frames in motivating people (Gächter et al., 2009) and has been applied in behavior change strategies. The website Stickk, for example, allows people to publicly **commit** to a positive behavior change (e.g. give up junk food), which may be coupled with the fear of loss—a cash penalty in the case of non-compliance. (See also **myopic loss aversion** and **regret aversion.**)

People's cultural background may influence the extent to which they are averse to losses (e.g. Wang et al., 2017)

M

Mental accounting

Mental accounting is a concept associated with the work of Richard Thaler (see Thaler, 2015, for a summary). According to Thaler, people think of value in relative rather than absolute terms. For example, they derive pleasure not just from an object's value, but also the quality of the deal—its transaction **utility** (Thaler, 1985). In addition, humans often fail to fully consider opportunity costs (tradeoffs) and are susceptible to the **sunk cost fallacy**.

Why are people willing to spend more when they pay with a credit card than cash (Prelec & Simester, 2001)? Why would more individuals spend $10 on a theater ticket if they had just lost a $10 bill than if they had to replace a lost ticket worth $10 (Kahneman & Tversky, 1984)? Why are people more likely to spend a small inheritance and invest a large one (Thaler, 1985)?

According to the theory of mental accounting, people treat money differently, depending on factors such as the money's origin and intended use, rather than thinking of it in terms of the "bottom line" as in formal accounting (Thaler, 1999). An important term underlying the theory is fungibility, the fact that all money is interchangable and has no labels. In mental accounting, people treat assets as less fungible than they really are. Even seasoned investors are susceptible to this bias when they view recent gains as disposable "house money" (Thaler & Johnson, 1990) that can be used in high-risk investments. In doing so, they make decisions on each mental account separately, losing out the big picture of the portfolio. (See also **partitioning** and **pain of paying** for ideas related to mental accounting.)

Consumers' tendency to work with mental accounts is reflected in various domains of applied behavioral science, especially in the financial services industry. Examples include banks offering multiple accounts with savings goal labels, which make mental accounting more explicit, as well as third-party services that provide consumers with aggregate financial information across different financial institutions (Zhang & Sussman, 2018).

Mindless eating

Various cues non-consciously affect the amount and quality of people's consumption of food. Cues often serve as benchmarks in the environment, and they may include serving containers, packaging, people, labels, and atmospheric factors. They suggest to the consumer what and how much is normal, appropriate, typical, or reasonable to consume. Perceptual biases contribute to a distorted sense of consumption; for example, people underestimate calories in larger servings and tend to serve themselves more when using larger utensils, plates, or bowls (Wansink et al., 2009).

Brian Wansink, the most prominent academic in behavioral food science, has faced allegations of scientific misconduct and several article retractions (Ducharme, 2018).

Money illusion

The term 'money illusion' has been coined by Irving Fisher (1928) and refers to people's tendency to think of monetary values in nominal rather than real terms. This usually occurs when we neglect to consider money's decrease in purchasing power as a result of inflation. Investors, for example, may focus on more salient nominal returns rather than real returns that also account for inflation (Shafir et al., 1997).

Myopic loss aversion

Myopic **loss aversion** occurs when investors take a view of their investments that is strongly focused on the short term, leading them to react too negatively to recent losses, which may be at the expense of long-term benefits (Thaler et al., 1997). This phenomenon is influenced by narrow framing, which is the result of investors considering specific investments (e.g. an individual stock or a trade) without taking into account the bigger picture (e.g. a portfolio as a whole or a sequence of trades over time) (Kahneman & Lovallo, 1993). A large-scale field experiment has shown that individuals who receive information about investment performance too frequently tend to underinvest in riskier assets,

losing out on the potential for better long-term gains (Larson et al., 2016).

N

Naive allocation

Decision researchers have found that people prefer to spread limited resources evenly across a set of possibilities (see also **1/N heuristic**). This can be referred to as 'naive allocation'. For example, consumers may invest equal amounts of money across different investment options regardless of their quality. Similarly, the **diversification bias** shows that consumers like to spread out consumption choices across a variety of goods. Research suggests that **choice architects** can work with these tendencies due to decision makers' partition dependence. For instance, by separating healthy food menu options into different menu categories (e.g. 'fruits', 'vegetables') and combining unhealthy options into one single menu category (e.g. 'candies and cookies'), one can steer consumers toward choosing more healthy options and fewer unhealthy options (Johnson et al., 2012).

Nudge

According to Thaler and Sunstein (2008, p. 6), a nudge is

> any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic **incentives**. To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates. Putting the fruit at eye level counts as a nudge. Banning junk food does not.

Perhaps the most frequently mentioned nudge is the setting of **defaults**, which are pre-set courses of action that take effect if nothing is specified by the decision-maker. This type of nudge, which works with a human tendency for inaction, appears to be particularly successful, as people may stick with a choice for many years (Gill, 2018).

On a cost-adjusted basis, the effectiveness of nudges is often greater than that of traditional approaches (Benartzi et al., 2017).

Questions about the theoretical and practical value of nudging have been explored (Kosters & Van der Heijden, 2015) with respect to their ability to produce lasting behavior change (Frey & Rogers, 2014), as well as their assumptions of irrationality and lack of agency (Gigerenzer, 2015). There may also be limits to nudging due to non-cognitive constraints and population differences, such as a lack of financial resources if nudges are designed to increase savings (Loibl et al., 2016). Limits in the application of nudges speak to the value of experimentation in order to test behavioral interventions prior to their implementation.

As a complementary approach that addresses the shortcomings of nudges, Hertwig and Grüne-Yanoff (2017) propose the concept of boosts, a decision-making aid that fosters people's competence to make informed choices. (See also **choice architecture**.)

1/N (heuristic)

1/N is a trade-off heuristic, one that assigns equal weights to all cues or alternatives (Gigerenzer & Gaissmaier, 2011). Under the 1/N rule, resources are allocated equally to each of N alternatives. For example, in the (one-shot) **ultimatum game**, participants most frequently split their money equally. Similarly, people often hedge their money in investments by allocating equal amounts to different options. 1/N is a form of **naive allocation** of resources.

O

Optimism bias

People tend to overestimate the probability of positive events and underestimate the probability of negative events happening to them in the future (Sharot, 2011). For example, we may underestimate our risk of getting cancer and overestimate our future success on the job market. A number of factors can explain unrealistic optimism, including perceived control and being in a good mood (Helweg-Larsen & Shepperd, 2001). (See also **overconfidence**.)

Ostrich effect

See **Information avoidance**

Overconfidence (effect)

The overconfidence effect is observed when people's subjective confidence in their own ability is greater than their objective (actual) performance. It is frequently measured by having experimental participants answer general knowledge test questions. They are then asked to rate how confident they are in their answers on a scale. Overconfidence is measured by calculating the score for a person's average confidence rating relative to the actual proportion of questions answered correctly.

A big range of issues have been attributed to overconfidence more generally, including the high rates of entrepreneurs who enter a market despite the low chances of success (Moore & Healy, 2008). Among investors, overconfidence has been associated with excessive risk-taking (e.g. Hirshleifer & Luo, 2001), concentrated portfolios (e.g. Odean, 1998) and overtrading (e.g. Grinblatt & Keloharju, 2009). The **planning fallacy** is another example of overconfidence, where people underestimate the length of time it will take them to complete a task, often ignoring past experience (Buehler et al., 1994). (See also **optimism bias**.)

Over-justification effect

This effect occurs when a person's intrinsic interest in a previously unrewarded activity decreases after they engage in that activity as a means to achieving an extrinsic goal (e.g. financial reward) (Deci et al., 1999). As a result, the number of hours worked by volunteers, for instance, may be negatively affected by small financial rewards (Frey & Goette, 1999) (see also **incentives**).

P

Pain of paying

People don't like to spend money. We experience pain of paying (Zellermayer, 1996), because we are **loss averse**. The pain of paying plays an important role in consumer self-regulation to keep spending in check (Prelec & Loewenstein, 1998). This pain is thought to be reduced in credit card purchases, because plastic is less tangible than cash, the depletion of resources (money) is less visible, and payment is deferred. Different personality types experience different levels of pain of paying, which can affect spending decisions. Tightwads, for instance, experience more of this pain than spendthrifts. As a result, tightwads are particularly sensitive to marketing contexts that make spending less painful (Rick, 2018). (See also **mental accounting**.)

Partition dependence

See **Naive allocation**

Partitioning

The rate of consumption can be decreased by physically partitioning resources into smaller units, for example cookies wrapped individually or money divided into several envelopes. When a resource is divided into smaller units (e.g. several packs of

chips), consumers encounter additional decision points—a psychological hurdle encouraging them to stop and think. In addition to the cost incurred when resources are used, opening a partitioned pool of resources incurs a psychological transgression cost, such as feelings of guilt (Cheema & Soman, 2008). Related research has found that separate mental payment accounts (i.e. envelopes with money) can disrupt a shopping momentum effect that may occur after an initial purchase (Dhar et al., 2007). (For related ideas, see also **mental accounting**).

Peak-end rule

According to the peak-end rule, our memory of past experience (pleasant or unpleasant) does not correspond to an average level of positive or negative feelings, but to the most extreme point and the end of the episode (Kahneman, 2000b). The rule developed from the finding that evaluations of a past episode seem to be determined by a weighted average of 'snapshots' of an experience, such as moments in a film, thus neglecting its actual duration (Fredrickson & Kahneman, 1993), as well research showing that people would prefer to repeat a painful experience if it is followed by a slightly less painful one (Kahneman et al., 1993). In terms of memories, remembered **utility** is more important than total utility (Kahneman, 2000a). People's memories of prototypical moments are related to the judgments made when people apply a **representativeness heuristic** (Kahneman, 2000b).

Planning fallacy

Originally proposed by Kahneman and Tversky (1979b), the planning fallacy is the tendency for individuals or teams to underestimate the time and resources it will take to complete a project. This error occurs when forecasters overestimate their ability and underestimate the possible risk associated with a project. Without proper training teams of individuals can exacerbate this phenomena causing projects to be based on the team's confidence rather than statistical projections.

One way to combat the planning fallacy is to use a method termed Reference Class Forecasting (Flyvbjerg et al., 2005; Kahneman & Tversky, 1979b). This method begins by creating a benchmark using data on similar projects. Then estimates are built based on variances from the benchmark, depending on variables related to the project at hand. For example, a construction company might estimate that building a house will take five weeks instead of the average reference class time of six weeks, because the team at hand is larger and more skilled than previous project teams. (See also **optimism bias**, **overconfidence**.)

Possibility effect

See **Certainty/possibility effects**

Precommitment

Humans need a continuous and consistent self-image (Cialdini, 2008). In an effort to align future behavior, being consistent is best achieved by making a **commitment**. Thus, precommitting to a goal is one of the most frequently applied behavioral devices to achieve positive change. Committing to a specific future action (e.g. staying healthy by going to the gym) at a particular time (e.g. at 7am on Mondays, Wednesdays and Fridays) tends to better motivate action while also reducing **procrastination** (Sunstein, 2014).

The 'Save More Tomorrow' program, aimed at helping employees save more money (Thaler & Benartzi, 2004), illustrates precommitment alongside other ideas from behavioral economics. The program also avoids the perception of **loss** that would be felt with a reduction in disposable income, because consumers commit to saving future increases in income. People's **inertia** makes it more likely that they will stick with the program, because they have to opt out to leave.

Preference

In economics, preferences are evident in theoretically optimal choices or real (behavioral) choices when people decide between alternatives. Preferences also imply an ordering of different options in terms of expected levels of happiness, gratification, **utility**, etc. (Arrow, 1958). Measurement of preferences may rely on **willingness to pay (WTP)** and **willingness to accept (WTA)**. Preferences are sometimes elicited in survey research, which may be associated with a range of problems, such as the hypothetical bias, when stated preferences are

different from those expressed in actual choices, or response effects, when subjects return the answer that they perceive the researcher 'expects'. Armin Falk and colleagues have developed cross-culturally valid survey questions that are good predictors of preferences in behavioral experiments. These include questions about risk taking (see **prospect theory**), **social preferences** (e.g. about **reciprocity**) and **time discounting** (Falk et al., 2012).

Preference reversal

Preference reversal (Lichtenstein & Slovic, 1973) refers to a change in the relative frequency by which one option is favored over another in behavioral experiments, as may be evident in the less-is-better effect or **ratio bias**, for example, or **framing effects** more generally. The preferred ordering of a pair of choices is often found to depend on how the choice is presented; this effect contradicts the predictions of rational choice theory. (See also **transitive/intransitive preferences**.)

Present bias

The present bias refers to the tendency of people to give stronger weight to payoffs that are closer to the present time when considering trade-offs between two future moments (O'Donoghue & Rabin, 1999). For example, a present-biased person might prefer to receive ten dollars today over receiving fifteen dollars tomorrow, but wouldn't mind waiting an extra day if the choice were for the same amounts one year from today versus one year and one day from today (see **time discounting**). The concept of present bias is often used more generally to describe impatience or immediate gratification in decision-making.

Primacy effect

See **Serial-position effect**

(Conceptual) Priming

Conceptual priming is a technique and process applied in psychology that engages people in a task or exposes them to stimuli. The prime consists of meanings (e.g. words) that activate associated memories (schema, stereotypes, attitudes, etc.). This process may then influence people's performance on a subsequent task (Tulving et al., 1982). For example, one study primed consumers with words representing either 'prestige' US retail brands (Tiffany, Neiman Marcus, and Nordstrom) or 'thrift' brands (Wal-Mart, Kmart, and Dollar Store). In an ostensibly unrelated task, participants primed with prestige names then gave higher preference ratings to prestige as opposed to thrift product options (Chartrand et al., 2008). Conceptual priming is different from processes that do not rely on activating meanings, such as perceptual priming (priming similar forms), the mere exposure effect (repeated exposure increases liking), affective priming (subliminal exposure to stimuli evokes positive or negative emotions) (Murphy & Zajonc, 1993), or the perception-behavior link (e.g. mimicry) (Chartrand & Bargh, 1999).

The technique of conceptual priming has become a promising approach in the field of economics, particularly in the study of the economic effects of social identity (see **identity economics**) and **social norms** (Cohn & Maréchal, 2016).

(Myopic) Procrastination

People often put off decisions, which may be due to **self-control** problems (leading to **present bias**), **inertia**, or the complexity of decision-making (see **choice overload**). Various **nudge** tools, such as **pre-commitment**, can be used to help individuals overcome procrastination. Choice architects can also help by providing a limited time window for action (see **scarcity heuristic**) or a focus on **satisficing** (Johnson et al., 2012).

Projection bias

In behavioral economics, projection bias refers to people's assumption that their own tastes or **preferences** will remain the same over time (Loewenstein et al., 2003). Both transient preferences in the short-term (e.g. due to hunger or weather conditions) and long-term changes in tastes can lead to this bias. For example, people may overestimate the positive impact of a career promotion due to an under-appreciation of **(hedonic) adaptation**, put above-optimal variety in their planning for future consumption (see **diversification bias**), or underestimate the future selling price of an item by not taking into account the **endowment effect**. Consumers' under-appreciation of **habit** formation (associated

	GAINS	LOSSES
HIGH PROBABILITY	95% chance to win $10,000	95% chance to lose $10,000
(Certainty Effect)	Fear of disappointment	Hope to avoid loss
	RISK-AVERSE	RISK-SEEKING
LOW PROBABILITY	5% chance to win $10,000	5% chance to lose $10,000
(Possibility Effect)	Hope of large gain	Fear of large loss
	RISK-SEEKING	RISK-AVERSE

Figure 1. Prospect Theory Quadrant

with higher consumption levels over time) may lead to projection bias in planning for the future, such as retirement savings.

Projection bias also affects choices in other settings, such as medical decisions (Loewenstein, 2005), gym attendance (Acland & Levy, 2015), catalog orders (Conlin et al., 2007), as well as car and housing markets (Busse et al., 2012).

Prospect theory

Prospect theory is a behavioral model that shows how people decide between alternatives that involve risk and uncertainty (e.g. % likelihood of gains or losses). It demonstrates that people think in terms of expected **utility** relative to a **reference** point (e.g. current wealth) rather than absolute outcomes. Prospect theory was developed by **framing** risky choices and indicates that people are **loss-averse**; since individuals dislike losses more than equivalent gains, they are more willing to take risks to avoid a loss. Due to the biased weighting of probabilities (see **certainty/possibility effects**) and loss aversion, the theory leads to the following pattern in relation to risk (Kahneman & Tversky, 1979a; Kahneman, 2011).

Prospect theory has been applied in diverse economic settings, such as consumption choice, labor supply, and insurance (Barberis, 2013).

R

Ratio bias

We find it harder to deal with proportions or ratios than with absolute numbers. For example, when asked to evaluate two movie rental plans with a contracted scale (e.g. 7 and 9 new movies per week for Plans A and B, respectively) as opposed to an equivalent offering with an expanded scale (364 and 468 movies per year, respectively), consumers favor the better plan (Plan B) more in the scale expansion than contraction condition (Burson et al., 2009). This is because our experiential system—unlike the rational system—encodes information as concrete representations, and absolute numbers are more concrete than ratios or percentages (Kirkpatrick & Epstein, 1992). (See also **framing**, **dual-system theory**, **affect heuristic**.)

Reciprocity

Reciprocity is a **social norm** that involves in-kind exchanges between people—responding to another's action with another equivalent action. It is usually positive (e.g. returning a favor), but it can

also be negative (e.g. punishing a negative action) (Fehr & Gächter, 2000). Reciprocity is of interest to behavioral economists because it does not involve an economic exchange, and it has been studied by means of experimental games (see **behavioral game theory**). Organizations often apply reciprocity norms in practice. Charities take advantage of reciprocity if they include small gifts in solicitation letters (e.g. Falk, 2007), while hospitals may ask former patients for donations (e.g. Chuan et al., 2018).

Reciprocity is also used as a social influence tool in the form of 'reciprocal concessions', an approach also known as the 'door-in-the-face' technique. It occurs when a person makes an initial large request (e.g. to buy an expensive product), followed up by a smaller request (e.g. a less expensive option), if the initial request is denied by the responder. The responder then feels obligated to 'return the favor' by agreeing to the conceded request (Cialdini et al., 1975).

Recency effect

See **Serial-position effect**

Recognition heuristic

While a core heuristic in the *heuristics and biases* tradition of Tversky and Kahneman is **availability**, a conceptually similar heuristic proposed in Gigerenzer's *fast and frugal* tradition is recognition. In the fast and frugal view, the application of heuristics is an "ecologically rational" strategy that makes best use of the limited information available to individuals (Goldstein & Gigerenzer, 2002). Recognition is an easily accessible cue that simplifies decision-making and indicates that sometimes less knowledge can lead to more accurate inferences. In one experiment, participants had to judge which one of two cities had the greater population size. Results showed that the vast majority of choices were based on recognition of the city name. What's more, the study indicated a less-is-more effect, whereby people's guesses are more accurate in a domain of which they have little knowledge than one about which they know a lot. American participants did better on German cities, while German participants had higher scores on American cities (Goldstein & Gigerenzer, 2002). (See also **satisficing**.)

Reference dependence

Reference dependence is one of the fundamental principles of prospect theory and behavioral economics more generally. In **prospect theory** (Kahneman & Tversky, 1979a), people evaluate outcomes relative to a reference point, and then classify gains and losses (see also **loss aversion**, **endowment effect**). Reference dependence can apply to any decision involving risk and uncertainty. Online privacy research, for example, has shown that identical privacy notices do not always result in the same levels of disclosure (Adjerid et al., 2013). Consumers evaluate privacy notices relative to the status quo—their current level of protection. When privacy notices are preceded by notices that are less protective, people disclose more compared to those who have experienced no change in privacy protection. The converse is the case if preceding privacy notices are more protective.

Regret aversion

When people fear that their decision will turn out to be wrong in hindsight, they exhibit regret aversion. Regret-averse people may fear the consequences of both errors of omission (e.g. not buying the right investment property) and commission (e.g. buying the wrong investment property) (Seiler et al., 2008). The effect of anticipated regret is particularly well-studied in the domain of health, such as people's decisions about medical treatments. A meta-analysis in this area suggests that anticipated regret is a better predictor of intentions and behavior than other kinds of anticipated negative emotions and evaluations of risk (Brewer et al., 2016). (See also **loss aversion**, **status quo bias**, **sunk cost fallacy**, **fear of missing out**, **information avoidance**, and **action bias**.)

Regulatory focus theory

The psychological theory of regulatory focus (Florack et al., 2013; Higgins, 1998) holds that human motivation is rooted in the approach of pleasure and the avoidance of pain and differentiates a promotion focus from a prevention focus. The former involves the pursuit of goals that are achievement- or advancement-related, characterized by eagerness, whereas the latter focuses on security and protection, characterized by vigilance. For example,

a person can become healthy by either engaging in physical activity and eating organic food, or refraining from bad habits such as smoking or eating junk food. Prevention and promotion orientations are a matter of both enduring dispositions and situational factors.

According to *regulatory fit* theory, messages and **frames** that are presented as gains are more influential under a promotion focus, whereas those presented as losses carry more weight in a prevention focus. For example, research by Lee and Aaker (2004) found that 'gain frames' in advertising ("Get energized") lead to more favorable attitudes when the body of the advertising message is written in promotional terms (e.g. emphasizing the energy benefits of drinking grape juice), whilst 'loss frames' ("Don't miss out on getting energized!") have a more favorable effect when the main body of the ad focuses on prevention (e.g. stressing the cancer reduction benefits of drinking grape juice).

Representativeness heuristic

Representativeness is one of the major general purpose **heuristics**, along with **availability"Availability heuristic"**and **affect**. It is used when we judge the probability that an object or event A belongs to class B by looking at the degree to which A resembles B. When we do this, we neglect information about the general probability of B occurring (its base rate) (Kahneman & Tversky, 1972). Consider the following problem:

Bob is an opera fan who enjoys touring art museums when on holiday. Growing up, he enjoyed playing chess with family members and friends. Which situation is more likely?

A. Bob plays trumpet for a major symphony orchestra
B. Bob is a farmer

A large proportion of people will choose A in the above problem, because Bob's description matches the stereotype we may hold about classical musicians rather than farmers. In reality, the likelihood of B being true is far greater, because farmers make up a much larger proportion of the population.

Representativeness-based evaluations are a common cognitive shortcut across contexts. For example, a consumer may infer a relatively high product quality from a store (generic) brand if its packaging is designed to resemble a national brand (Kardes et al., 2004). Representativeness is also at work if people think that a very cold winter is indicative of the absence of global warming (Schubert & Stadelmann, 2015) or when gamblers prefer lottery tickets with random-looking number sequences (e.g. 7, 16, 23, ...) over those with patterned sequences (e.g. 10, 20, 30, ...) (Krawczyk & Rachubik, 2019). In finance, investors may prefer to buy a stock that had abnormally high recent returns (the extrapolation bias) or misattribute a company's positive characteristics (e .g. high quality goods) as an indicator of a good investment (Chen et al., 2007).

Risk-as-feelings

'Consequentialist' perspectives of decision-making under risk or uncertainty (risky-choice theories, see e.g. **prospect theory**) tend to either focus on cognitive factors alone or consider emotions as an anticipated outcome of a decision.

The risk-as-feelings hypothesis (Loewenstein et al., 2001), on the other hand, also includes emotions as an anticipatory factor, namely feelings at the moment of decision-making.

In contrast to theories such as the **affect heuristic**, where feelings play an informational role helping people to decide between alternatives, risk-as-feelings can account for cases where choices (e.g. refusal to fly due to a severe anxiety about air travel) diverge from what individuals would objectively consider the best course of action.

S

Satisficing

According to Herbert Simon, people tend to make decisions by satisficing (a combination of sufficing and satisfying) rather than optimizing (Simon, 1956); decisions are often simply 'good enough' in light of the costs and constraints involved. As a **heuristic**, satisficing individuals will choose options that meet their most basic decision criteria. A focus on satisficing can be used by **choice architects** when decision makers are prone to procrastination (Johnson et al., 2012).

Scarcity (heuristic)

When an object or resource is less readily available (e.g. due to limited quantity or time), we tend to perceive it as more valuable (Cialdini, 2008). Scarcity appeals are often used in marketing to induce purchases. Marketing messages with limited quantity appeals are thought to be more effective than limited time appeals, because they create a sense of competition among consumers (Aggarwal et al., 2011). An experiment (Lee & Seidle, 2012) that used wristwatch advertisements as stimuli exposed participants to one of two different product descriptions "Exclusive limited edition. Hurry, limited stocks" or "New edition. Many items in stock". They then had to indicate how much they would be willing to pay for the product. The average consumer was willing to pay an additional 50% if the watch was advertised as scarce.

Scarcity can be used as an effective strategy by **choice architects** to get people who put off decisions (myopic procrastinators) to act (Johnson et al., 2012).

Scarcity (psychology of)

People have a "mental bandwidth," or brainpower, made up of attention, cognition, and **self-control** (Mullainathan & Sharif, 2013), which consists of finite resources that may become reduced or **depleted**. The scarcity mindset entails a feeling of not having enough of something. According to Mullainathan and Sharif, anyone can experience cognitive scarcity, but it is particularly pronounced for people living in poverty. On the positive side, this may induce limited focus that can be used productively. The downside is 'tunneling', which inhibits the cognitive power needed to solve problems, reason, or retain information. Reduced bandwidth also impairs executive control, compromising people's ability to plan and increasing impulsiveness whereby the focus becomes immediate—put food on the table, find shelter, or pay the utility bill (See also **present bias**).

The financial and life worries associated with poverty, and the difficult tradeoffs low-income individuals must make on a regular basis, all reduce their cognitive capacity. Limits on self-control or planning may lead some individuals to sacrifice future rewards in favor of short-term needs. **Procrastination** over important tasks is also more likely, as is avoidance of expressing negative emotions.

Self-control

Self-control, in psychology, is a cognitive process that serves to restrain certain behaviors and emotions vis-a-vis temptations and impulses. This aspect of self-regulation allows individuals to achieve goals (Diamond, 2013). (See also **intertemporal choice**, **present bias**, **dual-self model**, **dual-system theory**, **ego depletion**, and **decision fatigue**.)

Serial-position effect

The serial-position effect refers to the finding that items (e.g. word, picture or action) that are located either at the beginning (primacy effect) or end (recency effect) of a list are more easily remembered (Ebbinghaus, 1913). These effects have also been extensively studied in social psychology. Research on persuasion, for example, has found primacy effects to be stronger when the issue in a message is relevant or familiar to individuals, and recency effect more likely to occur when the issue is less relevant or familiar to them (Haugtvedt & Wegener, 1994; Lana, 1961).

The serial-position effect should not be confused

with more general order effects, which refers to context effects produced by the order of items, such as questions in a research instrument. (See also anchoring and peak-end rule.)

Sludge

The two defining characteristics of a sludge (Thaler, 2018) are "friction and bad intentions" (Goldhill, 2019). While Richard Thaler strongly advocates nudging for good by making desirable behavior easier, a sludge does the opposite: It makes a process more difficult in order to arrive at an outcome that is not in the best interest of the sludged. Examples of sludges include product rebates that require difficult procedures, subscription cancellations that can only be done with a phone call, and complicated or long government student aid application forms.

Even when a sludge is associated with a beneficial behavior (as in student aid, voter registrations or driver's licenses, for example), costs can be excessive. These costs may be a difficulty in acquiring information, unnecessary amounts of time spent, or psychological detriments, such as frustration (Sunstein, 2020).

Social norm

Social norms signal appropriate behavior and are classed as behavioral expectations or rules within a group of people (Dolan et al., 2010). Social norms of exchange, such as **reciprocity**, are different from market exchange norms (Ariely, 2008). Normative feedback (e.g. how one's energy consumption level compares to the regional average) is often used in behavior change programs (Allcott, 2011) and has been particularly effective to prompt pro-environmental behavior (Farrow et al., 2017). This feedback can either be descriptive, representing what most people do for the purpose of comparison (e.g. "The majority of guests in this room reuse their towels"; Goldstein et al., 2008), or injunctive, communicating approved or disapproved behavior (e.g. "Please don't…."; Cialdini et al., 2006). The latter is often more effective when an undesirable behavior is more prevalent than desirable behavior (Cialdini, 2008).

Social preferences

Social preferences (e.g. Fehr & Fischbacher, 2002) are one type of **preference** investigated in behavioral economics and relate to the concepts of **reciprocity**, **altruism**, **inequity aversion**, and **fairness**.

Social proof

The influence exerted by others on our behavior can be expressed as being either normative or informational. Normative influence implies conformity in order to be accepted or liked (Aronson et al., 2005), while informational influence occurs in ambiguous situations where we are uncertain about how to behave and look to others for information or cues. Social proof is an informational influence (or descriptive norm) and can lead to **herd behavior**. It is also sometimes referred to as a **heuristic**. Research suggests that receiving information about how others behave (social proof) leads to greater compliance among people from collectivist cultures, whereas information on the individual's past behavior (consistency/**commitment**) is associated with greater compliance for people from individualist cultures (Cialdini et al., 1999).

Status quo bias

Status quo bias is evident when people prefer things to stay the same by doing nothing (see also **inertia**) or by sticking with a decision made previously (Samuelson & Zeckhauser, 1988). This may happen even when only small transition costs are involved and the importance of the decision is great.

Field data from university health plan enrolments, for example, show a large disparity in health plan choices between new and existing enrollees. One particular plan with significantly more favorable premiums and deductibles had a growing market share among new employees, but a significantly lower share among older enrollees. This suggests that a lack of switching could not be explained by unchanging **preferences**.

Samuelson and Zeckhauser note that status quo bias is consistent with **loss aversion**, and that it could be psychologically explained by previously made **commitments**, **sunk cost thinking**, **cognitive dissonance**, a need to feel in control and **regret avoidance**. The latter is based on Kahneman and Tversky's observation that people feel greater re-

gret for bad outcomes that result from new actions taken than for bad consequences that are the consequence of inaction (Kahneman & Tversky, 1982).

While status quo bias is frequently considered to be irrational, sticking to choices that worked in the past is often a safe and less difficult decision due to informational and cognitive limitations (see **bounded rationality**). For example, status quo bias is more likely when there is **choice overload** (Dean et al., 2017) or high uncertainty and deliberation costs (Nebel, 2015).

Sunk cost fallacy

Individuals commit the sunk cost fallacy when they continue a behavior or endeavor as a result of previously invested resources (time, money or effort) (Arkes & Blumer, 1985). This fallacy, which is related to **loss aversion** and **status quo bias**, can also be viewed as bias resulting from an ongoing **commitment**.

For example, individuals sometimes order too much food and then over-eat just to "get their money's worth". Similarly, a person may have a $20 ticket to a concert and then drive for hours through a blizzard, just because s/he feels that s/he has to attend due to having made the initial investment. If the costs outweigh the benefits, the extra costs incurred (inconvenience, time or even money) are held in a different **mental account** than the one associated with the ticket transaction (Thaler, 1999).

Research suggests that rats, mice and humans are all sensitive to sunk costs after they have made the decision to pursue a reward (Sweis et al., 2018).

System 1/2

See **Dual-system theory**

T

Take-the-best (heuristic)

Take-the-best is a simple decision-making shortcut that people may apply when choosing between alternatives. It is a one-reason decision rule, a type of **heuristic** where judgments are based on a single "good" reason only, ignoring other cues (Gigerenzer & Gaissmaier, 2011). Using the take-the-best heuristic, a decision maker will base the choice on one attribute that is perceived to discriminate most effectively between the options (Gigerenzer & Goldstein, 1996). Airport customs officers, for example, may determine whether a passenger is selected for a search by choosing the best of various cues, such as airport of origin, nationality, or amount of luggage (Pachur & Marinello, 2013). One study investigated voters' perceptions of how US presidential candidates would handle the single issue that voters regarded as most important, such as the state of the economy or foreign policy. A model based on this issue (as a take-the-best attribute used by potential voters) correctly chose the winner of the popular vote in 97% of all predictions (Graefe & Armstrong, 2012).

Take-the-first (heuristic)

Take-the-first is a fluency **heuristic**. Fluency-based decision-making strategies occur when different alternatives are recognized, but the one that is recognized faster is given higher value with respect to a criterion (Gigerenzer & Gaissmaier, 2011). In the case of take-the-first, decision-makers simply choose the first alternative that comes to mind (Johnson & Raab, 2003). Similar to other **fast and frugal** approaches, this strategy is most suitable in situations that present limitations to people's ability to analyze information carefully. When experienced handball players were asked to decide between taking a shot or passing the ball in video sequences, the first option that came to mind tended to be superior to later options or a condition under which when they had more time to analyze the situation.

Time (temporal) discounting

Time discounting research investigates differences in the relative valuation placed on rewards (usually money or goods) at different points in time by comparing its valuation at an earlier date

with one for a later date (Frederick et al., 2002). Evidence shows that present rewards are weighted more heavily than future ones. Once rewards are very distant in time, they cease to be valuable. Delay discounting can be explained by impulsivity and a tendency for immediate gratification (see **self-control**), and it is particularly evident for addictions such as nicotine (Bickel et al., 1999).

Hyperbolic discounting theory suggests that discounting is not time-consistent; it is neither linear nor occurs at a constant rate. It is usually studied by asking people questions such as "Would you rather receive £100 today or £120 a month from today?" or "Would you rather receive £100 a year from today or £120 a year and one month from today?" Results show that people are happier to wait an extra month for a larger reward when it is in the distant future. In hyperbolic discounting, values placed on rewards decrease very rapidly for small delay periods and then fall more slowly for longer delays (Laibson, 1997). (See also **present bias**.)

Research has shown different ways to reduce discounting, such as **primed** future focus (Sheffer et al., 2016), mental simulation of future experiences (e.g. Stein et al., 2016), and interactions with visual representations of one's future self (Hershfield et al., 2011).

Transitive/intransitive preferences

Preference transitivity is a hallmark of rational choice theory. It holds that if, out of a set of options, A is preferred to B and B to C, then A must also be preferred to C (e.g. von Neumann & Morgenstern, 1947),. Intransitive preferences (i.e. C is preferred to A) violate the transitivity assumption and are sometimes used to indicate **System 1 vs 2** decision-making (Gallo et al., 2016). (See also **preference reversal** and **decoy effect**.)

Trust

Trust pervades human societies. It is indispensable in friendships, love, family, organizations and politics. Interpersonal trust is a mental construct with implications for social functioning and economic behavior as studied by **trust games**, for example.

Although neoclassical economic theory suggests that trust in strangers is irrational, trust and trustworthiness can be widely observed across societies. In fact, **reciprocity** exists as a basic element of human relationships and behavior, and this is accounted for in the trust extended to an anonymous counterpart (Berg et al., 1995). The nature of trusting behavior is a multi-faceted part of psychology, investigated in terms of underlying dispositions, intergroup processes, and cognitive expectations (Evans & Krueger, 2009). Behavioral and biological evidence indicates that trusting is not simply a special case of risk-taking, but based rather on important forms of **social preferences**, such as betrayal aversion (Fehr, 2010).

Both trust and trustworthiness increase when individuals are closer socially, but the latter declines when partners come from different social groups, such as nationality or race. Furthermore, high status individuals are found to be able to elicit more trustworthiness in others (Glaeser et al., 2000). For example, CEOs are considerably more trusting and exhibit more trustworthiness than students. Trust seems to reinforce trustworthy behavior. In a behavioral experiment, trustworthiness was highest when the threat to punish was available but not used, and lowest when the threat to punish was actually used. Paradoxically, however, most CEOs and students used the punishment threat; although CEOs made use of it significantly less (Fehr & List, 2004).

Trust game

Similar to the **dictator game**, this game asks participants to split money between themselves and someone else. However, the trust game first asks Player A to determine an initial endowment of zero or a higher value (e.g. $5). The money is then multiplied (e.g. tripled to $15) by the experimenter and given to Player B, who is then asked to return an amount of zero or a higher value back to Player A. The game is about **reciprocity** and **trust**, because Player A must decide how much of the endowment to give to Player B in the hope of receiving at least the same amount in return. In the original experiment (Berg et al., 1995), 30 out of 32 first players sent money, and 11 of these 30 decisions resulted in a payback that was greater than the initial amount sent. This finding confounds the prediction offered by standard economic assumptions (see *homo eco-*

nomicus) that there would be no trust. However, as with other games, critics have raised questions about what the trust game actually measures (Brülhart & Usunier, 2012). (See also **ultimatum game**.)

U

Ultimatum game

The ultimatum game is an early example of research that uncovered violations of standard assumptions of rationality (see *homo economicus*). In the experiment, one player (the proposer/allocator) is endowed with a sum of money and asked to split it between him/herself and an anonymous player (the responder/recipient). The recipient may either accept the allocator's proposal or reject it, in which case neither of the players will receive anything. From a traditional game-theoretic perspective, the allocator should only offer a token amount and the recipient should accept it. However, results showed that most allocators offered more than just a token payment, and many went as far as offering an equal split. Some offers were declined by recipients, suggesting that they were willing to make a sacrifice when they felt that the offer was unfair (see also **inequity aversion** and **fairness**) (Guth et al., 1982). (See also **dictator game** and **trust game**.)

Utility

In economics, utility (e.g. Stigler, 1950) refers to the benefits (satisfaction or happiness) consumers derive from a good, and it can be measured based on individuals' choices between alternatives or **preferences** evident in their **willingness to pay or accept**. Behavioral economists have questioned past assumptions that utility is always maximized, and they have worked with both traditional and new utility measures.

- Expected utility (Bernoulli, 1954 [1738]) has been used in economics as well as game and decision theory, including prospect theory, and is based on choices with uncertain outcomes.
- Discounted utility is a form of utility used in the intertemporal choice domain of behavioral economics (Berns et al., 2007).
- Experience(d) utility (Kahneman et al., 1997) relates to actual (hedonic) experiences associated with an outcome (in contrast to choice-based decision utility), which is associated with theories on forecasting errors like the diversification bias.
- Remembered utility (Kahneman et al., 1997) suggests that people's choices are also based on their memories of past events or experiences and is invoked in the peak-end rule.
- Instant utility and forecasted utility have been used in the area of intertemporal choice, such as research on the empathy gap, showing that forecasted utility is biased in the direction of instant utility (Camerer & Loewenstein, 2004).
- Procedural utility is relevant if people value not only outcomes, but also the processes that lead to these outcomes (Frey, Benz, & Stutzer, 2004).
- Social utility has been proposed in relation to game theory, where players not only always act self-interestedly, but also show concerns about the perceived intentions of other players and fairness (Camerer, 1997).
- Transaction utility accounts for perceived merit or quality of a deal, rather than just the value of a good or service relative to its price captured by acquisition utility (Thaler, 1985).

W

Willingness to pay (WTP) / willingness to accept (WTA)

In economics, willingness to accept (WTA) and willingness to pay (WTP) are measures of preference that do not rely on actual choices between alternative options. Instead, they ask individuals to specify monetary amounts. WTA is a measure of the minimum financial compensation that a person would need in order to part with a good or to put up with something undesirable (such as pollution or crime). Willingness to pay (WTP) is the opposite—the maximum amount of money someone is willing to pay for a good or to avoid something undesirable. According to standard economic intuition, WTP should be relatively stable across decision contexts and WTA should be very close to WTP for a given good.

Behavioral economics, however, has shown that WTP and WTA may be context-dependent. For example, Thaler (1985) found evidence that people presented with a hypothetical scenario of lying on a beach and craving a beer would be willing to pay significantly more for a beer purchased at a resort hotel as opposed to a rundown grocery store (see also transaction **utility** and **mental accounting**). In addition, sometimes the average WTA for a good exceeds its WTP, which may be indicative of an **endowment effect**, i.e. people value something more if they already own it. Research has also shown that the farther a good is from being an ordinary private (market) good, the more likely it is that WTA exceeds WTP. The WTA-to-WTP ratio is particularly high for health/safety and public/non-market goods (Horowitz & McConnel, 2002).

Winner's curse

The winner's curse describes the phenomenon that the winning bid of an auction tends to exceed the true (and uncertain to the bidders) value of the commodity, resulting, in effect, in the winner overpaying. Emotion, **cognitive biases** and incomplete information seem to account for this behavior, which can, in extremis, lead to **bubbles** in the stock or real estate markets.

In his seminal paper, "Anomalies: The Winner's Curse", Richard Thaler (1988) stated that if he were to auction of a jar of coins amongst his students, (1) the average bid would be significantly less than the actual value of the coins (bidders are risk averse) and (2) the winning bid would exceed the value of the jar (even if it might be overpriced). This is not consistent with the idea of all bidders being rational. In theory, if perfect information were available to everyone and all participants were completely rational in their decision-making and skilled at valuation, no overpayments should occur. However, the winner's curse, a robust and persistent deviation from theoretical predictions established in experimental economics, reflects **bounded rationality** quite well, since people have difficulty in performing contingent reasoning on future events (Charness & Levin, 2009) (see **intertemporal choice**). Not surprisingly, in an experimental demonstration of the winner's curse, the degree of uncertainty concerning the value of the commodity and the number of competing bidders were identified as the two factors that affect the incidence and magnitude of this curse (Bazerman & Samuelson, 1983).

In an attempt to overcome the winner's curse, an experiment has identified two factors that account for its persistence: a variability in the environment, which leads to ambiguous feedback (i.e. choices and outcomes being only partially correlated), and the tendency of decision makers to learn adaptively. Therefore, reducing the variance in the feedback (such that choices and outcomes are correlated), performance can be significantly improved (Bereby-Meyer & Grosskopf, 2008).

Z

Zero price effect

The zero price effect suggests that traditional cost-benefits models cannot account for the psychological effect of getting something for free. A linear model assumes that changes in cost are the same at all price levels and benefits stay the same. As a result, a decrease in price will make a good equally more or less attractive at all price points. The zero price model, on the other hand, suggests that there will be an increase in a good's intrinsic value when the price is reduced to zero (Shampanier et al., 2007). Free goods have extra pulling power, as a reduction in price from $1 to zero is more powerful than a reduction from $2 to $1. This is particularly true for hedonic products—things that give us pleasure or enjoyment (e.g. Hossain & Saini, 2015). A core psychological explanation for the zero price effect has been the **affect heuristic**, whereby options that have no downside (no cost) trigger a more positive affective response.

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APPENDIX

Author Profiles

Dan Goldstein (Introduction)

Dan Goldstein is Senior Principal Research Manager and local leader at Microsoft Research New York City as well as an adjust professor and distinguished scholar at The Wharton School of the University of Pennsylvania. Prior to Microsoft, Dan was a professor at London Business School and Principal Research Scientist at Yahoo Research.

Dan has degrees in computer science and cognitive psychology, with a PhD from the University of Chicago. He has taught or researched at Columbia University, Harvard University, Stanford University, and the Max Planck Institute in Germany, where he received the Otto Hahn Medal.

Dan has been on the academic advisory board of the UK's Behavioral Insights Team since its founding in the UK government's Cabinet Office. He was President of the Society for Judgment and Decision Making, the largest academic organization in Behavioral Economics.

Kathleen Vohs (Guest Editorial)

Kathleen Vohs is the Distinguished McKnight University Professor and Land O'Lakes Chair in Marketing at University of Minnesota's Carlson School of Management. She has authored more than 250 scholarly publications and served as the editor of nine books, and she has written extensively on self-control, interpersonal relationships, self-esteem, meaning in life, lie detection, and sex. Vohs has received several awards and honors. Vohs previously held the University of British Columbia's Canada Research Chair in Marketing Science and Consumer Psychology, University of Minnesota's McKnight Land-Grant Professorship and McKnight Presidential Fellowship, and the Honorary Chair in Experimental Consumer Research at Groningen University, Netherlands. In 2014, she won the Humboldt Foundation's Anneliese Maier Research Award, a competition across the sciences, humanities, law, and economics. She has been named a Highly Cited Researcher by Thomson Reuter's ISI Web of Science, a distinction given to the top 1% of scholars worldwide based on citations. Vohs was named as one of the world's Top 25 behavioral economists by thebestschools.org.

Avni Shah (Guest Editorial)

Avni Shah is an Assistant Professor of Marketing in the Department of Management at the University of Toronto Scarborough, with a cross-appointment to the marketing area at the Rotman School of Management and the Munk School of Global Affairs. Using a multi-method approach combining field and laboratory experiments as well as empirical modeling, her research investigates how payment processes (e.g., payment methods, pricing structures, payment timing) and social factors, such as one's family or peers, influence consumer spending, saving, and well-being. Her work explores outcomes affecting frequent, short-term decisions, such as whether to buy a product or choose a healthy item at a restaurant, as well as decisions that have substantial long-term consequences, such as choosing to save for retirement or to refinance a mortgage.

Avni's work has been published in *Journal of Consumer Research, Journal of Marketing Research, Journal of Urban Economics*, and *Psychological Science* and featured in several policy briefings and in top

media outlets. She received her Ph.D. in Business Administration from Duke University's Fuqua School of Business and her A.B. from Dartmouth College.

Alain Samson (Editor)

Alain Samson is the editor of the Behavioral Economics Guide, founder of BehavioralEconomics.com and Chief Science Officer at Syntoniq. In the past, he has worked as a consultant, researcher and scientific advisor. His experience spans multiple sectors, including finance, consumer goods, media, higher education, energy and government.

Alain studied at UC Berkeley, the University of Michigan and the London School of Economics, where he obtained a PhD in Social Psychology. His scholarly interests have been eclectic, including culture and cognition, social perception, consumer psychology and behavioral economics. He has published articles in scholarly journals in the fields of management, consumer behavior and economic psychology. He is the author of Consumed, a *Psychology Today* online popular science column about behavioral science.

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Contributing Organizations

Australian Securities and Investments Commission (ASIC)

The Australian Securities and Investments Commission (ASIC) is Australia's integrated corporate, markets, financial services, and consumer credit regulator. ASIC's vision is for a fair, strong, and efficient financial system for all Australians. To realise our vision, we use all our regulatory tools to change behaviours to drive good consumer and investor outcomes, act against misconduct to maintain trust and integrity in the financial system, promote strong and innovative development of the financial system and help Australians to be in control of their financial lives.

ASIC established its Behavioural Research and Policy Unit in 2014.

asic.gov.au

Behavior & Law

Behavior & Law is a company dedicated to research, scientific dissemination and teaching in behavioral sciences and forensic sciences. Since its foundation in 2008, it has specialized in the application of these sciences to the field of public and private security.

In the area of public security, Behavior & Law has stood out for its collaboration with police forces from different countries (Mexico, Colombia, Ecuador, USA, etc.), obtaining various national and international acknowledgements. Regarding private security, it has stood out for the creation of the SAVE meta-protocol for fraud management, a method for training teams within private companies to fight internal and external forms of fraud. In recent years, large insurance and financial companies have been trained in this method.

Behavior & Law has been intensifying its work in behavioral economics, currently focusing on several lines of research, one of them within the collaboration with the Welfare Economics group of the UNED. Currently, Behavior & Law is offering a Master's degree in Behavioral Economics, in collaboration with the Madrid University UDIMA.

www.behaviorandlaw.com

BeWay

BeWay is a major consulting company specializing in behavioral sciences in Spain and Latin America. BeWay is a multidisciplinary team composed of more than 40 psychologists, sociologists, political scientists, economists, data scientists, programmers, systems architects, designers, and marketers, with vast experience in the research and development of successful behavioral interventions. Our interventions follow the scientific process and use the existing scientific evidence. By using a rigorous methodology, we achieve trustworthy findings that clients can rely upon.

www.beway.org

Dectech

Dectech strives to provide the most accurate and best value forecasts available on how people will behave in new situations. Founded in 2002, we've conducted more than 400 studies involving over three million participants. We hold that people make very different decisions depending on their context and often struggle to self-report their beliefs and motives. So we developed Behaviourlab, a randomised controlled trial approach that immerses participants in a replica of the real-world decision environment. Over the years we've shown how Behaviourlab can provide higher accuracy forecasts and more actionable insights.

www.dectech.co.uk

Final Mile

Final Mile was inspired by intellectual inquiry. Its founders were deeply curious about the potential of behavioural economics and behavioural sciences to explain human decision-making and behaviour more reliably than traditional models of economics or psychology alone.

Founded in 2007, with headquarters in New York City and offices in Johannesburg and Mumbai, Final Mile is an award-winning research & design consultancy built on the precepts of behavioural economics, cognitive neuroscience, and human-centred design with the goal of building behavioural sciences and design rooted practice. Fractal Analytics, a global leader in artificial intelligence and analytics that powers decision-making in Fortune 500 companies, acquired Final Mile in 2018.

Final Mile addresses behavioural challenges in social development contexts by systematically understanding the role of emotions, heuristics and context in the decision-making process and developing design interventions that influence behaviour. As one of the first behavioural science and design consultancies, Final Mile has unique and proven capabilities in addressing complex behavioural challenges, in areas ranging from global health and financial inclusion to public safety.

www.thefinalmile.com

Frontier Economics

Frontier Economics is a consulting firm with over 250 economists across London, Berlin, Brussels, Cologne, Dublin, Madrid and Paris. We specialise in competition, regulation and strategy, across all major sectors and areas of economic analysis.

Our clients benefit from objective advice, clearly expressed, that helps to inform key decisions. To get to the heart of what matters, you need both analytical expertise and creative problem solving. Frontier Economics combines both to take on some of the biggest questions facing business and society.

We combine our expertise in economics with behavioural sciences to develop a richer picture of the present, helping us to advise our clients on the right decisions for them, for future success. We have one of the largest economic regulation practices in Europe – our behavioural economics work supports wider engagement with regulators and helps develop regulatory policy. Our work on customer strategy centres around understanding the actual behaviours of our clients' customers to help develop innovative customer-based solutions.

www.frontier-economics.com

ING

ING is a global bank with a strong European base. Our more than 57,000 employees serve around 38 million customers, corporate clients and financial institutions in over 40 countries. Our purpose is to empower people to stay a step ahead in life and in business. Our products include savings, payments, investments, loans and mortgages in most of our retail markets. For our Wholesale Banking clients we provide specialised lending, tailored corporate finance, debt and equity market solutions, sustainable finance solutions, payments & cash management and trade and treasury services.

Customer experience is what differentiates us and we're continuously innovating to improve it. We also partner with others to bring disruptive ideas to market faster. Our shares are listed in Amsterdam (INGA NA, INGA.AS), Brussels and New York (ADRs: ING US, ING.N).

www.ing.com

Lirio

Lirio is the leader in behavior change AI, combining behavioral science with artificial intelligence to move people to better health. Through its Precision Nudging™ technology, Lirio's intelligent behavior change journeys assemble and deliver tailored behavioral interventions to overcome unique barriers to engaging with and acting on health recommendations. By scaling personalized health interventions, Lirio delivers patient-focused experiences that initiate and drive sustained behaviors across a select population, optimize patient engagement, close gaps in care, lower costs, and measurably improve health outcomes.

The company was recently awarded Inc.'s 2021 Best Workplaces and is HITRUST®-certified for information security.

www.lirio.com

Neovantas

Neovantas is a top international management consultancy focused on accelerating change through advanced analytics and behavioral science. We focus on "making things happen" to assure business results in a sustainable way over time. Our consulting team is specialized by sector (retail banking, insurance, telecoms, and utilities) and functions (advanced analytics and behavioral science)

We build strong, lasting relationships with our clients through the effectiveness of our teams, our integrity, our professional excellence, and our entrepreneurial spirit. We aspire to be one of the market leaders in providing businesses with unique, pragmatic, and high-impact recommendations and solutions with our behavioral data approach.

Our international presence has been expanded with projects both in Europe (Spain, Portugal, Germany, Italy, and Poland) and in Latin America (Mexico and Brazil).

www.neovantas.com

Open Evidence

Open Evidence is a research and consulting firm working on social and behavioural sciences. Behavioural studies are one of Open Evidence's main areas of research.

Since 2012, we delivered more that 20 behavioural studies for the European Commission and its agencies, including the following focused on financial services: "Consumer testing of digital disclosures in pension tracking systems across the EU"; "Behavioural Research on Insurance Distribution and Advertising via digital channels"; "Behavioural Research in relation to consumers' experiences and outcomes in relation to buying and using of natural catastrophe insurance protection products"; "Behavioural Research in relation to travel insurance products: implications of COVID-19 on consumer outcomes considering consumer behaviours in acquisition, usage and disposition decisions".

open-evidence.com

Oxera

Oxera is a leading European economics and finance consultancy that inspires better decisions, helping you solve complex challenges and build stronger strategies. Our approach is grounded in academic curiosity and enriched by the experience of a diverse team of people, who are based from our offices in Amsterdam, Berlin, Brussels, London, Milan, Oxford, Paris, and Rome.

We are proud of our reputation for independence, integrity and analytical excellence. We combine our core skills (competition economics, finance, data analytics, and behavioural economics) with creative thinking to advise on regulation, strategy, product design and pricing, customer communications, and deliver innovative and practical solutions for our clients.

We conduct behavioural experiments for regulators and governments, as well as firms. Previous experiments include remedy design, investigations into market design, and behavioural industrial organisation. Oxera has advised on all major European regulatory and competition investigations, and has vast experience in quantifying damages and valuing assets in litigation cases.

We have unrivalled experience in delivering high-quality training courses in the fields of behavioural economics, competition policy, conduct risk and economic regulation.

www.oxera.com

Standard Bank

Standard Bank Group is Africa's largest financial institution that offers banking and financial services to individuals, businesses, institutions and corporations in Africa and abroad. Africa is our home, and our belief in the possibilities of this continent motivates us to drive her growth.

We believe that dreams matter in driving growth and that we must always find new ways of making them possible. That is why we are evolving from being a traditional bank to a digitally-enabled services organisation that delivers smart solutions and innovations. We do this by putting people at the centre of what we do – because their dreams reflect the possibility of this great continent.

Our vision is to be the leading financial services organisation in, for and across Africa, delivering exceptional client experiences and superior value. As we move to become a services organisation, we are building ecosystems of trusted partner organisations – a shift that will see us become an advisor and enabler of sustainable growth.

www.standardbank.co.za