Partitioning Menus to Nudge Single-item Choice

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Abstract

Decision makers must often choose items from a menu of options. Examples include employees picking investments from a set of retirement savings plans, citizens selecting a political representative from a list of candidates, or physicians choosing medical treatments from an order set. Options often need to be organized or grouped in some way, which raises the question of whether grouping menu items perturbs the options ultimately chosen by decision makers. In a series of experiments, we find evidence of partition dependence for single-item choice, where individuals are more likely to choose options that are listed separately rather than as part of a group (holding the total number of options constant). Unlike prior work on multi-item allocation decisions, the traditional explanation of partition dependence due to a bias towards even allocation cannot apply to single-item choice, because singular choices are not divisible. Instead, we find evidence that menu partitions influence choice because decision makers view partitions as communicating information about what items are most frequently chosen (i.e., descriptive social norms). Our findings suggest that partitioning of the menu space for single-item decisions can have a sizable influence on behavior, and holds promise as a simple and effective tool for policymakers and choice architects.

Keywords: decision making, choice architecture, partition dependence, social norms

Public Significance Statement

When individuals choose from a menu of options, those options must be grouped or partitioned in some way. We find decision makers are more likely to choose from response categories that are more finely grouped or partitioned. Our findings suggest that the strategic partitioning of menu options holds promise as a simple and effective policy tool, without imposing additional costs or restricting the set of options available to decision makers.

Partitioning Menus to Nudge Single-item Choice

Decisions are influenced by how options are presented, ordered, framed, and described. Based on this simple but powerful insight, governments around the world have become interested in designing behaviorally-informed "choice architecture" policies to enhance public welfare and promote other public priorities (Sunstein, 2013; Thaler & Sunstein, 2008, 2021). Examples include policies that nudge employees to save more for retirement by making automatic enrollment the default designation, nudge homeowners to consume less energy by comparing energy usage to that of one's neighbors, and nudge students to take advantage of college federal loans by making financial aid forms less daunting (Allcott & Rogers, 2014; Bettinger, Long, Oreopoulos, & Sanbonmatsu, 2012; Johnson & Goldstein, 2003; Madrian & Shea, 2001).

A primary justification for nudging is that choice architecture is inevitable and inescapable — policymakers and marketers, knowingly or not, design environments that will invariably affect how people choose (Thaler & Sunstein, 2003). As such, choice architects confront a series of decisions when constructing a decision environment. Some design decisions are unavoidable, such as how to frame a question or how to order response options (e.g., Dayan & Bar-Hillel, 2011); other design details are discretionary, such as designating a particular option as the default (e.g., Madrian & Shea, 2001). For instance, any consumption decision with more than one option means choice architects must determine how to order those options. However, given a list of options, the choice architect is not necessarily required to set one as the default (Carroll, Choi, Laibson, Madrian, & Metrick, 2009; Spital, 1995). Any unavoidable element of a decision environment can be thought of as a fundamental building block of choice architecture, in that all forms of choice architecture will contain it.

In this paper, we introduce a new fundamental building block of choice architecture for selection of a single option from a list. Examples of single-item choice include citizens deciding which candidate to vote for public office, patrons ordering an entree from a restaurant menu, physicians choosing a medical prescription from an electronic order set, or commuters selecting a mode of transportation when heading to work. We find evidence of partition dependence for single-item choice (what we refer to as *single-item partition dependence*), in which decision makers are more likely to choose from response categories that are more finely grouped or partitioned. Our findings suggest that strategic partitioning of the menu space can have a sizable influence on choice and behavior, and holds promise as a simple and effective policy tool.

Menu Grouping and Choice

When constructing a choice menu, there is often a need to group items in order to reduce complexity and organize options (e.g., Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976; B. Tversky & Hemenway, 1984). For instance, a wine merchant may wish to group wines by the geographic region of production (California, Italian, and French wines), by grape varietal (Merlot, Pinot Noir, and Malbec wines), by price point (low-priced, medium-priced, and high-priced wines), or by color (red and white wines). Note that menus with three or more options necessarily require a decision to be made about grouping (including no grouping at all).[1] As the number of options increase, so too do the number of potential groupings or partitions.

While the partitioning of options may help individuals navigate the option space more efficiently, such design decisions can also serve to bias choice. Past work finds that for multi-item *allocation decisions*, in which a decision maker divides or distributes a fixed set of resources, choices are partition dependent because individuals tend to be biased towards even allocation (e.g., Fox, Ratner, & Lieb, 2005). To illustrate, consider the following two scenarios. In scenario A, an employee is asked to allocate earnings to a savings plan from a menu that groups options according to domestic stocks, international stocks, and bonds. In scenario B, the employee is instead asked to construct a portfolio from a menu that groups options according to stocks, domestic bonds, and international bonds. If allocations are partition dependent, then a bias towards even allocation will lead to a relatively stock-heavy portfolio in scenario A (e.g., 1/3 to domestic stocks, 1/3 to international stocks, and 1/3 to bonds) but will lead to a relatively bond-heavy portfolio in scenario B (e.g., 1/3 to stocks, 1/3 to domestic bonds, and 1/3 to international bonds). Decision

[1] For instance, take a menu composed of three options: A, B, and C. One can construct the following choice menus, where the union operator $\cup$ denotes grouping: $\{A,B,C\}$,$\{A,B\cup C\}$,$\{A\cup B,C\}$, or $\{A\cup C,B\}$.

makers have been found to display partition dependence for allocation decisions in both laboratory and field settings, and across a number of domains including consumption decisions, judgments under uncertainty (where beliefs are allocated over the space of possibilities), motivation, cue weighting, personal finance, diversity hiring, corporate capital allocation, assessments of fairness, and parental investment (Bardolet, Fox, & Lovallo, 2011; Bogard, West, & Fox, 2024; Feng, Liu, Wang, & Savani, 2020; Fox & Clemen, 2005; Hertwig, Davis, & Sulloway, 2002; Martin & Norton, 2009; Shah & Oppenheimer, 2011; Sonnemann, Camerer, Fox, & Langer, 2013; West, Ülkümen, Arundel, & Fox, 2021).

An open question is whether partition dependence also occurs in the domain of single-item choice. Given that many important decisions involve single-item choice rather than multi-item allocation,[2] strategic partitioning of the menu space holds promise as an attractive tool for choice architects, policymakers, and marketers. However, single-item choice represents a fundamental departure from prior work because the standard explanation for partition dependence — a bias towards even allocation — cannot apply to single choices from menus, as single choices are not divisible.[3] To give an example, a wine merchant may decide to separate red wines while grouping white wines together (Merlots, Pinot Noirs, Malbecs, and Whites), or could instead separate white wines while grouping red wines together (Chardonnays, Pinot Grigios, Sauvignon Blancs, and

[2]Demarcating the exact boundary between single-item and multi-item (i.e., allocation) decisions is tricky because singular choices can often be viewed as part of a broader consumption stream or portfolio of choices. For instance, one can construe the act of ordering dessert at a restaurant as a one-off decision, or as embedded within a larger set of dieting choices over time (e.g., "If I order dessert tonight, I'll have to make up for it by having a light salad tomorrow"). Another example is how a single hiring decision can instead be viewed as part of a broader portfolio of personnel decisions to increase diversity in an organization (e.g., Feng et al., 2020). The extant literature suggests decision makers usually bracket too *narrowly*, often failing to appreciate that aggregating across decisions can lead to greater utility maximization (Ellis & Freeman, 2020; Read, Loewenstein, & Rabin, 1999). One implication of narrow bracketing is that individuals will often treat decisions as singular choices, even when they could be construed otherwise.

[3]The idea that bias towards even allocation does not extend to single-item choice has also been noted by Read and Loewenstein (1995). They compared sequential decisions, in which participants chose a snack to eat each day for three consecutive days, to planned consumption decisions, in which participants chose in advance three snacks to be consumed over the next three days. Participants showed a strong tendency to diversify when planning consumption in advance, but tended to choose their favorite option when presented with the choices sequentially (Simonson, 1990). In explaining these findings, the authors suggested that diversification cannot occur when an item is viewed as a single distinct choice: "simultaneous choices are presented to subjects in the form of a package, and perhaps the most straightforward choice heuristic applicable to such packages is diversification. In the sequential choice condition, in contrast, subjects are presented with the choices one at a time, and the natural choice heuristic applicable to a single choice is to choose the single most preferred option" (p. 38).

Reds). For customers who only purchase a single bottle of wine, an allocation strategy of 1/*n* across partitions is not possible. Thus, if partitioning of the menu-space continues to be observed for single-item choice (e.g., the menu partition affects the likelihood a customer purchases a bottle of red wine), then psychological processes other than naive diversification must be at play.

In what follows, we demonstrate that decision makers display partition dependence — often markedly so — for single-item choice. Along the way, we explore two mechanisms that may give rise to single-item partition dependence. The first is that menu partitions bias the allocation of attention: individuals may spend relatively more time attending to, and mentally elaborating upon, menu items that are unpacked (Janiszewski, Kuo, & Tavassoli, 2013). The second is that menu partitions communicate information about descriptive social norms: menu partitions may influence choice because decision makers view them as a signal of what options are frequently selected by others (Cialdini & Trost, 1998). To the extent that decision makers look to descriptive norms for guidance — as what is commonly chosen by others may represent a signal of option quality (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992) and/or normatively appropriate behavior (Bearden & Rose, 1990) — menu partitions may reveal task-relevant information.

Transparent Reporting

For all studies we determined sample size in advance of data collection. We preregistered hypotheses and analysis plans for Studies 1A, 1B, 2, and 5. For each study a small number of observations with duplicate IP addresses are excluded; the sample sizes reported below reflect the total number of participants after exclusions. The only demographic information we collected was participant age and gender, and this was always done at the end of each study. Study material, data, code, and preregistration documents can be found at https://researchbox.org/227&PEER_REVIEW _passcode=ZQVQIK. We analyzed data using Stata, version 16.1.

Study 1A: Demonstrating Single-item Partition Dependence

In Study 1A, we tested single-item partition dependence for basic consumption decisions. Participants responded to menus in which all items from one category were individually listed or unpacked, while items from another category were clustered together. This paradigm approximates common menu partitions where a merchant lists out certain categories of goods (such as when a liquor vendor website lists out its selection of Bourbon, Scotch, and Rye whiskeys) while relegating other goods to a residual category (such as if that same website groups all barware, glassware, and cocktail books together as "accessories").[4] If participants exhibit partition dependence for single-item choice, then we should see greater choice share for options from more finely partitioned categories compared to options from more coarsely partitioned categories.

Method

We recruited a sample of 299 participants from Amazon.com's Mechanical Turk labor market (MTurk) to participate in return for a flat cash payment (46% male, mean age = 35 years, age range: 19–74 years).

Participants were presented with menus of consumer goods, and indicated the item they would most prefer to receive. To encourage truthful and thoughtful responding, we notified participants at the start of the study that some of them would be selected at random to receive one of their chosen options, and that we would follow-up with these participants in order to claim their prize. Participants made four choice, presented in random order, from menus of (1) movie DVDs, (2) books, (3) one-year magazine subscriptions, and (4) organizations to which a charitable contribution would be made in their name.

Each trial consisted of a menu of six options partitioned into two categories of three options each. The movie menu consisted of science-fiction movies and romantic comedies; the book menu consisted of behavioral science and life science books; the magazine menu consisted of popular science and world news magazines; the charity menu consisted of animal and environmental charities. For each trial, we randomly selected one category of items to be listed individually while the other category was grouped into a single listing (see Figure 1 for an example). To prevent random

[4]We note that when options are relegated to a residual response category, they are usually also associated with increased effort costs. For example, websites selling consumer goods may bury unpopular items "deeper" in the website (i.e., they are displayed less prominently on the website), and therefore such items often take additional time and effort to locate. In all studies, we partition menu items in a way that holds effort costs constant across conditions.

Figure 1: Example of Menu Partition (Study 1A)

Animal Charities Unpacked

From the list below, choose one charitable organization to receive a $10 donation in your name:

- Humane Society
- Animal Legal Defense Fund
- Society for the Prevention of Cruelty to Animals (SPCA)
- An environment-based charity: your choice of either the Natural Resource Defense Council, Sierra Club, or Environmental Defense Fund

From the list above, please write down <u>one</u> organization to receive your donation: ___________________

Animal Charities Packed

From the list below, choose one charitable organization to receive a $10 donation in your name:

- Natural Resource Defense Council
- Sierra Club
- Environmental Defense Fund
- An animal-based charity: your choice of either the Humane Society, Animal Legal Defense Fund, or the Society for the Prevention of Cruelty to Animals (SPCA)

From the list above, please write down <u>one</u> organization to receive your donation: ___________________

or thoughtless responding, participants wrote out their preference in an open text field.[5] Writing out a response, rather than registering a preference by clicking on a response option, also ensures that effort costs remain constant across experimental conditions. We also note that regardless of the menu partition, participants were presented with the same set of items and selected only one item. To control for possible order effects, we counterbalanced (at the participant-level) the position of the grouped-category by listing it as either the first or last option in the menu.

[5]Some participants provided unusable responses, and we excluded these responses from the analysis. The number of omitted responses ranged from 9 to 17 depending on the domain. A subset of these omitted responses were cases where participants wrote the entire grouped category instead of a single item (e.g., a participant writing "an animal-based charity" instead of specifying a specific animal-based charity). Because omitting these responses potentially biases results in favor of our hypothesis, we also examined the results when including all omitted responses and coding these observations to go *against* our hypothesis. All domains remain significant at $p \leq 0.001$ even when using this conservative coding scheme. We provide full details and robustness tests for Study 1A, as well as all subsequent studies, in section 1 of the Supplemental Material.

Analysis Strategy

To test for partition dependence, we compare choice percentages for groups of items listed individually ("unpacked" items) to those same items grouped into a single listing ("packed" items). When combining responses across choice domains, we use logistic regression where the outcome variable is choosing an item from a target group (e.g., for the charity domain, 0 = not choosing an animal-based charity, 1 = choosing an animal-based charity) and our predictor variable is whether the menu is partitioned such that the focal group is packed or unpacked (0 = packed, 1 = unpacked). The particular item group we designate as focal does not affect the analysis, since each domain contains only two groups of items. Our model also includes trial/domain fixed-effects and robust standard errors clustered by participants. For all analyses in this paper using logistic regression, we report the average marginal treatment effect across experimental conditions.

Results

We find clear evidence of single-item partition dependence. Across domains we observed a 36 percentage point increase in choosing unpacked items compared to packed items (see Table 1). In all four domains, choices reliably varied as a function of menu partition (all p-values < 0.001). Furthermore, the size of our effect was not reliably affected by whether the grouped option was positioned as the first or last listing on the menu ($p = 0.411$ for the interaction term between menu partition and grouped-item position).[6]

Study 1B: Chance Gambles

In Study 1B we examined whether single-item partition dependence extends to decisions under risk, and also used a different technique for constructing menu partitions. In Study 1A menu

[6] When examining interaction effects from binary choice data, we report p-values from the interaction term of the logit model. An alternative approach is to examine the change in marginal treatment effects (e.g., whether the size of the menu partitioning effect — that is, the difference in predicted probabilities — is reliably larger when the packed category is positioned at the bottom or top of the menu). While these two approaches are identical for ordinary least squares (OLS), they are not equivalent for models that make nonlinear transformations to predictor variables (such as when using logistic regression; see McCabe, Halvorson, King, Cao, & Kim, 2022). For all results reported in this paper, coefficient signs for the interaction are the same across the two approaches, and p-values that are statistically significant/nonsignificant using one approach (at $p < 0.05$) are also significant/nonsignificant using the other approach.

Table 1: Percentage of Participants Choosing an Item from Group A (Study 1A)

Domain	Group A	Group B	Group A Unpacked	Group A Packed	Difference
Charities	Animal	Environmental	85.4	52.9	32.5***
Movies	Science Fiction	Romantic Comedies	78.1	54.2	23.9***
Books	Behavioral Science	Life Science	79.1	31.7	47.4***
Magazines	Popular Science	World News	70.0	28.2	41.8***

Notes: "Difference" represents the difference in choice share for choosing an item from Group A when that category is unpacked versus packed. *** $p \leq 0.001$.

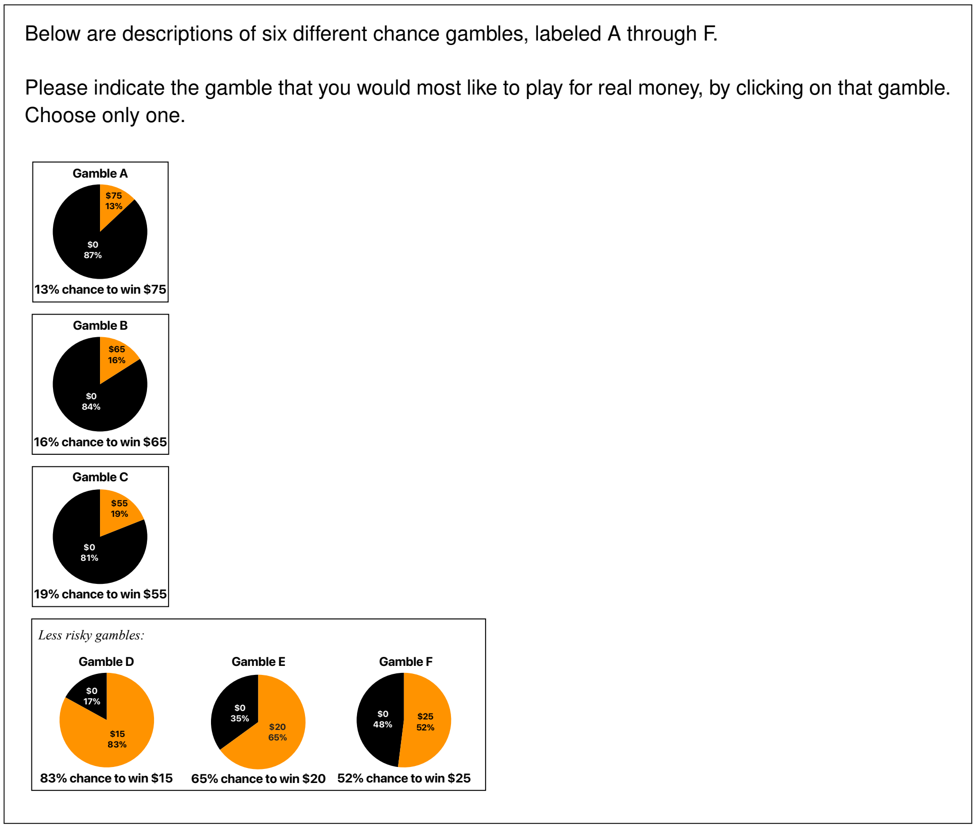
partitions were generated by individually listing some options and clustering others; in Study 1B we presented participants with the same graphical information for all gambles but changed the borders that encompassed different gambles. Doing so leverages the gestalt principle of *common region*, where elements tend to be perceived as grouped together when they lie within an enclosing contour (Palmer, 1992). If participants display partition dependence for single-item choice under risk, then we should again expect to see greater choice share for gambles from more finely partitioned categories compared to gambles from more coarsely partitioned categories.

Method

We recruited a sample of 199 participants from MTurk (53% male, mean age = 36 years, age range: 18–76 years). Participants were told they would be shown six gambles that varied in their degree of riskiness, and to choose the gamble they most prefer. We informed participants that five of them would be randomly selected to play their gamble for additional bonus money.

Participants were then shown six gambles, labeled A–F. The gambles were constructed to be roughly equal in value to a certain payment of $10, based on traditional prospect theory parameters (A. Tversky & Kahneman, 1992). We presented gambles each accompanied by a pie chart illustrating the relevant payoffs and probabilities, and randomly assigned participants to choose from one of two menu partitions. Illustrated by Figure 2, half of participants chose from a menu where the three "more risky gambles" were unpacked (by separately drawing a border around each gamble) and the three "less risky gambles" were packed together (by grouping all three gambles within a single border). The other half of participants viewed the complementary menu partition. Participants were allowed to choose only one gamble and registered their preference by directly

Figure 2: Example of Menu Partition (Study 1B)



clicking on that gamble. As in Study 1A, we counterbalanced whether the grouped category was positioned at the top or bottom of the menu.

Analysis Strategy

We use a two-sample test of proportions to compare the percentage of choices for one of the three riskier gambles when risky gambles were packed versus unpacked. To examine positioning effects (i.e., whether the position of the grouped category affects our results), we conduct a similar logistic regression to that used in Study 1A. Since participants only completed a single trial, we use robust standard errors rather than participant-clustered standard errors.

Results

Participants displayed single-item partition dependence over chance gambles. Only 7% of participants selected a more risky gamble when those gambles were packed together, compared to 22% when more risky gambles were unpacked ($z = 2.80$, $p = 0.005$). Thus, while participants were generally risk averse, preferences for riskier gambles increased threefold when they were partitioned separately compared to when those same gambles were partitioned into a single grouping. Furthermore, our results were not reliably affected by whether the grouped category was positioned at the top or bottom of the menu ($p = 0.845$ for the interaction term between menu partition and grouped-item position).

Study 2: Do Partitions Bias Attention?

Our first two studies found clear evidence of partition dependence for single-item choice, and all subsequent studies replicate such effects while examining potential mechanisms for single-item partition dependence. Although a bias towards equal allocation cannot explain single-item choice (since singular choices cannot be divided), perhaps decision makers are biased in how they *allocate attention* to options. Individuals may spend relatively more time focusing and elaborating on unpacked items, which ultimately increases the appeal of desirable options (Bhatnagar & Orquin, 2022). If the allocation of attention is partition dependent (i.e., greater attention to options listed separately than options listed as part of a group), then this could explain the results found in Studies 1A and 1B.

An attention-based account generates a clear and testable prediction, namely that the pattern of findings we observe should reverse when participants are asked to choose from a menu of unpleasant options. Since participants are more likely to avoid negative stimuli that receive relatively greater attention (Janiszewski et al., 2013), the increased attention or elaboration due to unpacking a category of unpleasant options should make those options especially unappealing and less likely to be selected (for a similar logic, see Brenner, Rottenstreich, Sood, & Bilgin, 2007). Thus, an attention-based account would predict a reversal of the partitioning effect for negative stimuli, with participants especially likely to select items from packed categories over unpacked categories. Conversely, if we continue to see a partitioning effect similar to our previous studies, then this would suggest that single-item partition dependence operates through mechanisms other than the biased allocation of attention.

Method

We recruited a sample of 201 participants from MTurk to participate in return for a flat cash payment (55% male, mean age = 34 years, age range: 19–84 years). Participants were asked to imagine performing one of six hour-long household chores. Half of the participants responded to a menu with the indoor activities unpacked (kitchen cleaning, vacuuming, folding and washing laundry) and half responded to a menu with the outdoor activities unpacked (cleaning rain gutters, lawn-mowing, weeding). As before, we counterbalanced the position of the packed/unpacked categories across participants.

Analysis Strategy

We compare the percentage of choices for an indoor chore when the menu either packed or unpacked listings for indoor chores. To examine positioning effects (i.e., whether the position of the grouped category affects our results), we conduct a logistic regression similar to that in Study 1B.

Results

Contrary to an attention-based account of partition dependence, we found a large partitioning effect similar to that found in Studies 1A and 1B. Participants were more likely to choose indoor chores when those items were listed individually as opposed to when those same items were grouped together (82% vs. 44%; $z = 5.01$, $p < 0.001$). Unlike our previous studies, we also observe a significant interaction between menu partition and grouped-item position ($p = 0.043$ for the interaction term). That is, the size of the partitioning effect was reliably larger when the packed item was placed at the bottom of the menu (54 percentage point marginal effect; $p < 0.001$) compared to when it was placed at the top of the menu (22 percentage point marginal effect; $p = 0.026$). Regardless of grouped-item position, the results of Study 2 suggest that menu partitions exert an influence on choice contrary to that expected if menu partitions biased attention towards unpacked options.

Study 3: Do Menu Partitions Communicate Information?

We next examine another explanation for single-item partition dependence, namely that partitioning the menu space communicates task-relevant information.[7] For instance, Benartzi and Thaler (2001) speculated that employees engage in naive diversification when saving for retirement because they recognize their lack of financial sophistication and trust their employer has constructed a selection of funds that meets the needs of its employees. Similarly, conversational norms dictate information should only be as granular as necessary (i.e., the conversational maxim of quantity; Grice, 1975), and decision makers assume such norms about granularity hold when confronting a menu of choices (Zhang & Schwarz, 2012). Furthermore, two logically equivalent menus can potentially communicate different information whenever decision makers believe menu partitions are not constructed at random (see Krijnen, Tannenbaum, & Fox, 2017; McKenzie & Nelson, 2003; Prelec, Wernerfelt, & Zettelmeyer, 1997; Sher & McKenzie, 2006, 2014).

In Study 3, we test whether menu partitions signal information concerning *descriptive social norms*. For instance, it is plausible decision makers assume choice architects and policymakers tend to allocate menu space to those options that are more popular, while clustering less popular options together or relegating them to a residual "other" category. Since beliefs about how other people decide is a powerful influence on one's own behavior (Bearden, Netemeyer, & Teel, 1989; Cialdini & Goldstein, 2004; Cialdini, Kallgren, & Reno, 1991), menu partitions may exert their influence by structuring beliefs about what options are commonly chosen. Stated more precisely, this account suggests that decision makers act as if menu partitions abide by a "principle of maximum entropy" over the distribution of preferences in a given population (Jaynes, 1957). That is, given a set of possible ways to partition the menu space, choice architects divide the menu in a way that tries to most evenly allocate the distribution of preferences across options (and thus, more popular items are listed separately rather than grouped).

According to this information-leakage account, participants should view an item as relatively

[7] The speculation that menu partitions may signal information has also been suggested by Kahneman and Tversky (1982), Fox and colleagues (Fox & Clemen, 2005; Fox et al., 2005), and Martin and Norton (2009).

Figure 3: Example of Choice and Judgment Task (Study 3)

Example choice trial

Imagine you win an all expenses paid trip to one country of your choice. Which of the following countries would you prefer to visit?

A. France
B. Germany
C. Italy
D. Asian country (your choice of either China, Japan, or Vietnam)

Which country would you choose? (Please list one country name) ___________________

Example estimation trial

Other respondents to this survey will be presented with the following:

Imagine you win an all expenses paid trip to one country of your choice. Which of the following countries would you prefer to visit?

A. France
B. Germany
C. Italy
D. Asian country (your choice of either China, Japan, or Vietnam)

What percentage of other respondents of this survey would you estimate answer each of the following? (Please give numbers between 0 and 100 so that your numbers sum to 100%)

France ______ %
Germany ______ %
Italy ______ %
Asian country (your choice of either China, Japan, or Vietnam) ______ %

more popular (i.e., more frequently chosen by others) when individually listed than when grouped with other items. Also, to the extent that inferences about descriptive norms causally influence consumption decisions, beliefs about item popularity should statistically mediate menu partitioning effects.

Method

We recruited a sample of 154 participants from MTurk (69% male, mean age = 28 years, range: 18–72 years). Similar to Study 1A, participants were asked to make consumption decisions from a menu of options. We also asked participants to judge the relative popularity of each menu item as an empirical measure of inferred descriptive norms.

Choices and judgments were elicited in separate blocks. For the choice block we presented participants with four hypothetical choice menus; for each menu, half of the items were listed individually and the other half of items were clustered into a single response option. As in our previous studies, we counterbalanced the position of the packed category to be either the first or last position. For the judgment block, we presented participants with the same menu partitions they viewed in the choice block and asked them to estimate the percentage of respondents in the study who would choose each option, with all estimates summing to 100 (see Figure 3 for an example). We randomized the order of domains within each block, and also counterbalanced the order of the two task blocks: half of the participants completed the choice block first and judgment block second, the other half completed the study in the reverse order. Counterbalancing the task blocks allowed us to compare response tendencies between the first and second blocks and rule out potential spillover effects (for instance, judgments of item popularity being influenced by one's prior choices, e.g., Ross, Greene, & House, 1977).

Analysis Strategy

To test for partition dependence, we compare choice percentages between unpacked and packed items. When combining responses across choice domains, we conduct a logistic regression where the outcome variable is choosing an item from a target group and our predictor variable is whether the menu is partitioned such that the focal group is packed or unpacked (0 = packed, 1 = unpacked). Similar to previous studies, we include domain fixed-effects and cluster standard errors by participants. When examining inferences about item popularity we use OLS regression instead of a logit model.

Results

Table 2 provides a summary of the results. Again, we find a robust partitioning effect on choice. Across domains, we observe a 36 percentage point increase in choosing unpacked items compared to packed items ($p < 0.001$). In all four domains, choices reliably varied as a function of the menu partition (p-values < 0.010).

Consistent with an information-based account, menu partitions also influenced inferences about descriptive norms. On average, there was a 23 percentage point increase in judged popularity

Table 2: Study 3 Results

Domain	Group A	Group B	Choices (%) Group A Unpacked	Choices (%) Group A Packed	Choices (%) Difference	Judgments (mean estimate) Group A Unpacked	Judgments (mean estimate) Group A Packed	Judgments (mean estimate) Difference
Vacations	Europe	Asia	71.8	51.3	20.5**	69.8	54.3	15.5***
Entertainment	Sports	Cultural	62.7	27.8	34.8***	77.5	56.5	21.0***
Weekend trip	West Coast	East Coast	81.3	51.9	29.4***	61.9	41.9	20.1***
Desert	Cookies	Ice Cream	83.7	23.0	60.8***	65.0	30.8	34.2***

Notes: “Difference” represents the difference in choice share (or for judgment blocks, the difference in average estimated percentages) for choosing an item from Group A when that category is unpacked versus packed. Any discrepancies in difference scores shown in the table are due to rounding error. ** $p \leq 0.01$, *** $p \leq 0.001$.

for unpacked items compared to packed items ($p < 0.001$). In all four domains, judgments reliably varied as a function of the menu partition (p-values < 0.001).

As in Study 2, we find an (unexpected) interaction between menu partition and grouped-item position (p-values were 0.006 and 0.024 for the interaction terms on choices and inferences, respectively). For choices, the partitioning effect was reliably larger when the packed category was placed at the bottom of the menu (50 percentage point marginal effect; $p < 0.001$) compared to when it was placed at the top of the menu (24 percentage point marginal effect; $p < 0.001$). For judgments, menu partitions also had a larger effect on judgments of item popularity when the packed category was placed at the bottom of the menu (28 percentage point marginal effect; $p < 0.001$) than when it was placed at the top of the menu (18 percentage point marginal effect; $p < 0.001$). We return to the issue of positioning effects in the general discussion.

Menu partitions strongly influenced both choices and beliefs about item popularity, and we next examine the relationship between the two. Consistent with an information-based account, the correlation between choice and judged popularity was positive and significant ($r = 0.41$, $p < 0.001$ across participants and domains). The average correlation within participants and across domains was $r = 0.35$; the average correlation across participants and within domains was $r = 0.46$. Since one’s choices can affect beliefs about how others choose (e.g., Ross et al., 1977), we also examined whether block order (i.e., choosing first and then estimating item popularity, or vice versa) influenced our results. Neither choices nor judgments of item popularity were reliably affected by the order of task block (for the interaction between menu partition and block order, p-values were 0.511 for choices and 0.602 for judgments). Furthermore, we found similar results when restricting the analysis to only the first block that participants completed, where spillover effects cannot occur (see section 2 of the Supplementary Material).

Lastly, we examined whether beliefs about descriptive norms statistically mediate participant choice. In other words, does the menu partitioning effect reduce in size when we statistically adjust for beliefs about how frequently items are chosen by others? To examine this, we performed a Sobel-Goodman mediation test using bootstrapped standard errors based on 10,000 resamples clustered at the participant level, along with domain fixed effects and adjustments to the test procedure to account for potential scaling artifacts that can arise when using binary choice data[8,9] (Karlson, Holm, & Breen, 2012; Preacher & Hayes, 2008; Shrout & Bolger, 2002). Using this procedure we find a reliable mediation effect, with inferences of item popularity mediating 51% the menu partitioning effect on choice ($b_{indirect} = 0.92$, SE = 0.20, 95% CI [0.57, 1.33]). Furthermore, we find a reliable indirect effect both when restricting the analysis to participants that provided choices first ($b_{indirect} = 0.95$, SE = 0.28, 95% CI [0.50, 1.58]), and to participants that provided judgments of item popularity first ($b_{indirect} = 0.95$, SE = 0.32, 95% CI [0.46, 1.64]).

Study 4: Blocking Inferences

The results of Study 3 suggest that menu partitions influence beliefs — when confronted with a set of options, decision makers tend to infer that unpacked items are more popular than packed items. The results of Study 3 also suggest that the shift in beliefs caused by partitioning of the option set may help to explain single-item partition dependence. However, a limitation of Study 3 is that its design does not allow one to definitively conclude that the causal chain flows from menu partitions to inferences of popularity, and then from inferred popularity to choice. Both

[8]We report tests for mediation using the standard framework based on linear structural equation models (e.g., Preacher & Hayes, 2008). Recently, researchers have suggested an alternative test of statistical mediation based on the potential outcomes framework to causal inference (Imai, Keele, & Tingley, 2010). This procedure also returns a reliable mediation effect, with inferences of item popularity mediating 50% of the menu partitioning effect on choice. Another advantage of the potential outcomes approach to mediation is that it allows us to test the degree to which our results are robust to potential violations of confounding between the mediator and outcome variable (i.e., assumptions of sequential ignorability). We report the results of this sensitivity test, along with the full details for the potential outcomes mediation procedure, in section 3 of the Supplemental Material.

[9]All bootstrapping procedures reported in this paper use bias-corrected confidence intervals (Efron, 1987).

our putative mediator (judged descriptive norms) and outcome variable (choice) were exposed to the experimental treatment (the partitioning of the menu), and so we cannot decisively rule out the reverse causal pathway (i.e., that participant choice is causally prior to beliefs about item popularity, Imai, Tingley, & Yamamoto, 2013; Pieters, 2017; Spencer, Zanna, & Fong, 2005) or that an unobserved third variable influences both item popularity and choice (see Simonsohn, 2022).

In Study 4 we directly manipulate beliefs about descriptive norms independent of menu partitions. If the information gleaned from a menu partition plays a causal role in determining choice, then partitioning effects should be attenuated whenever decision makers fail to extract information provided by the menu partition. To do this, we first asked participants to state their beliefs about item popularity of each group *before* exposing them to the menu partition. We anticipated that having participants first state their descriptive norm beliefs would inoculate any informational effects provided by the partition, and should therefore attenuate observed partitioning effects on choice. Thus, Study 4 uses a "blockage" design (Pirlott & MacKinnon, 2016) to test the hypothesis that menu partitions are causally mediated by beliefs about descriptive norms.

Method

We recruited a sample of 302 participants from MTurk[10] (65% male, mean age = 29 years, range: 18–60 years). Participants first responded to a simple attention check (Oppenheimer, Meyvis, & Davidenko, 2009), and only those who passed the attention check were allowed to continue participating in the study.

Participants were presented with the same four choices as in Study 3. For each menu, half of the items were listed individually and the other half of items were clustered into a single response option. Unlike Study 3 where choices and judgments were elicited in separate blocks, participants were randomly assigned to either estimate the two grouped categories immediately before or after exposure to the menu partition (see Figure 4 for an example). Also different from Study 3 is that participants estimated the relative popularity of category groupings, rather than for each response

[10] One participant reported their age as 520 years old; we assume this was a typo, and omit this response when calculating age statistics for the sample.

Figure 4: Example of Choice and Judgment Task (Study 4)

Example choice trial

Imagine you win an all expenses paid trip to one country of your choice. Which of the following countries would you prefer to visit?

A. France
B. Germany
C. Italy
D. Asian country (your choice of either China, Japan, or Vietnam)

Which country would you choose? (Please list <u>one</u> country name below) ___________________

Example estimation trial

Consider the two different types of vacation destinations below. Presented with these options, what proportion of people would choose an all expenses paid trip to either a European country or an Asian country? Please provide your best guess. Note that answers should sum to 100.

European country (choice of either France, Germany, or Italy) ______ %
Asian country (choice of either China, Japan, or Vietnam) ______ %

option. Thus, some participants provided estimates of popularity for a category of items before exposure to a specific menu partitioning of those categories (estimate-first condition), while others provided popularity estimates after viewing and responding to the menu partition (partition-first condition). We expected that single-item partition dependence would be attenuated in the estimate-first condition compared to the partition-first condition, because participants in the latter condition would assess descriptive norms for themselves before being exposed to a partition that might otherwise leak such information.

Analysis Strategy

To test for partition dependence, we compare choice percentages between unpacked and packed items. To examine if partitioning effects are attenuated in the estimation-first condition, we use logistic regression in which choices are regressed onto menu partition (0 = packed, 1 = packed), elicitation sequence (0 = partition-first condition, 1 = estimate-first condition), and the interaction between the two. When combining responses across choice domains, we include domain fixed-effects and cluster standard errors by participants. When examining judgments about grouped category popularity we used OLS regression instead of a logit model.

Table 3: Study 4 Results

			Choose, then Estimate (choice %)			Estimate, then Choose (choice %)		
Domain	Group A	Group B	Group A Unpacked	Group A Packed	Difference	Group A Unpacked	Group A Packed	Difference
Vacations	Europe	Asia	73.0	49.4	23.6^{**}	73.4	54.4	19.5^{*}
Entertainment	Sports	Cultural	76.0	38.7	37.3^{***}	67.1	32.4	34.7^{***}
Weekend trip	West Coast	East Coast	83.3	44.2	39.2^{***}	73.0	56.2	16.8^{*}
Desert	Cookies	Ice Cream	84.4	20.5	63.9^{***}	76.5	31.6	44.8^{***}

Notes: “Difference” represents the difference in choice share for choosing an item from Group A when that category is unpacked versus packed. Any discrepancies in difference scores shown in the table are due to rounding error. * $p \leq 0.05$, ** $p \leq 0.10$, *** $p \leq 0.001$.

Results

Table 3 provides a summary of the results. We again find a robust partitioning effect on choice. Across choice domains and conditions, we observed a 35 percentage point increase in choosing unpacked items compared to packed items ($p < 0.001$). In all four domains, choices reliably varied as a function of the menu partition (p-values < 0.001). Furthermore, the size of our effect was not reliably impacted by whether the grouped option was positioned as the first or last option on the menu ($p = 0.972$ for the interaction term between menu partition and grouped-item position).

Our primary prediction was that partitioning effects would be attenuated (compared to our standard treatment) when participants first provided their judgments about descriptive norms before being exposed to menu partitions. As expected, we observe a reliable attenuation effect: in the partition-first condition we observed a 41 percentage point increase in choices for unpacked items as opposed to packed items, whereas the marginal effect decreased to 29 percentage points in the estimate-first condition. This 12 percentage point decrease was reliably different from chance ($p = 0.036$ for the interaction term between menu partition and elicitation sequence on choices). As shown in Table 3, this pattern of an attenuated partitioning effect was directionally consistent in all four domains.

Next, we examined inferences of item popularity (as noted earlier on, this was measured at the category level, rather than at the item level as in Study 3). Inferences should not be affected by the menu partition in the estimate-first condition (since participants had not yet been exposed to the menu partition), but should shift in the direction of the menu partition in the partition-first condition (similar to Study 3). As expected, participants who were first exposed to the menu partition rated items from the unpacked category as more popular than those from the packed category ($b = 3.49$, SE = 1.36, $p = 0.011$), whereas participants who first made judgments of item popularity before viewing the menu partition did not reliably differ across conditions ($b = -0.16$, SE = 1.39, $p = 0.908$). This difference in the size of the "inference gap" as a function of elicitation sequence was marginally significant ($p = 0.062$ for the interaction between elicitation sequence and menu partition on judged popularity).

Last, we conducted mediation tests using the same analysis strategy outlined in Study 3, but this time we performed separate mediation analyses depending on whether judgments of popularity were elicited before or after exposure to the menu partition.[11] As in Study 3, judgments of item popularity reliably mediated the effect of menu partitions on choice for participants who were first exposed to the menu partition ($b_{indirect} = 0.10$, SE = 0.05, 95% CI $[0.02, 0.22]$). Also as expected, judgments of popularity did not reliably mediate the partitioning effect on choice when participants first reported their estimates before exposure to the menu partition ($b_{indirect} = -0.01$, SE = 0.08, 95% CI $[-0.17,\ 0.14]$). Thus, beliefs about descriptive norms only reliably mediated menu partitioning effects when participants had in fact been exposed to menu partitions, and could thus extract information from them.

Taken together, Studies 3 and 4 suggest that menu partitions convey information about descriptive social norms. Individually-listed options are viewed as more popular (i.e., more frequently chosen) than options that are grouped together, and participants tended to choose the options they thought were more popular. Such a strategy may be reasonable to the extent that (a) menu partitions accurately reflect majority preference, (b) majority preference is positively correlated with an option's consumption utility, and (c) decision makers do not have more diagnostic sources of task-relevant information available when making a decision (assuming such alternative sources of information are no more costly to acquire).

[11] As in Study 3, we can also test for mediation using the potential outcomes framework outlined by Imai et al. (2010). Similar to the results reported above, we find a reliable indirect effect through judged popularity in the partition-first condition, but no reliable indirect effect in the estimate-first condition. Full details are provided in section 4 of the Supplemental Material.

Study 5: Moderation by Social Motivations

Studies 3 and 4 suggest that menu partitions influence beliefs about item popularity, and beliefs about item popularity influence choice. In Study 5 we test a corollary of this hypothesis, namely that single-item partition dependence should be especially pronounced for individuals most sensitive to descriptive social norms. We administer a susceptibility to interpersonal influence scale (Bearden et al., 1989), which measures the extent to which consumption decisions are driven by feelings of social approval from others (i.e., *normative* social influence) and by beliefs that other's decisions provide information about option quality (i.e., *informational* social influence). Since descriptive norms usually signal both what is commonly done and what is socially appropriate (e.g., Brauer & Chaurand, 2010; Eriksson, Strimling, & Coultas, 2015; Thøgersen, 2008), we can expect that either form of interpersonal influence may moderate the influence of menu partitions on choice. Stated differently, both scales may represent different shades of a generalized receptiveness by individuals to seek external social cues to guide one's decision. If so, then single-item partition dependence should be especially pronounced among these individuals.

In Study 5 we use the same design as in Study 3, where participants were asked to provide choices and infer the popularity of menu items, but also measure individual differences in susceptibility to interpersonal influence. By measuring both choices and beliefs, we can also isolate where in the causal chain any potential moderation effects occur. That is, we can examine whether participants high in interpersonal influence show pronounced partitioning effects because they are especially likely to infer item popularity from menu partitions (i.e, the *menu partition* $\longrightarrow$ *descriptive norm beliefs* pathway) or because these individuals give greater weight to considerations of item popularity when making a consumption decision (i.e., the *descriptive norm beliefs* $\longrightarrow$ *choice* pathway).

Method

We recruited a sample of 601 participants from MTurk (46% male, mean age = 41 years, range: 18–83 years). The procedure was similar to that in Study 3, in which participants responded to the same four choice domains, and completed both choice and judgment blocks in counterbalanced order.[12]

After completing both choice and judgment blocks, participants responded to an 8-item measure of susceptibility to interpersonal influence (Bearden et al., 1989). Participants completed four items from the susceptibility to normative influence (NSI) subscale, rating their agreement with each statement on 7-point scales from *strongly disagree* (-3) to *strongly agree* (3). Example items were “it is important that others like the products and brands I buy” and “when buying products, I generally purchase those brands that I think others will approve of.” We averaged the four items to create an index of NSI ($\alpha = 0.93$). Participants also completed four items from the susceptibility to informational influence (ISI) subscale. Example items were “to make sure I buy the right product or brand, I often observe what others are buying and using” and “I often consult other people to help choose the best alternative available from a product class.” We averaged the four items to create an index of ISI ($\alpha = 0.88$). We also counterbalanced across participants whether the four items from the NSI came first or second, and also randomized the order of statements within each subscale. The correlation between the two subscales was 0.44.

Analysis Strategy

We use the same analysis strategy as in Study 3. When examining moderation on choice, we perform logit regression when the dependent variable is choice, and OLS regression when the dependent variable is judgments of item popularity. Similar to our previous studies, when pooling across trials we include domain fixed effects and cluster standard errors by participants.

Results

Before turning to our moderation analysis, we examined whether our earlier findings replicate. We again observed a reliable menu partitioning effect, with an average 25 percentage point increase in choosing unpacked items over packed items ($p < 0.001$). We also again found that menu partitions influenced beliefs about social norms, with an average 26 percentage point increase in

[12] Study 5 included a few small differences from Study 3. In Study 5 the menu options were separated by bullet points instead of letters, and Study 5 used slightly different labels for the packed listing (e.g., “European country (your choice of either France, Germany, or Italy)” instead of “Europe (your choice of either France, Germany, or Italy)”).

Table 4: Study 5 Results

			Choices (%)			Judgments (mean estimate)		
Domain	Group A	Group B	Group A Unpacked	Group A Packed	Difference	Group A Unpacked	Group A Packed	Difference
Vacations	Europe	Asia	74.8	55.2	19.6^{***}	77.6	54.1	23.5^{***}
Entertainment	Sports	Cultural	63.4	38.1	25.3^{***}	80.3	52.2	28.1^{***}
Weekend trip	West Coast	East Coast	69.9	49.0	20.9^{***}	63.2	40.2	23.0^{***}
Desert	Cookies	Ice Cream	67.6	34.8	32.8^{***}	63.0	32.6	30.4^{***}

Notes: "Difference" represents the difference in choice share (or for judgment blocks, the difference in average estimated percentages) for choosing an item from Group A when that category is unpacked versus packed. Any discrepancies in difference scores shown in the table are due to rounding error. *** $p \leq 0.001$.

judged popularity for unpacked items compared to packed items ($p < 0.001$). Finally, we again found that judgments of item popularity fully mediated the menu partitioning effect on choice ($b_{indirect} = 1.26$, SE = 0.09, 95% CI [1.09, 1.44]). Table 4 presents the main results (see section 5 of the Supplemental Material for complete details).

We next examined whether menu partitioning effects were reliably moderated by NSI scores, ISI scores, or both. We report all moderation analyses in Table 5. To facilitate interpretation, we report unstandardized OLS coefficients but report p-values using logistic regression. Thus, coefficients can be interpreted as the percentage point increase in choosing from a given category of items as a linear function of an explanatory variable, and a positive coefficient for the interaction term represents the increase in menu partitioning effects as a linear function of the moderating variable. For instance, in Model 1 of Table 5 the "partition" coefficient indicates a 28.1 percentage point difference in choosing unpacked items compared to packed items (when NSI scores are set to 0), and that the size of this partitioning effect increases by 2.7 percentage points for every 1-point increase in NSI scores (as represented by the "partition $\times$ NSI" interaction term).

We begin by examining moderation of overall partition effects by susceptibility to normative social influence (Model 1) and informational social influence (Model 2). Shown in Model 1, we find a positive and marginally significant interaction term ($p = 0.060$), indicating that menu partitioning effects grew in size for those higher in susceptibility to normative social influence. Shown in Model 2, although partitioning effects grew in size as a function of ISI scores, the interaction term was not statistically significant ($p = 0.195$). Thus, menu partitioning effects were more pronounced for those most susceptible to interpersonal influence, especially normative social influence.

Table 5: Study 5 Results

	moderation of basic effect (partition → choice)		moderation of pathway 1 (partition → judgment)		moderation of pathway 2 (judgment → choice)	
	(1)	(2)	(3)	(4)	(5)	(6)
Partition	0.281***	0.242***	0.287***	0.259***	−0.004	−0.004
	(0.029)	(0.022)	(0.013)	(0.010)	(0.024)	(0.024)
NSI	−0.005		−0.012*		−0.012	
	(0.010)		(0.005)		(0.014)	
Partition × NSI	0.027†		0.019***			
	(0.015)		(0.006)			
ISI		−0.007		−0.008†		−0.017
		(0.011)		(0.005)		(0.015)
Partition × ISI		0.019		0.013*		
		(0.015)		(0.006)		
Judged Item Popularity					0.977***	0.920***
					(0.046)	(0.040)
Judged Item Popularity × NSI					0.040*	
					(0.022)	
Judged Item Popularity × ISI						0.035
						(0.024)
Domain Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2331	2331	2404	2404	2331	2331
Participants	601	601	601	601	601	601
R^2	.080	.078	.376	.374	.218	.216

Notes: OLS estimates with standard errors clustered at the participant-level. For models 1, 2, 5, and 6 the outcome variable was choosing an item from a target group (e.g., for the charity domain, 0 = not choosing an animal-based charity, 1 = choosing an animal-based charity). The outcome variable in models 3 and 4 was "Judged Item Popularity", or the estimated percentage of other participants selecting an item from the focal group (rescaled to fall between 0 and 1). "Partition" indicates whether the menu was partitioned such that the focal group was packed or unpacked (0 = packed, 1 = unpacked). "NSI" and "ISI" represent a participant's susceptibility to normative social influence and informational social influence score, respectively. Scores on the NSI and ISI can range from -3 to 3, with higher numbers reflecting greater susceptibility. All models include domain fixed effects. For models 1, 2, 5, and 6 we use significance stars based on logit regressions. † $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

We next turn to where in the causal chain, from menu partitions to judgments about item popularity or from judgments about item popularity to consumption decisions, that such moderation effects occur. Models 3 and 4 examine moderation for the first part of the causal chain (i.e., the *menu partition* ⟶ *descriptive norm beliefs* pathway). We find a reliable interaction effect for both NSI scores (Model 3: $p = 0.001$) and for ISI scores (Model 4: $p = 0.039$). On average, the size of the "judged popularity" gap across menu partitions increased by 1.9 percentage points for every 1-point increase in NSI scores, and by 1.3 percentage points for every 1-point increase in ISI scores.

Thus, participants high in susceptibility to interpersonal influence were especially likely to view unpacked menu items as more frequently chosen by others.

Models 5 and 6 examine the second part of the causal chain (i.e., the *descriptive norm beliefs* $\longrightarrow$ *choice* pathway). We find a positive reliable interaction between judgments of item popularity and NSI scores (Model 5: $p = 0.045$) but no reliable interaction effect between judgments and ISI scores (Model 6: $p = 0.194$). Thus, participants higher in susceptibility to normative social influence also placed greater weight when making a consumption decision (compared to low NSI participants) on how frequently chosen they thought an option was.

In summary, the results of Study 5 suggest that, like earlier studies, menu partitions are more likely to communicate information about descriptive social norms, which is positively correlated with how participants choose. Furthermore, we find that participants most susceptible to social norms (especially normative social influence) also tend to show more pronounced partition dependence. This appears to occur because these participants are both especially likely to interpret menu partitions as a signal of descriptive norms, and also because they give greater weight to considerations of descriptive norms (i.e., item popularity) when selecting an item to consume.

General Discussion

We provide evidence that single-item choice can be substantially influenced by how options are grouped or partitioned. In particular, participants were more likely to choose options that were individually listed compared to when those same options were grouped together (see also Brenner, Rottenstreich, & Sood, 1999; Feng et al., 2020; Tannenbaum et al., 2014). This was true across a wide range of choice settings, both hypothetical (Studies 2–5) and incentive-compatible (Studies 1A and 1B). The effect of partitioning the menu set was sizable, shifting choices by an average of 30 percentage points across studies (see Table 6 for an aggregated summary). Our findings suggest that the strategic partitioning of menus can be used as a simple and flexible tool that choice architects can deploy to affect behavior change (Johnson et al., 2012). Menu partitioning can be used by policymakers and marketers to supplement more traditional forms of choice architecture, such as

Table 6: Menu Partitioning Effects Across Studies

	Category Unpacked (choice %)	Category Packed (choice %)	Difference
Study 1A	78.2 (1.7)	41.8 (2.3)	36.4 (3.1)***
Study 1B	21.7 (3.9)	07.1 (2.8)	14.6 (4.8)**
Study 2	81.7 (4.3)	44.0 (5.4)	37.7 (6.9)***
Study 3	75.0 (2.9)	38.6 (3.1)	36.4 (4.4)***
Study 4	75.8 (2.0)	40.8 (2.1)	35.0 (3.0)***
Study 5	68.9 (1.5)	44.2 (1.5)	24.7 (2.1)***
Combined	69.4 (2.2)	39.6 (2.3)	29.8 (1.3)***

Notes: Percentage choosing an item from a target category when the menu is partitioned such that the focal group is packed or unpacked. Parentheses represent robust standard errors for Studies 1B and 2, and participant-clustered standard errors for all other studies. "Difference" represents the average marginal effect (i.e., difference in predicted probabilities) estimated from the logit model specified in the results section of each study. Combined results are estimated using study fixed-effects, with weights proportional to the inverse variance in the average marginal effect of each study. * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

setting defaults and ordering options, or alternatively as a substitute in cases where traditional choice architecture techniques are less well-suited (e.g., Keller, Harlam, Loewenstein, & Volpp, 2011).

Our results indicate that partitioning effects occur partly because menu partitions are seen as communicating task-relevant information. The current study contributes to a growing body of research suggesting that choice menus can influence behavior in unexpected ways through the information they tacitly communicate to the public (Krijnen et al., 2017; McKenzie, Sher, Leong, & Müller-Trede, 2018; Tannenbaum, Valasek, Knowles, & Ditto, 2013). For example, individuals are sensitive to how options are framed (e.g., whether a medical treatment is described as having a 90% survival rate or 10% mortality rate) partly because the framing of an option is thought to communicate information about salient reference points and, more generally, which options are endorsed by the choice architect (Keren, 2007; McKenzie & Nelson, 2003; Sher & McKenzie, 2006). Here we suggest that, in a similar fashion, individuals may assume that choice architects provide a range of options that roughly match the distribution of preferences in the population. Decision makers clearly extract information from the structure of choice menus, and one common structural property appears to be how menu items are grouped.

Since menu partitions can signal information about social norms, policymakers may wish to consider additional (and less obvious) complexities that arise when designing menu partitions (see

Krijnen et al., 2017). For example, choosing an option from a packed category may suggest that such a response is relatively uncommon or atypical, and thus has the potential to induce feelings of disapproval or stigma (Krishna, Herd, & Aydınoğlu, 2019). Conversely, listing items individually may unwittingly communicate to decision makers that those options are more popular than they actually are. Furthermore, if individuals distrust policymakers or view the menu partition as an intentional act of manipulation on the part of the choice architect, then those individuals may engage in reactive behaviors as a way of asserting their agency and autonomy (Brehm, 1966; Friestad & Wright, 1994; Krijnen et al., 2017).

Positioning Effects

In all studies, we not only varied menu partitions (i.e., whether a category of items was packed or unpacked), but also independently varied the position of the packed category to be placed at the top or bottom of the menu. In a subset of studies (Studies 2 and 3), we found a statistically significant interaction between the two factors, in which partitioning effects were larger when the packed category was placed at the bottom of the menu rather than at the top. One possibility is that participants infer descriptive norms from both menu partitions and the ordering of items, and that the two inferences reinforce each other. That is, decision makers are especially likely to infer that items are unpopular when they are both grouped together and placed at the end of a menu (consistent with the judged popularity results in Study 3), and as a result menu partitioning effects are especially large under these conditions.

To explore this finding more thoroughly, we aggregate data across all studies. Table 7 displays, for each study, the menu partitioning effect (i.e., the percentage point difference in choice across menu partitions) when the packed category was placed at the bottom or top of the menu. The last column of the Table also reports the difference between the two partitioning effects, with positive difference scores reflecting a larger effect when the packed category is placed at the bottom of the menu. As the Table shows, the difference score was positive in four of the six studies, and the two negative difference scores were negligible in size. Weighting each study by the inverse of its

Table 7: Menu Partitioning Effects by Packed Category Position

	Packed Category Placed on Bottom	Packed Category Placed on Top	Difference
Study 1A	34.1 (4.5)***	38.7 (4.2)***	−4.5 (6.2)
Study 1B	19.0 (7.3)**	08.7 (5.8)	10.3 (9.3)
Study 2	53.7 (9.2)***	22.2 (10.0)*	31.4 (13.5)*
Study 3	50.1 (6.3)***	24.5 (5.7)***	25.6 (8.5)*
Study 4	34.9 (4.3)***	35.2 (4.3)***	−0.3 (6.0)
Study 5	27.3 (3.0)***	21.9 (3.0)***	5.4 (4.3)
Combined	32.8 (1.9)***	26.5 (1.9)***	6.3 (2.7)*

Notes: The first two columns display the average marginal partitioning effect when the packed category is the bottom or top listing for each study, estimated from the logit model specified in the results section of each study. Parentheses represent robust standard errors for Studies 1B and 2, and participant-clustered standard errors for all other studies. ”Difference” displays the difference in average marginal effects between menu partitions when the packed category is the bottom vs. top listing. Combined results are estimated using study fixed-effects, with weights proportional to the inverse variance of each study. * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

variance (i.e., study fixed-effects),[13] we find a combined menu partitioning effect of 32.8 percentage points when the grouped category was placed at the bottom of the menu, and 26.5 percentage points when placed at the top of the menu. This 6.3 percentage point difference between partitioning effects for bottom and top listings was statistically reliable ($\chi^2(1) = 5.62, p = 0.018$). Thus, while menu partitioning effects were large and statistically significant regardless of menu position, they were somewhat larger when grouped items were placed at the end of the menu. As mentioned earlier, this may be due to inferences of descriptive norms being reinforced by the ordering of options. We also hasten to add, however, that the evidence for positioning effects is relatively weak and should be treated as tentative (i.e., in need of further corroboration). We leave this as an avenue for future research to explore.

Limitations and Future Directions

An open question is whether single-item partitioning effects are only observed among novice decision makers, who may be uncertain how to best choose for themselves. In a related project (Tannenbaum et al., 2014), we found that partitioning the response menu had a significant effect on

[13] If we instead use a random-effect model for the meta-analysis, which weights studies according to both their degree of precision and as a function of the variability in effects found across studies, we fail to find a significant positioning effect across studies ($\chi^2(1) = 2.25, p = 0.134$). The random effects model estimates a 9.9 difference across menu positions (i.e., a larger effect than the fixed effects model), but also contains more uncertainty in that estimate.

prescription decisions among practicing physicians. In hypothetical medical vignettes that described a patient's symptom history, physicians were less likely to prescribe treatments consistent with major clinical guidelines (e.g., over-the-counter drugs rather than antibiotics for acute respiratory infections) when "inappropriate" treatment options were unpacked. Although these effects were smaller than those observed in the current paper (on average, physicians in that sample showed an 11 percentage point partitioning effect), the findings suggest that partitioning effects can be found even among experienced decision makers in a domain with considerable consequences for public health.

An important direction for future research is in applying single-item partitioning to field settings. For instance, choice architects often wish to nudge consumers on a binary decision (such as Yes/No decisions on whether to donate to a charity, or to being vaccinated). Instead of simply asking whether an individual, say, wishes to donate or consents to being vaccinated, choice architects can more finely partition the desired response option as a way of nudging compliance. Taking the donation example, charitable organizations could provide respondents with many ways of saying "yes" to donation while providing only one way of saying "no" (e.g., "Yes, I would like to donate $10/$20/$30/$40/$50 dollars" vs "No, I would not like to donate"; Moon & VanEpps, 2020). To increase vaccination rates, public health officials could individually list out the different types of vaccines available for inoculating against a particular virus (e.g., "I consent to receiving the [Pfizer vaccine/Moderna/Johnson & Johnson] vaccine" vs "I do not consent to vaccination"). Our results suggest that to the extent that individuals display single-item partition dependence, interventions such as these are likely to help increase participation rates. Consistent with this account, recent research has found that quantity-integrated selling formats, under which decision makers simultaneously consider whether and how much to buy, often increase consumption rates compared to selling formats where purchasing and quantity decisions are resolved separately (Duke & Amir, 2021; Tavassoli & Visentin, 2021). One reason why this may occur is because quantity-integrated formats more finely partition the ways that decision makers can say "yes" to consumption.

Another avenue for future research is whether menu partitions communicate additional types of information besides information about descriptive norms. One natural candidate is whether menu partitions also sometimes communicate information about injunctive norms, since descriptive and injunctive norms often travel together (e.g., Brauer & Chaurand, 2010; Eriksson et al., 2015; Thøgersen, 2008). For instance, the default option in a choice set is often viewed as the recommended or endorsed by the choice architect (Dinner, Johnson, Goldstein, & Liu, 2011; McKenzie, Liersch, & Finkelstein, 2006; Tannenbaum & Ditto, 2021), and perhaps items that are packed or grouped together are viewed by individuals as an indication that the choice architect views these items as less suitable for most individuals. One implication is that if menu partitions are viewed as a tacit endorsement from the choice architect, then decision makers will likely only find such endorsements persuasive to the extent they trust the choice architect (see Krijnen et al., 2017; Tannenbaum & Ditto, 2021).

Similarly, one may speculate that packing or clustering a set of options may signal to individuals that such options are relatively similar to each other, compared to unpacked items in the choice set (e.g., Murphy & Brownell, 1985). To the extent that perceptions of similarity reduce attractiveness for all items (perhaps by inducing within-cluster comparisons; Brenner et al., 1999), it is possible that menu partitioning effects also operate through this channel. However, we note that while other types of menu-based inferences may contribute to partitioning effects, such additional mechanisms are unlikely to account for our complete set of results. As an example, in Study 1B all features of each option (i.e., the payoffs and probabilities associated with each gamble) were transparent, and so its unlikely that inferences of similarity can explain the results we observe. Furthermore, the results of Study 4 (in which we directly intervened on beliefs about descriptive norms) cannot be readily explained by perceptions of similarity or within-cluster comparisons due to variations in menu partitioning. Future work should explore other possible mechanisms, and the relative role of such psychological processes in explaining partitioning effects depending on the characteristics of the choice environment.

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