Partitioning Menus to Nudge Single-item Choice

David Tannenbaum,[1] Craig R. Fox,[2] and Noah J. Goldstein[2]

[1]University of Utah

[2]University of California, Los Angeles

Author Note:

David Tannenbaum: Eccles School of Business, University of Utah. Craig Fox: Anderson School of Management, Department of Psychology, and Geffen School of Medicine, UCLA. Noah Goldstein: Anderson School of Management, Department of Psychology, and Geffen School of Medicine, UCLA. Correspondence should be addressed to David Tannenbaum, Department of Management, University of Utah, 1655 Campus Center Dr, Salt Lake City, UT 84112. Email: david.tannenbaum@utah.edu.

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Abstract

Decision makers must often choose items from a menu of options. For instance, employees pick investments from a set of retirement savings plans, citizens select political representatives from a list of candidates, and physicians choose 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 affects 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 — a bias towards even allocation — cannot apply to single-item choice, because singular choices are not divisible. Instead, we find 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 show that partitioning of the menu space can strongly influence single-item choices, and may serve as a simple and effective tool for managers, policymakers, and choice architects.

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

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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 automatically enrolling them into a savings plan, nudge homeowners to consume less energy by comparing energy usage to that of their 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; Madrian & Shea, 2001).

A primary justification for nudging is that choice architecture is inevitable and inescapable — policymakers and managers, knowingly or not, design choice environments in ways that will invariably affect how people choose (Thaler & Sunstein, 2003). Some design choices are unavoidable, such as how to frame a question or order response options (e.g., Dayan & Bar-Hillel, 2011); other design details are discretionary, such as whether to designate a particular option as the default (e.g., Madrian & Shea, 2001). Any unavoidable feature of a decision environment can be thought of as an essential element of choice architecture, in that all forms of choice architecture will contain it.

In this paper, we examine an essential element of choice architecture for selection of a single option from a list. Examples include citizens deciding which candidate to vote for public office from a ballot, managers choosing an employee as project lead from a roster, physicians selecting a medical prescription from an electronic order set, or restaurant patrons ordering an entree from a menu. We provide 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 strongly influence choice and behavior, and may therefore serve 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 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, rosé, and white wines). Note that menus with three or more options necessarily require a decision to be made about grouping (including the decision to not group 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 elements can also bias choice. Past research 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 (Fox, Bardolet, & Lieb, 2005; Fox, Ratner, & Lieb, 2005). To illustrate, consider the following two firms. At firm 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. At firm B, the employee is instead asked to allocate earnings from a menu that groups options according to stocks, domestic bonds, and international bonds. A bias towards even allocation over identified groups will lead to a relatively stock-heavy portfolio for employees at firm 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 for employees at firm B (e.g., 1/3 to stocks, 1/3 to domestic bonds, and 1/3 to international bonds). Decision 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, judgment under uncertainty, motivation, cue weighting, 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,

[1] For instance, consider 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 $\{A\cup C,B\}$.

2002; Martin & Norton, 2009; Shah & Oppenheimer, 2011; Sonnemann, Camerer, Fox, & Langer, 2013).

An open question is whether partition dependence also occurs for single-item choice. To return to our previous investing example, suppose an employee must select a single financial asset from a menu consisting of three stocks and three bonds. In one setting the menu is partitioned such that stocks are individually listed while bonds are grouped into a single category, and in another setting bonds are individually listed while stocks are grouped together. If decision makers display single-item partition dependence, then this would imply they are more likely to choose stocks from the former menu than from the latter menu. However, such a pattern of results would represent a novel 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. If partition dependence occurs for single-item choice, then other psychological processes besides naive diversification must be at play.

The Current Studies

In this paper we examine the extent to which single-item partition dependence occurs, and why. Prior work has documented partition dependence for single-item choice in one-off hypothetical choice scenarios (Brenner, Rottenstreich, & Sood, 1999; Feng et al., 2020; Tannenbaum et al., 2015). Here, we examine single-item partition dependence across a diverse range of decision settings, including those involving real stakes (i.e., incentive-compatible choice) and complete information over all option attributes. More importantly, prior work does not examine mechanisms that explain when and why partition dependence occurs for single-item choice. Here, we investigate two candidate mechanisms.

The first mechanism we explore 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 more finely partitioned or unpacked. This *biased-attention* account implies that single-item partition dependence is largely unaffected by contextual factors, except through the redirection of attention. As we discuss in detail later on, a unique prediction made by this account is that single-

item partition dependence should reverse when choosing between negatively-valenced options, because attending to unpleasant options makes people less likely to choose them (Janiszewski, Kuo, & Tavassoli, 2013). We examine this prediction in Study 2 and fail to find support for the biased-attention account.

The second mechanism we explore is that menu partitions communicate information about descriptive social norms (Cialdini & Trost, 1998; Gerber & Rogers, 2009). This *information-leakage* account suggests that how a set of options is presented sends a signal to decision makers about what options are frequently chosen by others. For instance, if employees confront a menu of savings plans that individually list stocks, while lumping together bonds into a single category, then employees may infer that most individuals in this organization prefer to invest in relatively risky financial assets. To the extent that decision makers look to descriptive norms for guidance — since 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. More generally, this account suggests that single-item partition dependence will be closely tied to the social and organizational context in which such menus are presented, and will have a greater influence on individuals who dispositionally tend to look to the behavior of others to guide their own decisions (Krijnen, Tannenbaum, & Fox, 2017; McKenzie, Sher, Leong, & Müller-Trede, 2018). We examine these predictions in Studies 3-5, and find consistent support for the information-leakage hypothesis.

Transparent Reporting

For all studies we determined sample size in advance of data collection. We preregistered hypotheses and analysis plans for all studies except Study 3 and 4. 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 18.5.

Study 1A: Single-item Partition Dependence and Consumer Choice

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 partitions 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").[2] 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 decisions, 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

[2]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. In addition, for all applicable studies we counterbalanced category ordering so that the residual category was listed first for approximately half of participants.

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 one 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 one organization to receive your donation: _____

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 or thoughtless responding, participants wrote out their preference in an open text field.[3] 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

[3]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.

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.

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 group we designate as focal does not affect the analysis, since each domain contains only two groups of items. Our model also includes domain fixed-effects and robust standard errors clustered by participants. For all analyses in this paper using logistic regression, we report the average marginal 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 the menu partitioning 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).[4]

[4]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 difference in average marginal effects (i.e., predicted probabilities) when the packed category is positioned at the bottom versus top of the menu. While these two approaches are identical for ordinary least squares, 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. *** $p \leq 0.001$.

Study 1B: Single-item Partition Dependence and Risk Preferences

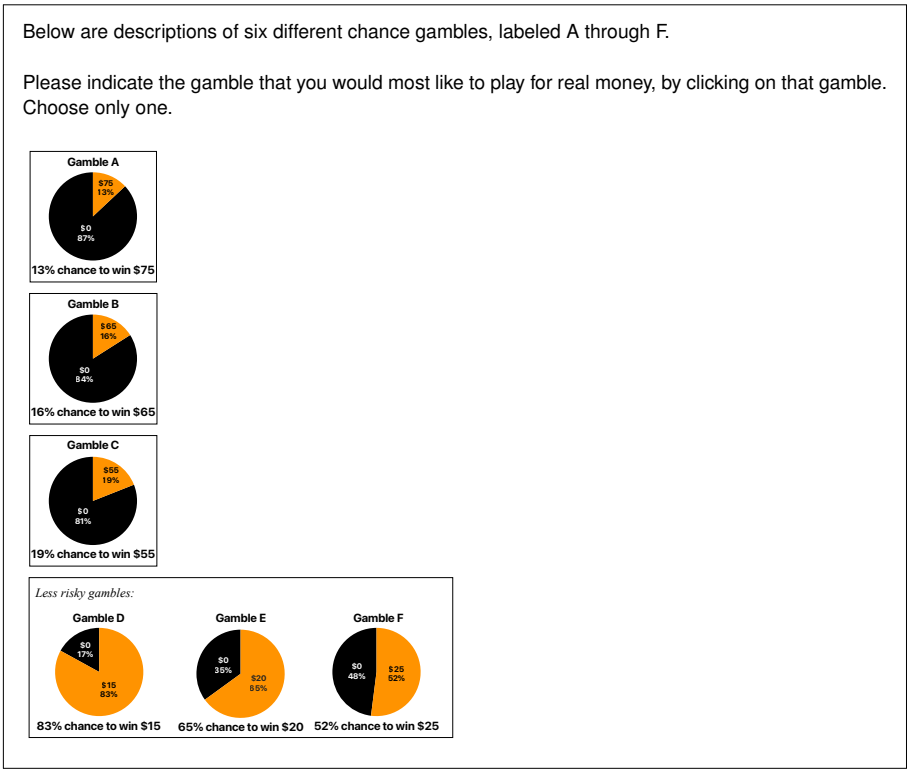
In Study 1B we examined whether single-item partition dependence extends to decisions under risk, and also used a different technique for constructing menu partitions. In Study 1A menu partitions were generated by individually listing some options and clustering others; in Study 1B we presented participants 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. As illustrated in Figure 2, half of participants chose from a menu

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



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 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. Because participants only completed a single trial, we use robust standard errors rather than participant-clustered standard errors.

Results

Participants exhibited single-item partition dependence over chance gambles. Only 7% of participants selected a riskier gamble when those gambles were packed together, compared to 22% when riskier 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 1C: Single-item Partition Dependence and Social Preferences

In Study 1C we examined whether single-item partition dependence extends to social preferences — how individuals think about their own material payoffs in relation to others. Participants played a dictator game in which they were asked to split $10 between themselves and an anonymous recipient from the same subject pool. Because decisions in the dictator game involve no strategic interaction with the recipient, they serve as a simple measure of self-regarding versus other-regarding behavior (Forsythe, Horowitz, Savin, & Sefton, 1994; Kahneman, Knetsch, & Thaler, 1986). If participants exhibit single-item partition dependence for social preferences, then we should expect to see more generous behavior when other-regarding offers are more finely partitioned compared to when such offers are more coarsely partitioned.

Method

We recruited a sample of 801 participants from CloudResearch Connect in return for a flat cash payment (48% male, mean age = 38 years, age range: 18–75 years). Participants were told they had been paired with another respondent, and that the interaction would remain anonymous (i.e, the identities of both participants would remain concealed from one another throughout the entirety of the study).

We informed all participants that they had been randomly assigned to the role of Player A, and that another participant had been assigned to the role of Player B. As Player A, they had been endowed with an additional $10 (USD) and could decide what amount, if any, to transfer to Player B. Participants first indicated a range of money to give to Player B, and on a follow-up page indicated an exact amount. Half of participants selected from an initial choice range where four of the five options were less than $2, while the other half of participants selected from a choice range where only one of the five options was less than $2 (see Figure 3 for an illustration). On a follow-up page, participants then specified an exact transfer amount to give to Player B in an open text box.[5]

Before making their allocation decisions, participants were told that 10 pairs of respondents would be randomly selected to have their choices honored for real money. When the study was complete, we assigned payoffs by randomly pairing 20 participants (half as Player A, and half as Player B) and paid them bonus amounts based on the decisions made by Player A.

Analysis Strategy

We expected that participants would transfer a greater amount of money to a recipient when relatively high transfer amounts were unpacked rather than packed. Since our two menu partitions intersect at a transfer amount of $2, we first compare the percentage of respondents who transfer $\geq$ $2 as a function of menu partitions using a two-sample test of proportions. We also compare the total amount of money given across the two menu partitions using a two-sample t-test.

When examining the distribution in dictator responses, past studies find response spikes at complete profit-maximization (i.e., giving nothing) and complete fairness (i.e., giving exactly half; see the meta-anlysis by Engel, 2011). Such responding is thought to arise partly because motives of complete profit-maximization and fairness serve as focal points that are applied in a heuristic manner (Chen & Fischbacher, 2020; Peysakhovich & Rand, 2016). We surmised that the effects of partitioning the menu space would be most pronounced among those who use non-heuristic

[5]For the open text box, participants were restricted to stating an amount within the initial choice range they had specified on the previous page. For instance, a participant selecting a transfer amount of "less than $2.00" was required to give a response between $0 and $1.99. However, due to a programming error, one participant that had selected "less than $2.00" was able to register a response of $121, which is clearly outside the range of potential transfer amounts. We recorded this answer as a missing observation.

Figure 3: Example of Menu Partition (Study 1C)

Less Generous Offers Unpacked

As Player A, you have been provisionally allocated an additional $10. Player B has not been allocated any additional money. Your decision is a simple one: decide what amount, if any, to transfer to Player B. Your choice can be anywhere from $0 to $10.

First, specify the range of money you would like to transfer:

- ☐ less than $0.50
- ☐ $0.50 to $0.99
- ☐ $1.00 to $1.49
- ☐ $1.50 to $1.99
- ☐ $2.00 or more

Please specify the exact amount you want to transfer to Player B: $ _____

Less Generous Offers Packed

As Player A, you have been provisionally allocated an additional $10. Player B has not been allocated any additional money. Your decision is a simple one: decide what amount, if any, to transfer to Player B. Your choice can be anywhere from $0 to $10.

First, specify the range of money you would like to transfer:

- ☐ less than $2.00
- ☐ $2.00 to $2.99
- ☐ $3.00 to $3.99
- ☐ $4.00 to $4.99
- ☐ $5.00 or more

Please specify the exact amount you want to transfer to Player B: $ _____

responding, and thus have not yet "made up their mind" before being exposed the menu of options. For this reason we planned (per our preregistration) to also examine responses excluding participants who gave exactly $0 or $5 from the analysis.

Results

As predicted, a greater proportion of participants gave $2 or more in the high transfer partition than in the low transfer partition (73% vs. 54%; $z = 5.64$, $p < 0.001$). When looking at final transfer amounts, participants also sent more money to Player B in the high transfer partition ($M = \$3.45$, $SD = 2.25$) than in the low transfer partition ($M = \$2.88$, $SD = 2.30$; $t(798) = 3.52$, $p < 0.001$, $d = 0.25$).

In our sample, 48% of participants transferred exactly $0 or $5. Restricting the data to only those participants who gave "nonheuristic" responses (i.e., any transfer amount besides $0 or $5), we again see that a greater proportion of respondents gave $2 or more in the high transfer partition

than in the low transfer partition (76% vs. 32%; $z = 9.08$, $p < 0.001$). When looking at final transfer amounts, participants also sent more money to Player B in the high transfer partition ($M = \$3.43$, $SD = 2.20$) than in the low transfer partition ($M = \$1.97$, $SD = 2.09$; $t(412) = 6.92$, $p < 0.001$, $d = 0.68$). Thus, while we observe single-item partition dependence regardless of our analysis, the effects we observe roughly double in size when restricting the data to participants who likely did not engage in heuristic responding.

In sum, across studies 1A–1C we find robust evidence for single-item partition dependence. We observe partition dependence for consumption decisions (study 1A), for risky decisions (study 1B), and for social decisions (study 1C). All studies involved decisions with real stakes (i.e., incentive-compatible choices), and manipulated the subjective partitioning of items using different elicitation formats. This included partitioning the description of options and asking participants to write-in a response, visually depicting menu partitions using enclosed borders, and directly embedding the grouping of options in the response menu itself. In all studies, we find participants are more likely to select options from more finely partitioned categories than from more coarsely partitioned categories.

Study 2: Do Partitions Bias Attention?

Our first three studies found clear evidence of partition dependence for single-item choice, and all subsequent studies replicate such effects while examining potential mechanisms. Although a bias toward equal allocation cannot explain single-item choice (as 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–1C.

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. Because 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 single-item partition dependence 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. Roughly half of the participants responded to a menu with indoor activities unpacked (kitchen cleaning, vacuuming, folding and washing laundry) and the remaining half of participants responded to a menu with 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 across menu partitions using a two-sample test of proportions. To examine positioning effects (i.e., whether the position of the grouped category affects our results), we conduct a logistic regression similar to that used in Study 1B.

Results

Contrary to the predictions of an attention-based account, we found a large partitioning effect similar to that found in our previus studies — this time for negatively-valenced options. 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 category 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.[6] 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 to have 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 when decision makers believe menu partitions are not constructed at random (see Krijnen et al., 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

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

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 (with more popular items listed separately rather than grouped).

According to this information-leakage account, participants should view an item as relatively 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 chose a single item from a menu of consumer choices. 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 (at the participant-level) 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 4 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

Figure 4: 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) _____ %

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 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 single-item 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 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 judgments, 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; $p < 0.001$). Likewise, for judgments, menu partitions 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-leakage 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

Table 2: Study 3 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	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. ** $p \leq 0.01$, *** $p \leq 0.001$.

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 qualitatively identical 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[7,8] (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 only participants that provided choices first ($b_{indirect} = 0.95$, SE = 0.28, 95% CI [0.50, 1.58]), or to only participants that provided judgments of item popularity first ($b_{indirect} = 0.95$, SE = 0.32, 95% CI [0.46, 1.64]).

[7]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 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., to violations 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.

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

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 judged popularity, and then from judged popularity to choice. Both our putative mediator (judgments of descriptive social 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 block information extraction, we 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[9] (65% male, mean age = 29 years, range: 18–60 years). Participants first responded to a simple attention check (Oppenheimer, Meyvis,

[9]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 5: 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 one 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) _____ %

& 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 relative popularity of the two grouped categories immediately before or after exposure to the menu partition (see Figure 5 for an example). Also different from Study 3 is that participants estimated the relative popularity of category groupings, rather than for each response 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 whether partitioning effects are attenuated in the estimation-first condition, we use logistic regression in which choices are regressed onto menu partition (0 = packed, 1 = unpacked), 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.

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 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 judgments of item popularity (as noted earlier on, this was measured at the category level rather than at the item level as in Study 3). We predicted that popularity judgments would not be affected by the menu partition in the estimate-first condition (since participants had

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. * $p \leq 0.05$, ** $p \leq 0.10$, *** $p \leq 0.001$.

not yet been exposed to the menu partition), but would shift in the direction of the menu partition in the partition-first condition (as in 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 and then viewed the menu partition did not reliably differ across conditions ($b = -0.16$, SE = 1.39, $p = 0.908$). The difference in the size of this "judgment 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.[10] 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 previously been exposed to menu partitions, and could extract information from them.

[10] 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.

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 by others) 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 for the targeted individual, and (c) decision makers do not have more diagnostic sources of task-relevant information available to them when making a decision (assuming such alternative sources of information are no more costly to acquire).

Study 5: Moderation by Social Motivations

Studies 3 and 4 suggest that menu partitions influence beliefs about descriptive social norms, and beliefs about descriptive social norms 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 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 (Deutchman, Kraft-Todd, Young, & McAuliffe, 2024; Eriksson, Strimling, & Coultas, 2015), 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 their decisions. If so, then single-item partition dependence should be especially pronounced among individuals relatively high in suceptibility to social influence.

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, and 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 suceptibility to interpersonal influence show pronounced partitioning effects because they are especially likely to infer item popularity from menu partitions (i.e, the *menu partition* $\longrightarrow$ *judged descriptive norm* pathway) and/or because these individuals give greater weight to considerations of item popularity when making a consumption decision (i.e., the *judged descriptive norm* $\longrightarrow$ *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.[11]

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 a 7-point scale 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 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.

[11] 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. *** $p \leq 0.001$.

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 from Study 3 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 judged popularity for unpacked items compared to packed items ($p < 0.001$). Finally, we again found that judgments of item popularity fully mediate 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

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	$0.027^{\dagger}$		0.019^{***}			
	(0.015)		(0.006)			
ISI		-0.007		$-0.008^{\dagger}$		-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. † $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

variable. For instance, in Model 1 (colulmn 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 × 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.

We next turn to where in the causal chain that such moderation effects occur. Models 3 and 4 examine moderation for the first part of the causal chain (i.e., the *menu partition* $\longrightarrow$ *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 single-item 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

Given that many important organizational decisions involve single-item choice rather than multi-item allocation, strategic partitioning of the menu space holds promise as an attractive tool for managers, policymakers, and choice architects. In this paper we show that single-item choice can be substantially influenced by how a set of items is partitioned. Participants were more likely to choose items that were individually listed compared to when those same items were grouped together. This was true across a wide range of choice settings, both hypothetical (Studies 2–5) and incentive-compatible (Studies 1A–1C). The effect of partitioning the menu set was sizable, shifting choices by an average of 28 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, flexible, and potent policy tool to affect behavior change (Johnson et al., 2012). Menu partitioning can be used by policymakers and managers to supplement more traditional forms of choice architecture, such as 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 signal to the public (Bogard, Reiff, Caruso, & Hershfield, 2024; Krijnen et al., 2017; McKenzie et al., 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 a 10% mortality rate) partly because the framing of an option is thought to communicate information about salient reference points and, more generally, about options endorsed by the choice architect (Keren, 2007; McKenzie & Nelson, 2003; Sher & McKenzie, 2006). Here we suggest that, in a similar fashion, individuals approach choice menus with the tacit assumption that managers, marketers, and other choice architects usually provide a range of options that roughly match the distribution of preferences in the population. As a result, the more finely a set of options

Table 6: Menu Partitioning Effects Across Studies

	Target Behavior Unpacked choice %	Target Behavior 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 1C	72.9 (2.2)	53.7 (2.5)	19.2 (3.3)***
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	69.9 (2.2)	41.6 (2.3)	28.3 (1.2)***

Notes: Percentage choosing an item from a target category when the menu is partitioned such that the focal group is packed or unpacked. For Study 1C, which did not unpack categories of items, we use the percentage transferring $2 or more to an anonymous recipient in a dictator game. Parentheses represent robust standard errors for Studies 1B, 1C, 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. * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

is partitioned, the more those options will be viewed as relatively popular in terms of market share.

If menu partitions communicate information about social norms, then policymakers may wish to consider additional (and less obvious) decision costs 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 as such has the potential to induce feelings of social 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 (with the exception of Study 1C), we experimentally varied menu partitions and 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 relevant studies. Table 7 displays 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 Table 7 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 variance (i.e., using study fixed-effects),[12] 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 hasten to add, however, that such positioning effects were not predicted a priori and relatively weak in size. As such, they should be treated as tentative and in need of further corroboration. We leave this as an avenue for future research to explore.

[12] If we instead use a random-effect model, 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.

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. We exclude Study 1C because we did not vary of the position of the packed category. 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. * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Limitations and Future Directions

An open question is whether single-item partition dependence is only observed among novice decision makers, who may be uncertain how to best choose for themselves. In a related project (Tannenbaum et al., 2015), we found that partitioning the response menu had a significant effect on 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. A fruitful avenue for future research would be to examine whether single-item partition dependence is less pronounced among those with greater task expertise or better-defined preferences, who are therefore less in need of such guidance or nudging (Camerer, Issacharoff, Loewenstein, O'Donoghue, & Rabin, 2003; Thaler & Sunstein, 2003).

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, 2023). Similarly, 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/Moderna/Johnson & Johnson vaccine" vs "I do not consent to vaccination"). Our results suggest that to the extent single-item partition dependence generalizes to other settings, interventions such as these are likely to help increase participation rates. Indeed, 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, 2023; 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 (Deutchman et al., 2024; Eriksson et al., 2015; Yip & Schweitzer, 2022). For instance, the default option in a choice set is often viewed as 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 seen as a signal that the choice architect views these items as less suitable for most individuals. One implication is that if unpacked menu items are viewed as tacit endorsements 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 of all items (perhaps by inducing within-cluster comparisons; see 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. Likewise, in Study 1C, where participants were asked to split a fixed amount of money with another participant, it is not clear how perceptions of similarity would affect these sorts of allocation decisions. The results of Study 4 (in which we directly intervened on beliefs about descriptive norms) also 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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