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Brief report

Choose for others as you would choose for yourself? A layered analysis of probabilistic preferential choice across social distances ☆

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ABSTRACT

The present study examines the effect of social distance on choice behavior through the lens of a probabilistic modeling framework. In an experiment, participants made incentive-compatible choices between lotteries in three different social distance conditions: self, friend, and stranger. We conduct a layered, within-subjects analysis that considers four properties of preferential choice. These properties vary in their granularity. At the coarsest level, we test whether choices are consistent with transitive underlying preferences. At a finer level of granularity, we evaluate whether each participant is best described as having fixed preferences with random errors or probabilistic preferences with error-free choices. In the latter case, we further distinguish three different bounds on response error rates. At the finest level, we identify the specific transitive preference ranking of the choice options that best describes a person's choices. At each level of the analysis, we find that the stability between the self and friend conditions exceeds that between the self and stranger conditions. Stability increases with the coarseness of the analysis: Nearly all people are consistent with transitive preferences regardless of the social distance condition, but only for very few do we infer the same preference ranking in every social distance condition. Overall, while it matters whether one makes a choice on behalf of a friend versus for a stranger, the differences are most apparent when analyzing the data at a detailed level of granularity.

1. Introduction

The majority of rational and behavioral choice research focuses on how people choose for their own consumption. However, people make many choices for others, such as buying a gift, cooking a meal for family, money managers making investment decisions, physicians choosing medical treatments, and union leaders negotiating collective bargaining contracts.

A growing body of research reports that people choose differently when they choose for others rather than for themselves (e.g., Atanasov, 2015; Barrafrem & Hausfeld, 2020; Batteux, Ferguson, & Tunney, 2019; Castillo, 2021; Chakravarty, Harrison, Haruvy, & Rutström, 2011; Chang, Chang, & Liao, 2015; Hermann, Mußhoff, & Rau, 2019; Hershfield & Kramer, 2017; Liu, Dallas, & Fitzsimons, 2019; Liu, Polman, Liu, & Jiao, 2018; Polman, 2012a, 2012b; Tu, Shaw, & Fishbach, 2016; Tunney & Ziegler, 2015). We move beyond

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a simple self-other dichotomy to investigate how decisions change with social distance. Social distance is a form of psychological distance that refers to the affective closeness between oneself and others (Trope & Liberman, 2010). It is centered at oneself and moves from close friends to acquaintances to strangers (Bogardus, 1926). We conducted an experiment to assess which aspects of the choice process are the same, and which are different, when a decision maker chooses for themselves, or for a close friend, or for a stranger. We organize this broader goal around a focal point, transitivity of preferences, a core property of rational decision making.

We make the important conceptual distinction between "preference" and "choice". *Preference* is an unobservable construct that reflects an agent's subjective comparative evaluation of options (Slovic, 1995). *Choices*, on the other hand, such as a decision maker choosing X when they are offered either X or Y, are observable. Many have argued that preference is unstable and susceptible to change, especially when a decision problem is described or framed in different ways (Slovic, Fischhoff, & Lichtenstein, 1980; Tversky & Kahneman, 1981). Likewise, observable behavior is inherently and highly variable, both within and across individuals. Even when making the same choices repeatedly a decision maker may choose X over Y in some instances, and choose Y over X in other instances. As we distinguish preference and choice, we should consider two potential sources of variability: uncertain preference or uncertain choice given a fixed preference.

We study choice processes through the lens of a well-established probabilistic modeling framework. This framework explicitly models uncertainty in either latent preferences or observable choices. It also allows us to classify decision makers according to four basic properties of the choice process: 1. (In)transitivity of the underlying preference, 2. the source of variability in observed behavior, and in the case of deterministic latent preferences, 3. information about the noisiness of observed choice behavior, and 4. specific latent preferences.

In a review and meta-analysis of research about decision making for others involving risk, Polman and Wu (2020) finds considerable variability between studies, suggesting that the overall effect of social distance on risky choice may be highly susceptible to moderating factors, study design features, and individual differences. We explore how conclusions about the effect of social distance on decision making may also be sensitive to the layer at which one analyzes the data. Our approach attends to the interplay between social distance, heterogeneity, and layers of analysis. We take a layered view of latent features of the decision process, and examine which layers may vary with social distance, while accounting for heterogeneity between and within subjects.

More broadly, this work builds on a recent discussion of philosophy of science issues relevant to behavioral research, including model parsimony, theoretical scope, the difficulty of navigating conjunctions of hypotheses in decision research, and the complicated relationship between observable behavior and hypothetical constructs (see, e.g., Davis-Stober & Regenwetter, 2019; Erev & Feigin, 2022; Hertwig & Pleskac, 2018; Kellen, 2022; Kellen, Davis-Stober, Dunn, & Kalish, 2021; Regenwetter & Robinson, 2017, 2019, 2022; Regenwetter, Robinson, & Wang, 2022a, 2022b; Scheibehenne, 2022). Our analyses eschew the common practice of extracting and interpreting patterns from data merely on the basis that they "show an effect". Our goal is not just to show an effect of social distance on choice patterns, but rather to identify which latent features of the decision process change, and which ones remain invariant, across social distance conditions.

We also avoid statistical models that are not fully grounded in substantive scientific theory, such as regression or ANOVA. Instead, following Regenwetter and Cavagnaro (2019), we use order-constrained models and methods that require only minimal auxiliary assumptions and stay true to the scientific hypothesis. Further, rather than aggregating data across people and/or stimuli as is common in behavioral science, we analyze each individual's data separately and model the conjunction of predictions across distinct stimuli. We assess the replicability of these within-subject results across participants (and, as reported in the Online Appendix, across experiments). This approach of treating individual participants as replication units has been referred to as a "small-N design" (Smith & Little, 2018). Finally, our layered analysis considers replicability at various levels of granularity, thereby providing a higher level of nuance, subtlety, and resolution for a collection of competing scientific hypotheses compared to standard approaches of merely comparing summary statistics.

2. Methods and models

The long literature on testing transitivity of preferences spans disciplines as diverse as biology, economics, psychology, and zoology. As Regenwetter, Dana, and Davis-Stober (2010, 2011), and Regenwetter, Davis-Stober, Smeulders, Fields, and Wang (2021) documented, that literature is plagued with conceptual, logical, mathematical, methodological, as well as statistical problems (see also Regenwetter & Robinson, 2017; Regenwetter et al., 2022a, for related broader discussions). For instance, the most influential paper on intransitivity of preferences, Tversky (1969), used incorrect statistical inference to support its findings (see also Iverson & Falmagne, 1985). Meanwhile, it has become possible to test models of transitivity properly using modern "order-constrained" data analytic methods that include both frequentist and Bayesian approaches (see Cavagnaro & Davis-Stober, 2014; He, Golman, & Bhatia, 2019; Park, Davis-Stober, Snyder, Messner, & Regenwetter, 2019; Regenwetter et al., 2018; Regenwetter & Davis-Stober, 2012, for examples). These methods are available in public-domain statistical software (Heck & Davis-Stober, 2019; Regenwetter et al., 2014; Zwilling, Cavagnaro, Regenwetter, Lim, Fields, & Zhang, 2019). These order-constrained methods do not require a utility framework, such as expected utility or prospect theory. They operate with a minimum of auxiliary and distributional assumptions (see also Regenwetter & Davis-Stober, 2017, for a review of common assumptions in the literature). A different approach uses multinomials instead of binomials (Birnbaum, 2011; Birnbaum & Bahra, 2012), but see also Regenwetter, Dana, Davis-Stober, and Guo (2011). Alternatively, Alós-Ferrer, Fehr, and Netzer (2021) and Alós-Ferrer and Garagnani (2024) incorporate reaction times.

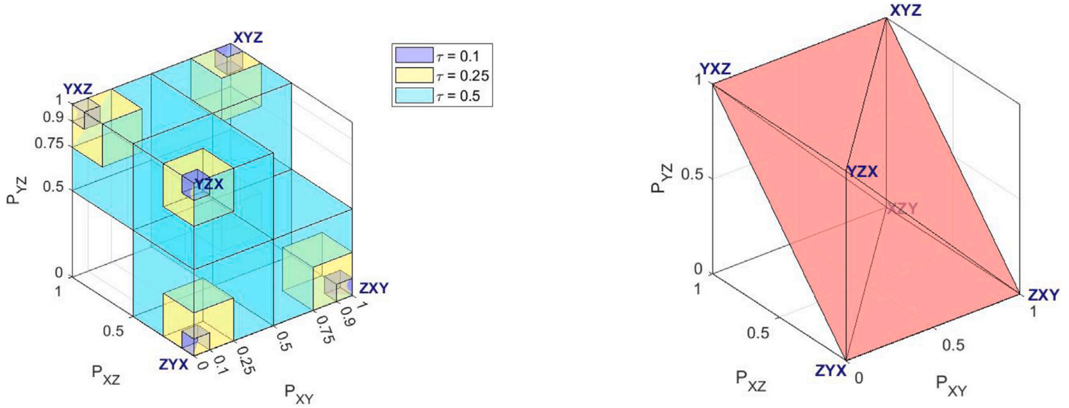

Fig. 1. Geometric representations of the error models (left) with error bounds $\tau = 0.1$ (purple), $\tau = 0.25$ (yellow), and $\tau = 0.5$ (blue) and random preference model (right) for preference patterns in the collection $\{XYZ, XZY, YXZ, YZX, ZXY, ZYX\}$.
Note. Each axis is a binary choice probability. The labeled corners (e.g., XYZ) correspond to deterministic and error-free choices. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.1. Four probabilistic choice models for transitive preference

Under the *weak utility* model (e.g. Block & Marschak, 1960; Luce & Suppes, 1965), each decision maker has a fixed preference but does not always choose the preferred option. Rather, each time they are presented with a pair of alternatives, there is some probability that they will choose the option that they do not actually prefer, i.e., they make probabilistic response errors. "Weak stochastic transitivity" (WST) is a weak utility model in which the underlying preference can be any transitive relation (i.e., ranking) over alternatives (see Block & Marschak, 1960; Iverson & Falmagne, 1985; Luce & Suppes, 1965; Regenwetter et al., 2010; Tversky, 1969). For any two choice alternatives, X, Y, let P_{XY} be the probability of choosing X in a choice between X and Y. Considering a third option Z, let P_{YZ} be the probability of choosing Y in a choice between Y and Z and let P_{XZ} be the probability of choosing X in a choice between X and Z. Formally, *weak stochastic transitivity* states that, for all (distinct) X, Y, Z,

$$\text{if } P_{XY} \geq \frac{1}{2} \quad \text{and} \quad P_{YZ} \geq \frac{1}{2} \quad \text{then it follows that} \quad P_{XZ} \geq \frac{1}{2}. \tag{1}$$

A decision maker with a fixed transitive preference who makes occasional probabilistic errors in choice satisfies WST. However, if preferences are dynamic, say, a decision maker wavers between different transitive preference patterns, then their choice probabilities can violate WST. According to a "random preference" model of transitive preference, and the associated "distribution-free random utility" model, all uncertainty (and resulting variability) in the overt choices of an individual is due to uncertainty in the person's latent transitive preferences, with no response error. This model is known under many different monikers across several disciplines, including "random preference" model, "(general) random utility" model, "mixture model of transitive preferences", criterion for the "rationalizability of binary choice", and the "linear ordering polytope" (see, e.g. Block & Marschak, 1960; Luce & Suppes, 1965; Regenwetter, Dana, & Davis-Stober, 2011). We skip the mathematical formulation of this model (see Regenwetter, Dana, & Davis-Stober, 2011, for a thorough introduction and explanation). Instead, we work with the fact that it implies a property called the *triangle inequalities* (TI) according to which, for all (distinct) X, Y, Z,

$$P_{XY} + P_{YZ} - P_{XZ} \leq 1. \tag{2}$$

When considering all pairs among a master set of no more than five distinct choice options, as we do for each master choice set in this study, these inequalities completely characterize the random preference model. We refer to this model with the acronym *LOP* because it is called the *linear ordering polytope* in the technical literature.

WST is an instance of a more general class of error models according to which the latent preference is transitive but unknown, and responses are error-prone. At a high level of generality, we can model error-prone choice by specifying some constraints on permissible error rates (Block & Marschak, 1960; Harless & Camerer, 1994; Tversky, 1969). Here, writing $X \succ Y$ to denote that X is deterministically preferred to Y, and τ for the upper bound on error rates, the general error model (aka the "supermajority" model of Regenwetter et al., 2014; Zwilling et al., 2019) states that for all (distinct) X, Y,

$$X \succ Y \quad \Leftrightarrow \quad P_{XY} > 1 - \tau. \tag{3}$$

We consider τ values of 0.5, 0.25, and 0.1. WST is the special case of this error model (3) when $\tau = 0.5$. The other two cases, because they place stronger restrictions on permissible error rates, are nested submodels of WST. Both WST and LOP contain other well-known models as lower-dimensional, nested submodels, including "Fechnerian" models such as Logit and Probit models, and "constant-error" models (see also Cavagnaro & Regenwetter, 2023).

Table 1
Layers of assumptions in probabilistic models of binary choice.

Model	Transitivity	Source of choice variability	Upper bound on error rate
WST	Yes	Response errors	0.5
Super75	Yes	Response errors	0.25
Super90	Yes	Response errors	0.1
LOP	Yes	Fluctuating preferences	No response errors
Unconstrained	No	No constraints	No constraints

Table 2
Model parsimony (diagonals) and overlap (off-diagonals), measured as volume in $[0,1]^3$ and in $[0,1]^{20}$.

	3D (Fig. 1)				20D (Experiment)			
	$3! = 6$ transitive rankings				$(5!)^2 = 14,400$ pairs of trans. rankings			
Model	LOP	WST	Super75	Super90	LOP	WST	Super75	Super90
LOP	$\frac{2}{3}$	0.625	0.078	0.005	.0025	0.0007	7×10^{-10}	7×10^{-18}
WST		$\frac{3}{4}$	0.09	0.006		.014	10^{-8}	10^{-16}
Super75			0.09	0.006			10^{-8}	10^{-16}
Super90				0.006				10^{-16}

Fig. 1 shows geometric representations of all three error models and the random preference model, for the case of three choice alternatives, X, Y and Z. Each coordinate is a choice probability. The labeled corners (e.g., XYZ), because their coordinates are zero and/or one, represent deterministic and error-free choices. The shaded regions on the left are the error models with the three different error bounds. The shape on the right is the random preference model. As the figure reveals, the two types of models, while grounded in conceptually different premises about the source of uncertainty in behavior, do overlap in their predictions about permissible choice probabilities. However, when considering two sets of five alternatives, as we do for each social distance condition in our experiment, the overlap is minuscule and each model is extremely parsimonious (Table 2).

In all, we consider five primary models: the four models of transitive preferences just described, and an unconstrained model in which preferences may be transitive or intransitive. We provide a summary of these models in Table 1. The models differ according to three features of the choice process: transitivity, source of variability, and, if applicable, upper bound on response error rates. Super75 and Super90 refer, respectively, to the models with τ values of 0.25, and 0.1 because they require the decision maker to (correctly) choose the preferred option at least 75%, respectively 90% of the time.

2.2. Order-constrained inference

Our analysis proceeds in stages as we assess each core property (i.e., layer) of the choice process. In each stage, the primary building block of our analysis is the Bayes factor (Kass & Raftery, 1995), which provides a direct and interpretable measurement for model fit and model selection. Bayes factors quantify the strength of evidence in favor of one model compared to another model by taking the ratio of their marginal likelihoods. For computation, we used QTest 2.1 (Zwilling et al., 2019) on PCs and on the Bridges supercomputer at the Pittsburgh Supercomputing Center.

Our conceptual, modeling, and statistical inference approach is similar to that of Cavagnaro and Davis-Stober (2014) and of Regenwetter et al. (2018). Both of these studies found broad support for transitive preferences and concluded that different individuals are often best described by different models of transitive preference.

The novelty here is that we aim to test not just specific models, but also properties that are shared by several models under consideration, at various levels of granularity. We do this by considering suitably identified Bayes factors for a given person, within each social distance condition, and stimulus set. At the coarsest level of granularity, we consider transitivity of preference per person and social distance condition. We infer that transitivity is supported when the average of the Bayes factors for the four transitive models, relative to the unconstrained model, exceeds 1.0. Whenever transitivity is supported, we proceed to consider the source of variability. The source of variability could either be random preferences (LOP) or probabilistic response errors (WST, Super75, and Super90). To select among these two hypotheses, we compare the Bayes factor for LOP with the average of the Bayes factors for WST, Super75, and Super90. The ratio of these two quantifies the evidence for one or the other source of variability, compared to the other. At the next level of granularity, we compare the Bayes factors for WST, Super75, and Super90, directly, to select among the three bounds on the error rate. At the finest level, we use Bayes factors to select among the 120 weak utility models of the 120 possible individual transitive preference rankings to find each person's most likely deterministic preference.

In sum, we use Bayes factors to both evaluate whether transitivity is satisfied and to quantify the evidence for the model that best represents the patterns in participants' choices. The primary goals of this study are to analyze choice behavior individually, to assess the source of heterogeneity, and to determine whether preferences that are transitive are so in different ways under different social distance conditions.

Fig. 2. Mobile device screen shot of a stimulus.
Note. Each colored area of the pie chart was the probability of winning the corresponding dollar amount. Besides this example, participants were asked to make choices stated as "Which option do you prefer, for **a close friend**?" or "Which option do you prefer, for **a stranger**?".

Table 3
Cash I & Cash II stimuli of Regenwetter, Dana, and Davis-Stober (2011) .

Cash I			Cash II		
Label	Probability	Payoff	Label	Probability	Payoff
a	7/24	$28.00	A	0.28	$31.43
b	8/24	$26.60	B	0.32	$27.50
c	9/24	$25.20	C	0.36	$24.44
d	10/24	$23.80	D	0.4	$22.00
e	11/24	$22.40	E	0.44	$20.00

3. Experiment

We presented choice problems to participants in a lab experiment. Each problem had two alternatives and a designated recipient, namely either the participant (self stimulus), or a close friend of the participant (friend stimulus), or an unspecified stranger (stranger stimulus). Participants were instructed to choose one of the two alternatives for the designated recipient in each choice problem. After completing the study, participants returned three weeks later to repeat it. We discuss the second round, which replicates the main findings from the first round, in Sections A and B of the Online Appendix. We pre-registered our stimuli, study design, and predictions on the Open Science Framework (OSF): https://osf.io/9hdfg.

3.1. Method

Participants and Incentives: We recruited 20 participants by posting flyers at the University of Illinois at Urbana-Champaign (UIUC). Participants were informed that two of their choices would be played out for real payment to the designated recipient in the form of an Amazon gift card. Participants provided the email address of a close friend to enable payment to the friend. Payments to the stranger were pooled across participants and later given to a student, selected by the psychology department at UIUC, at a departmental end-of-the-semester awards ceremony. Thus, even the experimenters did not know the identity of the stranger. On average, in each experiment, participants received a total payment of $17.00 (SD=1.38), comprised of a fixed $10.00 show-up fee and an average performance-based earning of $7.00 (SD=1.38); the close friends received an average total payment of $2.10 (SD=1.68), while the stranger received a total of $34.00.

Web-mobile platform: We used a novel web-mobile experimental platform under development by the Cognitive Computations and Social Dynamics Lab at UIUC (led by Dr. Hari Sundaram). The experimenter first configured the experiment through a web interface. Then, participants installed an app on their phones from which they could join the study.

Stimuli: Besides the three different social distance conditions, there were also two different types of stimuli: choices between lotteries (i.e., risky choice) and choices between time-delayed rewards (intertemporal choice). In the latter, the time delays turned out too short to induce impatience. Participants almost always chose the alternative with the larger dollar amount, regardless of the recipient. We provide the intertemporal stimuli and results in Section E of the Online Appendix. In this paper, we focus on the choices between lotteries.

While some recent approaches to stimulate inconsistencies in behavior consider different ways of providing information about a fixed set of lotteries, such as described versus experienced outcome probabilities (Hertwig & Erev, 2009), or such as coalesced versus split events (Ostermair, 2022), we consider a classical paradigm in which the probability of winning and the reward size trade-off against each other (Ranyard, Montgomery, Konstantinidis, & Taylor, 2020; Tversky, 1969). Following Tversky, we used the Cash I & Cash II stimulus sets of Regenwetter, Dana, and Davis-Stober (2011). Each set consists of the 10 possible pairwise combinations of a set of five lotteries (see Table 3). We showed each lottery as a wheel of chance. The area of the pie chart that was shaded red or blue was the probability of winning the corresponding dollar amount. Fig. 2 depicts an example of the mobile phone display

Table 4
Layered, within-subjects results.

DM	Social distance								
	Self			Friend			Stranger		
	Var. Source	$1-\tau$	Rankings	Var. Source	$1-\tau$	Rankings	Var. Source	$1-\tau$	Rankings
1	Response	0.5	abcde ABCDE	Response	0.5	abced ABCDE	Preference	0.5	abcde ABCDE
2	Response	0.9	edcba EDCBA	Response	0.9	edcba EDCBA	Response	0.9	edcba EDCBA
3	Response	0.9	abcde ABCDE	Response	0.9	abcde ABCDE	x	–	–
4	Response	0.9	abcde ABCDE	Response	0.9	abcde ABCDE	Response	0.9	abcde ABCDE
5	Response	0.75	debca ECDAB	Preference	0.5	debca CDEAB	Preference	0.5	debca CDEAB
6	Response	0.75	edcba ECDBA	Response	0.75	edbca EDCBA	Response	0.75	edcab EDCBA
7	Preference	0.5	debca CBDEA	Preference	–	–	Preference	–	–
8	Response	0.75	edbca EDACB	Response	0.75	edbca DECAB	Preference	0.5	edbca ECDAB
9	Preference	0.5	aecbd EDABC	Preference	0.5	ecadb DEABC	Preference	0.5	adcbe EDBCA
10	x	–	–	x	–	–	x	–	–
11	Response	0.75	abcde ABCDE	Response	0.75	abcde ABCDE	Response	0.75	abcde ABCDE
12	Response	0.75	debca DEBCA	Response	0.9	abcde ABCDE	Response	0.9	abcde ABCDE
13	Preference	0.5	debca DABEC	Preference	0.5	ecdab DBACE	Preference	0.5	ebcda BDEAC
14	Response	0.9	decba EDCBA	Response	0.75	decba DECBA	Response	0.9	edcba EDCBA
15	x	0.75	edcba BAEDC	x	–	–	Response	0.9	abcde ABCDE
16	Response	0.9	abcde ABCDE	Response	0.9	abcde ABCDE	Preference	0.5	becad DEBAC
17	Response	0.9	edcba EDCBA	Response	0.9	edcba EDBCA	Response	0.9	edcba EDCBA
18	Response	0.75	edcba EDCBA	Response	0.75	edcba EDCBA	Preference	0.5	abcde ABDCE
19	Response	0.5	abcde ABCDE	Response	0.5	abcde ABCDE	Response	0.75	debca DECBA
20	Preference	0.5	eacdb EBDCA	Response	0.75	ecadb EDBCA	Preference	0.75	eacdb EDBCA

Note. Symbol x means transitivity was not supported. Dashes mean we do not infer best error bounds or rankings because none of the fixed preference models are supported by the data with a Bayes factor greater than 1.0.

for choosing among lotteries. These stimuli had previously only been used for testing transitivity of preference for oneself. In this experiment we combined each lottery pair with a designated recipient, yielding 60 risky choice stimuli.

Each participant made 934 choices, which were divided into 10 blocks. This total includes six repetitions of each of the 60 risky choice stimuli, six repetitions of each of 60 intertemporal stimuli, and 214 distractors. The distractors consisted of randomized risky and intertemporal option pairs, as well as stimuli from Guo (2018) and Regenwetter et al. (2018). The order of choice presentation was randomized across participants and across blocks. To reduce memory effects, the stimulus shown to participants in any given trial had not appeared in the previous four trials. Additional details and a demo of our experiment can be accessed through this url: https://osf.io/zxrau/.

3.2. Analysis

The Bayes factors for each model, participant, social distance condition, and stimulus set are available in Section C of the Online Appendix. Those tables summarize a large scale quantitative analysis that has too many moving parts to include here in detail. Instead, Table 4 shows whether transitivity is supported, the most likely source of variability, the most likely bound on error rate, and the best transitive ranking, for each participant and social distance condition, jointly across both stimulus sets. We find individual differences at all layers of the analysis, and within each social distance condition. At the first layer, and coarsest level of granularity, nearly all participants are best described as having transitive preferences in each social distance condition. Moving to the next layer, the source of choice variability, we classify more than twice as many participants as having random preferences (i.e., LOP) when choosing for strangers than when choosing for oneself or for a friend (9, 4, and 4 individuals, respectively). Notably, three of the four decision makers classified as having random preferences when choosing for themselves are also best described as having random preferences when choosing for a friend and when choosing for a stranger. Drilling down further to the inferred bounds on error rates, we find some participants best described by each value of τ. Qualitatively, there seems to be greater variability in this measure across participants (i.e., down each column) than across social distance conditions (i.e., across each row). Finally, we observe a great variety of the best-fitting preference rankings. Both lexicographic (ABCDE, abcde) and reverse-lexicographic (EDCBA, edcba) orders are well represented, but do not appear significantly more often in any social distance condition compared to another. These particular rankings are notable because they are consistent with a lexicographic heuristic decision process that prioritizes either the option with the highest probability of winning (EDCBA) or the option with the largest prize (ABCDE).

Next, we examine the stability of these classifications across social distances. Table 5 summarizes the information in Table 4 by reporting, within each layer, the number of decision makers whose classifications match across different combinations of social distances. For each layer, a decision maker may have the same classification for all three social distances, or they may have the same classification for two social distances but a different one for the third, or they may have different classifications for all three social distances. In all there are five possible patterns of matches. Using set notation, we write $\{S, Fr, Str\}$ to denote the case where the classification is the same in all three social distance conditions. For the cases where the classification is the same in two conditions but different in the third, we write $\{S, Fr\}\{Str\}$ when the match is between Self and Friend (hence Stranger is the odd one out),

Table 5
Concordance across social distances at different layers of analysis.

Layer	Pattern of matching classifications					
	{S, Fr, Str}	{S, Fr} {Str}	{S, Str} {Fr}	{S} {Fr, Str}	{S} {Fr} {Str}	N
(In)transitivity	18	2	0	0	0	20
Source of Variability	11	4	1	1	0	17
Bound on Error Rates	8	4	1	3	0	16
Preference Rankings	3	3	2	2	6	16
Total	40	13	4	6	6	69

Note. In cases where a participant cannot be classified at a given layer in a given social distance condition, the participant does not belong in any of the five patterns of matching classifications in that layer. We omit those participants from the analysis at those layers. For example, we only consider 17 participants at the layer of Source of Variability because, as shown in Table 4, there are three participants (DMs 3, 10, and 15) for whom we could not identify a best source of variability in at least one social distance condition due to transitivity not being supported by the data. Even though we classify DM 3 as has having probabilistic responses in both the Self and Friend conditions, we cannot say whether or not the source of variability in the Stranger condition also matches because transitivity is not supported by the data for DM 3 in the Stranger condition.

$\{S, Str\}\{Fr\}$ when the match is between Self and Stranger, and $\{Fr, Str\}\{S\}$ when the match is between Self and Stranger. Finally, we write $\{Fr\}\{Str\}\{S\}$ for the case where the classifications are different in all three social distance conditions.

Several patterns emerge in Table 5. First, in the column totals, we find that the most frequent pattern is $\{S, Fr, Str\}$, namely identical classifications across three social distance conditions. The least frequent pattern is $\{S, Str\}\{Fr\}$, i.e., the same classification for Self and Stranger, but a different one for Friend. This pattern holds separately within each layer except for Preference Ranking, where the most frequent pattern is $\{S\}\{Fr\}\{Str\}$. More generally, we find that the frequency of the $\{S, Fr, Str\}$ pattern decreases as we move to finer levels of granularity in the analysis: 90% (18 out of 20) match for (In)transitivity, 65% (11 out of 17) for Source of Variability, 50% (8 out of 16) match for Bound on Error Rates, and just 19% (2 out of 16) for Preference Rankings. We also find that a matching classification between Self and Friend is more common than a matching classification between Self and Stranger. In other words, most participants tend to choose the same way for a friend as they do for themselves, and relatively few tend to choose the same way for a stranger as they do for themselves. Moreover, we find more matches between Friend and Self conditions than between Friend and Stranger conditions, suggesting that choosing for a friend is more like choosing for oneself than it is like choosing for a stranger.

4. Conclusions and discussion

We investigated the choice processes of decision makers across three social distance conditions: self, friend, and stranger. We analyzed the data within subjects, with a dual focus on what changes and what stays the same across conditions. Our model-based analysis eschewed highly structured, parametric accounts of risk attitudes in favor of basic, non-parametric features of rational decision making, such as transitivity of preference and the source of choice variability.

Overall, we found that choosing for a friend is more like choosing for oneself than it is like choosing for a stranger. However, we also found considerable heterogeneity across participants within each social distance condition. As a result, the differences between conditions were not systematic. That is to say, we did not find evidence favoring a particular property in one condition and a different particular property in another condition.

We found less consistency across social distances (within subjects) as we considered finer-grained properties of the choice process (Table 5). We found that nearly all participants' choices were consistent with transitive preferences regardless of the social distance condition, but seldomly with the same specific ranking of alternatives. This finding aligns with our earlier cited work that has found violations of transitivity to be rare (c.f. Alós-Ferrer, Fehr, & Garagnani, 2023; Birnbaum, 2023; Butler & Pogrebna, 2018; Ranyard et al., 2020). However, regardless of the layer, we found the greatest consistency between the self and friend conditions, and the least consistency between the self and stranger conditions.

The heterogeneity we found across individuals highlights the importance of analyzing data within subjects. Any modal or aggregate classification of the group would not be descriptive of many individuals within the group. However, although our within-subjects design alleviates many of the problems associated with group-level analyses, it nevertheless has its own limitations. Participants might have been affected by the large number of choices in the experiment and switched their decision strategy from a compensatory one to a simple heuristic. They also may have gradually paid less attention to whether they were making decisions for themselves or for others. However, we found no evidence of such systematic changes over the time course of either experiment. Moreover, such phenomena that relate to participant fatigue and stationarity would presumably affect all three social distance conditions similarly. As such, they would be unlikely to affect our main qualitative findings about relationships between conditions. Moreover, results from the second round of the experiment, reported in the Online Appendix, replicate the main findings of the first round, lending credence to the robustness of these findings.

Our results suggest that degree of social distance may be an important consideration for modeling the many instances of choosing for others in everyday life. In future work, it may be worthwhile to examine a broader variety of social distance targets, such as co-workers or family members. Future work may also consider collecting more data from the same person over a longer period, in more contexts, and while participants are immersed in real-life contexts, as physical proximity to others (e.g., a close friend) may have a potential impact on the decisions people make. Such extensions of the current paradigm would require significant advances in research infrastructure for controlled experiments in the field.

Disclosures

This paper is based on Xiaozhi Yang's 2019 honor's thesis at the University of Illinois at Urbana-Champaign (UIUC). This honors project was embedded within a larger, collaborative research program between the Regenwetter and Cavagnaro labs with the Sundaram lab (Computer Science, UIUC). The collaborative work with the Sundaram lab developed the mobile app that we used for data collection in this study. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the opinions or official policies, either expressed or implied, of NSF, colleagues, or the authors' home institutions.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.joep.2024.102754.

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