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Childhood Poverty and Its Impact on Financial Decision Making Under Threat: A Preregistered Replication of Griskevicius et al. (2011b)

Joe J. Gladstone[1], Meredith Lehman[2], and Mallory Decker[2]
[1] Department of Marketing, Leeds School of Business, University of Colorado Boulder
[2] Department of Organizational Behavior, Leeds School of Business, University of Colorado Boulder

We investigated the influence of childhood poverty on financial decision making under threat by replicating the findings of Griskevicius et al. (2011b), which found that individuals from lower socioeconomic backgrounds tend to make riskier financial decisions and prefer immediate over delayed gratification when exposed to mortality cues. Following an extension of life history theory to individual behaviors, the original research argued that these behaviors reflect a faster and riskier strategy to cope with survival threats. In a preregistered replication using the same procedures and instruments as the original study, we tested this hypothesis with a sample size 14.2 times larger than the original (1,010 vs. 71). We replicated the effect of mortality salience on risk-taking for people who experienced childhood poverty but with a substantially smaller effect size ($\eta^2 = 0.004$ vs. $\eta^2 = 0.17$ in the original). We failed to find any effect on time preferences in contrast to the original study's medium effect size ($\eta^2 = 0.046$). Although our findings partially support the results of Griskevicius et al. (2011b) on poverty and financial decision making, the drastically reduced effect sizes challenge the practical significance of these findings. Our replication results underscore the importance of large sample studies in understanding the effects of childhood socioeconomic status on future life decisions. They also suggest that frameworks beyond life history theory may be needed to reliably capture such relationships.

Public Significance Statement

This study attempted to replicate influential research linking childhood poverty to riskier financial decision making under mortality threat. Using a large, diverse sample, we found limited support for this hypothesis, with a significant but very small effect on risk-taking and no effect on temporal discounting. These findings challenge the original study's conclusions and their real-world relevance. Our work underscores the need for well-powered replications to test the reliability of findings on poverty and decision making. More broadly, it suggests that the application of evolutionary frameworks such as life history theory to individual human behaviors requires careful validation. Understanding how early life conditions shape adult choices remains an important goal, but overgeneralizing from single studies can lead us astray. Cumulative evidence from robust, multimethod research is essential to inform effective interventions and policies that improve decision making and well-being for individuals from all backgrounds.

Keywords: financial risk, temporal discounting, socioeconomic status, mortality, replication

Consider two friends, Jessica and Alice, who come from contrasting socioeconomic backgrounds. Jessica grew up in poverty, whereas Alice enjoyed a privileged upbringing. As adults, they both experience a traumatic event, such as the global COVID-19 pandemic. How does their behavior change—and differ—in response to this event? Griskevicius et al. (2011b) posited that one's childhood environment plays a crucial role in shaping reactions to perceived threats. In this context, Jessica's exposure to scarcity and instability

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Mallory Decker https://orcid.org/0000-0001-8696-3737
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Correspondence concerning this article should be addressed to Joe J. Gladstone, Department of Marketing, Leeds School of Business, University of Colorado Boulder, 995 Regent Drive, Boulder, CO 80309, United States. Email: Joe.Gladstone@colorado.edu

might predispose her to pursue immediate and riskier rewards as an adaptive mechanism to cope with an unpredictable and hostile environment. This idea is derived from life history theory (LHT), which proposes that organisms adjust their survival and reproductive strategies according to the availability and stability of resources (Ellis et al., 2009). This theory provides insights into understanding why individuals from lower socioeconomic backgrounds might exhibit more short-term-oriented financial decision making under conditions of uncertainty and danger.

LHT is an evolutionary framework that explains variation and trade-offs in organisms' allocation of resources toward survival and reproduction (Del Giudice et al., 2015; Roff, 1992). Although LHT originated in the biological sciences to explain plant and nonhuman animals' phenotypic diversity as a response to environmental cues (Roff, 1992), developmental psychology scholars have adapted the theory's principles to explain varying human strategies in response to environmental harshness and unpredictability (Ellis et al., 2009). According to this application of LHT, individuals adopt a life history strategy that varies from fast to slow along a spectrum (Del Giudice et al., 2015; Griskevicius et al., 2013). Fast strategies are characterized by early sexual development, high reproductive investment, short-term orientation, impulsivity, and risk seeking. These behaviors are beneficial in environments where survival is precarious and resources are limited. Slow strategies are characterized by late sexual development, low reproductive investment, long-term orientation, risk avoidance, and self-regulation. These behaviors are beneficial in environments where survival is more certain and resources are more plentiful.

Scholars have also extrapolated from LHT that early life stress can prime an individual's response to stress later in life, triggering latent behavioral patterns associated with life history strategies in highly stressful situations (Ellis & Cabeza de Baca, 2017; Griskevicius et al., 2011b, Griskevicius et al., 2013). Therefore, the emergence of adaptive responses stemming from early life environments depends on current stress levels, such as mortality salience and resource scarcity. In the context of Jessica and Alice, this suggests that Alice, having experienced a more stable and resource-rich environment, is more likely to adopt a slow life history strategy, which is characterized by long-term planning, risk aversion, and self-control in response to challenging situations such as the COVID-19 pandemic.

The application of LHT to individual human behaviors has sparked intense debate within evolutionary psychology and behavioral ecology (Frankenhuis & Nettle, 2020). Critics such as Zietsch and Sidari (2020) argue that extrapolating species-level life history predictions to explain individual variation is fundamentally flawed. They contend that human behavioral plasticity and the complexity of modern environments render simple fast–slow continuum models inadequate for capturing the nuances of individual decision making. Moreover, Baldini (2015) mathematically demonstrated that optimal life history strategies can vary among individuals even in identical environments, challenging the assumption that shared conditions produce uniform responses. Conversely, proponents of individual-level LHT applications, such as Del Giudice (2020), argue that the theory provides a valuable framework for understanding the patterns of covariation in human behavioral and physiological traits. Del Giudice suggested that apparent inconsistencies in empirical findings may stem from overlooking crucial moderating variables or misspecifying relevant environmental dimensions. Nettle and Frankenhuis (2020) proposed a reconciliatory perspective, advocating for a "phenotypic gambit" approach that uses LHT to generate testable predictions about individual differences without assuming direct genetic encoding of behavioral strategies. This ongoing controversy underscores the need for rigorous empirical tests of LHT predictions at the individual level. Our high-powered replication of Griskevicius et al.'s (2011b) study contributes to this critical discourse by examining whether the purported life history effects on decision making are robust and generalizable across more diverse populations.

The study by Griskevicius et al. (2011b), which explores the relationship between childhood socioeconomic status (SES) and financial decision making under conditions of uncertainty and threat, is an influential contribution to the literature supporting LHTs relevance to individual human behavior. The authors hypothesized that individuals from lower SES backgrounds are more likely to take risks and choose immediate rewards over delayed ones when exposed to mortality cues as a way of adapting to an unpredictable and harsh environment. The authors conducted experiments on university students and found compelling evidence supporting their hypotheses.

Although the study by Griskevicius et al. (2011b) has been influential, it has several limitations that warrant further investigation. First, their small sample sizes ($N = 97$, $N = 71$, and $N = 44$ for Experiments 1, 2, and 3, respectively) raise concerns about the reliability and generalizability of their findings. Small samples can lead to inflated effect sizes and increased risk of false positives (Button et al., 2013). Second, their study relied on a relatively homogeneous sample of university students, potentially limiting the generalizability of their findings to broader populations. These limitations underscore the need for a high-powered replication with a more diverse sample to establish the robustness of their results.

In this article, we conducted a high-powered replication of the study by Griskevicius et al. (2011b) using a larger and more representative sample of participants. Our primary motivation stemmed from the critical importance of validating influential findings in psychological science, particularly those with potential real-world implications such as understanding financial decision making under stress. The article by Griskevicius et al. (2011b), with more than 1,100 citations (Google Scholar, August 2024), has significantly influenced the field by applying LHT principles to individual decision making. This application, while influential, remains controversial within the scientific community.

The impact of this work extends beyond its immediate findings. Subsequent research has built upon and expanded the authors' conclusions, linking childhood SES and risk-taking with chronic disease in late life (Miller et al., 2011) and various nonfinancial risky behaviors such as substance abuse, sexual risk-taking, and aggressive conduct (Duffy et al., 2018; Mishra, 2014; Rung & Madden, 2018). However, recent studies have challenged these findings, casting doubt on whether childhood SES truly interacts with current stress cues to predict risk-taking or temporal discounting behaviors (Amir et al., 2018; Pepper et al., 2017).

Given these conflicting results and the ongoing debate about applying LHT to individual behaviors, we approached this replication with an open mind. We recognized the possibility of replicating the original findings, finding no effect, or discovering more nuanced relationships among the variables. Our goal was not to confirm or refute the original study but rather to provide a robust, high-powered investigation that could offer valuable insights into the reliability and generalizability of these effects.

We selected the second experiment from Griskevicius et al. (2011b) for replication because it was central to their claims and incorporated measures for both risk-taking and temporal discounting behaviors. We tested the same hypotheses as the original study—that mortality cues would induce individuals from lower socioeconomic backgrounds to take greater risks and prefer immediate rewards, consistent with a faster life history strategy, whereas individuals from higher socioeconomic backgrounds would take fewer risks and prefer larger, delayed rewards, aligning with a slower life history strategy.

By employing a larger and more demographically diverse sample, we aimed to provide a more comprehensive examination of how childhood SES influences financial decision making under conditions of uncertainty and threat. This approach allowed us to not only test the replicability of the original findings but also to explore potential moderating factors and boundary conditions that may not have been apparent in the original study.

Method

Transparency and Openness

We preregistered our hypotheses, research design, and analysis plan on AsPredicted before collecting and analyzing the data (https://aspredicted.org/9XT_FCW). In the following sections, we detail how we determined sample size, all data exclusions, all manipulations, and all measures in the study, in accordance with Journal Article Reporting Standards (Appelbaum et al., 2018). In addition, all study materials, data, and analysis code are available online on the Open Science Framework at https://osf.io/kxy96/?view_only=c1cd295775734d09a87f8bce5f03baa3.

Study Design and Procedure

We obtained copies of the original experiment materials from the authors to ensure the fidelity of our replication. We followed the original research design by Griskevicius et al. (2011b), which employed a between-participants design featuring two conditions (mortality salient vs. control) and measures for risk preference and delayed gratification. In addition, we included a measure of perceived childhood SES to account for the potential effects of early life SES on financial decision making.

Participants were randomly allocated to either a mortality salience condition or a control condition. In the mortality salience condition, participants read an article titled "Dangerous Times Ahead: Life and Death in the 21st Century," which described recent trends toward violence and death in the United States and concluded with a statement that these trends reflect the reality of the future environment, which would be treacherous. The article was designed to resemble a realistic newspaper article, using *The New York Times* logo, font, and style.[1]

In the control condition, participants read an article of similar length and formatting (approximately 600 words) that described a person searching for his lost keys over the course of an afternoon. The wording of these articles is provided in additional online material (https://osf.io/kxy96/?view_only=c1cd295775734d09a87f8bce5f03baa3). We used the same articles as Griskevicius et al. (2011a), who conducted a pilot test and found that the two articles elicited the same amount of general arousal; however, the mortality prime led participants to view the world as more uncertain and unsafe. To enhance the relatability of the control condition article for our more diverse sample, we made minor adjustments to remove specific references to university students.

Comparison With Original Study

Although we aimed to replicate the study of Griskevicius et al. (2011b) as closely as possible, several key differences exist between our replication and the original study. These differences, summarized in Table 1, reflect our efforts to enhance the robustness and generalizability of the findings, as well as adapt the study to current best practices in psychological research.

Power Analysis and Sample Size Determination

Our study aimed to replicate and extend the research of Griskevicius et al. (2011b) by utilizing a larger and more diverse sample. The original study, conducted in person at a large public university, included a modest sample of 71 students participating for course credit. This sample size provided sufficient power only for detecting large interaction effects (Simonsohn, 2015).

To ensure a robust replication, we performed a power analysis based on Cohen's (1988) guidelines for effect sizes in regression models. Using G*Power software, we specified our smallest effect size of interest as $f^2 = 0.02$, corresponding to a small effect in a regression model with three independent variables (experimental condition, childhood SES, and their interaction). Initial calculations indicated that a sample of 395 participants would be required to achieve 80% power with a significance level of $\alpha = .05$.

However, considering the complexities associated with detecting interaction effects in moderated regression analyses, we adopted a more conservative approach. Interaction effects often exhibit reduced power due to lower reliability and the nonnormal distribution of the product variable (Aiken et al., 1991; McClelland & Judd, 1993; Shieh, 2009), as well as the shape of the interaction itself (Blake & Gangestad, 2020; Champoux & Peters, 1987).

Our analysis indicated that a sample size of 921 participants would provide 99% power to reliably detect a small effect ($f^2 = 0.02$) at a significance level of 0.05. This decision to aim for 99% power, substantially higher than conventional thresholds, was driven by the specific challenges of detecting interaction effects and the ongoing debates surrounding the applicability of LHT to individual behaviors. Based on these considerations, we attempted to recruit 1,000 participants from the United States using Prolific Academic, resulting in 1,030 completed surveys. This final sample exceeded our target and further bolstered the study's statistical power.

Participant Recruitment and Characteristics

Our study redesigned the experiment for online administration using Prolific, a platform known for providing high-quality data and demographically diverse participants (Palan & Schitter, 2018). This

[1] The University of Colorado Boulder Institutional Review Board classified our study as exempt (22-0574), and we did not include a postsurvey debrief regarding our manipulations.

Table 1
Key Methodological Differences Between Original Study and Current Replication

Characteristic	Original study	Replication study
Sample size	71	1,010
Participants	University students	General adult population
M_{age}	20.8 years	40.4 years
Data collection	In-person, laboratory setting	Online, using Prolific
Geographic location	Single university in the United States	Diverse U.S. locations
SES measure	Childhood SES only	Childhood and adult SES
Mortality prime	Original news article about local shooting	Same article, minor adjustments
Control condition	Article about lost keys	Same article, minor adjustments
Attention checks	Not reported	Implemented
Minimum reading time	Not reported	60 s
Preregistration	Not preregistered	Preregistered
Data availability	Not publicly available	Publicly available

Note. SES = socioeconomic status.

approach offered some advantages over the original study's reliance on a university student sample, including increased statistical robustness through a larger sample size and greater demographic diversity.

We recruited participants from Prolific's U.S. participant pool, resulting in a sample notably more diverse in terms of age and socioeconomic background compared to the original study's university-based cohort. The demographic composition of our sample included 48.9% men, 48.4% women, and 2.7% nonbinary/other individuals, with an average age of 40.4 years (SD = 14.6). Although the majority of participants identified as White (85.48%), our sample also included representation from Asian (4.78%), Black (4.39%), multiracial (3.29%), and other (2.07%) ethnic groups.

This broader demographic range offered by Prolific represents a significant improvement over traditional university subject pools. However, it is crucial to acknowledge that our sample's composition does not fully mirror the diversity of the general U.S. population (Palan & Schitter, 2018). This limitation should be carefully considered when interpreting and generalizing our results.

Data Quality and Exclusion Criteria

In contrast to the original study by Griskevicius et al. (2011b), which did not report data exclusions or attention checks, we implemented rigorous quality control measures to enhance data integrity and minimize nonhuman or careless responding (Meade & Craig, 2012; Stosic et al., 2024).

To enhance the effectiveness of the experimental manipulation, we imposed a minimum 60-s viewing time for the assigned article (Hauser et al., 2019). Participants demonstrated adequate engagement with the material, spending an average of 3 min and 13 s (SD = 2 min, 17 s) on the manipulation page.

In line with our preregistered protocol, we employed condition-specific attention checks. These multiple-choice questions directly related to the content of the assigned article (e.g., "In the article you read, which of the following items was lost?"). Participants failing these checks were excluded from the final analysis.

Of the initial 1,030 respondents, 20 (1.94%) failed the attention check and were subsequently removed, resulting in a final sample of 1,010 participants. Our final sample size (N = 1,010) represents a 14.2-fold increase over the original study (N = 71), substantially enhancing our statistical power to detect the hypothesized effects of childhood SES on financial decision making under conditions of uncertainty and threat.

Measures

Risk Preference and Time Preference

We employed the same outcome measures as the original study (Griskevicius et al., 2011b) to assess risk preference and time preference (also known as temporal discounting or delay of gratification). Risk preference was measured using a series of seven dichotomous choices. Participants were asked to choose between a 50% chance of receiving $800 and a certain amount ranging from $100 to $700 in $100 increments. The propensity for risk-taking was quantified by summing the number of risky options chosen (range = 0–7; M = 1.48, SD = 1.40). Higher scores indicate greater risk preference.

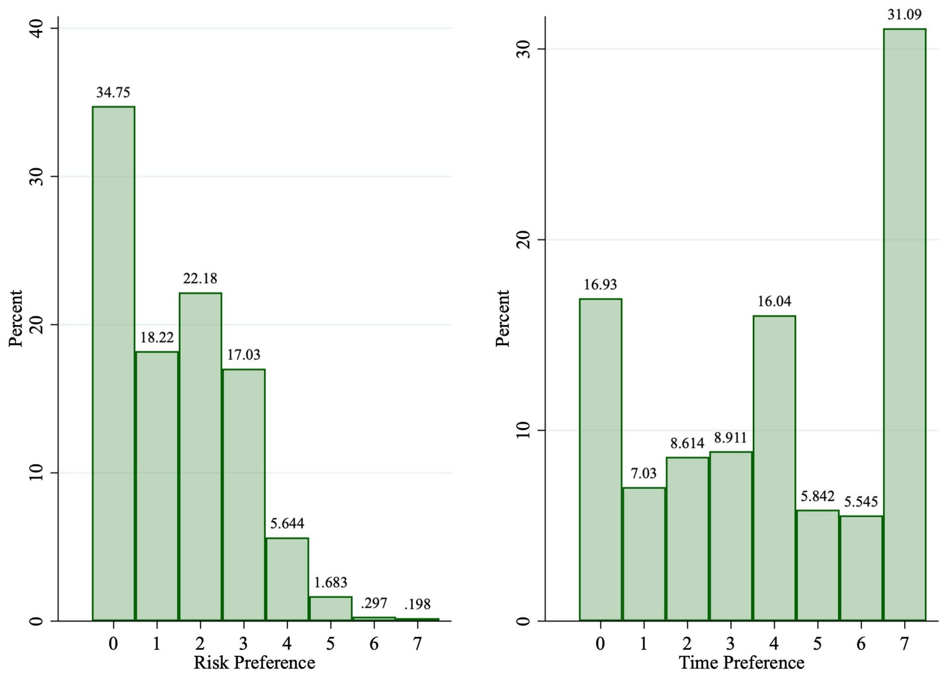
To assess time preference, participants made seven dichotomous choices between receiving $100 the next day or a larger amount 90 days later. The delayed amounts ranged from $110 to $170 in $10 increments. The propensity for immediate gratification was calculated by summing the number of times participants chose the smaller, immediate rewards (range = 0–7; M = 3.95, SD = 2.62). Higher scores indicate a stronger preference for immediate gratification.

Both risk preference and time preference measures exhibited sufficient variability to enable meaningful analysis of individual differences. The distributions of risk preference and time preference scores are illustrated in Figure 1.

Childhood and Adult SES

Participants' childhood SES was assessed using a three-item self-report questionnaire that gauged their agreement with the statements: "My family usually had enough money for things when I was growing up," "I grew up in a relatively wealthy neighborhood," and "I felt relatively wealthy compared to the other kids in my school." Responses were rated on a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*), and a composite continuous variable for childhood SES was calculated and standardized (α = .85). It is important to note that these items measure perceived

Figure 1
Distribution of Risk Preference and Time Preference Scores



Note. The left panel shows the distribution of risk preference scores, where higher scores indicate greater risk-taking propensity. The right panel displays the distribution of time preference scores, where higher scores reflect a stronger preference for immediate rewards. Both measures range from 0 to 7. Values above each bar represent the percentage of participants selecting that option. See the online article for the color version of this figure.

childhood economic status rather than objective socioeconomic indicators. This distinction is important, as subjective perceptions may not always align with actual economic circumstances. Consequently, these measures should be interpreted as proxies for true SES, offering insight into participants' economic self-concept rather than their factual economic positioning during childhood.

To evaluate current (adult) SES, three additional items were included (α = .83): "I have enough money to buy things I want," "I don't need to worry too much about paying my bills," and "I don't think I'll have to worry about money too much in the future" (α = .88). As shown in Table 2, the interitem correlations indicated that childhood SES and adult SES were distinct but related constructs, with a moderate positive correlation of $r = .32$.

Education level shows weak to moderate correlations with both childhood SES ($r = .19$) and adult SES ($r = .29$), suggesting that educational attainment is somewhat related to, but distinct from, both past and current SES perceptions. Current income level correlates more strongly with adult SES ($r = .46$) than with childhood SES ($r = .19$), as expected. We further consider implications of the correlations between our control and focal variables in the Discussion section.

Control Variables

In addition to the main variables of interest, we collected demographic information on participants as control variables. This included gender, age in years, income (12 categories ranging from "less than $10,000" to "$150,000 or more"), and education level (eight categories ranging from "less than high school degree" to "professional degree [JD, MD]").

Preregistered Analysis Plan

We followed our preregistered analysis plan to conduct a replication of Griskevicius et al.'s (2011b) second experiment. We used ordinary least squares linear regression models to test our hypotheses, with risk preference and time preference as separate dependent variables.

The study employed linear regression to examine the effects of mortality salience (a categorical predictor) and childhood SES (a continuous predictor) on risk and time preferences (continuous outcomes). This method was selected for its capacity to model the hypothesized interaction between these variables while controlling for demographic factors such as age, gender, income, and education. This approach also facilitated a clear comparison with the original study's findings, enabling us to assess the replicability and robustness of the previously reported effects in our larger, more diverse sample.

The independent variables in each model were the experimental condition (coded as 0 for control and 1 for mortality salience), childhood SES (standardized to have a mean of 0 and a standard deviation of 1), and their interaction. We report the results of these models both with and without covariates for gender, age, income, and education level.

Table 2
Correlations Between Childhood SES, Adult SES, and Current Socioeconomic Indicators

Variable	1	2	3	4	5	6	7	8	9	10
1. Childhood SES Item 1	—									
2. Childhood SES Item 2	.64	—								
3. Childhood SES Item 3	.63	.71	—							
4. Composite childhood SES	.87	.89	.88	—						
5. Adult SES Item 1	.34	.28	.33	.36	—					
6. Adult SES Item 2	.23	.20	.22	.25	.75	—				
7. Adult SES Item 3	.24	.21	.27	.27	.66	.73	—			
8. Composite adult SES	.30	.26	.30	.32	.89	.92	.89	—		
9. Education level	.17	.17	.17	.19	.28	.27	.25	.29	—	
10. Current income level	.14	.18	.18	.19	.44	.45	.36	.46	.35	—

Note. N = 1,010. Composite SES scores are calculated as the mean of the respective items. All correlations are significant at $p < .001$. SES = socioeconomic status.

To complement our preregistered analyses, we performed Bayesian analyses on model results with p values exceeding .05. Bayesian analyses provide a more informative interpretation of nonsignificant results by quantifying the strength of evidence for the null hypothesis relative to the alternative hypothesis. By reporting Bayes factors (BFs), we aim to distinguish between the absence of an effect (i.e., evidence of no effect) and inconclusive results (i.e., insufficient evidence to draw firm conclusions). We also conducted exploratory analyses that were not preregistered, which we clearly label as such in the Results section.

Results

We collected data on participants' risk preferences, time preferences, childhood and adult SES, and demographic information. Before presenting our main analyses, we provide descriptive statistics and correlations for these key variables in Table 3.

Preregistered Analyses

Risk Preference

Table 4 reports the results of our linear regression models. Our analysis showed a significant interaction between childhood SES and experimental condition on risk preferences when control variables were included, $b = -0.12$, $SE = 0.06$, $t(1001) = -2.08$, $p = .038$, $\beta = -0.086$. This interaction was slightly attenuated in the model excluding control variables, $b = -0.11$, $SE = 0.06$, $t(1006) = -1.82$, $p = .069$, $\beta = -0.077$. Figure 2 illustrates the interaction effect. Participants who reported growing up in resource-scarce environments chose more risky options when exposed to mortality cues, whereas those who reported growing up in resource-plentiful childhood environments chose less risky options when exposed to mortality cues. This result appears to support our hypothesis on risk preferences and replicate the finding of Griskevicius et al. (2011b).

Time Preference

Our results demonstrated a nonsignificant interaction between childhood SES and the experimental condition (mortality vs. control) on preference for more immediate financial rewards, with controls: $b = -0.02$, $SE = 0.06$, $t(1001) = -0.29$, $p = .774$, $\beta = -0.025$, and without controls: $b = -0.01$, $SE = 0.06$, $t(1006) = -0.22$, $p = .827$, $\beta = -0.028$. As shown in Figure 3, participants' preference for more immediate financial rewards did not vary by childhood SES or mortality prime. These results do not support our hypothesis or Griskevicius et al.'s (2011b) application of LHT in this context.

Effect Size Comparisons

Our study provides a critical reevaluation of the effect sizes for risk and time preferences originally reported by Griskevicius et al. (2011b). Our findings reveal substantially smaller effect sizes, challenging the robustness and generalizability of the original study's conclusions.

For risk preference, we observed an extremely small interaction effect (with controls: $\beta = -0.086$, $\eta^2 = 0.004$; without controls: $\beta = -0.077$, $\eta^2 = 0.003$), falling below the conventional threshold for

Table 3
Descriptive Statistics and Correlations for Key Variables

Variable	*M*	*SD*	Min	Max	1	2	3	4	5	6	7	8
1. Risk preference	1.48	1.40	0	7	—							
2. Time preference (impulsivity)	3.95	2.62	0	7	−.04	—						
3. Childhood SES	3.51	1.52	1	7	$.06^{\dagger}$	−.02	—					
4. Adult SES	3.62	1.68	1	7	.03	$.17^{***}$	$.32^{***}$	—				
5. Age	40.45	14.60	18	91	$-.17^{***}$	−.03	$-.06^{\dagger}$	$.11^{***}$	—			
6. Gender (female)	48.42%		0	1	$-.12^{***}$	.05	.01	−.03	$.12^{***}$	—		
7. Income (categorical)	6.21	3.36	1	12	$.06^{*}$	$-.14^{***}$	$.19^{***}$	$.46^{***}$	.03	.02	—	
8. Education (categorical)	4.11	1.41	1	8	.05	$-.24^{***}$	$.19^{***}$	$.29^{***}$	$.19^{***}$	.05	$.35^{***}$	—

Note. Risk preference and time preference were measured on scales from 0 to 7. Childhood and adult SES were measured on scales from 1 to 7. Gender is reported as the percentage of female participants. Income and education are reported as categorical variables. Min = minimum; Max = maximum; SES = socioeconomic status.
$^{\dagger} p < .1$. $^{*} p < .05$. $^{***} p < .001$.

Table 4
Results of Linear Regression Models Predicting Risk Preference (Models 1 and 2) and Time Preference (Models 3 and 4)

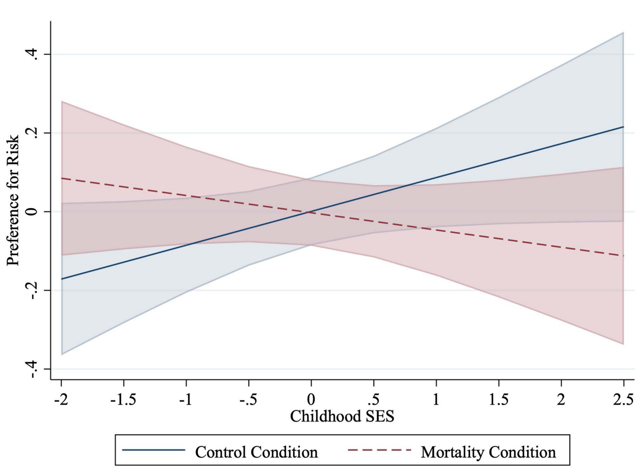
	Risk preference				Time preference			
	Model 1		Model 2		Model 3		Model 4	
Variable	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Intercept	0.00	0.04	0.33*	0.13	0.01	0.04	0.69***	0.13
Childhood SES	−0.00	0.06	−0.00	0.06	−0.05	0.06	−0.07	0.06
Mortality prime	0.11**	0.04	0.09*	0.04	−0.11**	0.04	−0.02	0.04
Childhood SES × Mortality Prime	−0.11†	0.06	−0.12*	0.06	−0.01	0.06	−0.02	0.06
Female			−0.21***	0.06			0.11†	0.06
Age			−0.01***	0.00			0.00	0.00
Education			0.04†	0.02			−0.16***	0.02
Income			0.01	0.01			−0.02	0.01
N	1,010		1,009		1,010		1,009	

Note. *SE* = standard error; SES = socioeconomic status.
† $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

small effects ($\beta = 0.10$, $\eta^2 = 0.01$). The effect size for time preference was negligible (with controls: $\beta = -0.025$, $\eta^2 = 0.0003$; without controls: $\beta = -0.028$, $\eta^2 = 0.0004$). These results starkly contrast with the original study's reported large effect size for risk preference ($\eta^2 = 0.17$) and medium effect size for time preference ($\eta^2 = 0.046$).

Although the effect sizes for risk preference are statistically significant at the .05 level, their practical significance in real-world terms is likely negligible. To illustrate, the largest effect size we observed ($\beta = -0.086$) translates to a minimal difference in risk-taking behavior between individuals from low and high perceived childhood SES backgrounds. In practical terms, this effect size means that if we compare two groups of 100 people each—one from a perceived low childhood SES background (−1 *SD*) and one from a perceived high childhood SES background (+1 *SD*)—we would expect to see a difference of less than one risky choice (0.6 choices) between the groups on our seven-item measure. Such small effects are unlikely to manifest in observable differences in real-world financial behaviors or outcomes.

Figure 2
Relationship Between Childhood SES and Preference for Riskier Options Under the Influence of a Mortality Prime Versus Control



Note. Shaded error bands represent 95% confidence intervals. SES = socioeconomic status. See the online article for the color version of this figure.

These disparities prompt critical questions about the stability and reliability of the findings from the original study. The increased sample size in our study likely contributes to a more accurate estimation of these effect sizes, suggesting that the original study may have been underpowered to detect the smaller effect magnitudes we have identified. Our results not only failed to replicate the time preference hypothesis but also indicated a substantially smaller effect size for risk preference than that reported by Griskevicius et al. (2011b).

Although small effects can theoretically accumulate over time or across multiple decisions (Götz et al., 2022), the extremely small effect sizes observed in our study suggest that childhood SES and mortality salience, as operationalized here, play a negligible role in shaping adult financial decisions. These factors are likely just two of many influences on financial decision making, with minimal practical impact.

Thus, our preregistered replication study casts considerable doubt on the original study's conclusions. These findings underscore the importance of considering not only statistical significance but also effect sizes and their real-world implications when interpreting research results in financial decision making. They also highlight the value of large-scale replications in refining our understanding of psychological phenomena and their practical relevance.

Exploratory Analyses

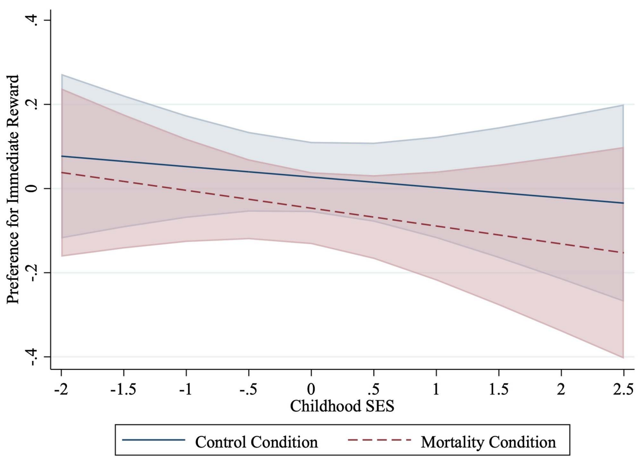
We conducted additional analyses that were not preregistered to further investigate the relationships between perceived childhood economic status, the experimental condition, and decision making.

Bayesian Analyses

To complement our frequentist approach and provide a more precise interpretation of our results, we conducted Bayesian analyses. This method quantifies the relative evidence for the null hypothesis compared to the alternative hypothesis, offering valuable insights particularly when traditional null hypothesis significance testing yields nonsignificant or ambiguous results (Wagenmakers et al., 2018).

Figure 3

Relationship Between Childhood SES and Preference for More Immediate Financial Reward Under the Influence of a Mortality Prime Versus Control



Note. Shaded error bands represent 95% confidence intervals. SES = socioeconomic status. See the online article for the color version of this figure.

For risk preferences, we compared models with and without the interaction term (Childhood SES × Mortality Prime) using BFs. The BF_{10} was 0.003, indicating strong evidence in favor of the null model ($BF_{10} < 1/100$; Jeffreys, 1961). This suggests that the data are far more likely under the model without the interaction term, challenging the robustness of the interaction effect observed in our initial analysis and casting doubt on the reliability of replicating the original study's findings.

For time preferences, a similar Bayesian analysis yielded a BF_{10} of 0.001, providing very strong evidence against the presence of an interaction effect. This indicates that the data are 1,000 times more likely under the model without the interaction term, further supporting our frequentist results that showed no significant interaction between perceived childhood SES and mortality primes on time preference.

These Bayesian analyses offer a more comprehensive evaluation of our findings, moving beyond the binary decision making of null hypothesis significance testing. By quantifying the strength of evidence against the hypothesized interaction effects, we mitigate concerns about potential Type II errors and provide a clearer assessment of the evidence (or lack thereof) for the original study's claims.

Combined SES

We combined the six items measuring both perceived childhood and adult SES ($\alpha = .85$), reasoning that a combined measure would be more relevant for our adult sample, as opposed to the student sample in the original study. In addition, a life-spanning operationalization of SES (specifically, the income proxy for SES used in the original study) may point to explanatory models beyond LHT. That is, Griskevicius et al.'s (2011b) interpretation of their findings specifies that childhood SES, irrespective of current status, should have a distinct impact on risky behavior in accordance with LHT. Our exploratory results indicate no such distinction, and in fact, combined SES produces results nearly identical to childhood SES alone. We found a significant interaction between combined SES and the experimental condition (mortality vs. control) on preference for riskier options, $b = -0.12$, $SE = 0.06$, $t(1006) = -1.98$, $p = .047$, $\beta = -.086$. This effect remained significant when controlling for potential confounding variables, $b = -0.13$, $SE = 0.06$, $t(1001) = -2.17$, $p = .030$, $\beta = -.092$. Once again, these effect sizes were small. As in our preregistered examination of childhood SES above, we did not observe a significant relationship for delayed discounting.

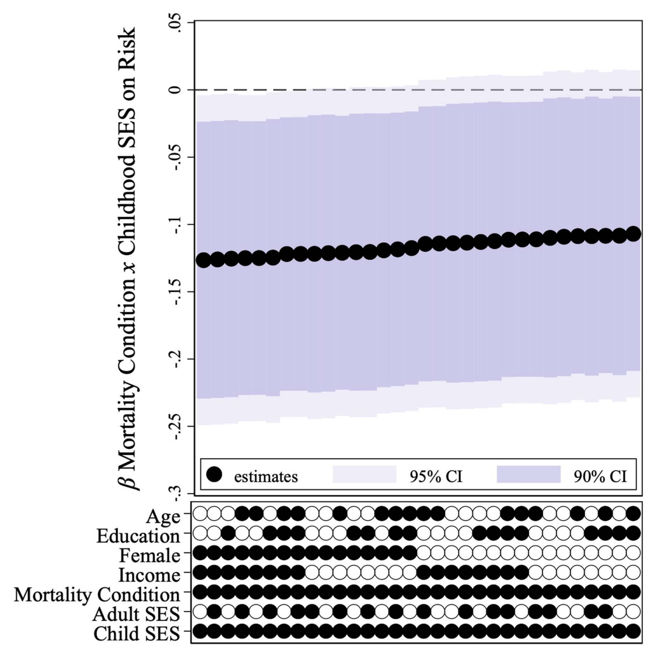
Specification Curve Analysis

We utilized specification curve analysis to evaluate the robustness of our primary finding against variations in covariate selection, including individual control variables and adult SES. This method systematically explores and tests all plausible model specifications, assessing the consistency of the results across diverse data analysis choices.

Figure 4 illustrates the output of this analysis. It shows that the regression coefficients from various model specifications maintained a consistent direction. However, most of the 95% confidence intervals included zero, indicating that most models failed to reach the .05 significance level. Despite this, the directionality of the coefficients remained stable across different specifications.

Figure 4

Specification Curve Analysis Presenting Coefficients From Each Plausible Model Specification



Note. Each dot symbolizes an individual regression coefficient estimate, whereas the shading illustrates the 95% CI surrounding that estimate. Filled circles in the lower panel indicate whether a variable was incorporated in the corresponding model above. SES = socioeconomic status; CI = confidence interval. See the online article for the color version of this figure.

Discussion

We conducted a direct and preregistered replication study of the second experiment by Griskevicius et al. (2011b), which showed that childhood resource scarcity and mortality salience interacted to influence risk and time preferences. We followed the same procedures and measures as closely as possible, using a sample size over 14 times that of the original experiment. Our findings partially replicated the risk-taking results of Griskevicius et al. (2011b), showing a significant interaction between childhood resource scarcity and mortality salience on risk preferences, such that participants who reported growing up in resource-scarce environments preferred riskier options when primed with mortality cues, whereas those who reported growing up in resource-plentiful environments preferred less risky options. This result is consistent with the idea that childhood resource scarcity triggers a faster life history strategy that favors immediate rewards and risk-taking (Del Giudice et al., 2015; Roff, 1992; Stearns, 1992).

However, the effect was no longer significant at the .05 level without the inclusion of covariates, and the effect size for risk was notably smaller than the original study, suggesting that their findings may not be robust. The effect size that we observed was extremely small (with controls: $\eta^2 = 0.004$; without controls: $\eta^2 = 0.003$), falling below the conventional threshold for small effects ($\eta^2 = 0.01$). These findings imply that while we detected a statistically significant interaction between childhood resource scarcity and mortality salience on risk preferences, the effect we find is so small as to raise substantial doubts about its practical relevance and applicability in real-world contexts. In addition, we did not replicate the original study's findings on temporal discounting, finding no evidence of an interaction between childhood resource scarcity and mortality salience. This result challenges the notion that childhood resource scarcity influences time preferences in a consistent way across different contexts.

Exploring the Nonreplication of Temporal Discounting Results

We consider two possible reasons for the nonreplication of Griskevicius et al.'s (2011b) findings regarding the impact of childhood SES and mortality salience on temporal discounting in our study. One possible explanation is that the original finding was a false positive resulting from chance or error. The original study showed a weaker effect size for temporal discounting ($\eta^2 = 0.046$) than for risk ($\eta^2 = 0.17$), suggesting that the former effect was less robust and more susceptible to noise. Moreover, the original study had low statistical power and a small sample size ($N = 71$), which increased the likelihood of obtaining spurious results. In contrast, our replication study had high power and a large sample size ($N = 1{,}010$), which enhanced the precision and validity of our estimates. Therefore, it is plausible that the original finding on temporal discounting may have been a spurious result that does not reflect a true phenomenon.

The second account for the nonreplication of the original finding on temporal discounting is that experimental design differences could have moderated the effect. The most salient difference between the original study and ours concerns sample diversity in terms of age and income level. Griskevicius et al. (2011b) recognized the restricted range of income levels in their student sample and proposed that by using a homogeneous, relatively affluent university sample, this might have diminished their effect size. They further suggested that individuals from lower resource backgrounds would show stronger reactions to mortality cues, "shifting life history strategies even more dramatically" (p. 1023). However, our effect size was considerably smaller despite a more representative sample of lower income individuals. Our sample's self-reported household income data closely aligned with broader population demographics,[2] indicating that increased socioeconomic diversity did not amplify the findings but could have potentially attenuated them. This result contradicts Griskevicius et al.'s conjecture that individuals from more resource-deprived backgrounds might respond more intensely to mortality primes.

Participant age may partly account for the nonreplication of the original finding on temporal discounting. Our sample was much older than that of Griskevicius et al. ($M = 40.4$ vs. 20.8 years old), and this age difference may have affected participants' responses to our mortality prime. Previous studies have shown that mortality salience differentially influences financial decision making across age groups. For instance, young adults exposed to mortality salience primes gave less to charity, whereas older adults gave more (Roberts & Maxfield, 2019). This suggests that younger adults may become more impulsive and present-oriented when confronted with mortality cues, whereas older adults may become more cautious and future-oriented. Furthermore, research has indicated age differences in temporal discounting, with middle-aged respondents discounting less than younger and older respondents (Göllner et al., 2018; Read & Read, 2004). Therefore, age may have moderated the effect of mortality salience and childhood SES on temporal discounting, and the nonreplication could be attributed to confounding effects of age.

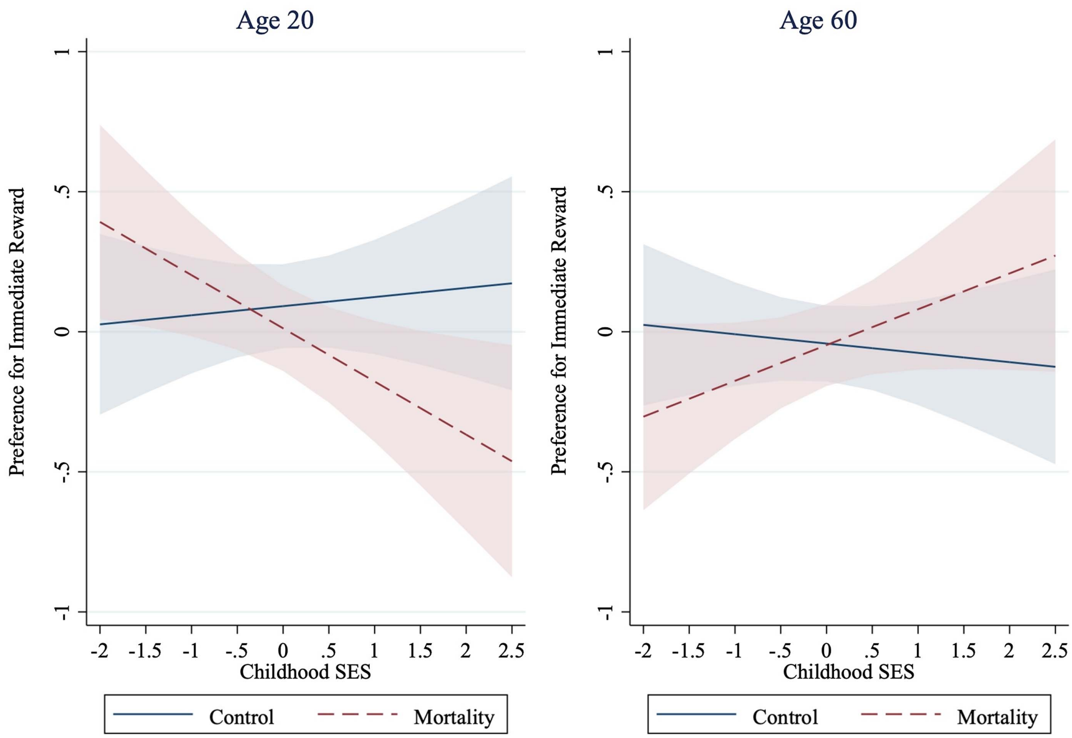
To examine these potential explanations empirically, we conducted an exploratory analysis testing the three-way interactions between mortality salience, perceived childhood SES, and income or age (Mortality × Childhood SES × Income/Mortality × Childhood SES × Age). We did not find a significant three-way interaction for income, $b = -.013$, $SE = .018$, $t(1002) = -0.70$, $p = .483$. Based on these nonsignificant results alone, we cannot conclude whether the absence of a significant three-way interaction with income reflects a true null effect or an indeterminate result due to insufficient evidence. However, we found a significant three-way interaction for age, $b = .010$, $SE = .004$, $t(1001) = 2.30$, $p = .022$, indicating that age moderated the effect of mortality salience and childhood SES on temporal discounting.

Figure 5 shows the three-way interaction with age, illustrating how the mortality condition and SES interacted at two different life stages: age 20 (similar to the sample age of the original study) and age 60. We observed that the hypothesized interaction was more apparent in the younger group. Younger participants from low SES backgrounds who were exposed to mortality cues exhibited a preference for more immediate rewards, whereas those from high SES backgrounds showed a preference for more delayed rewards. This pattern was inverted in the older age group.

Our finding that age may moderate the effect of perceived childhood SES and mortality salience on temporal discounting

[2] Our sample comprises 26.0% of individuals whose annual household income is under \$30,000. In comparison, according to 2021 U.S. Census data, 25.7% of household incomes were below \$35,000 (U.S. Census Bureau & Statista Research Department, 2022).

Figure 5
Relationship Between Childhood SES and Preference for More Immediate Financial Reward Under the Influence of a Mortality Prime Versus Control at Ages 20 and 60



Note. Shaded error bands represent 95% confidence intervals. SES = socioeconomic status. See the online article for the color version of this figure.

aligns with existing literature on age-related changes in decision making. For instance, Read and Read (2004) found that middle-aged adults show less temporal discounting compared to younger and older adults. Similarly, Löckenhoff et al. (2011) reported age-related differences in the neural correlates of temporal discounting. In the context of LHT, Ellis et al. (2009) have suggested that life history strategies may shift across the lifespan, potentially explaining why our more age-diverse sample yielded different results from the original study's student sample. These age-related effects underscore the importance of considering developmental factors when applying LHT to individual behaviors and highlight a potential limitation of studies that rely solely on young adult samples.

It is important to underscore that these findings are exploratory in nature and should be interpreted with due caution. Nevertheless, they suggest that age may have been a factor contributing to the nonreplication of the original finding on temporal discounting. Furthermore, these results imply that proponents of LHT should carefully consider the potential variability in how childhood SES influences decision making across different life stages.

Finally, our mode of data collection could have also played a role in the nonreplication of the original finding on temporal discounting. We conducted our study online using a web-based survey platform, whereas Griskevicius et al. conducted their study in a classroom laboratory setting. This methodological difference could have affected the impact of mortality salience on participants' behavior in several ways. First, online studies may provide less experimental control than laboratory studies, as participants in online settings could be more distracted, less attentive, or less motivated than those in laboratory settings (Gosling & Mason, 2015). This may have reduced the effectiveness of our mortality prime and weakened its influence on participants' temporal discounting, despite evidence that our manipulation was successful (i.e., average time spent on the manipulation page, attention check pass rate). Second, online studies may have lower social presence and psychological realism than laboratory studies, as online participants may feel less accountable, less identifiable, or less engaged than laboratory participants (Reips & Krantz, 2010). This could have reduced the salience of our mortality prime and weakened its influence on participants' temporal discounting. These potential effects of the mode of data collection might account for why we did not observe the same effect as Griskevicius et al. on temporal discounting.

SES Measures: Methodological Considerations

Our analysis incorporated education level and reported household income as control variables alongside our focal measures of perceived childhood and adult SES, with correlations reported in Table 2. The moderate correlations observed between perceived childhood SES and adult socioeconomic indicators, including educational attainment, suggest that the effects we report likely extend beyond financial decision making. These relationships point to broader cognitive–social advantages potentially rooted in early life experiences, aligning with research demonstrating the pervasive influence of childhood socioeconomic circumstances on cognitive development, educational trajectories, and later-life outcomes (Bradley & Corwyn, 2002; Duncan et al., 1998). The link between perceived childhood SES and adult decision-making processes likely reflects a complex interplay of factors. These may include differential access to educational resources, exposure to diverse problem-solving strategies, and the development of executive functions crucial for decision making (Hackman et al., 2015). Consequently, while our study focused on financial risk-taking and temporal discounting, the observed effects of childhood SES may indicate more generalized cognitive and social advantages influencing decision making across various domains.

In addition, we acknowledge the potential discrepancy between perceived socioeconomic childhood status and actual childhood SES. Perceived SES may be influenced by various biasing factors, such as social comparison, memory biases, and current economic status. For instance, childhood memories of relative wealth may be distorted by school environment: a child from a middle-class family might recall feeling less affluent if they attended a wealthy private school, but more fortunate if they attended a public school in a lower income area. Still, perceptions shape reality and often drive behavior (e.g., Adams, 1965; Ferguson & Bargh, 2004; Ivers et al., 2009), and thus perceived SES may yet be a more accurate variable for exploring cognitive processes, development, and outcomes than actual SES. We suggest that future research incorporate both subjective and objective measures of childhood SES to better understand their relative influences on adult decision making.

Relation to Prior Replications

Two previous articles also attempted to replicate the findings of Griskevicius et al. (2011b). Pepper et al. (2017) conducted three direct replications with smaller samples of U.K. students and adults ($N = 72$, 159, and 162) and found no interaction between perceived childhood SES and mortality salience on risk preference or time preference. They also found no effect in a meta-analysis of the three replications and suggested that demographic and cultural differences might explain the discrepancy. Frederick et al. (2016) also attempted to replicate and extend Griskevicius et al.'s (2011b) findings on impulsivity using a small sample of university undergraduates ($N = 71$). However, they used a different mortality prime and focused only on delay discounting. They also found no significant interaction between childhood environment and priming condition. These studies reflect the general difficulty of replicating the effects of priming on behavior (see Cesario, 2014).

Our study differs from previous replication attempts in several ways that might account for our distinct results. First, we used a larger and more diverse sample of participants. Second, we used the same mortality prime as Griskevicius et al. (2011b), which consisted of a news article about a fatal shooting in a nearby town. Pepper et al. (2017) modified the original prime to suit a British audience, by changing references to gun violence to knife attacks. Frederick et al. (2016) used a different prime altogether, which involved asking participants to write about their own death. These changes might have altered the intensity or salience of the mortality cue or introduced confounding factors such as cultural differences or self-awareness. Nonetheless, we believe that the most parsimonious explanation for the discrepant findings is that the current high-powered replication attempts provide more accurate and more valid effect size estimates. Considering the small effect sizes of most psychological phenomena (Götz et al., 2022), our results underscore the need for researchers to use samples with sufficient power to test their hypotheses.

Implications for LHT Applied to Individual Behavior

Using a larger and more diverse sample than two prior replication attempts, our mixed findings ultimately cast doubt on Griskevicius et al.'s (2011b) application of LHT to individual risk-taking and temporal discounting behaviors. Specifically, our results fail to support a relationship between childhood SES and temporal discounting, while finding notably smaller effect sizes for the relationship between childhood SES and risk-taking. We acknowledge that the latter relationship is statistically significant and thus appears to provide partial support for the original study's findings; however, a more holistic interpretation must account for our replication's much higher power to detect true effect sizes. Our findings suggest that the original study was not adequately powered to reliably detect its reported effect sizes, and as such, the minimal effect sizes we find provide nuanced insight into a relationship that may have limited practical impact on real-world decision making.

Although we previously discussed differences between our replication and the original study that may partially explain discrepant findings, in our view these methodological distinctions do not adequately account for the stark discrepancies in effect sizes. Our results challenge the assumption that childhood SES significantly affects individual life history strategies under conditions of mortality salience as an explanation for observable real-world differences in risk-taking and risk-avoidant behaviors. Given the ongoing scholarly debate about the applicability of LHT to individual behaviors, our findings underscore the need to consider alternative explanations more seriously.

Finally, our exploratory analyses revealed that combined childhood and adult SES had a nearly identical significant effect on risk-taking behaviors as perceived childhood SES alone. This result challenges the exclusive importance of childhood SES while supporting a broader connection between an individual's overall financial security and risk-taking behaviors. Consequently, LHT, while relevant, may not be the sole or most plausible explanation for the observed variations in human decision-making behavior. This finding underscores the need for a more nuanced understanding of the factors influencing risk-taking, temporal discounting, and financial decision making across different socioeconomic contexts.

Conclusion

In conclusion, we attempted to replicate the findings of Griskevicius et al. (2011b) on the effect of childhood SES and mortality salience on risk and time preferences. We partially replicated the authors' findings on risk preferences, but the effect size for risk preferences was small enough to cast doubt on its practical significance and the robustness of the original findings. We did not find sufficient evidence to support the hypothesized effect of childhood SES and mortality salience on temporal discounting. Our exploratory analyses provide tentative evidence that age moderated the effect of mortality salience and childhood SES on temporal discounting, indicating that life stage may affect decision making under different life conditions. Overall, we interpret our results as challenging the practical applicability of LHT to individual differences in risk preferences and temporal discounting under mortality salience. Our findings question the reliability and generalizability of previous findings in this domain, emphasize the importance of high-powered replications, and caution against overgeneralizing the results of single studies.

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