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Leveraging Psychological Fit to Encourage Saving Behavior

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Despite their best intentions, most people fail to save enough for the future. In this research, we demonstrate that people are more successful at saving when their savings goals are aligned with their Big Five personality traits. Study 1 uses a nationally representative sample of 2,447 U.K. citizens to test whether people whose self-declared savings goals more closely match their Big Five personality also report higher levels of savings. We apply specification curve analyses to minimize the risk of having arbitrary analytical decisions produce false-positive results. As our findings show, person-goal fit significantly predicted savings across all 48 specifications. Study 2 expands these findings by testing whether psychological fit can influence savings even if the saving goals are not formulated by the individuals themselves but instead suggested by a technology service designed to help them save. In a field experiment with 6,056 U.S.-based low-income users of a nonprofit Fintech app (with <$100 in current savings), we show that people who were encouraged to save $100 over the course of a month were more likely to achieve this target if they were encouraged to save toward personality-matched goals. Our research provides support for the theory of psychological fit, showing that an alignment between an individual's Big Five personality traits and the personality appeal of a saving goal can help increase savings, even among those who struggle the most.

Public Significance Statement
Our findings suggest that identifying the right saving goals—that is, those that allow individuals to envision how saving money today will empower them to satisfy their psychological needs and motivations in the future—could help people save. As such, they offer a novel perspective on how external actors—such as retail banks and FinTech applications—could use personality-matching to better connect with their customers and encourage them to save more effectively.

Keywords: Big Five, personality, savings, behavior change, psychological fit

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Millions of people begin the new year by setting ambitious goals for themselves. Among the most common goals is the intention to save for the future (e.g., down-payment to buy a home, retirement, or buying a special gift for a loved one; Palmer, 2018). However, the vast majority of individuals will fail to translate their noble intentions into dollars saved in their bank account (Baumeister, 2002; Martin, 2011), and levels of saving in much of the developed world remain critically low (Bernheim et al., 2001; Federal Reserve Board, 2019; World Economic Forum, 2017). Most households in the United States are not prepared to deal with unforeseen shocks to their income or the financial responsibilities of

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This study was not preregistered. All analysis code is available on Open Science Framework at https://osf.io/cx3ur/ (Matz & Gladstone, 2021). The data will be made available by the authors upon reasonable request.

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living into older age (Laibson, 1997; Merton, 2014; Mitchell & Moore, 1998; Skinner, 2007). In 2020, 53% of Americans report living from paycheck to paycheck, 62% do not have enough savings to cover 3 months of living expenses, and more than 10% could not cover a single week without getting paid (Berger, 2020).

What makes saving money such a challenging task? Similar to dieting or exercising, saving requires individuals to make a sacrifice in the "now" to be rewarded in the future (Laibson et al., 1998). Given that people tend to have a bias toward the present (Frederick et al., 2002; Malkoc & Zauberman, 2006; O'Donoghue & Rabin, 1999), the decision to save requires high levels of self-regulation (Moffitt et al., 2011). Furthermore, the costs of saving are often very real and tangible (e.g., not being able to take a vacation or buy a new pair of shoes), whereas the benefits of saving are often uncertain and abstract (e.g., the ability to manage a period of unemployment, which may or may not happen; Ülkümen & Cheema, 2011). Hence, even though people report being motivated to save, the cognitive and affective barriers they encounter along the way lead to a wide gap between intentions and actions (Rabinovich & Webley, 2007).

How can we help individuals close this intention–action gap? While the mere act of setting goals is an important first step in boosting achievement motivation and persistence (Ariely & Wertenbroch, 2002; Gollwitzer, 1999; Gómez-Miñambres, 2012), research has highlighted the importance of setting savings goals in the right way (Bryan & Hershfield, 2013; Hershfield et al., 2011; Tam & Dholakia, 2014). The idea behind much of this work is to make the future benefits of saving more tangible and salient, and therefore more competitive with the immediate gratification of spending today. Following this line of reasoning, research has shown that individuals are more likely to achieve their saving goals if the goals they set are specific and remain salient throughout the saving period (Locke & Latham, 2006; Ülkümen & Cheema, 2011). For example, Soman and Cheema found that savings rates among households rose higher when asked to attach a picture of their children to an envelope in which they stored their weekly savings. After 15 weeks, Indian households using envelopes with attached photos saved 450 rupees on average, compared with 403 rupees without pictures (11.7% increase). Households not only saved more, but they were also less likely to deplete their savings through spending (Soman & Cheema, 2011).

In this article, we shift the focus from setting goals in the right way to setting the right goals. While many savings goals—such as building an emergency fund and saving for retirement or for an inheritance—are commonly shared across individuals (Katona, 1975; Lee & Hanna, 2015), people also have unique tastes and preferences. We therefore expect that the degree to which individuals are motivated to achieve particular goals and take pleasure in their execution will vary considerably. In other words, not only do different goals satisfy different psychological needs, but whether or not working toward a certain goal translates into successful saving is likely to depend upon the characteristics of the individual. For example, individuals high on the personality trait agreeableness are characterized by their pro-social desire to help others (Habashi et al., 2016), and therefore, saving money to help provide for family members may be more gratifying and motivating for them, compared with saving toward an expensive sports car. Similarly, a conscientious person tends to plan ahead further into the future (Shaffer, 2020). Hence, their predisposition to consider longer term consequences might encourage them to save more for retirement than individuals who are less conscientious.

Following the logic of the outlined examples, we propose that people whose goals are more closely aligned with their psychological needs and motivations—their personality (Goldberg, 1999; McCrae & John, 1992)—will be more successful in seeing their intentions through. This proposition is supported by prior research showing that people are more likely to spend their money on products and services that match their own personality (Gladstone et al., 2021; Govers & Schoormans, 2005; Matz et al., 2016; Sirgy, 1985; Weston et al., 2018), or that are merely described in personality-congruent terms (Matz, Kosinski, et al., 2017). In addition, those individuals whose consumption is more closely aligned with their overall personality profile report higher levels of life satisfaction and positive affect (Matz et al., 2016). Given the positive cognitive and affective impact on psychological fit in the context of spending, we argue that psychological fit shapes not only decisions between alternative products but also in trade-offs between spending and saving. Specifically, we propose that people will be more successful at saving when they save toward goals that are aligned with their psychological needs and motivations.

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We provide evidence for this proposition in two complementary studies. Study 1 uses cross-sectional survey data of a representative sample of U.K. residents ($N = 2{,}447$) to test whether individuals whose personality is more closely aligned with their self-declared saving goals report higher levels of savings. Study 2 builds upon these findings in a field experiment that focuses on low-income individuals in the United States with very low levels of prior savings ($N = 6{,}056$). Instead of relying on individuals to set their saving goals in a personality-congruent way, Study 2 is aimed at testing whether third-party digital platforms can actively encourage saving behaviors by highlighting personality-congruent goals.

Study 1

In Study 1, we use a cross-sectional survey collected from a representative sample of 4,170 U.K. residents to investigate whether individuals whose personality is more closely aligned with their self-declared saving goals report higher levels of savings. The study received ethics approval from the University College London review board.

Method

Participants

The survey was commissioned by a U.K.-based charity in 2013 and investigated the financial behaviors of 4,170 U.K. households. Conducted by a professional polling company, the cross-sectional survey is representative of the overall U.K. population in terms of sociodemographics. The survey was conducted online, via telephone, and in person to ensure a full representation of different groups. For the purpose of analyses, we only included individuals who had indicated they were pursuing at least one of the 16 saving goals presented on our list (see Table 1), and who had complete records on all the measures. This resulted in a final analysis sample of $N = 2{,}447$ participants, who were pursuing an average of 3.04 goals ($SD = 2.14$; see online Supplemental Material 1, for evidence that the full and reduced sample are similar in their distributions of personality traits). All participants provided informed consent.

Measures

The survey included questions covering financial behaviors (i.e., savings, income), the Big Five personality traits (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) (Goldberg, 1999; McCrae & John, 1992), as well as several demographic and socioeconomic variables (i.e., age, gender, educational attainment, and employment status).

Personality Traits. The survey included a 15-item scale measuring the Big Five personality traits that were adapted from the British Household Panel Survey (Brice et al., 2002). The scale has been used by previous research investigating the personality predictors of savings behaviors (e.g., Brown & Taylor, 2014). Participants are asked to indicate their agreement with statements such as "I see myself as someone who is talkative" using a 7-point Likert scale that ranges from *strongly disagree* to *strongly agree*. Due to a mistake in the survey execution, one question measuring Agreeableness was left unusable for the purposes of analysis. Therefore, 14 items measure how individuals exhibit these traits. The wording for the 14 items is provided in online Supplemental Material 1. With Cronbach's α ranging from $\alpha = 0.31$ to 0.79 (Openness = 0.59, Conscientiousness = 0.31, Extraversion = 0.52, Agreeableness = 0.31, Neuroticism = 0.79), scale reliabilities were found to be low, but comparable to those reported in other short scales (Rammstedt & John, 2007). Although the reliability coefficients seem low by traditional standards, past research suggests that these α coefficients underestimate the actual reliability of these scales due to their brevity (Donnellan & Lucas, 2008; Lucas & Donnellan, 2011).

Savings. Total savings were measured in the survey by asking: "Which of the following best describes the total amount of savings your household has at the moment?" Responses were recorded in 16 bands (1 = nothing to 16 = £50,001+). Approximately 18% of participants reported holding no savings. To ensure all respondents answered the question using the same definition of savings, the following introductory text was provided before the question:

> We'd now like to ask you some questions about the way that your household saves. If you live in a multi-person household (e.g., students, sharers), please answer on your own behalf when asked about your household. Again, by savings we mean cash or investments that can be

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turned into cash at short notice. Please note that this means we are not asking about saving into a pension or other long-term investments.

Debt. Debt was measured by asking: "Which of the following best describes the total amount of debt your household owes at the moment?" Responses were recorded using the same 16 bands used for savings, ranging from *nothing* to *£50,000+*. About 43% of participants reported having no debts.

Income. Income was recorded using a list of 13 categories (1 = up to £7,000 to 13 = £83,001 or more). The mean response was 4.8, which corresponds to approximately £28,000, which is close to the average U.K. household income of ~£27,000.

Control Variables. We used participants' self-reported age (1 = 18–24 to 6 = 65+), gender (0 = male, 1 = female), education level (1 = no education/primary education, 2 = high school, 3 = university, 4 = higher degree), and employment status (1 = not in employment, 2 = full time, 30 hr or more per week, 3 = part time, 8–29 hr per week, 4 = retired) as controls. The control variables were chosen based on prior work suggesting that they are related to financial health and saving behaviors (Bernheim et al., 2001; Hershfield et al., 2011). See online Supplemental Material 2, for distributions of the control variables.

Saving Goals. Participants were asked to indicate their saving goals from a list of 16 discrete options, including "For holidays or other leisure expenditures," "So I can leave some money to a family-member," and "For a deposit to buy a property" (see Table 1). The list of saving goals was generated through qualitative consumer research conducted by the charity research partner. Participants could also indicate "Other" if none of the 16 categories applied to them. From the full sample, 2,447 participants indicated they saved toward at least one of the 16 categories. The list of savings goals was designed to cover a broad range of the most commonly cited reasons people give for saving money but is not an exhaustive list (see Discussion section).

Personality of Saving Goals. To estimate the personality characteristics associated with each of the 16 savings goals, we recruited 200 workers on Prolific Academic to rate the list of 16 discrete saving goals according to their Big Five personality traits (Peer et al., 2017). We excluded 38 workers who failed the attention checks we had set, leaving us with 162 raters. The raters were from the United Kingdom and had a mean age of 34.38 (SD = 12.55), with a minimum age of 19 and a maximum age of 69. Borrowing from prior literature, these raters were asked to think of the spending goal as if it was a person and rate their characteristics on the five personality traits using a 7-point scale with bipolar ends that were taken from the Ten-Item-Personality-Inventory (Gosling et al., 2003). We calculated interrater agreement for each saving goal and personality trait using r_{wg} (James et al., 1993), which is a function of (a) the observed, empirical variance in the judge's ratings, and (b) the estimated variance in ratings if the judges' ratings were random. The r_{wg} score can be interpreted as the proportion of variance that can be attributed to agreement (O'Neill, 2017), and ranges anywhere between 0 (*complete disagreement*) and 1 (*complete agreement*). With an average r_{wg} score of 0.39 (SD = 0.11), interrater agreement was found to be relatively weak (Woehr et al., 2015). As we outline in more detail in the discussion of Study 1, the low reliabilities of saving goals make it more difficult for us to detect a relationship between personality fit and savings. The average personality profiles alongside their r_{wg} scores are displayed in Table 1. Overall, the ratings showed good face validity, with saving toward holidays and leisure expenditures being rated as highly extraverted, savings toward a family member's future as highly agreeable, and savings to provide a regular income over the next 12 months and retirement as highly conscientious.

Notably, the goal ratings skew toward high levels of conscientiousness. Given the association of savings with planning and self-control (Fernbach et al., 2015; Lynch et al., 2010), this is not surprising. In fact, prior research has established a robust relationship between conscientiousness and savings (Brown & Taylor, 2014; Duckworth et al., 2012; Ebert et al., 2021; Mosca & McCrory, 2016). To account for this variation, we estimate the effect of person-goal fit controlling for saving goals fixed effects and participants' personality traits.

Person-Goal Fit. To calculate the fit between participant (p) and goal (g) personality, we first estimated the overall personality of a participant's saving goals by averaging the personality profiles from each of their saving goals. That is, if a participant reported that they were saving toward repaying a loan, going on a holiday, and leaving money to a family member, the ratings for each of these goals and personality

Table 1
List of 16 Discrete Saving Goals Alongside Their Absolute Occurrence, Personality Rating and Average Income

Saving goal	Count	*O*	*C*	*E*	*A*	*N*	Income (*SD*)
For unexpected expenditures (a rainy day)	1,307	3.80 (0.23)	5.28 (0.35)	3.79 (0.23)	4.40 (0.48)	3.91 (0.30)	4.73 (2.35)
For no particular reason	445	3.80 (0.00)	4.40 (0.16)	3.95 (0.22)	3.96 (0.49)	3.50 (0.31)	4.85 (2.59)
To pay for bills (e.g., gas, electricity, Council Tax)	328	2.97 (0.37)	5.58 (0.40)	3.22 (0.40)	4.15 (0.36)	3.52 (0.36)	4.12 (2.36)
For a deposit to buy a property	267	3.78 (0.18)	5.90 (0.60)	3.96 (0.36)	4.78 (0.54)	2.94 (0.44)	5.62 (2.73)
Because I've always saved	695	2.93 (0.20)	5.21 (0.34)	3.00 (0.40)	4.25 (0.46)	3.33 (0.30)	4.96 (2.54)
For a planned purchase in the future (e.g., car, fridge)	522	3.77 (0.28)	5.67 (0.56)	3.97 (0.36)	4.67 (0.57)	2.87 (0.58)	5.13 (2.63)
For planned maintenance costs in the future (e.g., car repairs, home renovation)	613	3.35 (0.40)	5.81 (0.59)	3.30 (0.47)	4.38 (0.49)	3.44 (0.35)	4.82 (2.39)
For holidays or other leisure expenditures	970	5.35 (0.32)	4.78 (0.44)	5.66 (0.52)	5.10 (0.52)	3.06 (0.56)	4.93 (2.52)
To provide a regular income over the next 12 months	138	3.56 (0.42)	5.49 (0.45)	3.31 (0.55)	4.37 (0.51)	3.49 (0.28)	4.51 (2.27)
To provide income in retirement (please note we are not referring to pension saving)	538	3.20 (0.35)	5.83 (0.48)	3.19 (0.38)	4.65 (0.44)	3.14 (0.38)	5.55 (2.83)
Because it's a good investment in the long term	460	3.41 (0.26)	5.88 (0.52)	3.27 (0.29)	4.62 (0.41)	2.73 (0.53)	5.52 (2.80)
Because I don't spend all of my income	516	3.51 (0.21)	5.02 (0.29)	3.19 (0.31)	4.14 (0.48)	3.14 (0.39)	5.09 (2.60)
Because of a recent/upcoming event (e.g., marriage, birth of a child)	100	4.49 (0.43)	5.49 (0.53)	4.50 (0.41)	5.20 (0.46)	3.33 (0.44)	5.13 (2.67)
So I can leave some money to a family member when I die	241	3.28 (0.33)	5.72 (0.50)	3.18 (0.37)	5.46 (0.35)	3.42 (0.21)	4.99 (2.57)
For a family member's future (e.g., a child trust fund)	196	3.66 (0.25)	6.10 (0.61)	3.66 (0.38)	5.60 (0.52)	3.16 (0.41)	5.95 (2.77)
In order to repay a loan	96	3.42 (0.28)	4.95 (0.18)	3.74 (0.29)	3.95 (0.36)	4.25 (0.22)	5.23 (2.33)

Note. Personality ratings are measured 1–7 with interrater reliability scores r_{wg} in brackets. Income is measured 1–13 with standard deviations in brackets. The personality ratings are based on the judgments of 162 Prolific workers. The income estimates are based on the actual income distribution of participants who indicated savings toward the particular goal (measured in bands).

traits would be averaged to obtain a holistic profile of the participant's overall savings goals.

Next, we calculated the overall fit between participant and goal personality using four different distance measures that have previously been used in the study of personality fit (Bailey et al., 2020; Matz et al., 2016): Euclidean $\sqrt{\sum_i^n (x_i - y_i)^2}$, Manhattan $\sqrt{\sum_i^n |x_i - y_i|}$, Canberra $\sqrt{\sum_i^n \frac{|x_i - y_i|}{|x_i + y_i|}}$, and Supremum distance $argmax_i(|x_i - y_i|)$. In these formulas, x = participant personality, y = goal personality, and n = personality trait. Before calculating these measures, the personality scores of participants and overall saving goals were z-standardized. All distance scores were subtracted from 0, such that higher scores on the person-goal fit variables indicate a better overall fit between the participants' personality profile and that of their self-reported goals.

To account for the fact that the interrater reliabilities of some of the saving goals were close to zero, we calculated all fit measures twice. The first uses the full set of goals, and the second uses only goals with an $r_{\text{wg}} > 0.3$ (the suggested threshold for ratings that show weak agreement, Woehr et al., 2015) for each personality trait. Given that r_{wg} varies across the different personality traits, the number of saving goals retained in the second specification differed across the five traits (i.e., to calculate the Openness score of a person's saving goals, we considered all goals with an Openness $r_{\text{wg}} >$ 0.3, whereas we included all goals with a Conscientiousness $r_{\text{wg}} > 0.3$ when calculating the Conscientiousness score of the same saving goals). The distributions of the resulting eight fit measures (4 Distance Metrics × 2 Goal Sets) are displayed in Figure 1A.

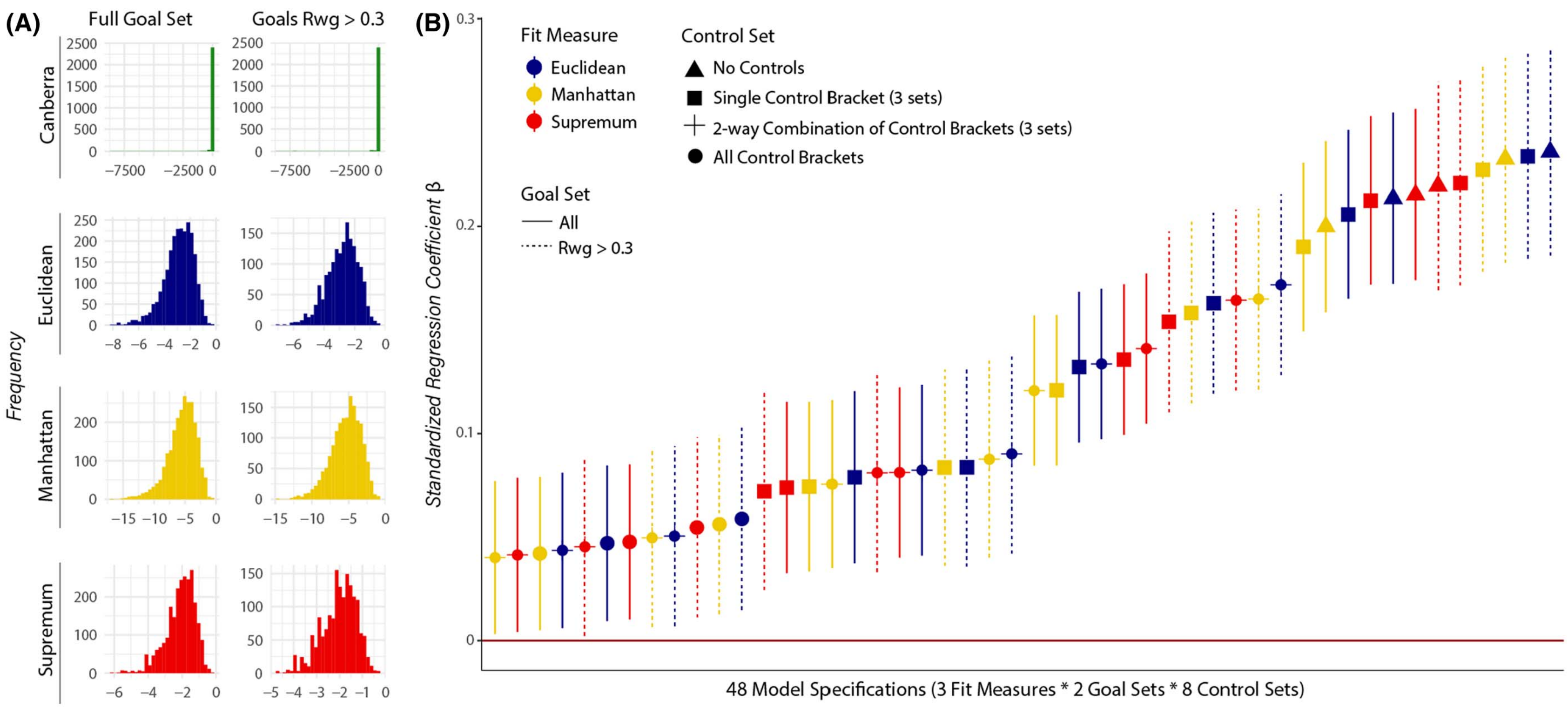
All fit measures except for the Canberra method showed an approximately normal distribution. The heavily skewed distribution of the Canberra measure might be explained by the fact that, compared to the other distance measures, Canberra distance is much more sensitive to small changes near zero (Gordon, 1999). While a valuable attribute in some contexts (e.g., outlier detection), this might limit the ability of the measure to distinguish meaningful deviations between the personality profiles of individuals and saving goals from random noise. Therefore, given the skewed distribution and lack of meaningful variance in the Canberra distance measure, we dropped these metrics from the subsequent analyses.

Analysis Plan

We use specification curve analyses to test the effect of person-goal fit on savings across a total of 48 specifications. Specification curve analyses were introduced to minimize the risk of having arbitrary analytical decisions produce

Figure 1

Distribution of Person-Goal Fit Measures (A) and Standardized Regression Coefficients of Person-Goal Fit Predicting Savings Across the 48 Model Specifications (B)



Note. (A) Distribution of fit measures for the full set of goals and the reduced set of goals with an interrater reliability of $r_{wg} > 0.3$. (B) Specification curve plotting the standardized regression coefficients of 48 specifications (with 95% confidence intervals) sorted by effect size. The Canberra fit measure was dropped from the analyses due to the heavily skewed distribution. See the online article for the color version of this figure.

false-positive results (Simonsohn et al., 2020). Instead of testing a hypothesis using a single model, specification curve analyses encourage researchers to test a wider range of theoretically meaningful options that may vary in the specific operationalization of (in)dependent variables, control strategies, or statistical analyses.

The 48 model specifications used in the current analyses are derived from a combination of different (a) fit measures (Eulidean, Manhattan, and Supremum), (b) goal sets (full set and smaller set with $r_{wg} > 0.3$), and (c) a series of control strategies. Given the large set of control variables, we first divide them into three control sets: sociodemographic (age, gender, education, income, employment), personality (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism), and saving goals (dummy coded across the 16 goals to indicate whether a person was saving toward the particular goal or not). The three control sets are subsequently used in all eight possible combinations, that is, (a) no controls, (b) sociodemographic, (c) personality, (d) saving goals, (e) sociodemographic + personality, (f) sociodemographic + saving goals, (g) personality + saving goals, and (h) all controls. All specifications use linear regression analyses to test the effect of person-goal fit on savings (see online Supplemental Material 3, for all zero-order correlations). Finally, we test the incremental fit of person-goal fit above and beyond the full set of control variables by comparing the full model (person-goal fit + all controls) to a base model that only includes the full set of controls using analysis of variance (ANOVA) analysis.

Transparency and Openness

This study was not preregistered. All analysis code is available on Open Science Framework (OSF; Matz & Gladstone, 2021). The data will be made available by the authors upon reasonable request.

Results

The results of the specification curves are displayed in Figure 1B, which plots the standardized regression coefficients of person-goal fit across the 48 analytical specifications alongside their 95% confidence intervals. Coefficients are ordered by effect size along the x axis. In line with our theoretical predictions, person-goal fit was found to be a significant predictor of savings in all 48 specifications, average(β) = 0.12, $SD(\beta) = 0.07$, min(β) = 0.04, max(β) = 0.24, suggesting that the degree to which participant's goals match their personality positively influences saving behavior (see Tables in online Supplemental Material 4, for all model outputs). The average increase in savings for each 1 SD increase in person-goal fit across all model specifications, translated to additional savings of approximately £1,700 (~$2,300).

As expected, the effects became smaller as more conservative sets of control variables were included in the models. When personality fit was tested in isolation it explained approximately 5% of the variance in savings. Although this number dropped to approximately 1% when considering incremental variance explained above and beyond all the other control variables, the findings of an ANOVA model comparison suggest that this difference remains statistically significant, $F(1) = 6.02$, $p = .014$; see Discussion section, for a deliberation on the importance of small but robust effects.

In addition to person-goal fit, we also found a robust positive effect of income on savings, average(β) = 0.31, $SD(\beta) = 0.026$, min(β) = 0.28, max(β) = 0.34, highlighting the fact that income plays an important role in the ability of individuals to save. Receiving a higher income makes it easier for an individual to put more of that money aside, as the relative cost of sacrificing expenditure in order to do so decreases. Although income was only weakly related to the number of saving goals ($r = 0.08$, $p < .001$), we anticipated that it could interact with our findings in more indirect ways, such as by influencing which saving goals an individual is able to set for themselves (see Table 1, for the average income level associated with each of the saving goals). For example, saving for a family member's future (e.g., in a trust fund) is a more frequently set goal for those with higher levels of income than saving toward the payment of bills. In addition to controlling for income in our analyses, we therefore also tested whether the effect of person-goal fit on savings varies across the income spectrum. To do so, we ran additional models that included the interaction effect of person-goal fit and income. The interaction was found to be nonsignificant in all model specifications, average(β) = −0.076, $SD(\beta) = 0.028$, min(β) = −0.12, max(β) = −0.025, suggesting that—even though income might influence which saving goals an individual sets—person-goal fit matters for both the rich and the poor.

Trait Specific Person-Goal Fit

In addition to examining the impact of overall person-goal fit on savings, we conducted a series of linear regression analyses to explore the impact of individual traits. Table 2 shows the results of five regression analyses predicting savings from the z-standardized participant and goal personalities as well as their two-way interaction. The coefficients show standardized effect sizes. We use an ANOVA test to compare the models' fit to a baseline model that includes the main effects but omits the interaction term.

The findings in Table 2 suggest that the observed effects were predominantly driven by the personality trait of Openness (and to a lesser, marginally significant degree, Neuroticism). These effects remain stable when (a) including the full set of control variables, (b) using polynomial regression analyses that add the squared personality terms, and

Table 2

Results of Five Linear Regression Analyses Predicting Savings From Participant and Goal Personality as Well as Their Two-Way Interaction

	Openness			Conscientiousness			Extraversion			Agreeableness			Neuroticism		
Predictors	β	95% CI	*p*	β	95% CI	*p*	β	95% CI	*p*	β	95% CI	*p*	β	95% CI	*p*
Person	−.04	[−.08–.00]	.066	.08	[.04–.12]	<.001	−.04	[−.08–.00]	.053	−.03	[−.07–.01]	.172	−.15	[−.20–−.11]	<.001
Goal	−.19	[−.23–−.15]	<.001	.11	[.07–.15]	<.001	−.21	[−.25–−.17]	<.001	.00	[−.04–.05]	.866	−.18	[−.22–−.14]	<.001
Person × Goal	.06	[.01–.10]	.008	.02	[−.02–.06]	.244	.01	[−.03–.05]	.635	−.01	[−.05–.03]	.659	.03	[−.01–.08]	.095
N		2,165			2,165			2,165			2,165			2,165	
R^2/adj-R^2		.040/.039			.017/.016			.047/.046			.001/−.000			.056/.055	
F test		$F(1) = .7.01, p = .008$			$F(1) = 1.36, p = .244$			$F(1) = .23, p = .635$			$F(1) = .20, p = .659$			$F(1) = 2.79, p = .095$	

Note. All coefficients and 95% confidence intervals are standardized. All models include the full set of control variables, which have been omitted in the output for readability purposes. The *F* test compares the model fit to that of a baseline model that includes all predictors except for the interaction term. CI = confidence interval.

(c) analysing all personality traits and interactions within a single model.

Discussion

Study 1 offers correlational evidence for the role of psychological fit in the context of saving behavior. However, the low internal consistencies of the personality measures as well as the low interrater reliabilities of saving goals pose a considerable challenge to the validity of our findings and likely lead to an underestimation of effects. The former is the result of our collaborative data collection effort being limited to a short 15-item questionnaire. To overcome this limitation, Study 2 uses a longer 30-item questionnaire with much higher scale reliabilities. The latter suggests that the same saving goal might take on a different meaning for different people, producing heterogeneity that we cannot control in Study 1. To alleviate this problem, Study 2 follows a different approach. Instead of observing people's natural variation in saving toward different goals, we experimentally frame saving along the Big Five personality dimensions. This shift allows us to not only test for the causality of psychological fit effects but also reduce some of the natural variations in the perceived personalities of different saving goals.

Study 2

Study 1 showed that individuals who set more personality-relevant saving goals for themselves are more successful in saving money. In Study 2, we ran a field experiment to test whether this effect can be translated into an intervention that actively encourages individuals to save toward personality-congruent goals. Instead of relying on an individual's ability to set the right goals for themselves, we investigate whether individuals are more likely to save when presented with personality-congruent saving goals by a third-party platform. The study received ethics approval from the Columbia University review board.

Method

Participants

Data were collected from users of the U.S.-based Fintech app SaverLife, a nonprofit set up to help those with lower incomes to develop long-term savings habits. Users of the app link their main banking provider with the SaverLife platform, enabling the platform to receive a read-only view of all accounts and transactions within the users' main banking relationship (e.g., checking, savings, or credit cards). SaverLife leverages this information to develop and measure the success of its incentives designed to encourage savings through prize-linked sweepstakes, where users have the chance to win cash and other prizes by meeting prespecified savings goals during time-defined challenges. The intervention in this study was embedded in a SaverLife challenge that encouraged users to save at least $100 over the course of 1 month in September 2020 ("Race-to-100"). The intervention was focused on encouraging individuals with negative, zero, or very low levels of prior savings (below $100). Understanding the efficacy of savings interventions in this group is particularly valuable as saving money is more challenging for low-income individuals (Beverly & Sherraden, 1999). This is because compared to high-income individuals, the costs of putting money to the side "today" are often felt more immediately among low-income individuals (Mauldin et al., 2016). At the same time, those with no or very little income or savings are those who also benefit the most from accumulating a financial safety net, even a modest one (Anderson & Baland, 2002). The fact that we did not observe a significant interaction effect between person-goal fit and income in Study 1 provided tentative evidence that matching saving goals to individuals' personality should lead to more successful saving outcomes even among this financially disadvantaged subpopulation.

Users of the SaverLife platform were invited to take part in a survey that included questions measuring the Big Five personality traits. Those who participated received immediate feedback on their responses in the form of a money personality profile. They were then asked for their consent to have their responses linked with their financial accounts. From all the individuals who completed the survey, 17,243 could be matched with their financial accounts. Of those, 12,018 fell into the targeted savings bracket of $100 and less. To ensure we were able to measure the effects of the intervention, we removed all participants who did not have a dedicated linked savings account, leaving us with a total eligible sample of 6,056 individuals. All participants were automatically entered into the intervention, but they could opt out of receiving emails related to the challenge in the first introductory email as well as each consecutive email related to the Race-to-100.

Measures

Personality. Personality traits were measured using the Big Five Inventory (BFI-2S; Soto & John, 2017), a 30-item questionnaire that captures the Big Five personality traits. Participants indicated their agreement with statements such as "I am someone who tends to be quiet" using a 7-point Likert scale, ranging from *strongly disagree* to *strongly agree*. With internal consistencies ranging of $\alpha = 0.65$ for Openness, $\alpha = 0.77$ for Conscientiousness, $\alpha = 0.70$ for Extraversion, $\alpha = 0.72$ for Agreeableness, and $\alpha = 0.83$ for Neuroticism, the scale reliabilities were found to range from acceptable to good. Percentile scores were calculated based on the norms published in the original BFI-2S validation (Soto & John, 2017)

Savings. We measured savings at two points in time: (a) Before the start of the intervention on August 31st 2020 (T1—i.e., current amount in the savings account) and (b) after the 30-day period of the intervention on September 30, 2020 (T2). On average, people targeted with the intervention had saved $2.39 before the intervention and $41.38 after the intervention (see Figure 2A, for distributions). Our main outcome of interest was whether participants reached the savings goal of $100. This is because the intervention messages were specifically designed to encourage individuals to save $100 but not to save more (or less) than this. We therefore expected people in the personality-matched condition to be more likely to reach their threshold goal amount, but not necessarily to save any more beyond this target amount (see online Supplemental Material 5, for additional analyses confirming this intuition). This is particularly true given that SaverLife runs their Race-to-100 challenges multiple times a year. Hence, users might be incentivized to save just over $100 in their SaverLife account to meet the current challenge's objective (and be entered into the prize draw), but use any additional savings toward the next challenge and prize money. Focusing on the binary metric also had the advantage of being the measure used by SaverLife to evaluate the success of the Race-to-100 campaign and to optimize their messaging.

Notably, users of the app were able to accrue a limited amount of debt in their savings account (i.e., the account has an overdraft facility). This was accounted for when determining whether participants managed to save $100 during the trial. If a user began the trial with a balance of say −$150 and ended the trial at −$50, they would have been considered successful in reaching the saving target.

Experimental Procedure

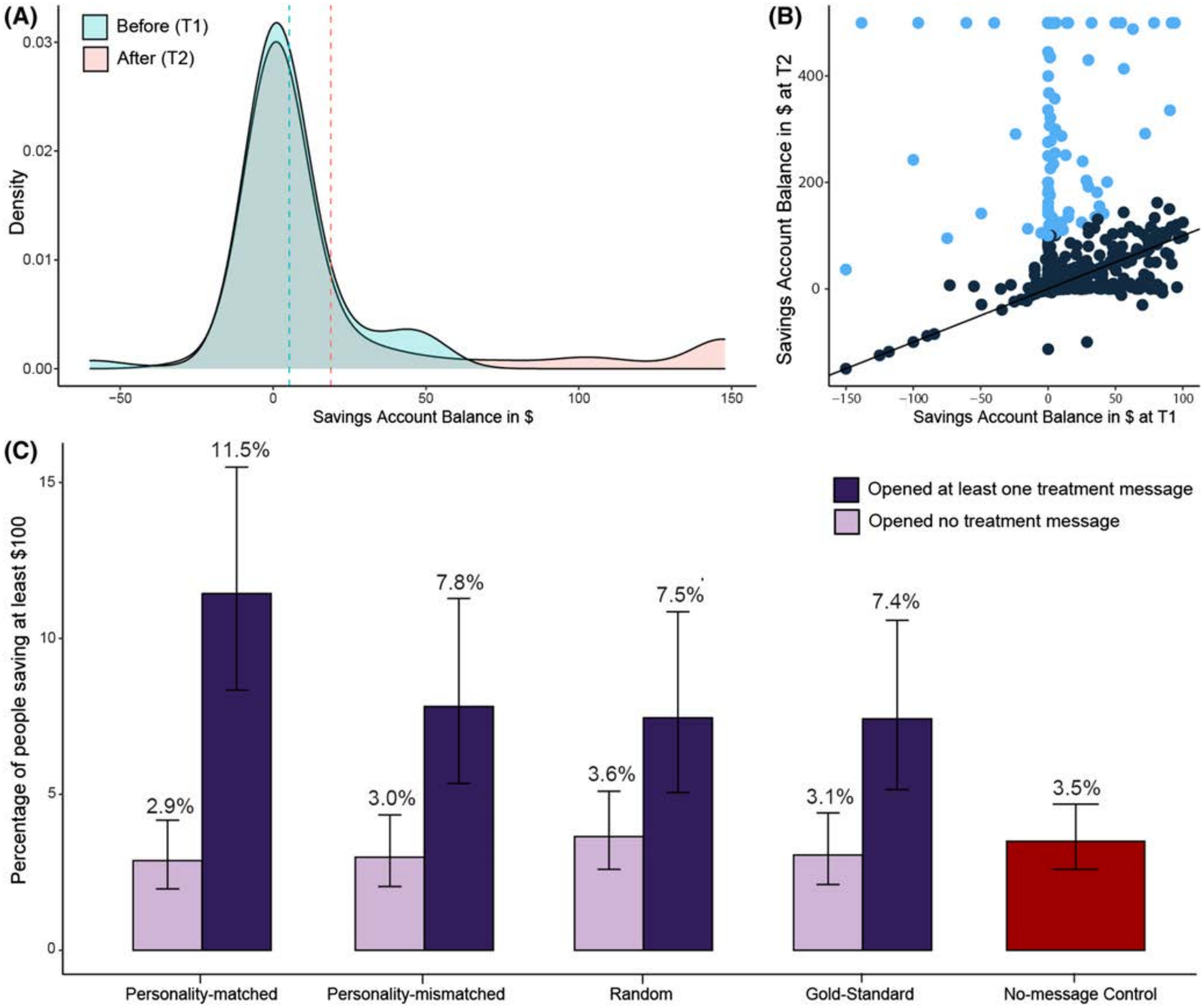
The experimental procedure is illustrated in Figure 3. The intervention consisted of five emails sent to participants over a 4-week period. The email content encouraged recipients to participate in the "Race-to-100" and save money in their dedicated savings account (see Figure 3D). We experimentally manipulated the content of these emails by randomly assigning participants to one of five conditions: (a) no messaging control group ($n = 1{,}204$), (b) gold-standard messaging ($n = 1{,}249$), (c) personality-matched messaging ($n = 1{,}212$), (d) personality-mismatched messaging ($n = 1{,}191$), and (e) random messaging ($n = 1{,}200$). The wording for each of the messages is provided in online Supplemental Material 6.

For the personality-matched and mismatched conditions, we segmented our sample into ten personality-based target groups using their most salient personality trait (5 Traits × High/Low Ends). That is, for each user, we first calculated the percentile score on each of the five personality traits and subsequently identified the trait for which the percentile score was furthest away from the 50% median. For example, the most extreme and salient trait for participant A in Figure 3B is Agreeableness in the 10th percentile. Participant A's Agreeableness score negatively deviates the most from the 50% median, resulting in them being classified as "low Agreeableness." In contrast, participant B's most salient trait is Conscientiousness in the 86th percentile, and they are therefore classified as "high Conscientiousness." As such, our personality-matched intervention is based on the most salient personality trait only.[1] Segmenting the entire SaverLife user base according to this procedure resulted in the breakdown of the sample displayed in Figure 3C.

The goals that participants were encouraged to save toward varied in their content based on each participant's experimental condition. Participants in the gold-standard condition received the general communication content that SaverLife had developed and optimized over multiple years. The messages encouraged users to save, without specifying a particular saving goal (e.g., "The Race to $100 begins today—a chance to win $100 if you save $100"). Given that the gold-standard condition is based on SaverLife's accumulated

[1] An alternative approach would be to identify extreme traits based on participants' raw personality scores. The vast majority (89.7%) would be assigned to the same personality group using this alternative method.

Figure 2
Descriptive Results of Study 2



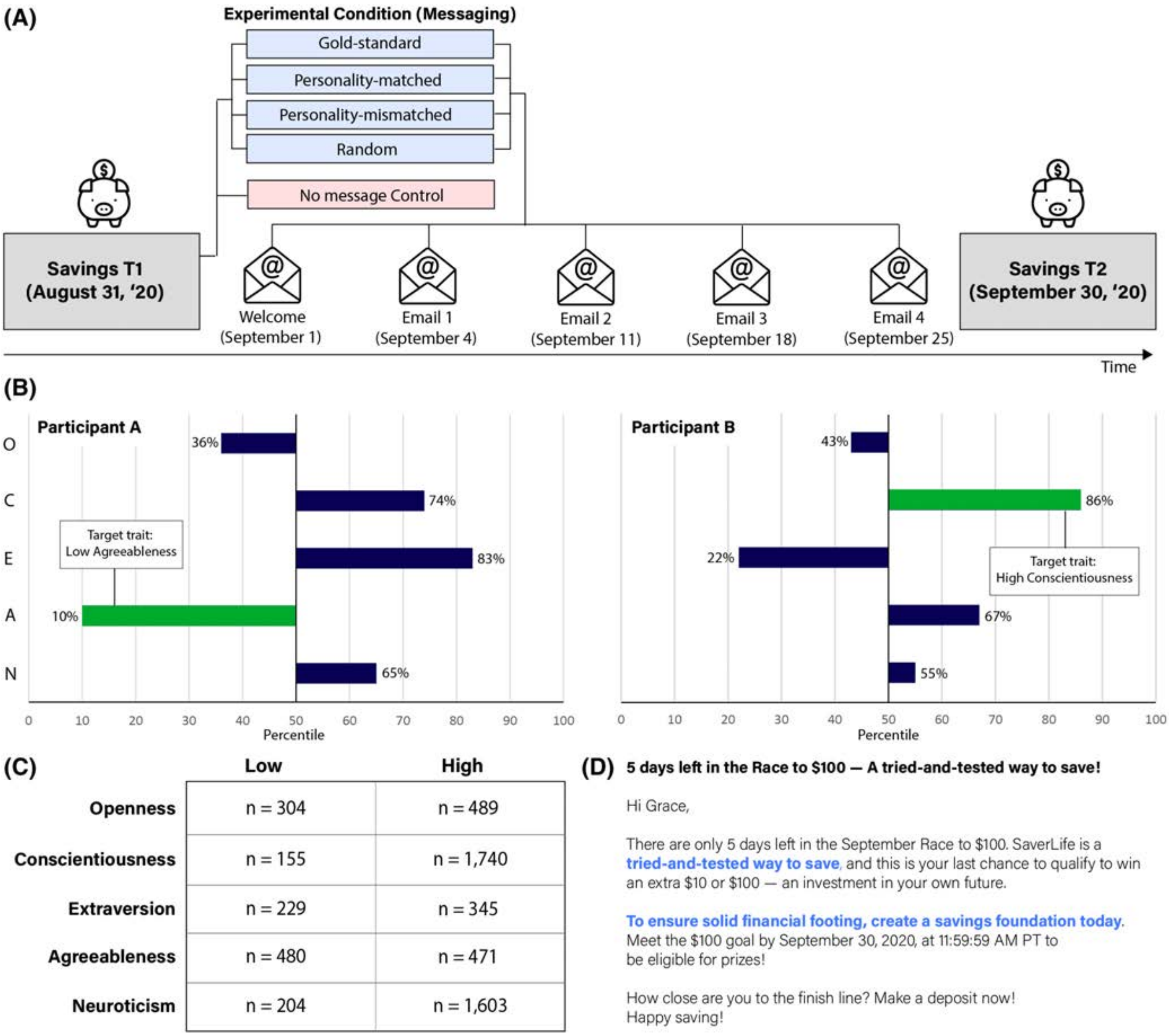
Note. (A) Distribution of savings among people who opened at least one message in the treatment arms before (blue) and after the intervention (red). (B) Scatterplot of savings before (*X* axis) and after (*Y* axis) the intervention, with individuals who managed to save during the period plotted above the line, and individuals who managed to save at least $100 plotted in light blue. (C) Percentages of individuals in each of the treatment arms (purple) as well as the control condition (red). Dark purple indicates the groups of individuals who opened at least one message, and light purple those in the relevant treatment group who did not open any messages. Error bars indicate 95% binomial confidence intervals. T1 = time 1; T2 = time 2. See the online article for the color version of this figure.

expertise on the topic as well as empirical feedback loops, it constituted an ambitious baseline comparison for the personality-matched condition for which messaging was only developed for this particular campaign and had not yet been optimized through an iterative process. Participants in the personality-matched condition received saving goals that were tailored to their most salient trait (e.g., high Openness for a participant in the high Openness target group), whereas participants in the personality-mismatched condition received saving goals that were tailored to the opposite end of their most salient trait (e.g., low Openness for a participant in the high Openness target group). Participants in the random message condition received one of the 11 possible sets of goals (10 personality-based and the gold standard), and those in the control condition received no messages. Figure 3D displays a sample email of the Week 5 messages tailored toward participants in the "low Openness" target group.

Analysis Plan (Intent to Treat vs. per Protocol)

A challenge in our research design is that participants assigned to a particular experimental condition did not

Figure 3
Overview of the Experimental Design and Materials



Note. (A) Timeline and design of experimental procedure. (B) Example profiles of users highlighting the way by which individuals were assigned to their most salient personality traits. (C) Number of individuals in each of the 10 personality target groups. (D) Sample message tailored to low Openness. T1 = time 1; T2 = time 2; PT = Pacific Time. See the online article for the color version of this figure.

always receive the expected treatment, as some recipients failed to open the treatment messages (i.e., noncompliance). This makes it difficult to cleanly compare savings goal achievement across the experimental groups. We respond to this by offering two sets of analyses. In the first, we present results comparing only participants who opened at least one of the intervention messages, in addition to those in the "no message" control group (*per protocol*). Of the 4,852 users targeted with one of the treatment messages, excluding those in the control condition who received no treatment, 1,312 users opened at least one of the emails sent to them by SaverLife. While this analysis may suffer from selection effects, online Supplemental Material 7 provides evidence that the subsample of participants who opened at least one message was similar to the full sample in their distributions of personality traits.

In addition to the analysis focused on those who opened at least one email, we follow this with an *intent-to-treat* analysis (Kruse et al., 2002). The intent-to-treat analysis includes all participants who were randomized to an experimental condition, regardless of whether the users received the treatment or not. This has the benefit of maintaining the prognostic balance generated from the original random treatment allocation, but generally produces more conservative estimates of treatment effects because of the dilution from noncompliance.

Transparency and Openness

This study was not preregistered. All analysis code is available on OSF (Matz & Gladstone, 2021). The data will be made available by the authors upon reasonable request.

Results

Figure 2A displays the distributions in savings for participants across all four intervention conditions who had opened an email before and after the intervention. The positive skew in the balances at Time 2 illustrates that following the intervention, a greater number of users had savings of more than \$100. Figure 2B plots the savings of each of the 1,312 individuals before the intervention (*X* axis) against those after the intervention (*Y* axis). Data points that lie above the black line indicate that a participant managed to save money throughout the month of September (31%), data points below the line indicate negative savings during the months (18%), and data points on the line indicate no change in savings (51%). Data points highlighted in light blue show those individuals who were successful in saving at least \$100 (8.4%).

Finally, Figure 2C displays the percentage of participants in each condition that successfully saved at least \$100 over the course of the Race-to-100 month. The graph allows us to compare individuals in the treatment arms who opened at least one of the messages (dark purple) to (a) the general control group which did not receive any messages (red) as well as (b) individuals in the treatment arms who did not open any messages and therefore did not receive the treatment itself (light purple). Across all conditions, those in the personality-matched condition who received the treatment saw the highest success rate with 11.4% reaching the \$100 savings goal, compared to 3.4% for the "no message" control group. Individuals who opened at least one message in the other treatment conditions were less successful than the personality-matched condition but more successful than the control condition (gold-standard message = 7.42%, random message = 7.46%, and personality-mismatched condition = 7.85%). Further supporting the effectiveness of the treatment, we find that individuals who were assigned to a treatment arm but who failed to read any of the messages experienced lower success rates comparable to the general control group (gold-standard message = 3.05%, random message = 3.64%, personality-matched = 2.87%, and personality-mismatched condition = 2.99%).

To test the statistical significance of the different treatments, we first ran logistic regression analyses on all subjects in the treatment conditions who had opened at least one of the messages as well as those in the general control condition ($n = 2{,}516$; see online Supplemental Material 8, for all zero-order correlations). Model 1 predicted the binary success metric (1 = saved \$100, 0 = failed to save \$100) from the condition fixed effect using the no-message control group as the reference condition. Mirroring the percentages displayed in Figure 2C, the personality-matched condition resulted in significantly higher success rates, $B = 1.27$, $SE(B) = 0.24$, *Odds Ratio* = 3.57, $p < .001$, indicating that an individual in the personality-matched condition was 3.57 times more likely to achieve the \$100 savings target than an individual in the control condition. The effect remained stable when (a) adding the target personality trait for each individual as an additional control variable in Model 2, $B = 1.25$, $SE(B) = 0.24$, *Odds Ratio* = 3.49, $p < .001$, and (b) considering only participants who managed to accumulate positive savings, rather than merely reducing debt; $B = 1.28$, $SE(B) = 0.24$, *Odds Ratio* = 3.60, $p < .001$; see online Supplemental Material 9, for full model output. While the treatment conditions had a significant effect on the likelihood of reaching the savings threshold, the model had a McFadden's pseudo-R^2 of 0.03, meaning the treatments overall explained only a relatively small proportion of the overall variance in savings likelihood.

We also considered the impact of personality-matched messages on the overall amount that participants saved. Supporting our intuition that the effectiveness of the treatment would be focused on people's ability to accomplish the \$100 saving goal but not necessarily to save additional money beyond this threshold, we only found a marginally significant effect of personality-matching when considering the absolute amount saved as our outcome measure, $B = 25.18$, $SE(B) = 13.42$, $p = .061$; see online Supplemental Material 5, for the full model output.

Importantly, the comparison of people in the treatment conditions who opened at least one message with people in the no-message control condition could be biased by selection effects. That is, SaverLife users who open at least one message might be generally more engaged than the average member in the control group. To alleviate these concerns, we conducted additional intent-to-treat analyses, which consider all participants in each treatment arm (including those who did not open any messages) when comparing the saving outcomes to those of the control condition. Given that the intent-to-treat analyses add substantial noise to all the treatment conditions, the magnitude of treatment effects dropped significantly across all conditions (McFadden's pseudo-R^2 of 0.01). However, the personality-matched condition was the only treatment condition that remained marginally significant, $B = 0.38$, $SE(B) = 0.20$, *odds ratio* = 1.46, $p < .059$. As before, this effect also remained robust when controlling for the participants' dominant personality trait, $B = 0.37$, $SE(B) = 0.21$, *odds ratio* $= 1.44$, $p < .074$.

In addition to the intent-to-treat analyses, we ran contrast analyses to compare the personality-matched condition to the other treatment conditions (focused again on participants who opened at least one message). Similar to the intent-to-treat analyses, the contrast analyses are free of selection biases. The personality-matched condition was found to be marginally more successful than the random and gold-standard conditions, random: $B = 0.47$, $SE(B) = 0.28$, *odds ratio* $= 1.60$, $p = .088$; gold-standard: $B = 0.48$, $SE(B) = 0.27$, *odds ratio* $= 1.61$, $p = .076$. That is, individuals in the personality-matched condition were between 52% and 61% more likely to achieve their saving goals than individuals in the other two treatment conditions. While we would have expected a larger difference between the personality-matched condition and the personality-mismatched condition, we found that the difference was of a similar magniture to the other comparisons, $B = 0.42$, $SE(B) = 0.28$, *Odds Ratio* $= 1.52$, $p = .126$. One possible explanation for why the mismatched personality messages did not perform as poorly as we had expected could be a novelty effect. While SaverLife users might have become accustomed to their standard communication and might be more exposed to personality-matching content as part of their everyday life, simply seeing different messages that highlight a novel angle to saving might have triggered more attention among participants in the mismatched personality groups (Allcott & Rogers, 2014).

Finally, additional analyses in online Supplemental Material 10 show that the aggregate effects between conditions that we report are not driven by differences in the effectiveness of the individual messages, and another set of analyses in online Supplemental Material 11 suggests that the effects of personality-matching were equally distributed across personality traits.

Discussion

Saving for the future is one of the most critical financial decisions individuals make. Holding even a small buffer of savings can help individuals with few financial resources cope with financial shocks and uncertainty (Federal Reserve Board, 2019). However, people's intentions to save often do not translate to changes in savings behavior (Baumeister, 2002; Martin, 2011). Across two studies with over 8,500 participants—a cross-sectional nationally representative survey in the United Kingdom and a field experiment in the United States—we showed that individuals are more likely to save when saving goals are aligned with their own psychological characteristics. While the survey findings from Study 1 are only correlational, the findings from the field experiment in Study 2 suggest that the effect we describe is causal: Personality-matched savings goals can increase goal attainment. In addition, the combination of the two studies suggests that matching saving goals to people's personality profiles is effective when (a) people set personality-congruent goals for themselves and when (b) third parties encourage saving by prompting individuals to consider personality-congruent saving goals. Notably, our results are consistent using different operationalizations of savings (i.e., self-reported total savings in Study 1 vs. a binary classification of achieving a savings target based on objective data in Study 2), highlighting the robustness of our findings.

While the effects of setting personality-matched saving goals were found to be robust and consistent, they were also found to be very small in magnitude. In both studies, personality-matching explained less than 5% of the variance. Notably, one reason we may expect small effects in Study 2 is the low-income sample under investigation. Saving behavior is characterized by a distinction between the *ability* to save (i.e., having surplus income beyond fulfilling basic needs) and the *willingness* to save (motivation and attitudes, Katona, 1975). Our personality-based intervention is designed to increase a person's willingness to save by increasing the value they associate with future rewards. However, even with the strongest motivation to save, some individuals will still be unable to do so because fulfilling basic needs leaves them without the discretionary resources needed to contribute toward their savings goal. Testing the effect of our manipulation in a context where many recipients lack the ability to save thus represents a highly conservative test of our hypothesis.

In addition, we argue that these effects can still be considered meaningful when acknowledging how difficult it is to get people to save more—especially those with extremely low initial savings—and how even small effects can add up when aggregated across a large population. This perspective is in line with recent calls to rethink the importance of small effects in psychological research (Götz et al., 2021; Matz, Gladstone, & Stillwell, 2017). Complex psychological phenomena such as saving behaviors are unlikely to be determined by a few strong predictors, necessitating psychologists and other social scientists to pursue a more nuanced approach to interpreting the practical relevance of effect sizes. For example, the 4.1% increase in the likelihood of people accomplishing their \$100 saving goal in Study 2 (personality-matched condition compared to the gold-standard message) only corresponds to a small effect size and could therefore be considered of minor practical importance. However, an increase of 4.1% could, in fact, have a considerable impact on society when considered at scale. If SaverLife or a more traditional banking provider were to apply this treatment to 1,000,000 people using personality-matched messaging rather than their standard communication, this could result in tens of thousands of additional users building a buffer of savings. Following this approach, digital tools and services targeted at saving behaviors (e.g., online banking, Fintech apps) might be able to use psychological fit as an intervention principle for encouraging savings behavior among large segments of the population.

Scientific and Practical Contributions

Our research contributes to the existing literature by studying the interactive effects between the characteristics of individuals and saving goals. While past research has sought to determine whether and how characteristics of savings goals, for example, goal specificity (Ülkümen & Cheema, 2011) or goal number (Soman & Zhao, 2011) or the characteristics of people (e.g., conscientious, self-controlled) shape savings outcomes, our approach focuses on the interaction between the two. In line with previous research highlighting the role of psychological fit in a variety of different contexts—ranging from relationships (Carli et al., 1991) and physical environments (Jokela et al., 2015) to job selection and satisfaction (Furnham & Schaeffer, 1984)—our work suggests that the extent to which saving goals are successful in driving behavior, might depend less on the specific content of the goal itself, and more on whether a particular goal aligns with the needs and motivations that are core to an individual.

In addition to providing descriptive insights into the psychology of savings, our findings also offer a prescriptive perspective into how external actors could intervene to motivate greater savings. While many people consider engaging with their finances boring at best and confusing at worst (Ward & Lynch, 2019), personality-matched messages could facilitate meaningful and enjoyable interactions that guide individuals toward achieving their savings goals. For example, highly agreeable customers could be matched to savings goals that best fulfill their desire to help other people, such as through buying gifts for family members. Highly open-minded individuals, on the other hand, could be given the opportunity to save for holidays and trips abroad. In line with Study 1, services might also offer users the opportunity to set their own saving goals but provide them with feedback on whether those goals appear to be aligned with their psychological needs and motivations. Our results suggest that these steps should facilitate greater goal achievement.

Limitations

The current research has a number of important limitations that should be addressed by future research. First, the low reliabilities of our personality measures in Study 1 (both for participants and saving goals) severely limit the conclusions we can draw from the study. Given that any true relationship is attenuated by low measurement reliabilities, our findings likely underestimate any true effects. Notably, the low interrater reliabilities of saving goals could also suggest meaningful heterogeneity in people's perception of different saving goals. That is, people might simply differ in how they think about and interpret the value of the goals we presented them with. Study 2 aimed to overcome this limitation by explicitly tailoring the expected value of saving to people's personality traits. Future research should investigate an alternative approach and test whether the effects of psychological fit in the context of saving get larger when the person who is saving is also the person evaluating the personality of the saving goal. In this case, person-goal fit would be a direct reflection of people's perception that their savings goals are aligned with their broader psychological motivations.

Second, there is a need to better understand the generalizability of these findings. While increasing savings balances among the most financially deprived is an important policy goal in itself, future research should replicate the intervention we describe in new samples to: (a) broaden the range of sociodemographic characteristics of the populations studied and (b) test the impact of the intervention in contexts where participants are not already motivated to save. This includes the investigation of psychological fit effects in non-Wester, Education, Industrialized, Rich and Democratic samples (Henrich et al., 2010). Given that a large body of research has uncovered a range of psychosocial interventions to increase savings among the world's poorest (Baranov et al., 2020; Haushofer et al., 2020; Soman & Cheema, 2011), future research should not only investigate the effectiveness of psychological fit in these contexts but also directly compare its effectiveness to other established interventions.

Third, saving might not always be an individual act but one that is embedded in a broader household system where finances are managed collectively between family members and romantic partners (Ward & Lynch, 2019). In both studies, we only capture the personality of a single household member and cannot account for potential diversity in personality traits across all household members. However, the possibility that individuals are influenced by the personality and goals of other household members should have added additional noise to our data making it more difficult to find significant effects by diluting the meaning of the personality fit measure. While the fact that we find consistent effects across Studies 1 and 2 hence speaks to the importance of psychological fit in the context of saving, future research should test whether its impact becomes diminished in larger households or between couples who are less congruent in their financial attitudes and personality.

Fourth, the mechanisms underlying the effect remain speculative and should be explicitly tested by future work. We propose that personality-matched goals positively influence the cost–benefit trade-off associated with savings by increasing the value of the future reward in the present. That is, saving will appear to be more valuable in the "now," if a person can experience high levels of anticipated happiness when thinking about how the money can be used in the future. Instead of saving generically for a rainy day, saving toward a positive outcome that satisfies important psychological needs should lower the perceived costs of putting money aside compared to the perceived value of future rewards. The outcome of this process might not always be anticipated happiness but could also be reduced anxiety. For example, highly neurotic or agreeable people might leverage personality-matched saving goals to imagine how saving today might protect them and their loved ones from unexpected and uncontrollable disasters in future. Investigating these and other potential mechanisms represents an avenue for future research.

Fifth, our experimental study investigated the causal effect of personality-tailored saving nudges on people's ability to save in the short term. However, it remains unclear to what extent these effects extend past the immediate intervention time frame and have a lasting impact on people's ability to save. In fact, the impact of financial interventions is often short-lived (Fernandes et al., 2014). Similarly, savings behaviors may also have been influenced by the specific timing of the experiment, which took place in 2020 during the COVID-19 pandemic. While the experimental approach we used means any impact of the pandemic on saving behavior should be consistent across all conditions, future research should explore whether the association of saving with people's core identity is both replicable and able to induce *sustained* behavior change.

Finally, future work should test for moderators that may enhance or limit the effectiveness of the personality-matched treatment messages. For example, is psychological fit more effective among young people who are still forming their own identity, or older people who are more settled in their self-views? In addition, future research should explore the value of different psychological traits. While we have focused our attention on matching saving goals to personality traits, there is a broad array of other psychological constructs that could prove to be valuable in the context of savings, including promotion versus prevention orientation (Zhou & Pham, 2004) and cognitive styles (Kozhevnikov, 2007).

Conclusion

Taken together, our findings suggest that not all savings goals are created equal: While saving toward one goal might be motivating for one person, it may not be so for another. To close the intention–action gap, we need to better understand what motivates an individual to make the sacrifice now and wait for a reward in the future. We have shown that matching saving goals to individuals' personality profiles provides a promising path to doing so.

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