MICHIGAN RETIREMENT AND DISABILITY RESEARCH CENTER
UNIVERSITY OF MICHIGAN

Promoting research on retirement, disability, and Social Security policy

Contextual and Social Predictors of Scam Susceptibility and Fraud Victimization

Aparajita Sur, Marguerite DeLiema, Ethan Brown

MRDRC WP 2021-429

UM21-15

Contextual and Social Predictors of Scam Susceptibility and Fraud Victimization

Aparajita Sur
University of Minnesota

Marguerite DeLiema
University of Minnesota

Ethan Brown
University of Minnesota

September 2021

Michigan Retirement and Disability Research Center, University of Michigan, P.O. Box 1248. Ann Arbor, MI 48104, mrdrc.isr.umich.edu, (734) 615-0422

Acknowledgements

The research reported herein was performed pursuant to a grant from the U.S. Social Security Administration (SSA) funded as part of the Retirement and Disability Research Consortium through the University of Michigan Retirement and Disability Research Center Award RDR18000002-03. The opinions and conclusions expressed are solely those of the author(s) and do not represent the opinions or policy of SSA or any agency of the federal government. Neither the United States government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this report. Reference herein to any specific commercial product, process or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply endorsement, recommendation or favoring by the United States government or any agency thereof.

Contextual and Social Predictors of Scam Susceptibility and Fraud Victimization

Abstract

Financial fraud targeting older adults is on the rise, with annual losses totaling in the billions of dollars. Prior cross-sectional and qualitative studies have reported that negative life events and social factors, such as poor psychological well-being and loneliness, are significant correlates of fraud, yet there is little research using longitudinal data to show that these social factors and life events precede (versus follow) victimization experiences, and no studies that examine the impact of modifying social variables on the risk of fraud and reducing scam susceptibility. In this study, we use repeated measures from the Rush Memory and Aging Project (MAP) decision making substudy to assess how negative life events and trajectories in social support, well-being, and loneliness affect susceptibility to scams and fraud victimization over the course of the study. Experiencing negative life events was not associated with the risk of self-reported fraud victimization, although negative life events were statistically significantly associated with greater scam susceptibility in unadjusted models. Using a causal inference analysis that simulates the impact of a social support intervention on the risk of fraud over time revealed that higher consistent social support increases the average probability of reporting fraud victimization over the study, contrary to study hypotheses. Although the magnitude of effects are small, consistent interventions that maximize psychological well-being and minimize loneliness significantly reduce average scam susceptibility. Effects are stronger for older adults who are divorced, widowed, or never married relative to those who are married or partnered.

Citation

Sur, Aparajita, Marguerite DeLiema, and Ethan Brown. 2021. “Contextual and Social Predictors of Scam Susceptibility and Fraud Victimization.” Ann Arbor, MI. University of Michigan Retirement and Disability Research Center (MRDRC) Working Paper; MRDRC WP 2021-429. https://mrdrc.isr.umich.edu/publications/papers/pdf/wp429.pdf

M
RDRC

Introduction

Greater numbers of older Americans are falling victim to fraud each year, and these numbers increased as a result of the COVID-19 pandemic. Nearly 12% of U.S. adults ages 65 to 74 and 8% of adults 75 and older reported that they were victims of a scam in 2017 (Anderson 2019). Although consumer complaints of fraud victimization decline with age, among those 70 and older, median losses per scam are two to four times higher than losses reported by adults younger than age 40 (Federal Trade Commission 2019). In addition to the billions of dollars lost annually to fraud and the emotional toll on victims, indirect societal costs include paying for the care and support of retirees who have lost their life savings and who are unable to return to the workforce to recoup losses.

Incremental progress has been made identifying what characteristics are associated with greater susceptibility to fraud. Differences in sample and survey methodologies yield mixed evidence that challenges conventional assumptions about fraud susceptibility. For example, large national prevalence studies indicate that older adults are *less likely* to be victims based on rates of self-reported fraud and consumer complaint data (see Ross et al. 2014), whereas other studies that examine age-related detriments in decision making (Boyle et al. 2012; Han et al. 2016a; Han et al. 2016b, Spreng et al. 2017; Yu et al. 2021) and social isolation and loneliness (e.g., Lee and Soberon-Ferrer 1997; Xing et al. 2020) suggest that seniors are *more* susceptible to scams. However, many of the studies on the cognitive, social, and emotional correlates of fraud (e.g., James et al. 2014; Grimm and Beach 2020; Yu et al. 2021) link risk factors to general susceptibility measures rather than actual reports of fraud victimization, and those that do are typically cross-sectional or qualitative (e.g., Alves and Wilson 2008; Anderson 2019; Cross 2016; DeLiema 2018).

Distinct from other types of financial crimes, fraud capitalizes on errors in decision making. Perpetrators use deception and misrepresentation to persuade their targets to pay or provide personal information. Work from Rush Alzheimer's Disease Research Center (ADRC) suggests that changes in brain structure and declines in functioning are associated with errors in health and financial decision making and greater scam susceptibility (e.g., Boyle et al. 2013; Han et al. 2016*a*; Han et al. 2015; Yu et al., 2017). Less research has used longitudinal data to investigate how social and contextual factors, such as negative life events and social and psychological characteristics, influence older adults' fraud susceptibility independent of cognitive status.

Lack of robust evidence on what modifiable risk factors impact susceptibility and predict victimization presents a challenge to fraud investigators and victim advocates who allocate limited protection resources to those most at risk. Using data from the Memory and Aging Project (MAP), this study aims to understand how contextual and psychosocial factors relate to scam susceptibility *and* self-reported fraud victimization over time. As a longitudinal panel study, MAP data accounts for the temporal ordering of life events, psychosocial factors, and fraud victimization.

Social and contextual correlates of fraud victimization

Negative life events, including widowhood, job loss, and hospitalization are more frequent in later life as people age, retire, and experience adverse changes in health. Anderson (2019) found that survey participants who experienced a serious negative life event in the past two years — such as the death of a family member or close friend, a serious injury or illness in their family, or the loss of a job — were more likely to report having also been the victim of a scam. Life events may increase fraud vulnerability by reducing social support and social activity, particularly if the event involves the loss of a spouse, a driver's license, or loss of function that limits activities outside of the home.

Using longitudinal data from the HRS, DeLiema (2015) found that widowhood and other negative life events occurring between 1999 and 2006 predicted fraud victimization. A major limitation of the HRS is that respondents are asked to retrospectively report fraud victimization occurring some time in the preceding five years, and psychosocial measures are administered only every four years. Thus, for some respondents, data on negative life events and other social factors are collected long before the incident of fraud occurs, too distant to capture the more immediate effects of these life changes on victimization risk.

Scholarship on the social and emotional factors associated with vulnerability to fraud and scams has grown in the past decade. Grimm and Beach (2020) recently reported that socially isolated older adults scored significantly higher on a measure of vulnerability to financial exploitation, measured as their ratings of the credibility of various scam messages. In a nonprobability sample of older Chinese participants, loneliness was associated with higher fraud susceptibility, as was having more medical needs (Xing et al., 2020). Using a community sample of older adults, Liu and colleagues (2017) found that negative interactions with close network members was associated with financial exploitation, even after controlling for other social factors. A study using longitudinal data from the Health and Retirement Study (HRS) to predict fraud victimization found that depression measured in 2002 was a significant predictor of self-reported fraud victimization occurring sometime between 2003 and

2008 (Lichtenberg et al. 2013). In a separate study, these researchers found that low social needs fulfillment predicted fraud (Lichtenberg et al. 2016).

Using cross-sectional data from the MAP study, James and colleagues (2014) reported that scam susceptibility was inversely associated with psychological well-being and perceived social support, but unlike previously described studies, scam susceptibility was not associated with depression or loneliness. This finding was echoed in a more recent study of Black older adults that found that psychological well-being was inversely associated with scam susceptibility, but depression, loneliness, and social network size were not (Yu et al. 2021). Loneliness was also not significantly associated with victimization in a sample of adults targeted by online romance scams (Buchanan and Whitty 2014).

Although there is a growing body of research documenting a link between psychosocial factors and vulnerability to fraud, mixed findings suggest that more research is needed to help clarify the relationship between loneliness, scam susceptibility, and fraud victimization. Moreover, no studies have assessed the impact on fraud risk of modifying loneliness and other psychosocial factors. Interventions that reduce loneliness by enhancing social connection and interaction, and interventions that improve self-efficacy and overall sense of well-being in older age may offer promising avenues of protection.

Study purpose

The purpose of this study is twofold. First, we aim to identify the longitudinal association between negative life events, fraud victimization, and scam susceptibility. The second aim is to assess whether simulated interventions that target older adults' levels of social support, psychological well-being, and loneliness can effectively reduce scam susceptibility and the probability of fraud victimization. We predict that negative life events increase scam susceptibility and the risk of fraud victimization over time. We also predict that increasing levels of social support reduce fraud victimization, and that increases in well-being and decreases in loneliness reduce susceptibility to scams among older adults. This project addresses a critical barrier to progress in aging and fraud victim research by helping identify events and social contexts that affect fraud susceptibility, and whether targeting modifiable psychosocial risk factors may help keep older adults safe from victimization.

Data and sample characteristics

Sample

This study uses data from the Rush Memory and Aging Project (MAP) decision-making substudy of participants 65 and older recruited from the Chicago area. At enrollment, all participants were free of known dementia and agreed to annual evaluations. Follow-up rates among survivors exceed 90%. Beginning in 2010, MAP participants were invited to enroll in a substudy on health and financial decision making (N=2,272). Each year, participants respond to a five-item scam susceptibility scale (e.g., "If a telemarketer calls me, I usually listen to what they have to say") and answer a question on fraud victimization in the past year (yes or no). Participants also undergo comprehensive clinical and cognitive assessments and complete social-behavioral measures on the occurrence of negative life events, social network size, perceived social support, psychological well-being, and loneliness.

Measures

Dependent variables

Fraud victimization is measured using a single item: “In the past year, were you a victim of financial fraud or have you been told you were a victim of financial fraud?” Responses are coded dichotomously such that yes=1. Three-hundred and twelve (24.5%) out of 1,272 total participants reported at least one instance of being a victim of fraud over the course of the study. Fraud was relatively rare; 8.78% of survey respondents reported fraud on average across the survey waves. See Appendix Table A.

Scam susceptibility is assessed as the participants’ agreement with five statements using a seven-point Likert scale (strongly disagree to strongly agree). Examples include, “I answer the phone whenever it rings, even if I do not know who is calling,” and “If something sounds too good to be true, it usually is.” Some items are reverse scored. Higher scores indicate greater susceptibility to scams. Participants’ average score at baseline is 2.71 out of 7.00.

Independent variables

Eighteen negative life events include having a spouse die, institutionalization of oneself or a family member, beginning to need help with daily activities, assuming care for someone else, among others. The overall score is the sum of the individual events that occurred in the prior 12 months (range 0 to 18), where higher scores indicate more negative life events. Approximately 21% of participants completed the negative life events scale at any point during their participation; and between 12% to 45% of enrolled participants responded at any given follow-up year.

Loneliness is measured with five items from a modified version of the de Jong-Gierveld Loneliness Scale (de Jong-Gierveld and Kamphuls 1985) and includes items such as “I often feel abandoned,” and, “I miss having a really close friend.” Participants rate their agreement with each item on a five-point Likert scale (strongly disagree to strongly agree). Responses are averaged and higher scores indicate greater feelings of perceived isolation.

Well-being is assessed with 18 items from a modified version of Ryff‘s Scales of Psychological Well-being (Springer and Hauser, 2006) that measures six dimensions of well-being: self-acceptance, autonomy, environmental mastery, purpose in life, positive relations with others, and personal growth. Participants receive a total score that is their average agreement with the 18 items on a seven-point Likert scale (strongly disagree to strongly agree).

Perceived social support is measured as the mean response to four items scored on a five-point Likert scale (strongly disagree to strongly agree). Items include (1) There is a special person who is around when I am in need, (2) There is a special person with whom I can share joys and sorrows, (3) I have a special person who is a real source of comfort to me, and (4) There is a special person in my life who cares about my feelings. Social network interaction quantifies the number of children, family, and close friends seen at least once a month. All social measures are administered at baseline and at each follow-up year.

Control variables are sex (male/female), education (college/less than college), age (continuous), annual household income (under $25K, $25K to $75K, and greater than $75K), and global cognitive function (z-score, continuous).

Descriptive analysis

Missingness in the MAP study and baseline statistics

The maximum follow-up year where a participant had data on our key variables was 10 years. There are several reasons why a MAP participant might not have data for a given variable in a follow up year:

1. **Rolling enrollment:** Participants who joined the study more recently had fewer years of data available. Approximately 58% of participants had data by the fourth follow-up year, and 34% by the seventh follow-up year.
2. **Attrition due to death:** Between 32 and 44 participants died each year.
3. **Missing entire survey records:** Of those alive in a given year, the median percentage of the sample with no records at all, across follow-up years, was 8.4%. We flagged a record as missing for a given follow-up year if a) there was a gap in an individual's participation in that follow-up year, or b) if there was a gap between an individual's last year of participation and their date of death.
4. **Missing variables:** Even in follow-up years where a participant had a survey record, they might not have been administered all the instruments and questionnaires needed for the present analysis. Occasionally this is due to cognitive impairment.

Figure 1: Missingness rates at the first seven follow-up years for enrolled participants

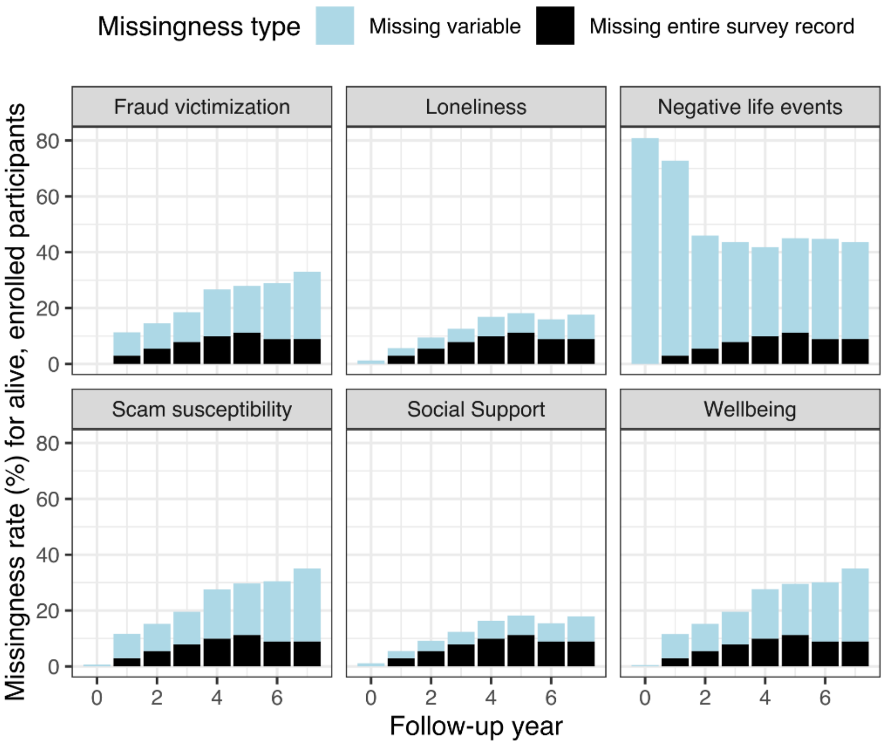


Figure 1 compares the percentage of alive, enrolled participants who had missing survey records or missing variables across follow-up years. Charts are adjusted for attrition due to death. Not all participants were administered the negative life events scale and so there was significant missing data on that measure. However, the missingness rates for other key measures were relatively low. For example, fraud victimization and scam susceptibility, which were both a part of the decision-making substudy, had less missingnesss, while the socioemotional measures all had missingness under 20%. Table 1 shows summary statistics of our key measures along with demographic variables at baseline, including missingness.

Table 1: Summary statistics for all participants at baseline

Variable (N = 1,272)	Mean [Min - Max]/Frequency	Missingness
Fraud victimization (Yes/No)	Yes: 85 (6.7%), No: 1187 (93.3%)	0 (0%)
Scam susceptibility (7-point Likert)	2.71 [1.00, 5.60]	8 (.6%)
Negative life events (0-18)	2.53 [0, 8.00]	1,029 (80.9%)
Loneliness (5-point Likert)	2.18 [1.00, 5.00]	16 (1.3%)
Social network interactions (#)	7.09 [0, 59.0]	15 (1.2%)
Perceived social support (5-point Likert)	4.38 [1.00, 5.00]	14 (1.1%)
Well-being (7-point Likert)	5.55 [3.00, 7.00]	6 (.5%)
Age (years)	79.1 [53.5, 99.8]	0 (0%)
Global cognitive function (z-score)	.129 [-3.07, 1.60]	9 (.7%)
Relationship status	Married: 516 (40.6%)	35 (2.8%)
Education	College: 766 (60.2%)	0 (0%)
Sex	Female: 961 (75.6%)	0 (0%)
Income	<25K: 269 (21.1%), 25-75K: 630 (51%)	52 (4.1%)

Variability in dependent measures and measurement error

Although our original analytic plan used change in scam susceptibility as the outcome variable of interest, the observed percentage of within-person variability in scam susceptibility was low and was indistinguishable from measurement error. The observed share of within-person variability in scam susceptibility, 34%, was actually lower than what would be expected due to measurement error alone with scam susceptibility stable over time, 37%, based on the reported internal consistency ICC of 0.63 (Boyle et al. 2019). Additionally, only 4% of year-to-year differences in scam susceptibility exceeded the minimum detectable difference (MDD) due to measurement error. Since there was not enough change over time in scam susceptibility for modeling year-to-year differences as an outcome variable, we instead used scam susceptibility without computing change scores.

Linear mixed models

Association between negative life events and subsequent fraud victimization and scam susceptibility

To test the hypothesis that negative life events predict higher scam susceptibility and a greater likelihood of fraud victimization, we used a two-level hierarchical linear modeling (HLM) approach. The longitudinal models predicting scam susceptibility were analyzed separately from the models predicting self-reported fraud victimization. As noted above, due to low variability in scam susceptibility, the outcome of interest in the longitudinal models was scam susceptibility (and separately fraud victimization), rather than *changes* in scam susceptibility scores between survey years.

The HLM method accounts for the nonindependence of each participant‘s responses across time points and simultaneously models within and between subject variance. HLM can also accommodate missing data at level 1 (missing time points), and a dichotomous outcome (fraud victimization=yes/no).

Models controlled for global cognitive function, sex, age, education, and income level (measured only at baseline). Results indicate whether negative life events predict scam susceptibility after controlling for cognitive, psychosocial, and socioeconomic factors. This same process was repeated using fraud victimization (yes/no) as the dichotomous outcome. All covariates, aside from sex, income, and education, were treated as time-varying.

Linear mixed model results

Negative life events and scam susceptibility

Qualitative evidence and cross-sectional surveys suggest that negative life events are a precursor to fraud, but these relationships have not been modeled longitudinally. We hypothesized that negative life events would be associated with higher subsequent scam susceptibility, and also greater odds of reporting fraud victimization the following year.

A series of linear mixed models was fit to address these hypotheses, with scam susceptibility as the outcome variable and reported negative life events as the focal predictor (Table 2). Model 1 shows that age is positively associated with scam susceptibility. On average, for every additional year of age there is a 0.010 point increase in scam susceptibility, 95% confidence interval (CI): [0.004, 0.015], $p < .01$. Although the effect size is small, Model 2 shows that negative life events are statistically significant and predict scam susceptibility. For every additional negative life event, scam susceptibility increases by 0.016 (95% CI: [0.004, 0.029]), $p < 0.05$. Since scam susceptibility is on a 1 to 5 scale, a 0.016 increase per life event is likely not substantively or clinically significant.

When social variables and other measures are added in Model 2 and Model 3, negative life events are no longer statistically significant and the effect sizes are similarly small. In Model 4, loneliness is positively associated with scam susceptibility (0.068; 95% CI: [0.014, 0.119]; $p < 0.05$). Global cognitive function is inversely associated with scam susceptibility (-0.245; 95% CI: [- 0.323, -0.193];$p < 0.001$), meaning that as global cognitive function increases, scam susceptibility decreases. Well-being (-0.126; 95% CI: [-0.185, -0.066]; $p < 0.001$) and income (-0.278; 95% CI: [-0.425, -0.131]; $p < 0.001$) are also inversely associated with scam susceptibility.

Negative life events and reported fraud victimization

Linear mixed models were also run with fraud victimization as the outcome variable, and reported negative life events as the focal predictor, controlling for social and demographic measures in Models 3 and 4 (Table 3). In contrast to scam susceptibility, Model 1 shows that every additional year of age is associated with a 28% *decrease* in the odds of reporting fraud victimization (95% CI: [0.957, 0.988]; p=.0004). However, after adjusting for other measures, the effect of age is reduced and no longer statistically significant. Negative life events are not statistically significant predictors of experiencing fraud in any of the models. In the fully adjusted model (Model 4) only global cognitive function and perceived social support are statistically significantly associated with fraud victimization (α = 0.05). Specifically, a one-point increase in social support is associated with a 39% *increase* in the odds of reporting victimization (95% CI: [1.044, 1.842]; p=.024) and a one standard deviation (z-score) increase in global cognitive function is associated with a 36% increase in the odds of reporting fraud victimization (95% CI: [1.009, 1.828]; p=.044).

Variance inflation factors were computed and all are less than two, indicating that multicollinearity is not a concern in any of the models predicting scam susceptibility and fraud victimization, even for related predictors such as income and education.

Table 2: Linear mixed effects models of scam susceptibility (n = 775)

	Models for scam susceptibility			
	(1)	(2)	(3)	(4)
Age	0.010** (0.004, 0.015)	0.010** (0.004, 0.015)	0.004 (−0.001, 0.010)	−0.003 (−0.009, 0.003)
Negative Life Events		0.016* (0.004, 0.029)	0.013 (−0.0002, 0.025)	0.013 (0.000, 0.026)
Social Network Interactions			−0.001 (−0.006, 0.004)	−0.0004 (−0.005, 0.004)
Loneliness			0.085** (0.031, 0.137)	0.068* (0.014, 0.119)
Social Support			−0.020 (−0.065, 0.026)	−0.013 (−0.058, 0.035)
Well-being			−0.175*** (−0.235, −0.115)	−0.126*** (−0.185, −0.066)
Global Cognitive Ability				−0.258*** (−0.323, −0.193)
Income: $25K–$75K				−0.001 (−0.116, 0.116)
Income: >$75K				−0.278*** (−0.425, −0.131)
At least 16 years of education				−0.033 (−0.135, 0.070)
Male				0.118* (0.006, 0.226)
Constant	1.816*** (1.342, 2.292)	1.781*** (1.312, 2.256)	3.105*** (2.442, 3.792)	3.513*** (2.851, 4.196)

Note: *p<0.05; **p<0.01; ***p<0.001; Numbers in parentheses indicate a 95% bootstrap confidence interval. Income less than $25,000 is the reference category.

Table 3: Linear mixed effects models of fraud victimization (n = 775)

	Models for fraud victimization			
	(1)	(2)	(3)	(4)
Age	0.972***	0.977*	0.977*	0.984
	(0.957, 0.988)	(0.957, 0.998)	(0.956, 0.998)	(0.962, 1.007)
Negative Life Events		1.038	1.028	1.031
		(0.963, 1.119)	(0.952, 1.109)	(0.954, 1.115)
Social Network Interactions			1.007	1.008
			(0.983, 1.030)	(0.985, 1.032)
Loneliness			1.199	1.209
			(0.895, 1.605)	(0.899, 1.626)
Social Support			1.449* (1.091, 1.923)	1.387* (1.044, 1.842)
Well-being			0.849	0.754
			(0.625, 1.152)	(0.552, 1.029)
Global Cognitive Ability				1.358* (1.009, 1.828)
Income: $25K to $75K				1.062
				(0.539, 1.264)
Income:> $75K				0.825
				(0.733, 1.539)
≥ 16 years of education				1.274
				(0.903, 1.798)
Male				1.034
				(0.722, 1.482)
Constant	0.775	0.542	0.178	0.177
	(0.209, 2.870)	(0.096, 3.071)	(0.009, 3.618)	(0.008, 3.825)

Note: *$p < 0.05$; **$p<0.01$; ***$p<0.001$; Numbers in parentheses indicate a 95% confidence interval for the odds ratio. Income less than $25,000 is the reference category.

Obtaining causal effects of psychosocial interventions on self-reported fraud victimization and scam susceptibility

G-computation algorithm procedures

In the longitudinal models estimating the probability of fraud victimization, well-being, social network engagement, and loneliness are likely confounders in the relationship between social support and fraud victimization. The effect size of social support changes by more than 10% when only one of the above social measures is added to a univariate social support model for fraud. This is not surprising as the social measures are highly correlated (See Appendix Figure A).

A causal inference analysis is valuable when confounding is strongly suspected. Due to the time-dependent nature of social factors and possible feedback loops with scam susceptibility and fraud victimization outcomes, associations from longitudinal models may be biased and misleading (Keogh et al. 2018). Standard longitudinal models estimate associations between fixed covariates and a longitudinal outcome, but these models are not equipped to account for time varying covariates and an outcome that may itself affect future covariates (i.e., fraud victimization may affect well-being, which in turn may affect the risk of future fraud victimization, which then affects future well-being).

A causal inference analysis is also valuable in estimating the direct effects of an intervention on an outcome. Social support, well-being and loneliness are modifiable risk factors for fraud victimization and scam susceptibility and thus could be the basis for an intervention. Since the setting is longitudinal, a social or psychological intervention would aim at increasing levels of that measure for all participants at multiple time points (e.g., a high social support trajectory).

We used the g-computation algorithm outlined by Wang and Arah (2015) to determine the causal effect of modifying social support, well-being, and loneliness trajectories on the average percent chance of fraud victimization and scam susceptibility for participants if they stayed alive for seven years. In practice, causal effects of an intervention on an outcome can be obtained if the intervention is randomly assigned to participants in a controlled experimental study. Random assignment ensures that confounders are adjusted for because treatment and control groups are comprised of randomly selected members with balanced baseline characteristics. G-computation is a statistical procedure that emulates random assignment in experimental studies. It first randomly generates a batch of participants with similar baseline characteristics to the actual participants from the observed study. The procedure then assigns values to an independent variable (the "intervention") for all these participants and simulates the potential outcomes that would occur as a result of those assignments. To compare several interventions or a control intervention, each is simulated on a new randomly generated batch of participants with similar baseline characteristics, and the potential outcomes are compared.

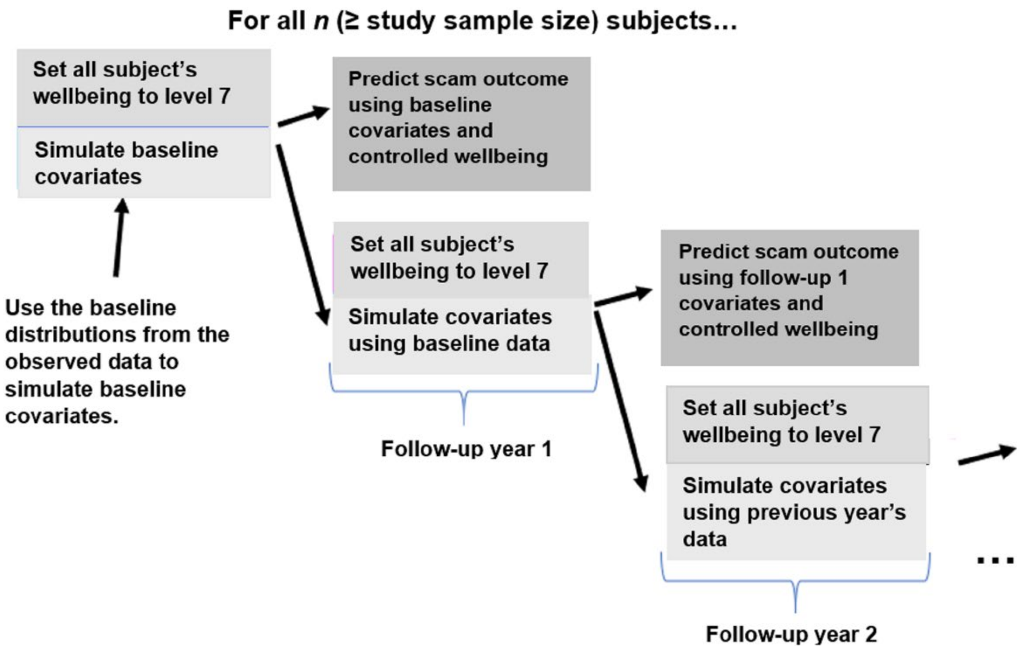
Prior studies have used g-computation, or microsimulation, to calculate the direct effect of different types of a particular exposure on an outcome of interest (i.e., if everyone was given a treatment, what potential outcomes would arise?). In this context, g-computation could answer the following question: What is the probability of fraud victimization or the mean level of scam susceptibility if *all* participants had a consistent level of social support, loneliness, or well-being throughout the study? We simulated this by manually assigning values of the social or psychological measure to all MAP participants for seven years, regardless of their other covariates. This eliminates the effect of confounding and the feedback loop on the relationship between the social measure and the outcome, because the social measure is manually assigned and held constant across study waves, mimicking the controlled nature of group assignment in experimental designs. Figure 2 presents the g-computation process for an intervention that ensures a high well-being (7 out of 7) for all participants consistently for seven years.

The direct effect of consistently modifying a psychological or social measure for seven years on a participant's probability of reporting fraud or average scam susceptibility was estimated with the following g-computation algorithm:

1. Use the observed data to fit models that predict the outcome (probability of reporting fraud victimization or average scam susceptibility), as well as all covariates not being intervened on (i.e., social network size, income, sex, education, etc.); if interested in subgroup analyses, include interactions of the subgroup and the social measure being intervened on.
2. Randomly generate the baseline covariates for a set number of participants, based on the baseline variable distributions from the observed data. In our analysis, we simulated 5,000 subjects.
3. Manually assign the score for the target social measure being intervened on (well-being, social support, or loneliness) for all participants.
4. Use the fitted models to simulate each participant's outcome and covariates for the following time point. Store each participant's outcome.
5. Assign the next social measure level for the trajectory of interest for all participants and simulate each participant's outcome and covariates for the following time point.
6. Repeat process described in #4 and #5 for all time points.
7. Calculate the appropriate summary measure for the outcome (percent of participants reporting fraud or the average scam susceptibility score) for each of the seven time points. Also calculate the *overall* average scam susceptibility and percent probability that a participant reports fraud across the seven survey years.

8. Repeat steps 1 to 7, 10,000 times to compute bootstrap confidence intervals for the measures calculated in step.

Figure 2: G-computation process used to simulate the impact of a consistent well-being intervention on average scam susceptibility scores over time



Note: Steps repeat a total of seven times (seven survey waves).

Specifically for fraud victimization interventions, we assessed the average percent chance of reporting fraud victimization across seven survey years for four different social support trajectories. In three of the social support trajectories (a.k.a., "interventions" or "treatments"), we manually assigned social support values for all participants at each survey wave. The three social support simulated interventions are: (1) *most optimal* consistent social support (all subjects assigned a score of 5 out of 5 for seven time points), (2) *optimal* consistent social support (all subjects assigned a score of 4 out of 5 for seven time points), (3) *least optimal* consistent social support (all subjects assigned a score of 3 out of 5 for seven time points).

For interventions aimed to reduce scam susceptibility, we assessed the average scam susceptibility across seven survey years for three different well-being and loneliness trajectories, as well as a trajectory that intervened on both well-being and loneliness at the same time. The simulated interventions aimed to reduce scam susceptibility were: (1) most optimal consistent well-being (all subjects assigned the highest possible well-being score of 7 out of 7 for seven time points), (2) most optimal consistent loneliness (all subjects assigned the lowest possible loneliness score of 1 out of 5 for seven time points), (3) optimal consistent well-being (well-being score of 6 out of 7 for all time points), (4) optimal consistent loneliness (loneliness score of 2 out of 5 for all time points), (5) least optimal consistent well-being (well-being score of 5 out of 7), (6) least optimal consistent loneliness (loneliness score of 3 out of 5 for all time points) and (7) a combined intervention of high well-being and low loneliness (all subjects are assigned a well-being score of 7 (highest) and a loneliness score of 1 (lowest) for all time points).

We chose trajectories of social support scores between 3 and 5 for interventions 1 to 3 because these are the most common scores for participants in the MAP study (98% of participants have social support scores between 3 and 5 at baseline). A similar reasoning was used to select well-being and loneliness trajectories.

Additionally, we simulated a natural course trajectory in fraud victimization and scam susceptibility (“no intervention”) as a means of comparison or control group. In these trajectories, we do not actively control the values of any psychological or social measure at any time point. Instead, values are simulated based on the observed data models and are what would naturally occur if there is no intervention.

Finally, to determine which subgroups would benefit most from the well-being and loneliness interventions — i.e., largest declines in average scam susceptibility, we added interactions between the psychosocial measures (loneliness and well-being) and the subgroups of interest. The subgroups included married or partnered versus divorced, widowed, and never married; and no cognitive impairment versus mild cognitive impairment. We removed the minority of participants who had moderate to severe cognitive impairment as their scam susceptibility scores were often missing and their scores may not be reliable. All simulations were run using the same observed data models, and later were separated by subgroup.

Overall, our g-computation models simulate how intervening on social measures would affect risk of fraud victimization or scam susceptibility if participants were alive through the course of seven years. Therefore, for all seven years we simulated the outcomes and covariates for the same number participants. To get precise estimates, we simulated 5,000 participants and used 10,000 bootstrap iterations. As highlighted by Snowden et al. (2011), g-computation relies on the positivity assumption requiring that there is a nonzero probability that a subject could be assigned all the psychosocial interventions assessed. We also assumed the time-ordering of certain variables (i.e., fraud victimization occurred as a result of social support and other covariates reported the previous year) and no unmeasured confounding. Finally, we assumed that the observed data models used for the simulations were correctly specified.

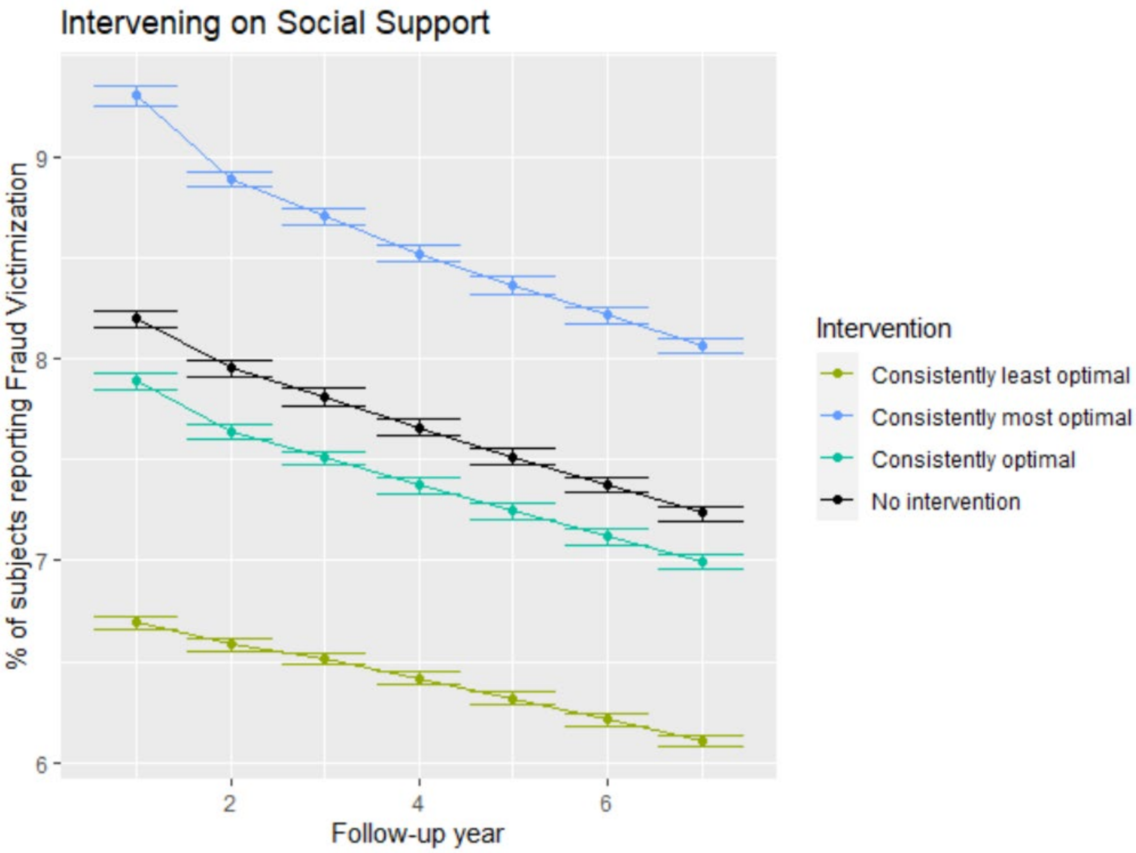
G-computation simulation results

We investigated the causal effect of different social support trajectories on reported fraud victimization. Similarly, we investigated the causal effect of different well-being and loneliness trajectories on scam susceptibility as these social measures are modifiable and significant predictors for scam susceptibility.

Intervening on social support to reduce fraud victimization

Figure 3 depicts the percent of subjects reporting fraud victimization across seven survey years for three different trajectories of social support. Contrary to study hypotheses, higher consistent social support trajectories significantly increase the average chance of reporting fraud victimization over the study as none of the confidence intervals overlap, although rates of self-reported fraud decrease over time. All social support interventions were significantly different than the natural course (no intervention in black). The average percent likelihood that a subject reported fraud victimization across the seven survey years for the natural course was 7.68% [95% CI: 7.63, 8.71], whereas the average percent chance that a subject reported fraud victimization for the *most optimal* social support intervention (score of 5 out of 5) was 8.58% [95% CI: 8.54, 8.62]. The second most optimal intervention (social support = 4) and least optimal intervention (social support = 3) significantly reduce the percent chance that a participant reports fraud over the course of the study.

Figure 3: The impact of consistent social support interventions on the percent of participants who reported fraud victimization over seven survey years



Note: The *most optimal* intervention was an assigned social support score of 5 (out of 5) for all seven years. The *optimal* intervention was an assigned social support score of 4 for all seven years, and the *least optimal* intervention was a social support score of 3 for all seven years. This score was lower than participants' average reported level of social support in the MAP study, the *no intervention* trajectory.

Intervening on well-being and loneliness to reduce scam susceptibility

While within subject variability was low, average scam susceptibility increased slightly over the course of the study (natural course trajectory), from an average of 2.53 to an average of 2.65. In our simulations, consistent well-being scores of 7 (the highest score possible) significantly decreased overall scam susceptibility for subjects alive across seven years compared to no intervention by 11.19% [95% CI: 10.81%, 11.56%]. Consistent well-being scores of 6 decreased average scam susceptibility by 4.05% [95% CI: 3.66%, 4.42%] (Table 4). The average well-being for subjects throughout the course of the MAP study was 5.55, therefore it was not surprising that our simulations showed that a consistent well-being score of 5 would increase overall scam susceptibility across seven years compared to no intervention.

We repeated the procedure with a simulation model that reduced loneliness to consistent scores of 1, 2, and 3 (out of 5). The only statistically significant decrease in average scam susceptibility occurred when loneliness was consistently reduced to the lowest level possible (-6.34% [95% CI: 6.72%, 5.9%]).

Overall, increasing well-being had a larger effect than reducing loneliness. However, a combined intervention that increased well-being to 7 and reduced loneliness to 1 produced the greatest reduction in average scam susceptibility (16.71% [95% CI: 6.72%, 5.9%]). These simulated interventions have the largest effects in the first two years, followed by more tempered effects in subsequent years.

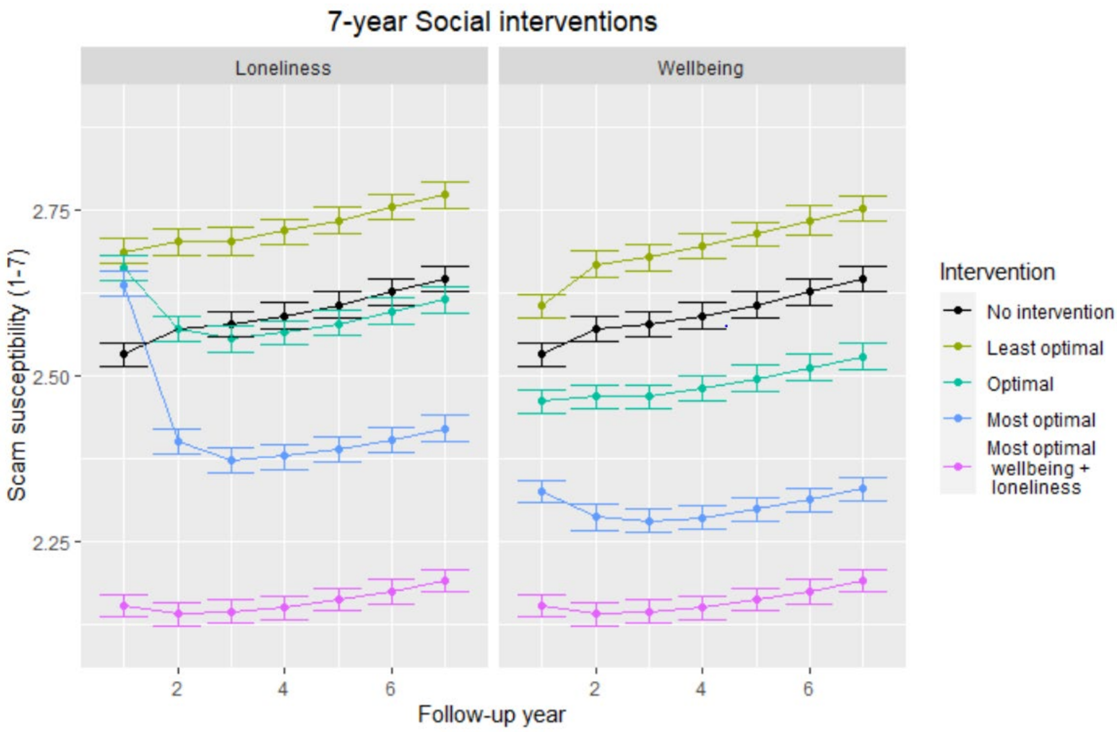
Table 4: Average scam susceptibility across seven years for all participants and by subgroup

	All	Mild cognitive impairment	No cognitive impairment	Divorced, widowed or never married	Married or partnered
No intervention	2.59 (2.59,2.6)	2.66 (2.64,2.68)	2.58 (2.57,2.59)	2.64 (2.62,2.65)	2.56 (2.55,2.57)
Most optimal consistent intervention					
Well-being = 7 + Loneliness = 1	2.16 (2.15,2.17)	2.20 (2.18,2.22)	2.16 (2.15,2.16)	2.16 (2.14,2.17)	2.16 (2.15,2.17)
% change in mean susceptibility	-16.71% (-17.04, -16.36)	-17.17% (-18.11,-16.21)	-16.5% (-16.86,-16.13)	-18.23% (-18.79,-17.68)	-15.55% (-15.99,-15.07)
Well-being = 7	2.30 (2.3,2.31)	2.4 (2.38,2.43)	2.29 (2.28,2.3)	2.32 (2.31,2.33)	2.29 (2.28,2.3)
% change in mean susceptibility	-11.19% (-11.56,-10.81)	-9.62% (-10.59,-8.61)	-11.28% (-11.67,-10.86)	-11.9% (-12.47,-11.32)	-10.64% (-11.16,-10.11)
Loneliness = 1	2.43 (2.42,2.44)	2.44 (2.42,2.46)	2.43 (2.42,2.44)	2.42 (2.41,2.43)	2.44 (2.43,2.45)
% change in mean susceptibility	-6.34% (-6.72, -5.9)	-8.31% (-9.21, -7.35)	-5.91% (-6.3, -5.44)	-8.18% (-8.76, -7.66)	-4.92% (-5.43, -4.41)
Optimal consistent intervention					
Well-being = 6	2.49 (2.48,2.5)	2.56 (2.54,2.58)	2.48(2.47,2.49)	2.52(2.51,2.53)	2.47(2.46,2.48)
% change in mean susceptibility	-4.05% (-4.42, -3.66)	-3.82% (-4.87, -2.74)	-4.03% (-4.41, -3.62)	-4.39% (-4.94, -3.83)	-3.78% (-4.32, -3.26)
Loneliness = 2	2.59 (2.58,2.6)	2.64 (2.61,2.66)	2.58 (2.58,2.59)	2.63 (2.62,2.64)	2.57 (2.55,2.58)
% change in mean susceptibility	-0.05% (-0.47,0.35)	-0.83% (-1.84,0.15)	0.11% (-0.32,0.53)	-0.23% (-0.81,0.36)	0.09% (-0.42,0.63)
Least optimal consistent intervention					
Well-being = 5	2.69 (2.69,2.7)	2.73 (2.71,2.75)	2.69 (2.68,2.69)	2.74 (2.73,2.76)	2.66 (2.65,2.67)
% change in mean susceptibility	3.85% (3.47,4.22)	2.73% (1.81,3.72)	4.02% (3.6,4.43)	4.08% (3.5,4.68)	3.67% (3.09,4.15)
Loneliness = 3	2.73 (2.72,2.74)	2.80 (2.78,2.82)	2.71 (2.7,2.72)	2.81 (2.8,2.82)	2.66 (2.65,2.67)
% change in mean susceptibility	5.06% (4.62,5.49)	5.41% (4.46,6.4)	4.89% (4.43,5.35)	6.65% (6.03,7.28)	3.85% (3.26,4.4)

Note: Values in parentheses are 95% confidence intervals; Percentage values represent the percent change in average scam susceptibility relative to no intervention (top row). Negative percentages represent the desired effect: a decrease in scam susceptibility.

Figure 4 depicts how the simulated interventions would affect average scam susceptibility for subjects alive throughout seven years. Intervening on well-being has the greatest benefit in the first two years: It immediately leads to a significant decrease in scam susceptibility within the first year and a well-being score of 7 continues the significantly decreasing trend into the second year. However, after two years, all the simulated psychosocial interventions have tempered effects, and there are no further significant declines in scam susceptibility.

Figure 4: The effects of consistent interventions on loneliness and well-being on scam susceptibility for participants throughout seven years of the study.



Note: The *least optimal* interventions are a consistent well-being score of 5 and consistent loneliness score of 3. The *optimal* interventions are a consistent well-being score of 6 and consistent loneliness score of 2. A consistent well-being score of 7 and loneliness score of 1 are the *most optimal* interventions.

Figures 5 and 6 show how the simulated interventions affect average scam susceptibility for subjects alive throughout seven years for different subgroups. The most optimal psychosocial interventions impacted subjects who were married or partnered significantly differently than those who were divorced, separated, or widowed. This result is particularly pronounced in the intervention on loneliness; the confidence intervals in Table 4 do not overlap. For those who are divorced, widowed, or never married, consistent low loneliness (1 out of 5) decreased overall average scam susceptibility across seven years by -8.18% [95% CI: -8.76,-7.66] compared to no intervention, whereas the reduction was only -4.92% [95% CI: -5.43, -4.41] for those who were married or partnered (Table 4). Analogously, the least optimal loneliness intervention increased overall average scam susceptibility across the seven years by 6.65% [95% CI: 6.03, 7.28] compared to no intervention, whereas the effect was more tempered for those who were married or partnered (3.85% increase [95% CI: 3.26,4.4]).

Figure 5: The effects of consistent well-being interventions on scam susceptibility for seven years for those with no cognitive impairment versus mild cognitive impairment, and those who are married or partnered versus divorced, widowed, or never married

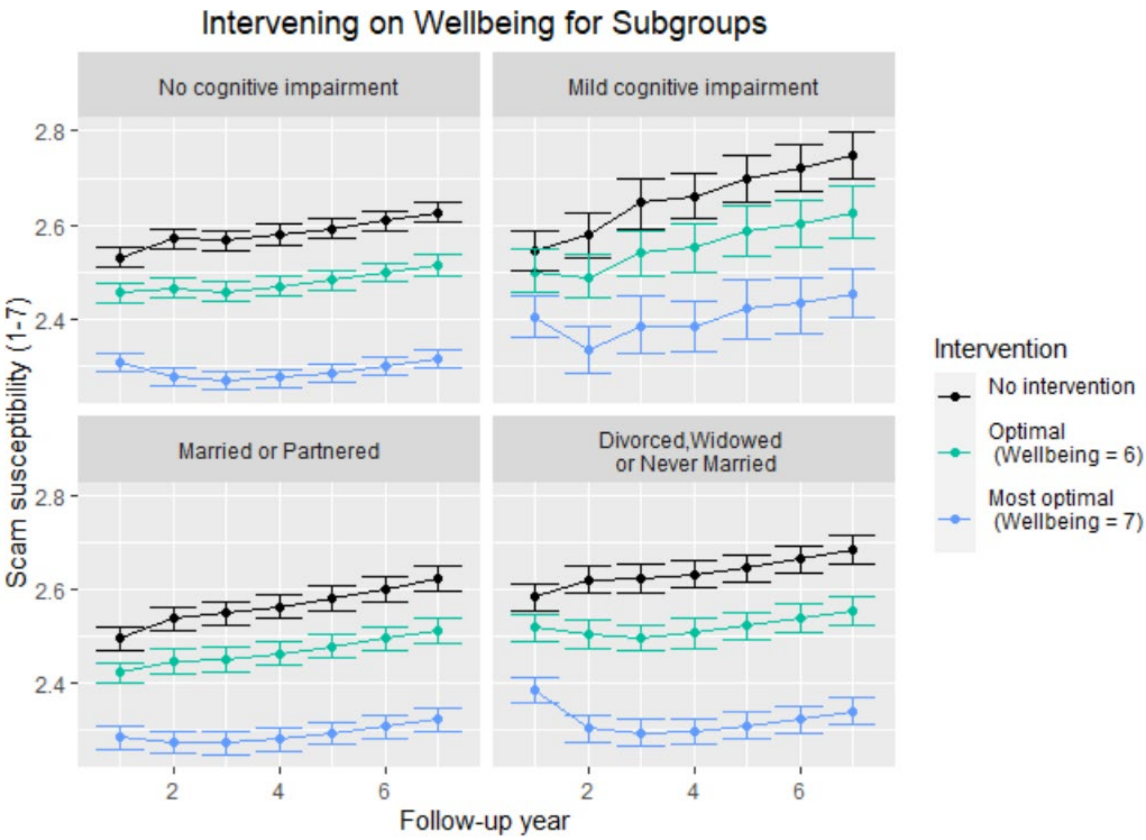
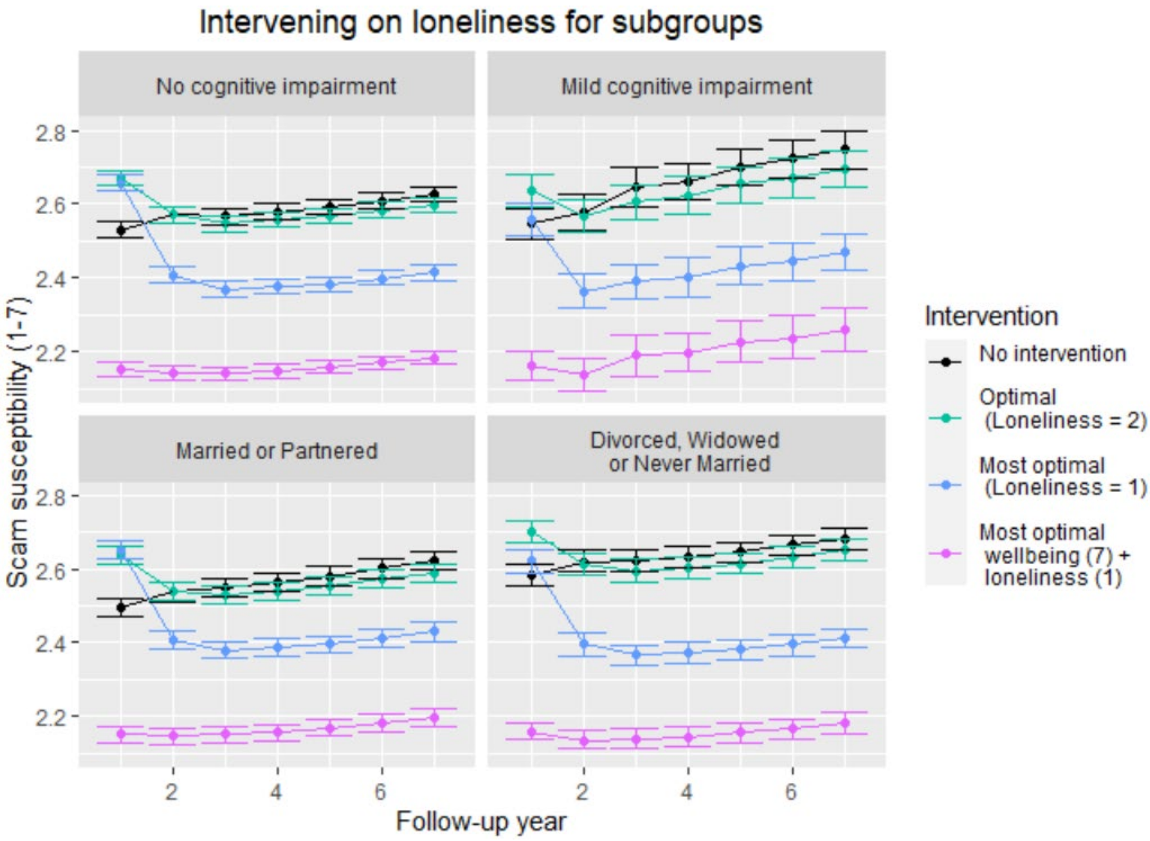


Figure 6: The effects of consistent interventions on loneliness on scam susceptibility for seven years for those with no cognitive impairment versus mild cognitive impairment, and those who are married or partnered versus divorced, widowed, or never married



Discussion

Negative life events as predictors of scam susceptibility and fraud victimization

Using a linear mixed modeling approach, we did not find that negative life events increased the risk of self-reported fraud victimization in subsequent survey years, although negative life events were statistically significantly associated (α = 0.05) with greater scam susceptibility in unadjusted models. The magnitude of the relationship was small, β=0.013, and the confidence interval approached 0, suggesting that life events do not have a substantive impact on behaviors associated with scam susceptibility such as talking with telemarketers.

There are several possible explanations for these null findings. The first is that there is substantial missing data on negative life events in the MAP study. Only 21% of participants completed the negative life events scale at any point during their participation, and only 12% to 45% responded at any given wave. For example, at baseline, 80% of participants had no data on negative life events. The extent of missing data may have reduced the statistical power to detect any significant effects of negative life events on fraud victimization.

Another possible explanation is that the window of vulnerability to fraud following a negative life event may be narrow, lasting only a few weeks or a few months. For example, a person who is hospitalized may recover her abilities in a short time, or a person who lost his driver's license may quickly adapt to relying on family or rideshare programs to get around. In this study, participants were asked about negative life events that occurred the past year, and their response to fraud victimization in the past year was taken from the following survey wave to avoid a potential reversal in the order of events. Although this allowed for appropriate causal ordering, for some individuals who reported a negative life event at year *t* and fraud the following year at *t*+1, the gap between when the negative life event occurred and when fraud occurred could have been two years, and possibly even longer. This prolonged delay may weaken the observed effect of negative life events on fraud and scam susceptibility, particularly if the effects of negative life events are only temporary. Future studies may find more robust effects using more frequent measurements of fraud and life events, or researchers may attempt to ask participants to recall *when* a negative life event or fraud occurred to adjust for the time delay between these experiences.

Third, different negative life events may have different effects on susceptibility to scams and fraud victimization. Widowhood may cause significant social changes including a loss of a financial decision-maker, becoming a caregiver may have no effect, and functional decline may actually lead to increased oversight and involvement from caregivers in the person's finances. People also vary in their emotional reactions to these events based on their sources of social support and individual characteristics (Comijs et al. 2011; Jopp and Schmitt 2010). Due to the extent of missing data and the relatively low occurrence of any specific life event in a given year, we did not assess the individual effects of specific negative life events on fraud victimization or scam susceptibility. Future studies may examine the effects of individual life events or the cumulative effects of multiple negative life events on fraud. Such research could suggest that only specific later life experiences produce greater levels of vulnerability (e.g., death of the household financial decision maker), or that effects vary based on individual differences in cognitive ability, resilience, availability of financial caregivers, and emotional coping style.

Contrary to our expectations based on cross sectional studies (see Anderson, 2019), experiencing negative life events was not substantively nor statistically significantly associated with a higher risk of self-reported fraud victimization, although negative life events were statistically significantly associated with greater scam susceptibility in unadjusted models ($\alpha = 0.05$). Findings may be the result of low statistical power due to missing data on negative life events, infrequent periods of assessment paired with a short duration of vulnerability after negative life events, lack of within-subject variability in scam susceptibility over time, or other forms of measurement error.

Impact of social support trajectories on fraud victimization

Study results suggest that social factors such as psychological well-being, loneliness, and perceived social support have differing effects on scam susceptibility and self-reported fraud victimization. The effects of psychological well-being and loneliness were statistically significant predictors of scam susceptibility in the theoretically expected directions (inverse and positive, respectively). The significant relationship between greater well-being and lower scam susceptibility has also been reported in prior studies using diverse MAP participants (James et al. 2014; Yu et al. 2021). In the models predicting fraud victimization, however, only perceived social support and global cognitive function were statistically significant predictors of victimization and in the unexpected positive direction. This suggests that as perceived social support and cognitive ability increase, the odds of reporting subsequent fraud victimization also increase.

These counterintuitive findings may stem from measurement error in self-reported fraud. First, in order to report fraud in the study, older participants must first remember if they experienced fraud in the past year. Those suffering from cognitive impairment may not recall victimization, especially if the incident happened months in the past. Second, participants must recognize and label the incident as a scam. Older adults with dementia or even mild cognitive impairment may be less likely to realize that they were deceived into giving money to a fraud criminal (versus to a legitimate person, business, or cause) and therefore be less likely to self-report fraud. Third, even if participants recall and recognize that they were victims of fraud, they must also to be willing to admit victimization in the survey.

Research indicates that fraud victims often feel ashamed and embarrassed that they were deceived (Deem 2000; DeLiema et al. 2017). These feelings could minimize their willingness to disclose fraud in a survey. Fear of losing financial autonomy may also motivate older victims to remain silent, especially individuals harboring concerns about declining cognitive abilities. By contrast, participants with higher cognitive function and more social support may be more comfortable reporting fraud victimization in the study. The supportive people in their lives may help them recognize and label an incident where they were deceived into paying money as a scam, increasing the likelihood that they acknowledge and report it in a survey. Under these assumptions, it is not that higher cognitive function and more social support actually *increase* the risk of being victimized, but rather that higher cognitive function and social support increase the odds of remembering and reporting fraud in the survey.

Results from the causal inference analysis using the g-computation statistical method tell a similar story about the relationship between social support and self-reported fraud victimization. Participants with higher consistent social support trajectories showed a higher average percent chance of reporting fraud victimization. There is a slightly higher than 2 percentage point difference between consistently high social support (average score of 5 out of 5) compared to consistently midlevel social support (average score of 3) in the average percent chance of reporting fraud victimization. Given that the chance of reporting fraud is only 8.78% on average at each survey wave in the MAP study, a 2 percentage point difference may be meaningful. In practice, social support interventions might involve fraud victim support groups or increased family involvement in an older victim's financial affairs. While increased family involvement generally may not be sufficient to prevent future fraud victimization, it may increase the older person's awareness that they were deceived.

Impact of psychological well-being and loneliness trajectories on scam susceptibility

In longitudinal models, increases in social support were significantly associated with an increase in self-reported fraud victimization, whereas lower well-being and higher loneliness were significantly associated with greater scam susceptibility in the expected directions. These psychosocial factors also had the largest effect sizes.

To build on these secondary findings, we used g-computation analysis and found that a simulated intervention that consistently provides high psychological well-being yields a significant reduction in scam susceptibility over time, and that an intervention that consistently reduces loneliness to the lowest level also significantly reduces susceptibility. Overall, consistently high well-being has a stronger impact on reducing scam susceptibility than consistently low levels of loneliness. Well-being includes concepts such as self-acceptance, autonomy, environmental mastery, purpose in life, positive relations with others, and personal growth. Our findings imply that there is an important link between behaviors associated with scam susceptibility and feelings of self-efficacy, purpose, and meaningful social connection. Future research may attempt to explore why these self-perceptions and relational characteristics make an older adult feel less obligated to answer a call from a telemarketer or be more likely to believe that when something sounds too good to be true, it usually is. Perhaps high levels of well-being give older adults more agency to reject false claims and hang up on telemarketers. And for those with high life satisfaction and fulfilled social needs, fraudulent opportunities promising wealth, status, or social connection may be less appealing.

“Solo agers,” or individuals who are divorced, widowed, and never married had higher levels of scam susceptibility over the seven year period than older adults who were married or partnered at baseline. Both simulated interventions had a stronger effect on solo agers. Despite starting with greater average scam susceptibility scores, the most optimal intervention reduced solo agers’ average scam susceptibility levels to the same extent, or even lower, as the same intervention for married/partnered older adults. The differential impact of the interventions on these two subgroups indicates that older adults who do not have a partner to monitor their finances or their phone interactions with strangers are promising targets for psychosocial interventions.

We did not find significantly stronger effects of the interventions for those with mild cognitive impairment compared to those with no impairment, suggesting that psychosocial interventions to reduce scam susceptibility do not provide greater benefits to those with poor cognitive functioning.

The combined interventions of reducing loneliness and increasing well-being had the most pronounced effect on scam susceptibility overall, indicating that an intervention that targets both social and psychological factors could offer the best protection against fraud. Consistent reductions in loneliness to the lowest possible level showed the largest effects in the first few years, after which average scam susceptibility remains relatively constant, albeit lower than the no intervention trajectory. Future research examining the effects of ending the intervention after year three to determine the future effect on scam susceptibility would be useful.

Implications for future research and practice

Applied interventions are a helpful next step to determine whether greater social support and improved psychological well-being can increase awareness of fraud and self-reported victimization and also buffer the risk of victimization. To better gauge the effect of psychosocial interventions on scam susceptibility, interventions could be tested in applied experimental studies that randomize participants into different treatment conditions. Interventions could include weekly social support groups, individual cognitive-behavioral therapy sessions, engagement in volunteer organizations or clubs, or a service that helps families become more involved in the older adults' financial decisions.

Future research may also assess the cost-effectiveness of these interventions and whether they produce more clinically meaningful reductions in susceptibility compared to the simulated interventions that have more modest effects.

Limitations

One limitation of g-computation is that the method simulates the measures for participants based on models derived from the observed data, but if these models are misclassified, this will affect the g-computation results. Our models had R^2 values between 0.1 and 0.4 which could be deemed low.

Data on marital status was only available at baseline. It is possible that some participants in lost their partners or became partnered later in the study and were misclassified in later years of the simulation.

The current analysis examined the overall average percent chance of reporting fraud victimization and the average scam susceptibility across all survey waves if an intervention is applied consistently. Future analyses could examine the effects of only intervening in the first two years compared to no intervention, as it may not be feasible to consistently intervene for seven years.

Well-being and loneliness interventions produced statistically significant reductions in scam susceptibility, but the clinical significance of these reductions is unclear. The combined loneliness and well-being intervention only reduced scam susceptibility by 16.7%. It is possible that applied interventions would produce more substantial reductions, but consistently reducing loneliness to the lowest possible level and increasing well-being to the highest possible level may not be feasible in real-world environments.

Conclusion

Our findings extend the important work of exploring contextual and psychosocial predictors of susceptibility and victimization and investigating possible psychosocial interventions for fraud. The current analysis employs g-computation models to assess the causal effect of repeated social support, loneliness, and well-being interventions on the average chance of reporting fraud victimization across subjects, and on their average scam susceptibility scores over seven years. From the causal inference analysis, we found that high levels of consistent social support lead to a higher average chance of reporting fraud victimization over the study. This may suggest that people providing high social support to older adults help them recognize and acknowledge scams that they experienced in the past year.

We also find that interventions that provide consistently high levels of psychological well-being and consistently low levels of loneliness reduce susceptibility to scams, although the effects are small and may not be clinically significant. Interventions that target both factors at the same time provide the most benefit, and effects are stronger for those who are widowed, divorced, and who never married. This indicates that solo agers may be a promising population to target with programs that enhance social engagement, self-efficacy, and sense of purpose.

References

Alves, L. M., & Wilson, S. R. (2008). The effects of loneliness on telemarketing fraud vulnerability among older adults*. Journal of Elder Abuse & Neglect, 20*(1), 63-85.

Anderson, K. B. (2019). Mass-market consumer fraud in the United States: A 2017 update. Federal Trade Commission. Washington, DC.

Boyle, P. A., Yu, L., Wilson, R. S., Gamble, K., Buchmana, A. S., & Bennett, D. A. (2012). Poor decision making is a consequence of cognitive decline among older persons without Alzheimers disease or mild cognitive impairment. *PloS One, 7*(8), e43647.

Boyle, P. A., Yu, L., Schneider, J. A., Wilson, R. S., & Bennett, D. A. (2019). Scam aware- ness related to incident Alzheimer dementia and mild cognitive impairment. *Lich*

Boyle, P. A., Yu, L., Wilson, R. S., Segawa, E., Buchman, A. S., & Bennett, D. A. (2013). Cognitive decline impairs financial and health literacy among community-based older persons without dementia. *Psychology and Aging, 28*(3), 614-624.

Buchanan, T., & Whitty, M. T. (2014). The online dating romance scam: Causes and consequences of victimhood. *Psychology, Crime & Law, 20*(3), 261-283.

Comijs, H. C., van den Kommer, T. N., Minnaar, R. W., Penninx, B. W., & Deeg, D. J. (2011). Accumulated and differential effects of life events on cognitive decline in older persons: Depending on depression, baseline cognition, or ApoE 4 status?. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 66*(1), i111-i120.

Cross, C. (2016). Theyre very lonely: Understanding the fraud victimisation of seniors. *International Journal for Crime, Justice and Social Democracy, 5*(4), 60.

Deem, D. L. (200). Notes from the field: Observations in working with the forgotten victims of personal financial crimes. *Journal of Elder Abuse & Neglect, 12*L(2), 33-48.

de Jong-Gierveld, J., & Kamphuls, F. (1985). The development of a Rasch-type loneliness scale. *Applied Psychological Measurement, 9*(3), 289-299.

DeLiema, M. (2018). Elder fraud and financial exploitation: Application of routine activity theory. *The Gerontologist, 58*(4), 706-718.

DeLiema, M. (2015). Using mixed methods to identify the characteristics of older fraud victims. Dissertation. University of Southern California.

DeLiema, M., Mottola, G. & Deevy, M. (2017). Findings from a pilot study to measure financial fraud in the United States. Report by the Stanford Center on Longevity and FINRA Investor Education Foundation.

Federal Trade Commission (2019). Protecting older consumers 2018-2019: A report of the Federal Trade Commission. Washington, DC.

Gimm, G., & Beach, S. (2020). Financial exploitation vulnerability and social isolation in older adults: Results from a longitudinal survey. *Innovation in Aging, 4*(1), 29.

Han, S. D., Boyle, P. A., Yu, L., Arfanakis, K., James, B. D., Fleischman, D. A., & Bennett, D. A. (2016a). Grey matter correlates of susceptibility to scams in community-dwelling older adults. *Brain Imaging and Behavior, 10*(2), 524-532.

Han, S. D., Boyle, P. A., James, B. D., Yu, L., & Bennett, D. A. (2016b). Mild cognitive impairment and susceptibility to scams in old age. Journal of Alzheimer’s Disease, 49 (3), 845- 851.

Han, S. D., Boyle, P. A., James, B. D., Yu, L., & Bennett, D. A. (2015). Mild cognitive impairment is associated with poorer decision making in community based older persons. *Journal of the American Geriatrics Society, 63*(4), 676-683.

James, B. D., Boyle, P. A., & Bennett, D. A. (2014). Correlates of susceptibility to scams in older adults without dementia. *Journal of Elder Abuse & Neglect, 26*(2), 107-122.

Jopp, D. S., & Schmitt, M. (2010). Dealing with negative life events: differential effects of personal resources, coping strategies, and control beliefs. *European Journal of Ageing, 7*(3), 167-180.

Keogh, R. H., Daniel, R. M., VanderWeele, T., & Vansteelandt, S. (2018). Analysis of lon- gitudinal studies with repeated outcome measures: Adjusting for time-dependent confounding using conventional methods. *American Journal of Epidemiology, 187*(5), 1085-1092.

Lee, J., & Soberon-Ferrer, H. (1997). Consumer vulnerability to fraud: Influencing factors. *Journal of Consumer Affairs*, 31(1), 70-89.

Lichtenberg, P. A., Stickney, L., & Paulson, D. (2013). Is psychological vulnerability related to the experience of fraud in older adults?. *Clinical Gerontologist*, *36*(2), 132-146.

Lichtenberg, P. A., Sugarman, M. A., Paulson, D., Ficker, L. J., & Rahman-Filipiak, A. (2016). Psychological and functional vulnerability predicts fraud cases in older adults: Results of a longitudinal study. *Clinical Gerontologist, 39*(1), 48-63.

Liu, P. J., Wood, S., Xi, P., Berger, D. E., & Wilber, K. (2017). The role of social support in elder financial exploitation using a community sample. *Innovation in aging, 1*(1).

Ross, M., Grossmann, I., & Schryer, E. (2014). Contrary to psychological and popular opinion, there is no compelling evidence that older adults are disproportionately victimized by consumer fraud. *Perspectives on Psychological Science, 9*(4), 427-442.

Snowden, J. M., Rose, S., Mortimer, K. M. (2011). Implementation of G-Computation on a simulated data set: Demonstration of a causal inference technique, *American Journal of Epidemiology, 173*(7), 731–738

Spreng, R. N., Cassidy, B. N., Darboh, B. S., DuPre, E., Lockrow, A. W., Setton, R., & Turner, G. R. (2017). Financial exploitation is associated with structural and functional brain differences in healthy older adults. *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences, 72*(10), 1365-1368.

Springer, K. W. & Hauser, R. M. (2006). An assessment of the construct validity of Ryffs scales of psychological well-being: Method, mode, and measurement effects. *Social Science Research, 35*(4), 1080-1102.

Wang, A., Arah, O. A. (2015). G-computation demonstration in causal mediation analysis. *European Journal of Epidemiology*, 30(10), 1119-1127.

Xing, T., Sun, F., Wang, K., Zhao, J., Wu, M., & Wu, J. (2020). Vulnerability to fraud among Chinese older adults: Do personality traits and loneliness matter?. *Journal of Elder Abuse & Neglect, 32*(1), 46-59.

Yu, L., Mottola, G., Barnes, L. L., Han, S. D., Wilson, R. S., Bennett, D. A., & Boyle, P. A. (2021). Correlates of susceptibility to scams in community-dwelling older Black adults. *Geron- tology,* 1-11.

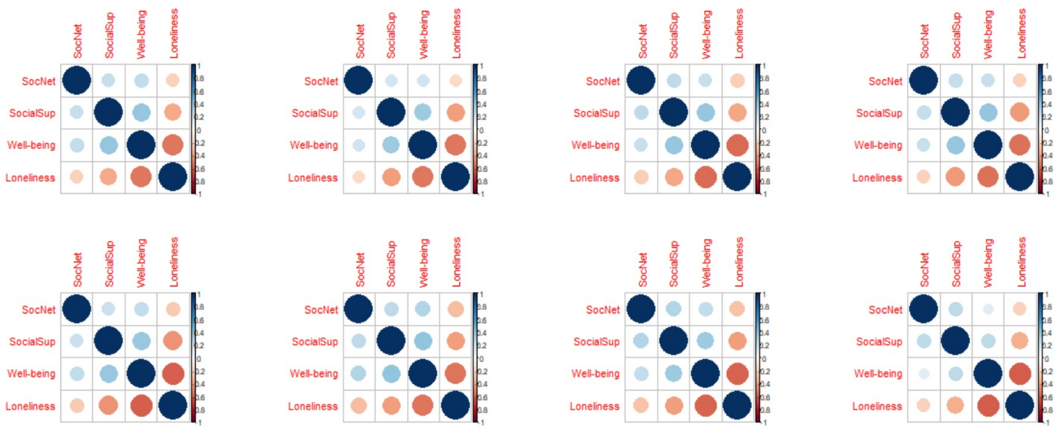
Yu, L., Wilson, R. S., Schneider, J. A., Bennett, D. A., & Boyle, P. A. (2017). Financial and health literacy predict incident Alzheimers disease dementia and pathology. *Journal of Alzheimer's Disease, 56*(4), 1485-14

Appendix

Table A: Number of fraud events reported by participants

Total number of fraud events	Number of subjects (n)
0	960
1	212
2	67
3	22
4	7
5	2
7	1
8	1
Missing	65

Figure A: Correlation coefficients between social measures well-being, loneliness, social network size, and social support for the first eight survey waves (including baseline)



Note: Correlation patterns are roughly consistent across survey years.