



The impact of financial strain on medication non-adherence: Influence of psychiatric medication use

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ARTICLE INFO

Keywords:

Adherence
Crowdsourcing
Income
Medicine
mTurk
Socioeconomic

ABSTRACT

Non-adherence to prescribed medications is a systemic public health concern. Financial strain, the extent to which an individual is unable to afford necessary items, may represent an important factor related to adherence. This study evaluated the association between financial strain and medication adherence as a function of medication type. Participants reporting a daily prescription for psychiatric or other chronic health conditions ($N = 231$) were sampled from the crowdsourcing website Amazon Mechanical Turk (mTurk). All participants completed measures of financial strain and other individual-difference factors related to adherence. Medication adherence was evaluated using a subjective scale (i.e., ARMS) and past month non-adherence rates. General financial strain showed a modest relationship with subjective scales of adherence, but not past month non-adherence rates. Medication-specific financial strain was associated with greater non-adherence, even after controlling for relevant demographic, socio-economic, and personality factors. Medication-specific financial strain also disproportionately affected individuals taking psychiatric medications relative to those not taking psychiatric medications. These findings emphasize the role that financial strain plays in medication adherence, and in particular, in psychiatric conditions. Future studies could design interventions targeting financial strain to improve clinical adherence, broadly, and psychiatric medication adherence, specifically.

1. Introduction

Adherence, defined as “the extent to which a person's behavior - taking medication, following a diet, or making healthy lifestyle changes - corresponds with agreed-upon recommendations from a health-care provider”, is a systemic public health concern (World Health Organization, 2003). To illustrate, non-adherence to prescribed medications by patients with bipolar disorder reduces remission and recovery rates, increases hospitalization and suicide risk, and generates inpatient medical costs twice those of adherent patients (Hong et al., 2011). Adherence rates across varied chronic health conditions remain discouragingly low and interventions to improve adherence generally unsuccessful. A systematic review of adherence in affective disorders, for example, found that approximately half of patients fail to take their medication as prescribed (Lingam and Scott, 2002). Low rates of adherence for other psychiatric and chronic health conditions are reported elsewhere (Brown and Bussell, 2011; Pucci and Martin, 2017; Yeaw

et al., 2009). Interventions have similarly demonstrated inconsistent and small magnitude effects with systematic reviews concluding heterogeneous efficacy, lack of generalizability across conditions, and limited data on long-term outcomes (Kripalani et al., 2007; Nieuwlaat et al., 2014; Ryan et al., 2014). Research is therefore needed to identify determinants of medication adherence to facilitate the development and implementation of novel evidence-based interventions.

One factor that may influence an individual's adherence to prescribed medications is socioeconomic status (SES) and accompanying financial resources. Traditional indicators of SES (e.g., income) show modest, but inconsistent, associations with adherence (Lemstra et al., 2012; Lucca et al., 2015; Mojtabei and Olfson, 2003). Income also fails to fully explain cost-related non-adherence as patients with moderate-to-high incomes will still report forgoing medications because of cost (Piette et al., 2004b). A smaller, but growing, literature has addressed these discrepancies by evaluating non-traditional measures of SES, such as financial strain. Financial strain represents the extent to which an

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<https://doi.org/10.1016/j.psychres.2018.11.055>

Received 7 June 2018; Received in revised form 31 October 2018; Accepted 24 November 2018

Available online 24 November 2018

0165-1781/ © 2018 Published by Elsevier B.V.

individual is unable to afford necessary items, such as food, housing, or medication (Pearlin et al., 1981). Compared to traditional measures of SES, financial strain may provide a more nuanced view by reflecting a balance of current income, savings, and expenditures with perceived financial resources. An extensive body of research has demonstrated the negative effects of financial strain on varied health outcomes, including increases in levels of depression and anxiety, escalations in the prevalence and severity of alcohol and tobacco use, and decreases in self-rated health (Dijkstra-Kersten et al., 2015; Kahn and Pearlin, 2006; Murayama et al., 2015; Nelson et al., 2008; Shaw et al., 2011; Szanton et al., 2010).

Previous studies have found that financial strain is associated with poorer adherence among patients with diabetes (Lyles et al., 2016) and cardiovascular conditions (Osborn et al., 2017). Medication-specific financial strain (i.e., perceived reductions in the ability to pay for medications) appears to play a particularly relevant role in determining adherence (Lyles et al., 2016). Such findings are consistent with a broader conceptual framework proposed by Piette and colleagues (Piette et al., 2006a) in which the cost-related burden of medication use is modulated by factors other than absolute cost (e.g., perceived financial burden, medication type, demographics). For example, cost-related non-adherence is generally higher for symptom-relieving (e.g., asthma) medications than for preventative (e.g., hypertension) ones, even after accounting for out-of-pocket costs (Piette et al., 2004a, 2006b). This finding is counter to typical observations that patients value shorter-term medication effects over longer-term ones (Chapman and Elstein, 1995) and emphasizes the relevance of studying moderators of cost-adherence relationships.

The purpose of this study was to evaluate the relationship of general and medication-specific financial strain with medication adherence. Participants reporting daily medication use for a variety of chronic health conditions completed a battery of items designed to capture features of SES and financial strain. A second objective was to determine if medication type moderated the association between general or medication-specific financial strain and adherence. We hypothesized that financial strain would be associated with greater non-adherence and that financial strain would differentially impact non-adherence by medication type.

2. Methods

2.1. Participants and general procedures

Participants were sampled from Amazon Mechanical Turk (mTurk). This crowdsourcing website is a highly efficient and cost-effective source for sampling diverse populations of which researchers may not otherwise have access. Existing studies on mTurk have supported the reliability and validity of cross-sectional data collection in the health sciences (Behrend et al., 2011; Buhrmester et al., 2011; Chandler and Shapiro, 2016; Kim and Hodgins, 2017). Prior research has also documented close correspondence between findings obtained using mTurk and traditional survey or laboratory samples thereby providing further support for the validity of the sampling methodology (Crump et al., 2013; Johnson et al., 2015; Strickland et al., 2016, 2017).

Potential participants were required to be age 18 years or older and have a 95% or higher approval rating on all previously submitted mTurk tasks, 50 or more previously approved tasks, and current residence in the United States. These requirements are consistent with other research conducted on mTurk and were used to help improve data quality and reduce rates of problematic responding such as social desirability biases (Cunningham et al., 2017; Peer et al., 2014; Strickland and Stoops, 2015). All participants also reviewed an informed consent document outlining the study and electronically verified that they understood and agreed to participate. The protocol was carried out in accordance with the Declaration of Helsinki and approved by the University of Kentucky Institutional Review Board.

All participants were required to self-report daily prescription medication use for psychiatric, cardiovascular, pain, and/or diabetes conditions to qualify. Participants were asked as a part of a screening questionnaire if they used a daily prescription medication and, if so, what broad category (e.g., cardiovascular, mental health) their prescribed medication(s) were indicated for (“What condition(s) is/are your current prescription medications prescribed for?”). No information on the specific medication or medication type (e.g., SSRI, antipsychotic, statin) was collected. This screening questionnaire also included information about recent illicit drug use and basic demographic information to conceal the specific qualifications for the study. Qualifying participants ($N = 252$) then had the opportunity to complete the remainder of the survey and received \$1.80 upon completion. Attention and validity checks were used throughout to identify non-systematic, inconsistent, or inattentive data. Participants were removed from data analysis when failing one or more attention checks ($n = 15$) or for missing data on one of the primary study variables ($n = 6$) for a final sample size of 231 participants.

2.2. Measures

2.2.1. Adherence to Refills and Medications Scale (ARMS)

Participants completed the Adherence to Refills and Medications Scale (ARMS) to evaluate self-reported adherence to current prescription medications (Kripalani et al., 2009). This questionnaire is a 12-item measure evaluating varied aspects of non-adherence (e.g., “How often do you forget to take your medication?”) with higher scores indicating greater non-adherence. The ARMS is easy to complete, accessible to patients with low literacy, and internally reliable with initial evidence suggesting improved validity over other self-reported adherence scales (Kripalani et al., 2009). Good internal reliability was observed in this sample (Cronbach's alpha [α] = 0.80), consistent with previous research (Kripalani et al., 2009). One item of the ARMS was specifically related to the cost of medications (“How often do you put off refilling your medicines because they cost too much money?”). Sensitivity analyses removing this item due to potential overlap with other study measures did not reveal changes in the patterns of results. Therefore, data from the full scale are presented.

2.2.2. Thirty-day adherence rates

Past month adherence rates were collected using the question “Over the last thirty days, how many days did you NOT take your prescription medication(s) as prescribed?” (emphasis included in the original question). This method is similar to those in clinical patient interviews in which patients are asked to estimate the frequency of non-adherence to medication regimens over a given time period (Farmer, 1999; Lam and Fresco, 2015). Higher values indicated greater non-adherence.

2.2.3. Personality and psychiatric factors

The Big Five Inventory (BFI), Barratt Impulsiveness Scale-11 (BIS-11), and Patient Health Questionnaire-9 (PHQ-9) were used to collect information related to the big five personality dimensions, trait impulsivity, and depression symptomology, respectively. These standardized items have extensive use in behavioral and health research and show good reliability and validity for measuring health behaviors (John and Srivastava, 1999; Kroenke et al., 2001; Patton et al., 1995). Total scores were calculated for the BIS-11 and PHQ-9 with higher scores indicating greater trait impulsivity and depression symptomology, respectively. Scores for the big five personality dimensions (extraversion, agreeableness, conscientiousness, neuroticism, and openness) were calculated using the subscales of the BFI. This sample showed good reliability for the BIS-11 ($\alpha = 0.72$) and excellent reliability for the BFI subscales (subscales $\alpha = 0.83$ – 0.91) and PHQ-9 ($\alpha = 0.92$).

2.2.4. General financial strain

Financial strain was measured using a version of the Economic

Strain Questionnaire (Kendzor et al., 2010; Pearlin et al., 1981). Participants were asked to report their difficulty in affording various items (e.g., food, clothing) on a three-point scale (no difficulty, some difficulty, great difficulty). Scores were computed as a total score of the seven items with higher scores reflecting greater strain. Financial strain was measured for participant's current and childhood conditions (i.e., “while you were growing up”). Internal reliability for both measures was high (Current $\alpha = 0.90$; Childhood $\alpha = 0.95$).

2.2.5. Medication financial strain

Medication-specific financial strain was measured using the item “In the past 12 months, did you use less medication than was prescribed because of cost?”. This dichotomous item was used in prior studies on medication adherence (Lyles et al., 2016). A yes response was considered endorsement of medication financial strain.

2.2.6. Objective SES

Objective measures of SES included yearly household income and employment. Wealth (assets – debts) was also collected as an alternative measure to income. Analyses substituting wealth for income did not reveal differences in the magnitude or significance of effects. Income was favored over wealth given the substantive variable skew for wealth that was not observed for income.

2.3. Data analysis

Demographic, personality, medication, and SES variables were first evaluated using descriptive statistics. The relationship between medication adherence and study variables was then explored using unadjusted analyses with Pearson bivariate correlations for ARMS scores and unadjusted negative binomial regression for 30-day non-adherence rates. The unique contribution of variables identified as statistically significant for either outcome variable at the unadjusted level was then determined using multivariable regression models. Potential moderation of the financial strain-adherence relationship by medication type was then evaluated. Interaction terms were computed and each medication type tested in individual moderation models. Significant interactions were followed by adjusted tests evaluating the unique interaction effect adjusting for other study covariates. Participants were only represented once in each model (no violations of independence assumptions were made). All tests were conducted in R statistical language (R Core Team, 2016) with a $\alpha = 0.05$.

3. Results

3.1. Participant characteristics and medication use

Participant characteristics are presented in Table 1. Participants tended to be female (66.2%), white (84.0%), and married or living as married (65.4%) with a college education (68.4%). One-third of participants reported full adherence during the past month (i.e., taking medication everyday as prescribed). Approximately one-fifth of participants reported experiencing medication-specific financial strain (21.7%).

Approximately two-thirds of participants reported use of medications for psychiatric conditions. Among those participants reporting psychiatric medication use, the majority reported a current diagnosis for anxiety (24.3%), depression (23.6%), or both (44.3%).

3.2. ARMS

3.2.1. Bivariate relationships

Table 2 contains bivariate relationships between ARMS scores and demographic, personality, medication, and SES variables. Significant bivariate relationships were observed between ARMS scores and age, agreeableness, conscientiousness, neuroticism, depression (PHQ-9

Table 1

Participant characteristics and medication use ($N = 231$).

	Mean/%	IQR
Demographics		
Age	38.2	28–47
Female	66.2%	
White	84.0%	
Married or living as married	65.4%	
College	68.4%	
Personality and psychiatric factors		
Extraversion	22.6	16–29
Agreeableness	33.6	28–38
Conscientiousness	33.3	28–40
Neuroticism	24.5	19–31
Openness	35.3	31–41
PHQ-9	8.2	3–12
BIS	67.2	62–72
Current medication history		
Psychiatric medication ^a	60.6%	
Cardiovascular medication ^a	33.8%	
Pain medication ^a	32.5%	
Diabetes medication ^a	6.5%	
B.I.D or greater	47.6%	
More than one medication	27.7%	
Socioeconomic Status		
Household yearly income (thousands)	47.2k	20k–70k
Wealth (thousands)	73.6k	–19k to 100k
Unemployed	10.8%	
General financial strain	12.0	8–15
Childhood financial strain	11.4	7–15
Medication-specific financial strain	21.7%	
Medication adherence		
ARMS	17.8	14–21
30-Day non-adherence rate	3.6	0–5

Note. PHQ-9 = Patient Health Questionnaire-9; ARMS = Adherence to Refills and Medications Scale; IQR = Interquartile Range.

^a Reported current use of indicated medication (participants could report more than one medication and those totals do not sum to 100%).

scores), taking pain or diabetes medication, and general and medication-specific financial strain (significant r values range .13–.53). These relationships were generally of a small-to-medium effect size except for medication financial strain, which showed a large effect size represented by higher ARMS scores for participants reporting strain ($r = .53$).

3.2.2. Adjusted regression models

Table 3 contains adjusted estimates for significant bivariate predictors of medication adherence. Two predictors remained significant in this adjusted model. Specifically, lower conscientiousness and endorsement of medication financial strain were significantly and uniquely associated with greater non-adherence (higher ARMS scores).

3.2.3. Moderation by medication-type

No significant interactions were observed between medication type and general or medication financial strain for ARMS scores.

3.3. Thirty-day non-adherence rates

3.3.1. Bivariate relationships

Table 2 contains bivariate relationships between 30-day non-adherence rates and demographic, personality, medication, and SES factors. Significant bivariate relationships were observed between 30-day non-adherence rates and age, agreeableness, conscientiousness, neuroticism, openness, depression (PHQ-9 scores), and medical financial strain. Medication financial strain again showed a large effect size reflected by non-adherence rates approximately doubling for participants reporting strain (IRR = 2.07).

Table 2
Medication adherence bivariate correlations (N = 231).

	ARMS <i>r</i>	30-Day Non-adherence rate IRR
Demographics		
Age	-.13*	1.01
Female	-.07	1.04
White	-.02	0.88
Married or living as married	-.12 [#]	0.78
College	.02	0.84
Unemployed	.02	0.87
Personality and psychiatric factors		
Extraversion	.00	1.00
Agreeableness	-.18**	0.96**
Conscientiousness	-.23***	0.96***
Neuroticism	.15*	1.03*
Openness	-.02	0.98*
PHQ-9	.25***	1.03 [#]
BIS	.11 [#]	1.00
Current medication history		
Psychiatric medication ^a	-.01	1.02
Cardiovascular medication ^a	-.08	0.93
Pain medication ^a	.15*	1.30
Diabetes medication ^a	.14*	0.94
B.I.D or greater	.19**	1.24
More than one indication	.10	1.25
Socioeconomic status		
Household yearly income	-.03	0.96
Unemployed	.02	0.87
General financial strain	.19**	1.03
Childhood financial strain	.04	1.02
Medication-specific financial strain	.53***	2.07***

Note. PHQ-9 = Patient Health Questionnaire-9; ARMS = Adherence to Refills and Medications Scale; IQR = Interquartile Range.

^a Reported current use of indicated medication

[#] *p* < .10;

* *p* < .05;

** *p* < .01;

*** *p* < .001.

Table 3
Adjusted models predicting medication adherence.

	ARMS β	30-Day Non-adherence rate IRR
Demographics		
Age	-.05	1.02**
Personality and psychiatric factors		
Agreeableness	-.07	0.97 [#]
Conscientiousness	-.15*	0.95***
Neuroticism	-.02	1.00
Openness	.03	0.99
PHQ-9	.01	1.00
Current medication history		
Pain medication ^a	.07	1.29
Diabetes medication ^a	.11 [#]	0.96
B.I.D or greater	.08	1.09
Socioeconomic status		
General financial strain	-.01	1.00
Medication-specific financial strain	.48***	2.05**

Note. PHQ-9 = Patient Health Questionnaire-9; ARMS = Adherence to Refills and Medications Scale; IQR = Interquartile Range.

^a Reported current use of indicated medication

[#] *p* < .10;

* *p* < .05;

** *p* < .01;

*** *p* < .001.

3.3.2. Adjusted regression models

Table 3 contains adjusted estimates for significant bivariate predictors of medication adherence. Four predictors were significant in this adjusted model. Specifically, older age, lower agreeableness/

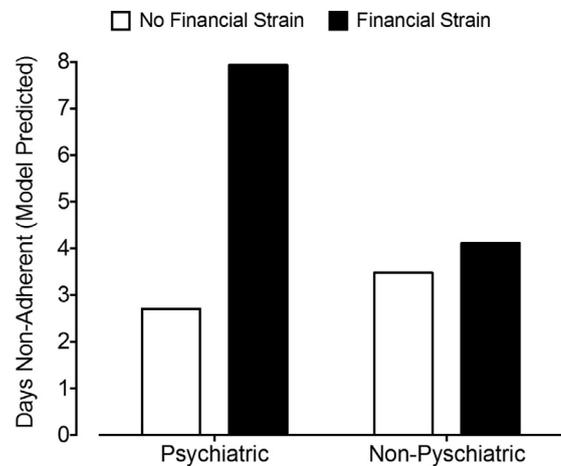


Fig. 1. Psychiatric medication use moderates the effect of medication financial strain on non-adherence. Participants (N = 231) with a chronic health condition reported past 30-day non-adherence rates to prescribed medications (y-axis). Plotted are estimated days of non-adherence for individuals reporting psychiatric medication use and those not reporting psychiatric medication use controlling for other socioeconomic factors (i.e., general financial strain [mean], childhood financial strain [mean], unemployment, and income [mean]). The medication financial strain by psychiatric medication interaction was significant in this model, reflected by a disproportionately greater increase in non-adherence under medication financial strain for individuals reporting psychiatric medication use.

conscientiousness, and medication financial strain were significantly and uniquely associated with greater non-adherence. Little attenuation of the medication financial strain effect was observed in the adjusted model (adjusted IRR = 2.05).

3.3.3. Moderation by medication type

Interactions between medication type and general/medication financial strain were not observed for cardiovascular, pain, or diabetes medications. A significant interaction was observed involving psychiatric medication use and medication financial strain, IRR = 2.43, *p* = .044. This interaction remained significant in an adjusted model after controlling for other SES variables, IRR = 2.48, *p* = .041. Plotted in Fig. 1 are the estimated non-adherence rates in this adjusted model. These estimates demonstrate that the effect of medication financial strain disproportionately influenced individuals reporting use of psychiatric medications. Additional models including all covariates evaluated in this study, prescription medication use for other conditions, and the use of medications for multiple conditions did not change the significance or direction of the psychiatric by medication financial strain interaction, IRR = 2.85, *p* = .01. Similarly, adjusting for ARMS scores in any of the tested models did not change the significance or pattern of the psychiatric by medication financial strain interaction, IRR > 2.31, *p* < .016.

4. Discussion

The purpose of this study was to evaluate the relationship between general/medication-specific financial strain and medication adherence. Modest effects for general financial strain were observed with ARMS scores, but not with 30-day non-adherence rates. Medication-specific financial strain, in contrast, was a robust predictor of both measures with individuals experiencing medication strain reporting an approximate two-fold increase in 30-day non-adherence. These effects remained after controlling for relevant sociodemographic, SES, and personality factors as well as the impact of current and childhood general financial strain. Such outcomes are similar to those reported in recent work with diabetic patients in which individuals experiencing

medication strain were less likely to fill a new prescription (Lyles et al., 2016). More broadly, these findings are consistent with conceptual models positing that non-cost factors, such as perceived ability to pay and resource strain, may alter cost-adherence relationships (Piette et al., 2006a).

Moderation models indicated that the influence of medication financial strain on non-adherence was greater for individuals reporting psychiatric medication use. Prior research has consistently identified depression and anxiety as key patient-level factors related to non-adherence (Bauer et al., 2017; Berry et al., 2015; Grenard et al., 2011; Zivin et al., 2010). Cost-related underuse has also been suggested to differ between perceived “essential” and “non-essential” medications wherein the former consists of preventative medications and the latter symptom-relieving ones (Soumerai et al., 1987). Medications for depression and other psychiatric conditions have been viewed as symptom-relieving in this research with greater rates of cost-related underuse observed and higher cost sensitivity relative to medications for hypertension, cholesterol, or diabetes (Goldman et al., 2004; Piette et al., 2004a; Soumerai et al., 1987; Stuart and Grana, 1998). These and the current findings reinforce the need for treatment providers to emphasize psychiatric medications as not just symptom-relieving, but as preventative medications. Emphasizing the preventative nature of psychiatric medication could improve adherence through not only the cost-adherence mechanism described here, but also through other mechanisms related to non-adherence in psychiatric medicine (e.g., beliefs about the necessity of medication and illness awareness) (Velligan et al., 2009).

Personality factors included in this study were also significant predictors of adherence. The relationship between adherence and conscientiousness was particularly robust and remained after controlling for other variables and in the moderation models tested. Other studies have observed similar associations suggesting that individuals with increased conscientiousness report greater adherence (Molloy et al., 2014). Controlling for conscientiousness and other individual difference factors in the adjusted and moderation models tested also indicates that the observed relationship between financial strain and adherence cannot be attributed to these other patient-level predictors of adherence.

This study is one of the first to evaluate medication use in chronic health conditions using mTurk. mTurk is a crowdsourcing website that has gained popularity for convenience sampling in the behavioral and medical sciences (Chandler and Shapiro, 2016; Keith et al., 2017; Woods et al., 2015). This growth is due, in part, to the improved demographic and geographic variability, access to hard-to-reach populations, and general time and cost efficiency that crowdsourcing affords. Research has generally supported the reliability and validity of the sampling approach (Behrend et al., 2011; Buhrmester et al., 2011; Crump et al., 2013; Johnson et al., 2015; Kim and Hodgins, 2017; Strickland et al., 2016,2017) and aspects of the current study reinforce this observation. For example, scale reliabilities for the BFI and other inventories were similar to those observed for in-person research. Rates of medication financial strain reported here (22%) were also similar to rates of failing to fill prescriptions because of cost (18%) observed in nationally representative sources (The Commonwealth Fund, 2018). The strengths of crowdsourcing and the promising observations of reliability and validity of the method highlight the potential benefits of mTurk for psychiatric and other health science research.

This study should be considered within the context of its limitations. First, only self-reported and retrospective assessments of medication adherence were collected. This limitation is particularly important given that some discrepancies have been noted between patient-level predictors of self-reported and verified adherence outcomes (Tang et al., 2014). Second, we did not collect information about the exact cost of each medication, which could represent a significant limitation given that psychiatric medications could be more expensive relative to others reported by the sample, such as blood pressure or

cholesterol medications. It is possible then that the relationship between financial strain and medication type could be due, in part, to differences in the absolute cost of each medication for these medical conditions. Models controlling for an individual's income did not alter the reported relationships, suggesting that an income-cost relationship alone would be unlikely to fully explain the association. Additionally, comparisons of an item from the ARMS directly indexing cost (“How often do you put off refilling your medicines because they cost too much money”) indicated that groups did not differ (data not shown, $p = .96$ for the comparison). Future studies would nevertheless benefit from including information about absolute medication cost to further explore this possible influence.

Third, although crowdsourcing helped to improve geographic and some clinical variability, limitations in demographic and diagnosis variability do exist. Prior research has reported that crowdsourced samples tend to be more educated, less religious, younger and less likely to be married, employed, or a racial minority compared to nationally representative sources (Berinsky et al., 2012; Huff and Tingley, 2015; Paolacci and Chandler, 2014). Other studies have found that these samples tend to report health behaviors that differ from nationally representative samples, including lower rates of exercise, asthma, and influenza vaccination and higher rates of depression (Walters et al., 2018) as well as higher rates of alcohol and illicit substance use (Shapiro et al., 2013; Strickland and Stoops, in press) (but see Caulkins et al., 2015 for information on the under-estimation of substance use in nationally representative sources). A possible sampling bias should be considered in the context of other literature demonstrating the validity of data collected from mTurk samples (see review in Chandler and Shapiro, 2016; Strickland and Stoops, in press). These studies have provided systematic and comprehensive evidence of validity by replicating findings from laboratory and clinical research on the mTurk platform (e.g., Crump et al., 2013; Johnson et al., 2015; Strickland et al., 2016,2017). These studies have also shown that self-admission of problematic responding (e.g., responding in socially acceptable ways or without paying attention) does not systematically differ between mTurk, community, and college samples (Necka et al., 2016). Further, data from the 2013 Medical Expenditure Panel Survey indicated that 16.7% of United States adults overall and 20.8% of white adults reported filling a prescription for psychiatric medication (Moore and Mattison, 2017). These values are similar to the 21.9% of individuals who were screened for the current study that reported current use of psychiatric medication, particularly considering the high percentage of white participants in the sampled participants. This sampling method did result in a psychiatric sample reporting primarily anxiety and/or depression diagnoses (92.1% of the psychiatric medication sample). A small percentage of participants reported serious mental illness (SMI) therefore making generalizations to SMI difficult. However, offsetting these limitations is the observation that online samples may be more comfortable sharing sensitive information as compared to face-to-face interviews (Kim and Hodgins, 2017; Shapiro et al., 2013). This strength may prove particularly advantageous for research in psychiatric populations given the potential stigma associated with these conditions. The online setting and related reductions in social pressure of reporting could have also helped offset problems in the validity of and social desirability bias related to self-reported adherence rates.

Fourth, we used sampling restrictions related to the number of HITs previously completed and past acceptance rates that could have resulted in additional bias for the sampled group. These sampling restrictions are commonly used in mTurk research to improve data quality and reduce undesired patterns of responding or automated responding (see reviews in Chandler and Shapiro, 2016; Strickland and Stoops, in press). For example, one study comparing individuals based on number of HITs or acceptance rates found that those of higher “productivity” (i.e., completed more than 100 HITs) or “reputation” (i.e., above 95% approval rating) provided answers with higher

reliability on previously developed measures, failed fewer attention checks, and showed lower rates of problematic responding (e.g., social desirability or central tendency biases) (Peer et al., 2014). It is possible that this restriction resulted in a sample that was more detail-oriented or conscientious and systematically differed in demographic or health history variables. Some research has indicated though that individuals do not systematically differ with respect to age, gender, or substance use history based on HIT number or approval criteria (Peer et al., 2014; Strickland and Stoops, 2018). The current study also found that the primary findings remained significant when controlling for conscientiousness as measured by the BFI.

Fifth, we did not collect information on the specific medications that each participant was prescribed. We therefore could not specifically evaluate the influence of type or class of medication for the effects reported here. Comparisons within the mental health prescription group by anxiety or depression diagnosis (e.g., reporting an anxiety diagnosis versus not reporting an anxiety diagnosis) did not reveal significant differences for financial strain or adherence variables. These findings indicate that anxiety or depression diagnoses were not systematically related to the moderator or outcome in moderation models (inclusion of these variables as model covariates also did not change the reported findings). However, future research would benefit from recording specific medications to provide a more precise measure of medication class as well as to determine if subtle differences may exist between varied medication types. It is also important to note that the 30-day adherence rate item was worded ambiguously such that affirmative answers could represent under- or over-taking of medications. Responses to free response questions included in the survey suggested that the majority of participants considered this question to represent under-taking of medication. Specifically, 76.5% of these responses included the word “forget” or “forgot” whereas only 1.3% referred to behaviors indicative of over-use (e.g., “I needed more than prescribed”). Finally, the two adherence measures used did not specifically capture intentional non-adherence due to anosognosia or other deliberate reasons for not taking medications (e.g., “I am not ill and do not need medication”). Therefore, our findings may only relate to relationships observed in motivated patients who understand the extent and nature of their chronic health condition. The use of measures that can index both intentional and unintentional forms of adherence as well as the sampling of participants with varying levels of insight would help determine the extent to which these results generalize.

The current study emphasizes the role that financial strain plays in medication adherence and the particularly relevant role for psychiatric conditions. Effects on adherence were clearly moderated by medication type with individuals taking psychiatric medications showing an increased susceptibility to medication-specific financial pressures. These outcomes suggest several strategies that could be incorporated in intervention design to improve adherence. For example, changes in drug dose or the inclusion of additional medications and/or behavioral services are common approaches to treatment non-response. However, such changes may unintentionally increase patient cost and exacerbate existing financial strain. Improving communication regarding the financial situation and burden of patients could help mitigate potential problems and improve adherence and clinical response. In support of this idea, improving physician trust has helped decrease cost-related concerns about medication use and facilitate improved adherence in prior work (Hall et al., 2001; Piette et al., 2005). Although such recommendations are currently speculative and require further empirical investigation, this study supports the viability of an approach targeting financial strain to improve clinical adherence, broadly, and psychiatric medication adherence, specifically.

Funding

This work was supported by internal funds from the University of Kentucky and National Science Foundation [grant number 1247392].

These funding sources had no role in study design, data collection or analysis, or preparation or submission of the manuscript. The authors declare that they have no conflict of interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psychres.2018.11.055.

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