Personality Assessment as a Supplementary Predictor of Tenant Behavior

Michael Tapia, Hogan Assessments

Brandon Ferrell, Hogan Assessments

Matt Lemming, Hogan Assessments

Rebekah Hogan, The University of Tulsa

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Abstract

Current tenant screening methods lack thorough research support and may be subject to adverse impact. This study proposes the use of personality assessment as a supplementary tool and provides evidence for the use of personality measures to predict tenant behavior, including Payments, Vacating, Maintenance, Cleaning, Landlord Interactions, and Causing Damages.

Introduction

The selection of rental applicants is as common as the selection of employment applicants. Both processes aim to achieve comparable outcomes (i.e., choose the best candidate available). Both follow similar processes (i.e., applying a set of selection criteria to predict behavioral performance). Lastly, both selection processes are subject to legislation and statistical critique aimed at limiting socioeconomic impact and ensuring performance-related selection outcomes.

Although both selection processes are comparable, one has advanced further in academic research, leaving a road map for the other to follow. Employment selection has developed into an industry of selection experts who work to produce high quality candidates without leaving an organization vulnerable to legal recourse. Key to the perspective of employment selection is the concept of "impact." Common practice acknowledges that unintentional biases that impact a protected class are not legally defensible unless the selection criteria is shown to have a "manifest relationship" to job performance (Griggs v. Duke Power Co., 1971). When developing selection criteria, the job relatedness must be considered, as well as the potential for adverse impact.

In the arena of tenant selection, disparate treatment is a theory of discrimination under Title VII of the United States Civil Rights Act (1964) and reaffirmed in Title VIII of the Civil Rights Act of 1968, also known as the Fair Housing Act. Disparate treatment describes a process by which individuals are treated unequally because of their membership in a protected class (Pager & Shepherd, 2008). The Civil Rights Act of 1964 prohibits employers from treating applicants in this manner. Similarly, the Fair Housing Act also "prohibits discrimination in the sale, rental, and financing of dwellings" based on an individual's membership in a protected class (Fair Housing Laws, n.d.).

Disparate impact is a legal doctrine under the Fair Housing Act that is synonymous with adverse impact in employment selection. It states that a policy that has a disproportionate impact on a protected class is discriminatory when there is no legitimate business need for the policy (Disparate Impact, n.d.). In a case heard by the Supreme Court, titled *Texas Department of Housing and Community Affairs v. Inclusive Communities Project* (2015), justices aligned the selection of rental applicants with the selection of job applicants, stating that "antidiscrimination laws must be construed to encompass disparate-impact claims when their text refers to the consequences of actions and not just to the mindset of actors" (pp. 10). Although new legislation was not created, the Supreme Court interpreted the text of the Fair Housing Act to conceptually align with adverse impact in employment selection, placing responsibility on the applicant screeners to account for unintentional discrimination through adverse selection methods. The implications for this decision may require thorough statistical analyses of common screening methods and open the door for alternative options.

Pager and Shepherd (2008) state that “the available evidence suggests that discrimination in rental and housing markets remains pervasive” (pp. 9). The remainder of this paper discusses two common tenant screening methods and the potential negative outcomes from each method. Further, we call for evidence supporting these methods and propose the application of personality assessment as a supplementary tool for screening rental applicants. We then conduct a confirmatory study to examine hypothesized relationships between personality measures and tenant behavior. Lastly, we discuss limitations and further research opportunities.

Common Tenant Screening Methods

Tenant screening is a method for predicting the likelihood that a particular rental applicant will make a “good” tenant. This typically includes a determination of the candidate’s financial and behavioral suitability (Dunn & Grabchuk, 2010). The following provides a brief critique of two common screening methods based on the available literature.

Credit Checks. Two of the most commonly used screening tools, credit scores and credit reports have become readily available online. A combination of credit score and credit disputes, obtained through online distributors, provides landlords with a brief look at an applicant’s financial capabilities. Nielson and Kuhn (2009) previously determined that there is little statistical evidence to support the claims that credit checks predict job performance. Evidence supporting the use of credit scores for tenant screening also seems to be limited. Even more concerning, there is a common theme highlighting the prevalence of errors and misleading information in credit reports (Dunn & Grabchuk, 2010; Kleysteuber, 2007; Nielsen & Kuhn, 2009). In our opinion, although credit scores may not always predict overall performance, we do believe the relationship between credit score and payment behaviors of tenants is face valid. However, due to inequalities in the credit market, we believe tenant screening methods that use credit scores could be vulnerable to adverse impact (Pager & Shepherd, 2008).

Criminal Background Checks. A criminal background check is a consumer report, obtained through public records, that provides information on arrests, criminal charges, and/or convictions (Dunn & Grabchuk, 2010). Thatcher (2008) proposed that the increase in prevalence of criminal background checks aligns with a progression towards increased landlord liability. This has made landlords more intent on identifying a potential for criminal activity and led to an “exclusionary environment that barely existed three decades ago” (Thacher, 2008, pp. 6). In the area of employment, some states avoid or prohibit the use of criminal background checks (Hight & Raphael, 2003) due to disproportional rates of imprisonment of racial minorities (Oyama, 2009). With regards to tenant screenings, this disproportional rate of incarceration may have the same effect on the use of criminal background checks. Due to higher rates of minority imprisonment, screening out potential tenants based on their criminal background is likely to result in adverse impact (Dunn & Grabchuk, 2010). Ehman (2015) stated that although the use of criminal history has become a common method in the screening of tenants, the “practice may be unlawful under fair housing laws because of its disparate impact on certain protected classes” (pp. 11).

Personality as a Predictor of Tenant Behavior

Due to the prevalent use of screening reports that include information described above, groups of people are finding it difficult to access rental housing and have been deemed the "unhousables" (Dunn & Grabchuk, 2010). With the potential for adverse impact and a lack of oversight to ensure accurate and complete records, the tenant screening business may currently be flawed. Examining the research on these screening methods produced little to no statistical evidence supporting the use of these tools for selecting tenant applicants. Further, a majority of the literature proposed that these methods have the potential to result in adverse impact (Dunn & Grabchuk, 2010; Ehman, 2015; Kleysteuber, 2007). Although difficult to prove, disparate impact claims are not uncommon (Dunn & Grabchuk, 2010). As the distinction between intentional and unintentional discrimination becomes irrelevant, property managers may find it crucial to apply screening methods that can limit the impact on protected classes.

For this reason, we believe that personality assessment will be useful to property managers. First, we propose that personality assessment, focused on prediction, will screen tenants effectively and limit current disparate impact trends. Based on an examination of meta-analyses, Oswald and Hough (2011) propose that Big Five personality variables do not contribute to adverse impact. This general view has been a prominent factor in the momentum shift embracing personality assessment for selection in employment.

Second, we propose that by understanding the personality of a tenant, a property manager can use targeted communications when negative tenant behaviors are expected to occur. For instance, a tenant that scores low on a measure of "Conscientiousness" may prompt a landlord to provide reminders of upcoming rent dues in order to proactively address the potential for late payments.

Tapia and Milane (2016) explored the potential for relationships between personality scales and tenant behaviors. They found that personality significantly predicted common tenant performance behaviors. Based on this, we propose that a property manager is concerned with six domains of tenant behavior and that these behaviors can be predicted using scales in our tenant personality assessment. Personality scales, tenant behavior domains, and definitions are presented in Table 1. The following are hypothesized relationships between these personality scales and tenant behavior domains:

> **Hypothesis 1:** Agreeableness and Responsibility will be significantly related to Payments, Vacating, Maintenance, Landlord Interactions, and Causing Damages.
>
> **Hypothesis 2:** Orderliness will be significantly related to Vacating, Maintenance, and Cleaning.
>
> **Hypothesis 3:** Stability will be significantly related to Maintenance, Landlord Interactions, and Causing Damages.
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> **Hypothesis 4:** Integrity will be significantly related to Payments, Vacating, and Landlord Interactions.

Hypothesis 5: Credit Score will be significantly related to Payments.

Method

Participants

Self-report surveys were administered to participants during a matched data collection at Hogan Assessment Systems using Amazon's Mechanical Turk (MTurk). Participants were isolated to those living in the United States and with a MTurk approval rating of 80 percent or higher. An initial round of 1,000 participants responded to a MTurk task asking participants to complete a short assessment. Based on validity checks and completion rates, a group of 450 participants from the original 1,000 were selected for a multi-wave data collection facilitated through R and the MTurkR GUI (R Core Team, 2013; Leeper, 2015). The sample obtained for this specific study included a total of 335 participants (151 males, 181 females, and 3 unidentified). Ages of online participants ranged from 18 to 64 with an average age of 34.7 years. Participants completed the tenant personality assessment and provided self-report behavior measures during a 45-minute data collection period that paid $6.00 for completion.

Measures

Tenant Personality Assessments. Development of the personality survey began by selecting predictive personality scales identified in Tapia and Milane's (2016) exploratory study of the relationship between personality and tenant behavior. Based on their findings, we constructed scales related to Conscientiousness (i.e., Orderliness and Responsibility), Stability, Agreeableness, and Integrity as a proxy measure for impression management. Scales and definitions are presented in Table 1. Bidirectional assessment items (BAIs) (Foster, Gaddis, & Ferrell, 2016) were written for each scale and forced participants to choose between two statements representing the low and high ends of the scales. Further, participants were asked if they "Usually" or "Always" agreed with the preferred statement. Descriptive statistics for each scale are presented in Table 2.

Tenant Behavior Self-Report. A behavioral taxonomy was developed based on Tapia and Milane's (2016) tenant behavior categories. Behavior domains were developed to be consistent with the "performance" of a tenant from the perspective of a property manager. Scales and definitions are presented in Table 1. Responses were rated on a Likert scale that ranged from 1 (Never) to 5 (Often) designating frequency in which the participant engaged in the behavior. Descriptive statistics for each scale are presented in Table 2.

Procedure

We collected survey data using Snap Survey linked to a MTurk post requesting the completion of the survey by a pre-selected group of online participants. Each participant provided responses on randomized personality items followed by self-report measures of tenant behavior and credit score. Credit score items required a score estimate (300-850) and asked if credit score had been checked in the past 12 months. Demographic items were matched by MTurk Worker ID from a previous round of data collection, including age, gender, and housing status.

Analyses

We aggregated items with negatively keyed items reverse coded to produce overall scores for the personality and behavioral domains. Next, we conducted reliability analyses on each scale and ran correlations between the personality scales and behavioral domain scores to look for significant relationships between individual characteristics and tenant behaviors. We also correlated credit score with each of the behavioral domains. However, because credit score and personality (in our opinion) are subject to change, we attempted to get an accurate view of personality and credit score as they relate to tenant behavior at a time of renting. Therefore, only participants that reported to currently be renting and to have checked their credit score in the past 12 months were included in the analysis of the relationship between personality/credit and tenant behavior.

Results

Reliabilities

Of the 335 participants that completed the assessments, 105 reported to be currently renting and to have checked their credit score in the past 12 months. The reliability statistics for each of the personality and behavioral scales is presented in the diagonal of Table 3. Each of the personality scales contained 8 items and had an alpha above .70. Behavioral scales ranged from 6 to 9 items and had alphas ranging from .58 to .81.

Correlations

Table 3 presents correlations between the personality scales and behavioral domains, as well as correlations between Credit Score and the rest of the measures. Agreeableness correlated significantly with all of the behavior domains. Orderliness correlated significantly with Maintenance, Cleaning, and Causing Damages. Responsibility correlated significantly with Vacating, Maintenance, Cleaning, Landlord Interactions, and Causing Damages. Stability correlated significantly with Landlord Interactions and Causing Damages. Integrity correlated significantly with Vacating, Maintenance, Cleaning, Landlord Interactions, and Causing Damages. Credit Score correlated significantly with Payments and Causing Damages. All correlations with Causing Damages were in the negative direction.

Discussion

Agreeableness. There was strong evidence of a relationship between Agreeableness and positive tenant behavior. In general, the more agreeable a tenant is, the more likely they are to make timely payments, vacate appropriately, maintain and clean the property, have a positive relationship with the landlord, and limit damages. Based on our first hypothesis, we did not expect Agreeableness to correlate with the Cleaning behavior measure; however, due to the strong correlation between Maintenance and Cleaning, it seems that higher Agreeableness is related to taking care of a rental property.

Orderliness. As expected, Orderliness correlated significantly with Maintenance and Cleaning. However, it did not correlate with the Vacating measure. Tenants with higher Orderliness scores may take more initiative to maintain and clean a property, though these scores are not related to a tenant's Vacating behavior. This may be due to the fact that Orderliness is more of an internal representation of Conscientiousness, such that when a tenant vacates a property, he or she may not be inclined to leave the property in a decent condition for others.

Responsibility. The measure of Responsibility did not correlate with Payments, but did correlate with the remainder of the behavior scales. Responsibility, an external representation of Conscientiousness, described a tenant's tendency to maintain and clean the property, fulfill landlord requests, limit damages, and vacate appropriately. The authors hypothesize that there was no relationship with Payments because the ability to make timely payments may be influenced by external factors, such as not having a job or a lack of financial opportunities that may be less manageable.

Stability. As hypothesized, Stability showed significant correlations with Landlord Interactions and Causing Damages. However, Stability did not correlate significantly with Maintenance. Tenants who are able to keep their composure regardless of the amount of negative stimulation may have better relationships overall. Further, an ability to keep one's composure may reduce the number of property damages that can result from an emotional outburst or retaliation for a perceived mistreatment.

Integrity. The measure of Integrity was significantly related to all of the behavior measures except for Payments, for which it approached significance. Integrity was included in the assessment to be used for prediction, but also as an interpretation of impression management. Overall, a tenant with a higher Integrity score is more likely to be considered a "good" tenant.

However, this scale was the most likely to be influenced by social desirability. For this reason, the interpretation of this scale in a real-world context would need to be used strategically with the other scales. For instance, a person who scores high on all personality measures, including the Integrity scale, may be impression managing and responding based on what he or she feels is desired by the landlord.

Credit Score. As one of the more common screening methods, we attempted to gather participant credit scores and limited our analyses to those that had checked their credit scores in the past 12 months. We found that Credit Score correlated significantly with Payments, as hypothesized, and Causing Damages. We hypothesize that Credit Score correlated with Causing Damages because a property manager is likely to report damage claims to credit reporting agencies. For this reason, a tenant that causes more damages is likely to have a lower credit score.

Conclusion and Implications

From this study, it seems that different selection criteria can predict different tenant behaviors. This can allow property managers to make decisions on how to screen tenants based on the behaviors they require from a tenant. For instance, a landlord that wants a tenant that is easy to work with may look at a prospective tenants scores on Agreeableness, Responsibility, Stability, and Integrity. Overall, the results were interpretable and provide justification for the use of personality assessments in predicting tenant behavior.

Another important finding in this study is that Credit Score does predict payment behavior, but lacks predictive validity with regards to other important tenant behaviors. This finding points to the need for a supplementary predictive measure, such as personality assessment, to help landlords find the best tenants available. Further, with an emphasis on fair housing practices, personality may help reduce the level of adverse impact currently prominent in the rental housing market.

Limitations and Future Research

Although findings were interpretable, there are limitations to the study that require further research to confirm our results. First, we used a sample from MTurk. Although the researchers took steps to identify a sample of respondents that (a) passed validity checks, (b) demonstrated a consistent completion rate, (c) reported to be currently renting, and (d) reported to have checked their credit score in the past 12 months, there are still concerns regarding the sample. Further research should attempt to gather personality and tenant performance data from property management groups. Rental organizations may be solicited to work with researchers to provide an unbiased look at credit, criminal background, and personality measures as they relate to tenant performance over a rental period. Lastly, the researchers call for tenant screening agencies to produce data that justifies the use of its screening methods in making rental recommendations based on commonly used screening measures.

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Table 1
Personality and Tenant Behavior Domain Scales and Definitions

	Scale	Definition
Personality Scales	Agreeableness	Describes the tendency to work towards common ground and cooperating with others. Individuals with high scores tend to avoid conflict and work to promote positive social interactions. Individuals with low scores are more willing to tolerate and engage in conflict, participating in arguments and deliberately choosing to express disagreement.
	Orderliness	Describes a preference for organization and keeping one's surroundings in order. Individuals with high scores may be more willing to clean and keep up with due dates and payments. Individuals with low scores may be less likely to regularly clean and may be less likely to remember important dates or responsibilities.
	Responsibility	Describes the tendency to follow through with expected behaviors and meeting the expectations of others. Individuals with high scores tend to take initiative and fulfill tasks required of them. Individuals with low scores tend to let themselves and others down.
	Stability	Describes a tendency to handle pressure and stress without reacting negatively. Individuals with high scores tend to have a consistent demeanor and do not overreact to uncomfortable situations. Individuals with lower scores tend to act differently depending on the situation, leading to negative reactions to stressful or provacative situations.
	Integrity	Describes the tendency to show modesty and act in a manner that follows a strong moral code. Very high scores can signify an individual who is potentially impression managing.
Behavior Domains	Payments	Behaviors that are related to matters of monetary responsibily, including rent, bills, and deposits.
	Vacating	Behaviors that are related to leaving the property at the end of a lease term.
	Maintenance	Behaviors that are related to properly maintaining a property's functionality.
	Cleaning	Behaviors that are related to properly maintaining a property's aesthetic presentation.
	Landlord Interactions	Behaviors that are related to communications with the landlord or property owner.
	Causing Damages	Behaviors that are related to harming the property, intentionally or unintentionally.

Table 2
Personality and Tenant Behavioral Domain Scale Descriptives

	Scale	# of Items	Min	Max	Mean	SD
Personality	Agreeableness	8	16	32	24.3	3.7
	Orderliness	8	13	32	24.6	4.6
	Responsibility	8	15	32	25.5	3.7
	Stability	8	10	32	23.3	4.9
	Integrity	8	17	32	24.7	3.7
Behavior Domains	Payments	7	23	35	33.0	2.8
	Vacating	6	18	30	27.9	3.0
	Maintenance	6	15	30	26.5	3.6
	Cleaning	6	18	30	27.9	3.0
	Landlord Interactions	9	28	45	42.2	3.7
	Causing Damages	6	6	21	7.4	2.4

Table 3

Correlations and Reliabilities of Tenant Behavior Domains and Personality Scales/Credit Score

				A.	B.	C.	D.	E.	F.	G.	H.	I.	J.	K.
Tenant Behavior Domains	A.	Payments	*r*	.68										
			n	100										
	B.	Vacating	*r*	.51*	.58									
			n	99	103									
	C.	Maintenance	*r*	.01	.39*	.64								
			n	97	100	102								
	D.	Cleaning	*r*	.17	.48*	.73*	.81							
			n	98	101	101	103							
	E.	Landlord Interactions	*r*	.55*	.50*	.42*	.55*	.77						
			n	96	99	97	98	100						
	F.	Causing Damages	*r*	.41*	-.56*	-.38*	-.45*	-.64*	.76					
			n	100	103	102	103	100	105					
Personality	G.	Agreeableness	*r*	**.21***	**.30***	**.35***	**.35***	**.34***	**-.36***	.76				
			n	99	102	100	101	99	103	103				
	H.	Orderliness	*r*	**.03**	**.08**	**.29***	**.45***	**.14**	**-.20***	.22*	.87			
			n	98	101	99	100	98	102	101	102			
	I.	Responsibility	*r*	**.05**	**.26***	**.32***	**.36***	**.28***	**-.31***	.56*	.60*	.73		
			n	100	103	102	103	100	105	103	102	105		
	J.	Stability	*r*	**.08**	**.09**	**.09**	**.15**	**.27***	**-.23***	.46*	.35*	.31*	.89	
			n	98	101	99	100	98	102	101	100	102	102	
	K.	Integrity	*r*	**.20**	**.26***	**.31***	**.28***	**.34***	**-.32***	.63*	.24*	.54*	.24*	.73
			n	99	102	101	102	99	104	102	101	104	101	104
		Credit Score	*r*	**.31***	**.17**	**-.08**	**-.02**	**.11**	**-.26***	0.11	-.08	-.07	.10	-.06
			n	100	103	102	103	100	105	103	102	105	102	104

Note. Only participants that were currently renting and had checked their credit score in the past 12 months included in analyses; *Significant Correlations ($p < .05$); Correlations in the diagonal represent alpha reliabilities.