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# Character Counts: Psychometric-Based Credit Scoring for Underbanked Consumers

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**Abstract:** Psychometric-based credit scores measure important personality traits that are characteristic of good borrowers' behaviors. While such data can potentially improve credit models for underbanked consumers, the utility of psychometric data in consumer lending is still largely understudied. The present study contributes to the literature in this respect, as it is one of the first studies to evaluate the efficacy of psychometric-based credit scores for predicting future loan defaults among underbanked consumers. The results from two culturally diverse samples of loan applicants (Sub-Saharan Africa, $n$ = 1113; Western Europe, $n$ = 1033) found that psychometric scores correlated significantly with future loan defaults (Gini = 0.28–0.31) and were incrementally valid above and beyond the banks' own credit scorecards. These results highlight the theoretical basis for personality in financial behaviors, as well as the practical utility that psychometric scores can have for credit decisioning in general and the facilitation of financial inclusion for underbanked consumer groups in particular.

**Keywords:** credit scoring; psychometrics; financial inclusion; unbanked

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## 1. Introduction

Traditional credit bureau scores remain the primary criterion for nearly all credit decisions (Fair Isaac Corporation 2023), but are fundamentally reliant upon applicants' historical credit information, as reported by formal financial institutions. It is for this reason that credit bureau scores are often low or unavailable for those who do not have bank accounts or credit cards, as well as for those who have inactive or dormant accounts. Such individuals are commonly referred to as being "unbanked" and "underbanked", respectively, and their prevalence is ubiquitous (McIntyre 2017). The World Bank estimates that there are approximately 1.4 billion unbanked individuals globally, representing roughly one-quarter of the adult world population, as well as another 13% of adults who have inactive accounts (Demirgüç-Kunt et al. 2022). Since many unbanked and underbanked consumers have either low or missing credit scores, they are routinely less eligible for basic financial services such as personal credit. On the other hand, new alternative forms of credit data have emerged in recent years, which are not dependent upon historical credit data and may therefore offer viable solutions to this problem. One form of alternative data, for example, uses psychometrics to evaluate creditworthiness based on a borrower's personal character. Unfortunately, the efficacy of psychometric solutions remains largely understudied in consumer credit. In light of this, the present paper is one of the first studies to assess the predictive validity of a psychometric model for estimating future loan defaults among underbanked consumer loan applicants.

## 2. Alternative Credit Data

In general, the inaccessibility of affordable credit can significantly inhibit personal financial growth and wellbeing, as well as the recovery from financial hardships such as those created by the COVID-19 pandemic (World Bank 2022). To help address this issue, internationally recognized strategic development goals have been defined to facilitate "financial inclusion" to better service underbanked consumers and small businesses (United Nations—Department of Economic and Social Affairs 2021). Yet, while better servicing that market segment may be an important catalyst for economic growth, as well as an opportunity for financial institutions to expand their portfolios, both are contingent upon the development of new credit risk models.

To these ends, a key element for building new credit models is the access to alternative sources of credit data. Indeed, alternative credit data solutions have gained increased attention by financial institutions around the world as a means to supplement or augment their existing models. Alternative credit data are primarily derived from available sources of payments and financial transactions, such as debit account information, telco and utility payments, and e-commerce activity. These data essentially serve as additional indicators of responsible financial behaviors, which can help to better estimate creditworthiness (Taylor 2018).

These solutions notwithstanding, sufficient sources of transactional data may not always be readily available or accessible, such as among consumers who deal primarily in cash, have little e-commerce activity, or those who simply prefer not to disclose their various personal accounts' information—the latter of whom may include up to 43% of consumers according to some estimates (Zest AI 2020). In such scenarios, non-transactional credit data may offer a promising alternative. One such type of non-transactional alternative credit data, for example, is based on psychometrics.

Psychometrics is an approach from applied psychology that typically uses structured self-report questionnaires, which are designed to tap into key character traits and competencies that are indicative of propensities towards certain behaviors (Janda 1998). In credit, psychometric solutions have been recognized as a potentially promising source of credit information (Josuweit 2018). According to Sadana et al. (2018), for example, "psychometric data has the potential to reach more people than traditional banking, as everybody has psychometric data/information even if they don't have collateral or social media profiles" (p. 48). Consumers themselves may also find favor in this type of alternative credit data. In one study, for example, when given the choice, approximately half of a European lenders' underbanked customers chose to take a psychometric survey as part of their loan application, rather than undergo a bank account scraping (Fine 2021).

Psychometric credit scoring solutions have gained popularity in recent years as supplements for traditional credit scores in both developing economies, such as Sub-Saharan Africa, as well as more western economies in Europe. Unfortunately, despite the potential value for psychometric credit scores, only sparce empirical evidence has been reported in the professional literature regarding their usage and utility, particularly among underbanked consumers.

## 3. Psychometric-Based Credit Data

Psychometric tools have proved to be useful in predicting human behaviors in diverse settings and geographies for over a century, such as in job performance and scholastic performance (Hogan et al. 1997), although their utility in predicting loan performance is still relatively novel.

In consumer finance, it has been suggested that behaviors related to loan repayments, particularly short-term loan repayments, are influenced by personal dispositional factors in addition to standard external economic factors (Bertrand et al. 2010; Webley and Nyhus 2001). Accordingly, reliably measuring certain psychometric factors could provide added estimates of loan repayment risks. From a theoretical perspective, borrowers who have high levels of traits such as "dependability", "self-control", and "internal loci of control", for example, may be more likely to honor their loan commitments (Letkiewicz and Fox 2014; Rustichini et al. 2012), be more cautious and responsible with their finances (Baumeister 2002; Livingstone and Lunt 1992; Moffitt et al. 2011; Romal and Kaplan 1995), and be more personally accountable for their financial situations (Webley and Nyhus 2001), respectively. Incorporating such traits in risk assessment models may therefore help to better understand the individual differences in payment behaviors and propensities towards defaults. Furthermore, it could be argued that such psychological traits might better explain certain types of defaults that are more closely related to poor decision making, as opposed to a lack of financial ability. These factors might include deciding to intentionally withhold payments, or failing to repay due to carelessness or procrastination. A broader review of the theoretical basis for psychometrics in credit scoring can be found in Goel and Rastogi (2023).

The literature reports several such personality dimensions that correlate with traditional credit scores (Bernerth et al. 2012; Klinger et al. 2013; Perry 2008) and indebtedness (Gathergood 2012; Liberati and Camillo 2018; Zuckerman and Kuhlman 2000), although correlations with actual loan performance have been less well studied. Recent, albeit limited, cross-sectional design studies validating psychometric data retrospectively against prior consumer loan performance (i.e., "back-testing") offer encouraging supportive evidence (Fine 2023; Woo and Sohn 2022). On the other hand, such back-testing studies have several limitations. For example, (a) they typically use convenience samples of volunteered existing customers, and may therefore suffer from at least some degree of sampling bias; (b) they are gathered in low-stakes scenarios (e.g., customer surveys) after loan approvals, so survey responses may therefore differ compared to high-stakes applicant settings, and (c) they examine restricted samples of banked customers, who may behave differently to unbanked applicants. Predictive research designs are therefore arguably more appropriate for studying operational psychometric score validities, although the majority of such studies on this topic in the literature have focused primarily on microbusiness credits (e.g., Arraiz et al. 2017; Dlugosch et al. 2017; Klinger et al. 2013), and thus are not necessarily applicable to consumer credit.

One notable exception is a paper by Djeundje et al. (2021). The authors examined the predictive validity of several hundred psychometric characteristics (e.g., moderation, teamwork, and integrity) and data points derived from email usage and demographic data among Nigerian and Mexican consumer bank customers. Djeundje et al. found a significant correlation between their machine learning models and customers' subsequent loan defaults. It should be noted, however, that Djeundje et al. trained their predictive models empirically, applying only the statistically significant parameters to their test sets. While that methodology may certainly optimize models for given datasets and/or populations, such models may not necessarily be transferable or generalizable across multiple or naïve samples. Accordingly, further evidence is still needed to demonstrate the predictive validity of existing psychometric models among underbanked consumers in high stakes settings (Goel and Rastogi 2023).

The present study presents such evidence from two culturally distinct samples from Sub-Saharan Africa and Western Europe. Overall, it is hypothesized that psychometric scores will be a significant classifier for predicting future loan defaults in both samples. It is further hypothesized that due to the unique nature of its measurement constructs compared to the banks' own credit scorecards, psychometric scores will add incremental validity when the two scores are regressed against future payment defaults.

The remaining sections of this paper will briefly review the methodology and materials used in this study, followed by a presentation of the primary results for testing the hypotheses, then finally a discussion of the applications and limitations of the present results.

## 4. Materials and Methods

### *4.1. Sample*

This study included two independent samples of consumer loan applicants. The first sample (Sample 1) was from a large online lender in Sub-Saharan Africa ($n$ = 1113), and the second sample (Sample 2) was from a large online lender located in Western Europe ($n$ = 1033). The samples were convenience samples that were chosen according to the availability of operational data that were gathered using similar research methods and contexts. The two distinct geographies sampled are especially significant, given that consistent results, despite the cultural differences, may imply the generalizability of the results. The samples' median age group was 31–40. Unfortunately, no further demographic information was available.

### *4.2. Measures*

#### 4.2.1. Psychometric Scores

This study used "Worthy Credit", a commercially available psychometric-based credit score (Fine 2016). Worthy Credit is a brief 19-item multiple-choice questionnaire, which takes an average of 3–4 min to complete. Worthy Credit provides a single overall risk score from 1–100, where the higher the score the better the risk. Scores are based on aggregated composites based on weighted facet scales measuring item response endorsements and item response times, such as dependability, trustworthiness, accountability, and self-control. Questionnaire items ask individuals to choose between two equally desirable statements. For example, "Which is most like you: 'I organize my finances carefully' or 'I avoid risky financial situations'". Other items ask individuals to rate the degree to which they agree or disagree to the statement based on a 5-point Likert-type scale from "completely disagree" to "completely agree". For example, "Accounts in overdraft should be charged high interest rates" and "everyone withholds payments once in a while". Worthy Credit's test-retest reliability has been found to be 0.70 and above, and its psychometric properties have been reported elsewhere (Fine 2023).

#### 4.2.2. Bank Scores

Participating lenders shared their own proprietary credit scores, which were based on alternative credit data (e.g., bank account information, telco information) and/or credit bureau data, where such data were available. In Sample 1, applicants with missing bank scores were considered by the participating lender to be among the highest credit risks, since no information about them was available, and were thus recommended by the lender to be assigned the lowest credit score of 400. The two samples' bank score scales are not directly comparable, but both were designed to evaluate financial creditworthiness and predict loan repayments.

#### 4.2.3. Loan Defaults

Loan defaults were defined as at least 60 days past due within the first 3–6 loan payments. All loan products were in the form of unsecured personal loans of less than approximately $1000, with terms between 1 and 24 months. Loan default information was provided by the participating financial institutions and was coded dichotomously as 1 (default) or 0 (no default).

### *4.3. Procedure*

A similar methodology was carried out for each sample, whereby the participating financial institutions (FIs) administered the psychometric survey as part of an online loan application to a sample of actual loan applicants. All applicants were considered to be underbanked, according to the FIs, but still met minimal bank criteria (e.g., age, employment status). As part of the procedures, credit was approved by the lenders to all participating applicants, regardless of their psychometric scores. This methodology allowed full variance in the psychometric score and avoided the typical restriction of the range in the predictor, if a cutoff score otherwise been used for decisioning. Borrowers' loan repayments in the successive months were then monitored for defaults, and this information was forwarded anonymously to the author together with the lender's own bank scores.

## 5. Results

Descriptive statistics for the samples' psychometric scores and default rates can be found in Table 1. The mean default rate for Sample 1 (7.4%) was significantly lower than that of Sample 2 (40.3%), $t(2144) = 19.58$, $p < 0.001$, which reflects possible differences in their loan products or businesses. Both samples had fairly normally distributed psychometric scores, with a slightly higher overall mean for Sample 2 customers, $t(2144) = 14.22$, $p < 0.001$.

**Table 1.** Descriptive statistics.

| | **Sample 1** | **Sample 2** |
|---|---|---|
| Region | S. S. Africa | W. Europe |
| *n* | 1113 | 1033 |
| Psychometric scores (mean) | 58.00 (±12.93) | 64.95 (±9.23) |
| Bank scores (mean) | 569.01 (±61.10) | 428.63 (±91.06) |
| Default rates | 7.37% | 40.27% |

*Note*: Standard deviations are shown in the parentheses.

Correlations between the psychometric scores and loan defaults were significant ($r = -0.15$ and $-0.25$ for Samples 1 and 2, respectively), and slightly lower than those of the bank scores ($r = -26$ and $-0.31$), as expected. The psychometric scores had relatively low but positive correlations with the bank scores ($r = 0.08$ and $0.22$), indicating that they represent at least partially independent constructs, without significant multicollinearity detected ($VIF = 1.0$ and $1.1$). See Table 2.

**Table 2.** Correlation coefficients.

| **Sample** | ***n*** | **Bank Score—Loan Default** | **Psychometric—Loan Default** | **Bank Score—Psychometric** |
|---|---|---|---|---|
| 1 | 1113 | −0.26 * | −0.15 * | 0.08 * |
| 2 | 1033 | −0.31 * | −0.25 * | 0.22 * |

* $p < 0.01$. *Notes*: Loan default (yes = 1, no = 0). Correlations with loan defaults are point-biserial coefficients ($r_{bs}$).

The psychometric model's accuracy in predicting loan defaults can be expressed in terms of the area under the receiver operating characteristic (ROC) curve (or AUC), i.e., true positives ("sensitivity") and false positives ("1-specificity") plotted along different score values (Stein 2007). See Figure 1. Accordingly, the AUCs for the psychometric score were 0.656 and 0.639 with associated Gini coefficients of 0.31 and 0.28, for Samples 1 and 2, respectively. Kolmogorov–Smirnov (KS) separation estimates were 0.27 and 0.20, respectively. See Table 3.

**Table 3.** Psychometric scores AUC coefficients and accuracies for loan defaults.

| **Sample** | ***n*** | **AUC** | **SE** | **CI** | **Gini** | **K-S** |
|---|---|---|---|---|---|---|
| 1 | 1113 | 0.656 | 0.03 | 0.594–0.719 | 0.31 | 0.27 |
| 2 | 1033 | 0.639 | 0.02 | 0.605–0.673 | 0.28 | 0.20 |

*Notes*: AUC = area under the receiver operating characteristic, Gini = 2 × AUC-1, K–S = Kolmogorov–Smirnov test.

To illustrate the potential application of these relationships, actuary tables can describe the estimated probabilities of default for specific psychometric score bands. See Figure 2. As shown in the graphs, the default rates in both samples decreased monotonically as the psychometric scores increased (Sample 1: $F(2, 1110) = 11.05$, $p < 0.001$; Sample 2: $F(2, 1030) = 31.90$, $p < 0.001$). Specifically, the estimated default rates went from 15.4% and 65.1% in the lower score bands of each sample (representing the bottom 15–20th percentile scores) to 3.7% and 22.4% in the higher score bands (representing the upper 15–20th percentile scores), respectively. In other words, the probability of default for the higher psychometric scorers was roughly 1/3 to 1/4 of the lower scorers, and approximately 1/2 of the samples' overall default rates.

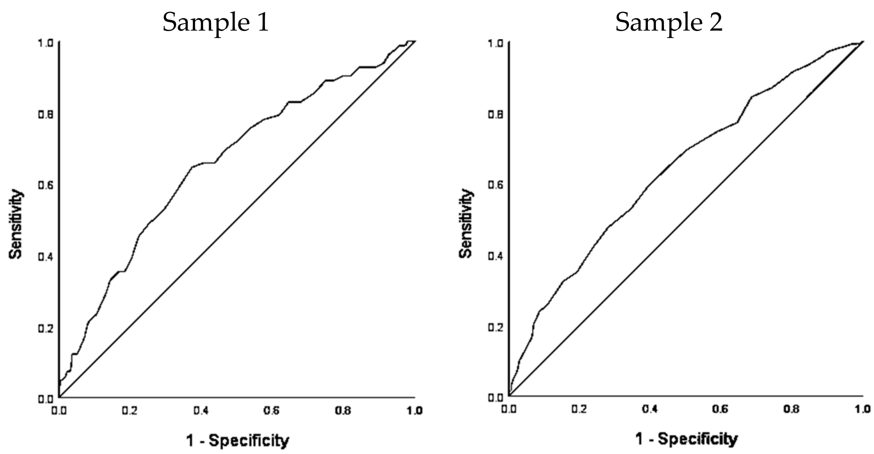


**Figure 1.** ROC curves.

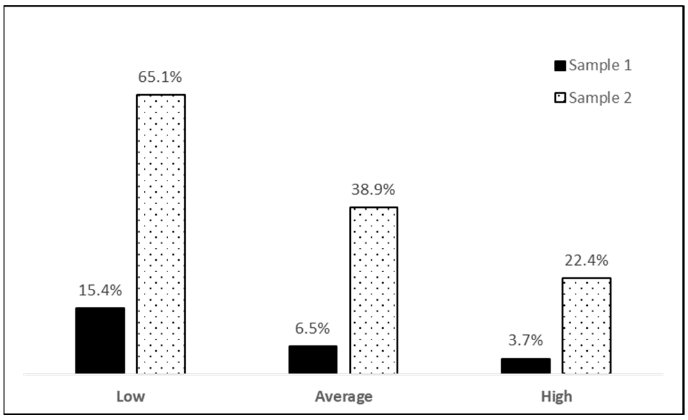


**Figure 2.** Default rates by psychometric score band. *Note*: Low and high score bands represent the bottom and top 15–20th score percentiles, respectively. Exact case numbers can be found in the tables below.

Hierarchical logistic regressions were then used to evaluate the psychometric scores' degree of incremental validity, after first accounting for the bank scores. As shown in Tables 4 and 5, the psychometric score remained a statically significant predictor of loan defaults in both samples: *Wald* = 17.21 and 34.55, $p < 0.01$. In addition, the psychometric score was responsible for an increase in the overall explained variance by 33–36%, whereby in Sample 1, the Nagelkerke $R^2$ increased from 0.12 to 0.16, and from 0.14 to 0.19 in Sample 2. Similarly, adding the psychometric scores to the regression equations resulted in an increase in the AUCs from 0.716 to 0.747 in Sample 1, and from 0.695 to 0.721 in Sample 2, representing a 14% and 13% percent increase in their associated Gini scores (0.43 to 0.49 and 0.39 to 0.44), respectively.

To further illustrate the potentially increased discrimination for estimated loan defaults, the psychometric scores were cross-referenced with the bank scores. See Tables 6 and 7. In each bank score band, the psychometric scores were able to discriminate between risk levels otherwise estimated by the bank score bands alone. For example, where Sample 1's average bank score band assumed a 6.6% probability of default, high psychometric scores within this band has just 2.7% defaults, compared to as much as 16.1% among low psychometric scorers in this band. In Sample 2, a similar pattern was found whereby the high bank score estimated a 19.6% default rate, for example, whereas high psychometric scores within this segment had just 12.2%, and low psychometric scorers had 44.4% defaults.

**Table 4.** Hierarchical logistic regression analysis (Sample 1).

| Predictors | *B* | *SE* | *Exp(B)* | *Wald* | *Nagelkerke* $R^2$ | $X^2$ | *AUC* |
|---|---|---|---|---|---|---|---|
| *Model 1* | | | | | | | |
| Constant | 3.46 | 0.73 | 31.65 | 22.31 * | | | |
| Bank score | −0.01 | 0.00 | 0.99 | 62.92 * | 0.12 | 56.25 * | 0.716 |
| *Model 2* | | | | | | | |
| Constant | 5.26 | 0.87 | 191.99 | 36.39 * | | | |
| Bank score | −0.01 | 0.00 | 0.99 | 55.13 * | | | |
| Psychometric score | −0.04 | 0.01 | 0.96 | 17.20 * | 0.16 | 73.90 * | 0.747 |

$n = 1113$; * $p < 0.01$.

**Table 5.** Hierarchical logistic regression analysis (Sample 2).

| Predictors | *B* | *SE* | *Exp(B)* | *Wald* | *Nagelkerke* $R^2$ | $X^2$ | *AUC* |
|---|---|---|---|---|---|---|---|
| *Model 1* | | | | | | | |
| Constant | 3.39 | 0.40 | 29.74 | 73.73 * | | | |
| Bank score | −0.01 | 0.00 | 0.99 | 90.27 * | 0.14 | 116.42 * | 0.695 |
| *Model 2* | | | | | | | |
| Constant | 5.99 | 0.61 | 400.43 | 96.51 * | | | |
| Bank score | −0.01 | 0.00 | 0.99 | 72.29 * | | | |
| Psychometric score | −0.05 | 0.01 | 0.96 | 34.55 * | 0.19 | 152.86 * | 0.721 |

$n = 1033$; * $p < 0.01$.

**Table 6.** Probabilities of default: bank score by psychometric score (Sample 1).

| Bank Score | Psychometric Score | | | |
|---|---|---|---|---|
| | **1–45** | **46–69** | **70–100** | **Total** |
| 400–574 | 23.9%<br>(71) | 11.5%<br>(243) | 8.2%<br>(61) | 13.3%<br>(375) |
| 575–594 | 16.1%<br>(56) | 5.5%<br>(235) | 2.7%<br>(75) | 6.6%<br>(366) |
| 595–700 | 2.1%<br>(48) | 2.5%<br>(243) | 1.2%<br>(81) | 2.2%<br>(372) |
| Total | 15.4%<br>(175) | 6.5%<br>(721) | 3.7%<br>(217) | 7.4%<br>(1113) |

*Note*: Sample sizes are shown in the parentheses.

**Table 7.** Probabilities of default: bank score by psychometric score (Sample 2).

| Bank Score | Psychometric Score | | | |
|---|---|---|---|---|
| | **1–55** | **56–74** | **75–100** | **Total** |
| 300–374 | 74.3%<br>(70) | 55.3%<br>(244) | 30.0%<br>(30) | 57.0%<br>(344) |
| 375–449 | 67.4%<br>(46) | 43.1%<br>(239) | 32.7%<br>(52) | 44.8%<br>(337) |
| 450–900 | 44.4%<br>(36) | 18.2%<br>(242) | 12.2%<br>(74) | 19.6%<br>(352) |
| Total | 65.1%<br>(152) | 38.9%<br>(725) | 22.4%<br>(156) | 40.3%<br>(1033) |

*Note*: Sample sizes are shown in the parentheses.

## 6. Discussion

It would be difficult to argue that personal character traits such as trustworthiness, responsibility, and dependability are not necessary requirements for good borrowing behaviors, yet such constructs are seldom applied to credit modeling procedures. Psychometric solutions incorporating such traits may offer a possible solution as a means to augment traditional credit models, especially among underbanked consumers. Unfortunately, notwithstanding limited prior cross-sectional consumer studies and prior research on micro-business lending, there is relatively little empirical evidence for the predictive validity of psychometric data in underbanked consumer credit.

In this respect, the present study contributes to the existing literature by studying the validity of a psychometric credit score among two independent samples of underbanked consumer loan applicants. The results of this study are encouraging and support the underlying premise that personal character is indeed indicative of consumer credit payments. Moreover, the results are strengthened by the fact that a generic psychometric model was applied to the samples a priori, and the psychometric model was not trained on the samples' own data. The results from both samples found loan applicants' psychometric scores to be significantly correlated with their subsequent loan defaults three to six months later. In addition, the psychometric model managed to significantly discriminate between defaulters and non-defaulters, as in both studies high scorers had roughly half the defaults of the other scorers.

In addition to the bivariate relationship with loan defaults, the results provide evidence that psychometric scores may be additive to a bank's existing credit scorecard. Specifically, when regressed together with the bank scores, the psychometric scores lifted the aggregated models' accuracies, with a significant increase of over thirty percent in the explained variance. These gains are facilitated, to at least some degree, by the partial independence between the two constructs, as shown by their low inter-correlations and as found here and in prior evidence (Bernerth et al. 2012; Fine 2023). Theoretically, it could be reasoned that these two types of credit scores explain different aspects of repayment behaviors. Having the *ability* to repay, for example, is measured by financial data, whereas psychometric scores may tap more into the *willingness* to repay. As such, considering that both aspects are important, psychometric scores should not be used as the sole measure for credit decisioning, without also qualifying one's financial ability to repay. To be sure, as in the present samples, minimal financial data, such as income and existing debt, can be readily available, even among unbanked consumers.

The practical applications of the psychometric scores indicate that high or low psychometric scorers within each of the bank's score categories may actually be reclassified as lower or higher risk, respectively. Accordingly, lenders might leverage this information to potentially approve more credit and/or higher limits among applicants with high psychometric scores. Moreover, among some of the lenders' marginal declines, high psychometric scores might make the difference between a credit approval and a credit decline. Conversely, while low psychometric scores might warrant issuing lower credit or denying credit among consumers with high bank scores and low psychometric scores, such customers might also benefit from closer loan servicing, such as proactive monitoring of payment schedules and educating borrowers to better manage their risks, rather than adversely affecting their credit decisions.

It is interesting to note that the present results confirm similar findings from prior research that used a back-testing methodology (e.g., Woo and Sohn 2022; Fine 2023), despite the latter's methodological limitations. One possible explanation might be related to the fact that personality-based measures are considered to be relatively stable over time (Hogan et al. 1997). Therefore, psychometric scores collected before and after the credit was issued may be assumed to be similar. Indeed, back-testing is a widely accepted approach in general psychological testing for this very reason (Janda 1998). Nevertheless, it would be difficult to apply psychometric data to credit models based on the empirical results of back-testing alone, particularly since they would not be likely to include declined or unbanked applicants, which the psychometric scores might specifically target. The present results managed to circumvent this issue by including full samples of underbanked consumers and unrestricted loan performance data for all psychometric and bank scores. A possible limitation to the present approach, however, is that fully banked customers were not included in the samples and therefore the results cannot be generalized based on these data alone. Subsequent research may consider collectively examining the results from both back-testing and forward testing among the banked and unbanked samples.

Another obvious limitation of this study, and one of psychometric data in general, that deserves mentioning is that they are dependent upon the quality of the applicants' self-reports. Faking or false responding can likely impact the results. This is perhaps an additional reason to study psychometric scores in high-stakes scenarios, such as in the present study, where credit decisioning outcomes may depend upon psychometric scores. The present study provides evidence that psychometric testing can still be valid and effective in realistic applicant settings, and whatever faking might have occurred was not significant enough to destroy the overall validity of the scores. Similar findings have been reported for psychometric testing carried out in other high-stakes settings, such as personnel selection (Ziegler et al. 2012). These results notwithstanding, it is recognized that any such conclusions are limited to the particular tool that was used, and that other tools might behave differently.

Finally, the consistent results found between the two samples studied here support the potential generalizability of psychometric models across regions and cultures. On the other hand, it is acknowledged that these two samples were essentially convenience samples that were not designed to be representative of their respective regions. It is suggested, therefore, that in order to better examine generalizability, future research should replicate studies similar to this in additional regions and across multiple samples. Further research is still needed to substantiate the usage and utility of psychometric-based testing in consumer credit as a solution for improving credit models in general, and particularly to facilitate financial inclusion.

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**Conflicts of Interest:** The author is affiliated with the publisher of the tool used in this study.

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