A model of psychosis and its relationship with impairment

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ABSTRACT

Purpose: Some studies suggest that positive symptoms of psychosis – clinical and sub-clinical alike – reflect a single, continuously distributed dimension in the population. It is unknown, however, whether such a spectrum of positive psychotic experiences is non-linearly related to outcomes such as daily functioning. This work aims to characterize the relationship between positive psychosis and impairment.

Methods: Data from the Office of National Statistics National Psychiatric Morbidity Surveys of Great Britain were used to establish measurement models of psychosis and impairment. Competing linear and nonlinear models of the relationship between the two latent variables were evaluated using mixture structural equation models (MSEMs).

Results: Positive psychosis is best modeled by a continuous, normal distribution. Increases in positive psychosis correlate with roughly linear increases in impairment.

Conclusions: Positive psychotic symptoms occur throughout the population without a discrete, pathological threshold. Functional deficits are linearly associated with the psychosis at all points along the continuum, and a significant portion of the population experiences subclinical psychosis.

Keywords: psychosis, functional impairment, structural equation model, schizophrenia

INTRODUCTION

Strong evidence suggests that common forms of psychopathology, such as internalizing and externalizing symptoms, are best conceived of as continuous latent constructs [1–5]. While there is strong evidence for the continuity of internalizing and externalizing psychopathology, evidence regarding psychosis is more equivocal. In at least one study fitting formal continuous and discrete latent variable models of psychosis, continuous models fit better overall [6]. Taxometric analyses of psychoses in a non-clinical sample also favor a dimensional model [7]. However, methods designed to clarify the latent distribution of psychosis cannot rule out the hypothesis that psychosis comprises discrete liability classes, and in many cases support such a hypothesis [8]. A review of taxometric research by Haslam, Holland, and Kuppens concluded that among all domains of psychopathology, evidence of taxonic structure was strongest in the areas of substance use disorders, autism, and schizoptypy [4].

Furthermore, psychosis may be distributed continuously in the population, but this distribution may be less important, in some contexts, than the form of the relationship between psychosis and impairment [9, 10]. In addition, the form of the relationship between psychosis and outcomes provides another perspective on understanding continuities and discontinuities in the construct. Even if a construct is psychometrically continuous in terms of its distribution in the population, it may be phenomenologically discontinuous in terms of its relationships with other variables [10]. The distribution of psychosis might hypothetically be comprised of two classes: a low-liability class in which psychosis-like experiences are weakly correlated, or even uncorrelated with impairment, as well as a second high-liability class in which the same symptoms are accompanied by a greater degree of impairment. If the psychosis distribution comprises mixtures of liability classes at the latent level, characterizing the form of its relationship with outcomes may help reveal the nature of those liabilities. To precisely understand how the range of psychotic symptoms and impairment correlate, we compared a series of competing models describing the range of psychotic symptoms, and their relationship with impairment.

METHODS

Sample

Data analyzed included the 2000 and 2007 Office of National Statistics National Psychiatric Morbidity Surveys of Great Britain [11–13]. The National Psychiatric Morbidity Survey (NPMS) is a cross-sectional assessment of psychopathology of adults living in private homes. The survey was initially performed in 1993, and replicated in 2000 and 2007. 1993 survey data was not used, as the 1993 iteration assessed impairment among only a subset of participants.

The NPMS 2000 and 2007 selected participants for inclusion based on a random sampling of postal addresses, stratified to be representative in terms of geography and socio-economic status. Participants were selected at random from among adults aged 16-74 residing in eligible households. Sampling weights take into account the dependence of participation upon household size, household non-response, age, gender and region. Further information regarding sampling is available in the NPMS survey method reports [13, 14]. 7,705 participants completed both the psychosis and impairment portions of the NPMS 2000. 7,400 participants completed both portions of the NPMS 2007.

Assessments

The Psychosis Screening Questionnaire (PSQ) was developed especially for the NPMS as a way to screen for psychotic symptoms [15]. The PSQ is comprised of 5 questions assessing experiences of mania, thought control, paranoia, strange experiences, and hallucinations over the course of the previous year. However, an item assessing mania was excluded from analyses, due to our focus on positive symptoms of psychosis. Each item was followed by a question probing for an alternative explanation of the psychosis. For example, the item assessing experiences of thought control was followed by a question asking whether the experience came about “in a way that many people would find hard to believe, for instance, through telepathy?” A response of “no” to the initial probe was scored as 0, a response of “yes” to the initial probe followed by a response of “no” to the follow-up item was coded as 1, and a response of “yes” followed by another “yes” was coded as a 2. The item assessing paranoia was followed by two such follow-up questions, and was coded using the same method on a scale of 0 to 3. The PSQ discriminates well in clinical settings (sensitivity .97, specificity .95). However, any measure’s performance in nonclinical settings will be significantly affected by the low base rate of psychoses in the general population. In addition, the PSQ was not developed with the evaluation of attenuated psychosis in mind, and may have failed to detect lower degrees of psychosis.

Impairment was assessed via the Short Form Health Survey (SF-12) and Activities of Daily Living (ADL) [16, 17]. Participants were asked to rate their own functioning over the past 4 weeks. Of the 19 items included in the NPMS, 3 items from the SF-12 were excluded from the analysis, to avoid confounding psychopathology and impairment constructs. These items ask participants how many times in the past 4 weeks they felt “calm and peaceful,” “downhearted and low," and "had a lot of energy," respectively. The SF-12 and ADL include a mixture of rating scales, ranging from a binary present/absent to a 6-point scale. Items were coded on the same scale in which they were originally assessed. Item 12 of the SF-12 asks participants "how much of the time has your physical health or emotional problems interfered with your social activities" on a 6-point ordinal scale, with 1 being "all the time" and 6 being "none of the time." This item was reverse coded so that higher numbers consistently indicated greater impairment.

The NPMS 2000 and 2007 surveys were not identical, due to survey revisions. Although both rated impairment via the ADL and SF-12, the NPMS 2007 appended 5 new items to the SF-12 and 1 new item to the ADL. These items were not included in the analysis in order to maintain consistency between surveys. In addition, the response format of the ADL was changed in the 2007 survey. In the 2000 survey, participants were asked 3 different questions about each activity of daily living: whether they had difficulty with the activity, whether they needed help to complete it, and whether they had access to help. In contrast, the 2007 survey assessed each area on a 3-point scale: 1 being no difficulty in the area, 2 indicating some difficulty, and 3 indicating "a lot" of difficulty. To maintain consistency between survey years, the follow-up items from the 2000 survey assessing the need for and availability of help were eliminated from analyses. The final impairment scales consisted of nine items from the SF-12 and seven items from the ADL, with two response options in the 2000 version of the ADL and three in the 2007 survey. The different response formats required the estimation of seven additional parameters in the 2007 models, as compared to the 2000 models, with the discrepancy increasing as a factor of the number of classes in the model.

Analysis

Confirmatory and Exploratory Factor Analyses.

Items of the PSQ, ADL and SF-12 were analyzed using exploratory and confirmatory factor analysis in Mplus, version 5 for Windows [18], in order to establish measurement models used in subsequent analyses. EFAs were estimated using maximum likelihood (ML) estimation with oblique (geomin) rotation. Due to the discrete nature of the indicator variables, and in order to calculate root mean squared error of approximation (RMSEA) values, EFAs were replicated using weighted least squares with mean and variance adjustment (WLSMV) estimation [19, 20]. Discrepancies between WLSMV- and ML- estimated factor loadings were minimal (WLSMV model estimates are available upon request).

Mixture Structural Equation Modeling

In traditional structural equation models, non-normal distributions can distort estimates of the relationship between latent variables. In MSEM, latent variables are modeled by a combination of classes, and this mixture of classes is used to represent the distribution of the latent variable. Mixture models are advantageous, because while each individual class is normally distributed, summing classes over the range of the latent variable can generate a non-normal marginal distribution. Classes in this context represent regions of the latent variable distribution, rather qualitatively different classes of subjects *per se,* and become the basis of a structural model that describes the relationship between two latent variables.

Many approaches to modeling non-linear relationships between two latent variables require the form of non-linearity be specified *a priori*; that is, the researcher must hypothesize the non-linearity to be quadratic, interactive, or of some other function [21–23]. Semiparametric mixture structural equation models (MSEMs), however, allow relationships between latent variables to be estimated without assuming the form of the function [24]. In MSEMs the measurement models – the factor loadings of items onto the latent variables – are assumed constant across subgroups. However, the slope and intercept of the structural equation model relating latent variables can be freed. Three MSEMs were estimated in our analyses [Please see reference 25 for a similar application of MSEM methods]:

Non-linear MSEM: In this model the slope is estimated individually for each class. Hypothetically, a class at the low range of the latent trait might represent normal variation in perceptual experiences, and within this class the slope between psychosis and impairment might be low in magnitude. In contrast, a class occupying the high range of the latent trait might represent a degree of psychopathology that that is highly correlated with impairment, and the slope between psychosis and impairment may be greater within this class. Integration of these parameters over classes, weighted by conditional probability of class membership, yields a non-linear estimate of the marginal relationship between the latent variables.

Slope-fixed MSEM: In the linear, slope-fixed model, the slope between latent variables is constrained to be equal across subgroups while the distribution of both of the latent variables is freely estimated. While the slope is constrained to be equal between classes, the regression intercepts can differ. Consequently, summing over classes can yield a marginal relationship that is non-linear. In this model both latent variables may be skewed.

Distribution-fixed MSEM: In the distribution-fixed MSEM one latent variable is constrained to a normal distribution, and both the slope and the distribution of the second latent variable are unconstrained. Even though the slope is freely estimated over classes, the mean and variance of one latent variable are fixed. By proxy, this forces the marginal relationship between latent variables to be linear. This results in a linear model in which the distribution of one latent variable may be skewed.

The fits of the three MSEMs were compared using information-theoretic indices: Bayesian information criterion (BIC) [26], integrated classification likelihood-BIC (ICL-BIC) [27], and the Akaike information criterion (AIC) [28]. These statistics perform well in comparing MSEMs [29, 32]. In addition to BIC, the Vuong-Lo-Mendell-Rubin test (VLMR) was used to compare models of K classes with those of K-1 classes [30-32].

MSEMs were fit using maximum-likelihood estimation in Mplus Version 5.2 for Windows with 500 random starts per run [18]. The PlotSEMM package for R version 2.11.1 for Windows was used to produce plots of the mixture probabilities and impairment/psychosis relationship [33].

RESULTS

Measurement Models

Psychosis

Fit statistics of the 1- and 2-factor models of the PSQ are presented in Table 1. Since only 4 items were available, a 3-factor model would be unidentified. BIC favored the 2-factor model in both the NPMS 2000 and NPMS 2007. BICs for the 1-factor models were 23137.26 and 19567.60 for the 2000 and 2007 samples, and 23131.76 and 19564.32 for 2-factor models. Estimated correlations between the two factors were very large, however (.93 and .99 in 2000 and 2007, respectively), suggesting the presence of a higher-order psychosis factor (note that a higher-order factor model would have the same fit as a correlated 2-factor model). Consistent with this interpretation, AIC values suggested a 1-factor model. Root mean squared error of approximation (RMSEA) values suggested adequate closeness of fit for both the 1-factor and 2-factor models in the 2000 and 2007 datasets.

Past analyses provide mixed support for both discrete and continuous models of the latent distribution of psychosis. To better describe the distribution of psychoses in this sample, we fit a series of discrete latent-trait models to the data. In these models the variance of each class was set to zero, to represent point values along the trait distribution [see reference 3 for a similar application of this method]. The best fitting discrete latent trait models, according to AIC values, were the 5- and 7-point models in the 2000 and 2007 datasets, respectively. However, according to the BIC, a single, normally-distributed latent trait model fit the data better than any discrete latent trait models. Moreover, many of the discrete latent trait models had convergence problems. From this we concluded that discrete models in general fit the data relatively poorly. Considered together, the results suggest that the distribution is continuous – as the best-fitting models were either explicitly continuous or required numerous points to represent the distribution – and normal. This is consistent with a similar analysis of this dataset in which the authors concluded that latent classes reflected ordered levels of severity of a continuous trait [34].

In view of the high correlation between factors in the 2-factor continuous latent-trait model, and because AIC supported use of a 1-factor model, we used the 1-factor model as the basis of subsequent structural equation models.

Impairment

Results of exploratory factor analysis of the joint ADL and SF-12 item pool are shown in Table 1. Fit statistics suggested that the joint item pool has a 3-factor structure in both the 2000 and 2007 survey. These factors reflected difficulty performing tasks inside the home and at work, reduced productivity attributed to emotional problems, and difficulty with logistical tasks such as paperwork and money management. The first factor was comprised of the same 10 items in both the 2000 and 2007 survey, and included items assessing difficulty engaging in moderate activity such as climbing stairs and vacuuming. Two items from the SF-12 constituted the second factor in the 2000 survey. These items asked participants whether the respondent's emotional problems caused them to accomplish less or work less carefully. In the 2007 survey an item that assessed social impairment also loaded onto this factor. The final factor reflected difficulty managing medical care, finances, and paperwork. In the 2000 survey, this factor included the item assessing social impairment. Correlations among the 3 factors were moderate to high. In the 2007 data, difficulty performing everyday tasks at home and at work correlated moderately with emotional impairment (r=.65) and medical/financial impairment (r=.68). Emotional impairment correlated moderately with medical/financial impairment (r=.60).

In order to determine the extent to which the three factors reflected a general impairment factor, we fit of a series of bifactor models. In these models each item loaded onto two factors: a specific factor and a general impairment factor. In one model, the specific factors represented the scale membership of each item (i.e., an SF-12 factor and an ADL factor). The other bifactor models included specific factors reflecting the 2- and 3-factor solutions identified in exploratory factor analyses.

The best-fitting bifactor model was the EFA-based 3-factor model. BIC values for this 3-factor bifactor model were 97324.11 and 113929.67 in the 2000 and 2007 datasets, respectively. However, bivariate models using the bifactor model of impairment failed to converge. In order to create a simple, stable measurement model of the impairment construct, we removed items that consistently loaded more heavily onto a specific factor than the general factor across datasets. These were items 6 and 7 of the SF-12, which assessed carelessness and reduced productivity attributed to emotional problems. A 1-factor model of impairment was fit from the remaining items. The fit statistics of this pared model were a notable improvement over the initial 1-factor model. RMSEA values of the revised impairment model were .07 and .08 in the 2000 and 2007 datasets, respectively, as compared to .1 in the original models. The final measurement model and factor loadings are illustrated in Figure 1.

Structural Equation Models

For both the 2000 and 2007 NPMS datasets, nonlinear, slope-fixed, and distribution-fixed MSEMs were estimated with two, three, and four latent classes, as well as a one-class, linear model (nonlinear and distribution-fixed models are equivalent to a linear model when only one latent class is estimated). Both variants of the distribution-fixed MSEM, in which either the psychosis or impairment latent variable was constrained to a normal distribution were estimated.

However, significant skew in the distribution of functional impairment symptoms resulted in very poor fit of models in which this variable was constrained to normality. Since BIC values for impairment-fixed models were all greater than psychosis-fixed models with an equal number of latent classes, only fits statistics for psychosis-fixed models are presented. NPMS 2000 and NPMS 2007 model fit statistics are presented in Tables 2 and 3, respectively.

In both the NPMS 2000 and NPMS 2007 surveys and across variations in the number of classes, linear models were optimal according to BIC, AIC, and ICL-BIC. The distribution-fixed model generally fit the 2000 survey data best, while the slope-fixed model was preferred in the 2007 survey. BIC and ICL-BIC suggested a 3-class solution in the 2000 dataset, while AIC and the VLMR test statistic supported four classes. In the 2007 dataset, BIC and ICL-BIC suggested two classes, while AIC and the VLMR statistics suggest four and three classes, respectively. BIC differences in the range of 2-6 indicate positive evidence for the model with the lower BIC, while differences in the range of 0-2 generally indicate only weak evidence in favor of that model [35]. By this metric, differences between the distribution- and slope-fixed models sharing a given number of classes were generally minor, while differences between models that share a structure but differ in the number of classes were significant.

Figure 2a illustrates the relationship between positive psychosis and impairment in the 2000 survey. Results from the 3-class distribution-fixed model are shown, due to research suggesting that BIC outperforms AIC in modeling non-normal latent variables in large samples [30] (results from the 4-class model are similar, and available upon request). The best-fitting 3-class model produced estimated class proportions of .66, .07, and .27, with mean estimated levels of impairment of -2.48, 2.57, and 0.0, respectively. Because the distribution of psychoses was fixed, mean levels of psychoses were 0.0 in all classes. In this model the marginal relationship between psychosis and impairment was .54 (standard error = .05).

Figure 2b illustrates the relationship between psychosis and impairment in the 2007 survey, as demonstrated by the 2-class slope-fixed model (results from the 3-class model are similar, and are available upon request). The best-fitting 2-class model produced estimated class proportions of .24 and .76, mean levels of psychoses of 0 and .347, and mean levels of impairment of 2.25 and 0.0, respectively. The marginal relationship between psychosis and impairment was .46 (standard error = .03).

As shown by the solid lines in Figures 2a and b, the marginal slope between psychosis and impairment was constant in the 2000 data, and slightly nonlinear in the 2007 survey data. In the 2007 model the slope relating psychosis and impairment increased at higher levels of psychosis.

CONCLUSIONS

Implications for conceptualizing psychosis

The results of our modeling are consistent with previous research showing a continuous, distribution of psychosis and psychosis-like experiences [36–39]. A continuous latent-trait model fits the data better than discrete latent-trait models, supporting a model of positive psychosis in which symptoms are normally distributed. The normal distribution may imply the existence of many etiological factors of small effect, rather than any particularly determinant factor [40].

These analyses estimated the relationship between psychosis and impairment to be essentially linear. No single point is a threshold past which psychotic symptoms cause significant impairment; rather, a linear, dose-dependent response relates symptoms and impairment, with more psychotic symptoms resulting in greater functional deficits. With no clear threshold, a portion of the undiagnosed population likely experiences psychoses. In addition, a linear relationship between psychosis and impairment indicates the sub-clinical population experiences some degree of impairment along with their symptoms.

Results of model comparisons in both the 2000 and 2007 surveys suggested that the slope relating impairment and psychosis is constant. However, the best-fitting models in the two datasets were not identical: a model in which the latent psychosis construct was constrained to be normal demonstrates the best fit in the 2000 iteration of the survey, while the 2007 survey was best described by models with a constant relationship between psychosis and impairment. As it is unlikely that the nature of the relationship between the two constructs changed within this interval, differences are perhaps better explained by changes in the response format of items measuring impairment (which was binary in 2000, but ordinal in 2007). Potentially, the altered response format of these items in 2007 changed the estimated impairment distribution, and consequently, via the relationship between psychosis and impairment, the estimated psychosis distribution as well. The mechanism by which shifts in the estimated distribution of one latent variable may effect changes in other parameters within a MSEM requires further research, but may be due to indirect improvements in measurement information. Practically, however, the differences between these models are minor. The marginal slopes between psychosis and impairment estimated in the two years share overlapping confidence intervals.

It is unclear whether the non-linearity in the 2007 marginal slope is practically significant. In this model, greater levels of psychosis are associated with an accelerating degree of impairment. This contrasts with the phenomenon noted by Nuevo and colleagues [41], who reported a non-linear relationship between health status and number of psychotic symptoms. In Nuevo's analysis, the relationship between psychotic symptoms was positive, but decelerated as the number of symptoms reported increased.

Areas requiring additional research

Psychotic symptoms are rare, and difficult to assess well in general population samples [42, 43]. Although the PSQ has demonstrated validity and discriminates well in clinical settings, it is possible that more comprehensive measures of psychosis may suggest different results, particularly in the lower range of psychopathology, and in the discrimination between discrete and continuous latent-trait models of psychosis. Similarly, the current research focused on positive symptoms of psychosis, and it is unclear whether the linear relationship between psychosis and impairment would continue to hold for the entire psychosis spectrum, including negative and disorganized symptoms. Future research would benefit from using assessments of psychosis with a wider range.

Furthermore, although the current measures of impairment are well-validated and reliable, it is possible that other measures of impairment (e.g., relying on other informants) might produce different conclusions. It is unclear, for example, how much insight individuals experiencing severe levels of positive symptoms have into their current functioning. Individuals diagnosed with non-affective psychoses are generally in poor agreement with caretakers and family members regarding their symptoms, safety to self and others, social needs, and level of functioning [44]. Future research using more diverse sources of information is needed.

Our findings complement those of van Nierop and colleagues, whose recent research suggests that self-reported psychotic experiences – even those that are later determined to be false positives – are associated with a higher risk of mood, anxiety, and substance disorders, and a greater frequency of help-seeking for psychiatric problems [45]. Further research is needed to determine whether the pattern between psychosis and impairment extends to treatment and outcome variables.

Lastly, the present study is cross-sectional in nature. Longitudinal research may reveal whether the linear relationship between positive psychosis and impairment holds constant over time. Some evidence indicates that negative symptoms are more stable and persistent than positive and disorganized symptoms, and that the two symptom dimensions tend to rise and fall independently over time [46, 47]. Analysis of the relationship between negative symptoms and impairment may reveal negative symptoms to be more stable predictors of impairment.

Despite these limitations, the current results suggest positive psychoses and impairment are related in a continuous, linear fashion. Clinicians may find it useful to assess psychoses and subtle psychosis-like experiences more frequently, in order to determine whether these symptoms may contribute to the functional impairment of their patients. Further research is necessary to understand the practical implications of sub-clinical psychoses.

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Table 1

Measurement Model Fit Statistics

Model	*k*	*ln(L)*	*AIC*	*BIC*	*RMSEA*
Psychosis					
2000 Survey					
1 Factor	13	-11510.46	**23046.92**	23137.26	0.03
2 Factors	12	-11512.19	23048.37	**23131.76**	0.03
2007 Survey					
1 Factor	13	-9725.89	**19477.78**	19567.60	0.05
2 Factors	12	-9728.71	19481.41	**19564.32**	0.03
Impairment					
2000 Survey					
1 Factor	44	-50303.65	100695.31	101001.09	0.10
2 Factors	45	-49431.74	98953.47	99266.21	0.07
3 Factors	46	-49074.43	98240.87	98560.55	0.06
3 Factor Bifactor	59	-48398.04	**96914.08**	**97324.11**	0.04
2007 Survey					
1 Factor	51	-58770.89	117643.79	117996.16	0.10
2 Factors	52	-58272.23	116648.46	117007.74	0.10
3 Factors	54	-57760.65	115629.30	116002.40	0.08
3 Factor Bifactor	67	-56666.37	**113466.75**	**113929.67**	0.05

Table 1 Model statistics include k, the number of parameters in the model, log-Likelihood Ln(L), the Akaike information criterion (AIC), Bayesian information criterion (BIC), and the root-mean square error of approximation (RMSEA). All values except RMSEA are taken from

the maximum-likelihood estimated model. RMSEA was taken from weighted least squares estimates. Optimal values of fit statistics are in bold.

Table 2

Mixture Structural Equation Model Comparisons: 2000 Survey

Model	*k*	*ln(L)*	*BIC*	*AIC*	*ICL-BIC*	*VLMR*
One class						
Slope-fixed	54	-56393.81	113270.89	112895.61	N/A	
Two classes						
Nonlinear	58	-56311.04	113141.15	112738.07	113142.52	
Slope-fixed	57	-56311.40	113132.93	112736.80	113134.32	
Distribution-fixed	57	-56311.21	**113132.56**	**112736.43**	**113133.92**	0.00
Three classes						
Nonlinear	62	-56295.98	113146.84	112715.96	113148.19	
Slope-fixed	60	-56296.42	113129.82	112712.85	113131.15	
Distribution-fixed	60	-56296.02	**113129.03**	**112712.05**	**113130.37**	0.00
Four classes						
Nonlinear	66	-56291.58	113173.84	112715.17	113175.29	
Slope-fixed	63	-56294.01	113151.85	112714.02	113153.11	
Distribution-fixed	63	-56292.30	**113148.43**	**112710.60**	**113149.88**	0.02

Table 2 Model statistics include k, the number of parameters in the model, log-Likelihood Ln(L), the Akaike information criterion (AIC), Bayesian information criterion (BIC), integrated classification likelihood-BIC (ICL-BIC), and the Vuong-Lo-Mendell-Rubin test statistic (VLMR). Optimal values of fit statistics are in bold.

Table 3

Mixture Structural Equation Model Comparisons: 2007 Survey

Model	*k*	*ln(L)*	*BIC*	*AIC*	*ICL-BIC*	*VLMR*
One class						
Slope-fixed	61	-63579.41	127702.29	127280.83	N/A	
Two classes						
Nonlinear	65	-63503.60	127586.31	**127137.21**	127587.56	
Slope-fixed	64	-63505.20	**127580.59**	127138.40	**127581.86**	0.00
Distribution-fixed	64	-63505.63	127581.45	127139.26	127582.59	
Three classes						
Nonlinear	69	-63497.16	127609.05	127132.31	127610.22	
Slope-fixed	67	-63497.95	**127592.83**	**127129.91**	**127593.97**	0.03
Distribution-fixed	67	-63500.69	127598.30	127135.38	127599.56	
Four classes						
Nonlinear	73	-63492.91	127636.19	127131.81	127637.44	
Slope-fixed	70	-63491.57	**127606.78**	**127123.14**	**127607.78**	0.76
Distribution-fixed	70	-63497.76	127619.17	127135.53	127620.20	

Table 3 Model statistics include k, the number of parameters in the model, log-Likelihood Ln(L), the Akaike information criterion (AIC), Bayesian information criterion (BIC), integrated classification likelihood-BIC (ICL-BIC), and the Vuong-Lo-Mendell-Rubin test statistic (VLMR). Optimal values of fit statistics are in bold.

Figure 1

Structural Equation Model Path Diagram

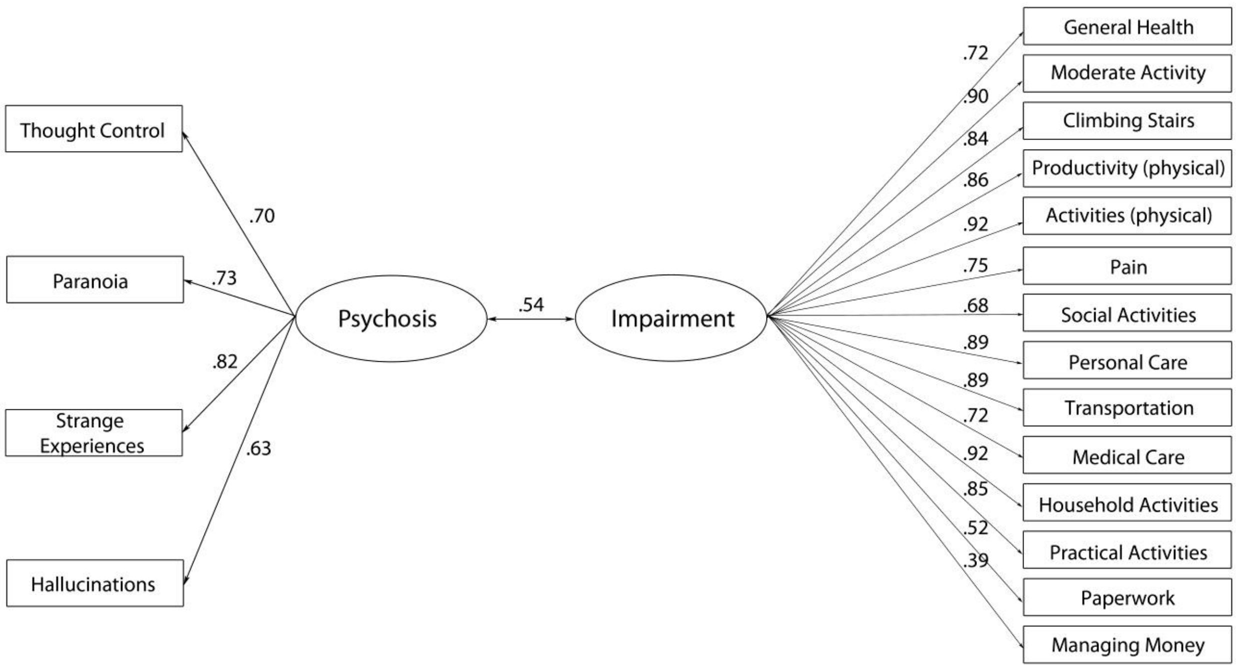

Fig. 1 Path diagram describing the final structural equation model relating psychosis and impairment, as estimated in the NPMS (National Psychiatric Morbidity Survey) 2000 dataset. Numbers over single-headed arrows indicate item loadings onto latent variables. .54 is the marginal correlation between the two latent constructs.

Figure 2

Contour Plots

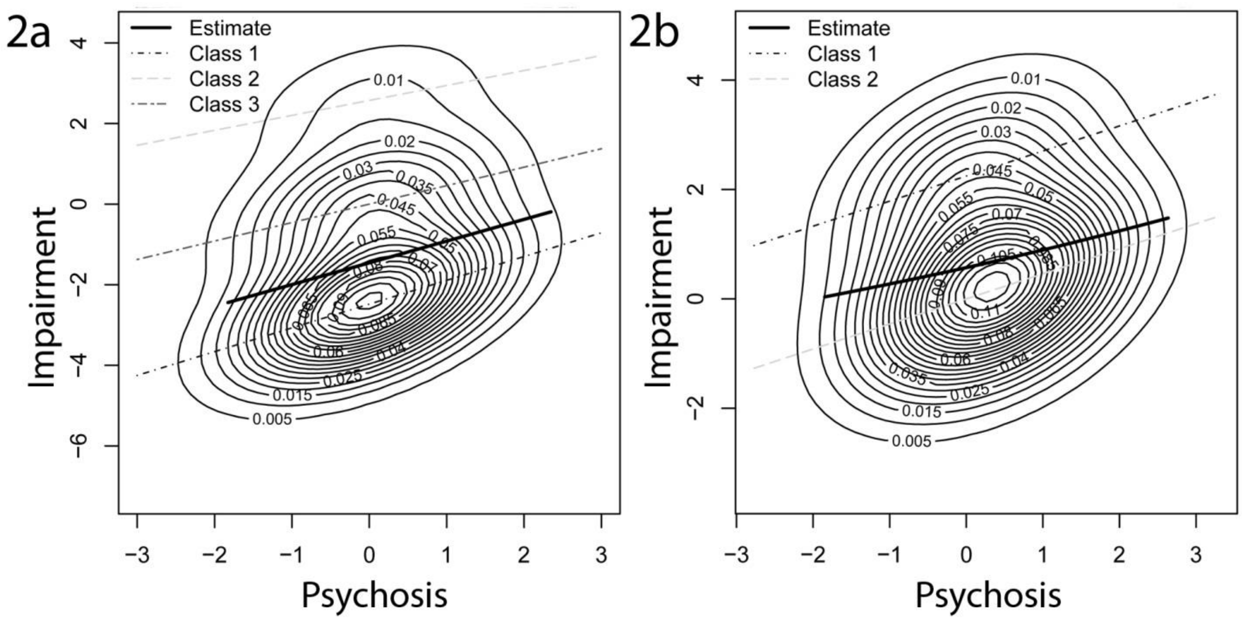

Fig. 2 Contour plots of the 3- and 2- class bivariate models for the NPMS (National Psychiatric Morbidity Survey) 2000 (2a) and 2007 (2b) datasets, respectively. Figure 2a depicts the distribution-fixed MSEM. Figure 2b depicts the slope-fixed MSEM. Dashed lines represent the relationship between psychosis and impairment within a latent class. Solid lines represent the same relationship, marginalized over all classes. The bivariate densities are shown via rings surrounding the population mean.