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HETEROGENEOUS TRAJECTORIES OF DEPRESSIVE SYMPTOMS AMONG MEN IN SOUTH AFRICA: EVIDENCE FROM LATENT GROWTH MIXTURE MODELING

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Abstract

The study examines the heterogeneous trajectories of depressive symptoms among men experiencing family changes and paying child maintenance in South Africa. A longitudinal study using the National Income Dynamics Study (NIDS) waves 1 to 5 (2008-2017) was conducted. The Latent Growth Curve Model (LGCM) was used to estimate the trajectory of growth or change in depressive symptoms among men aged 18 years and older in South Africa resulting in a sample of 9,102 men. Two classes of depressive symptoms among men were identified and categorized into the low and high symptom groups. The depressive symptom trajectory for men who experienced a family change was higher than that of men who did not experience a family change for both classes of the depressive symptoms. Men who did not pay child maintenance had higher trajectories of depressive symptoms compared to the men who paid child maintenance for both the low symptom and the high symptom groups. There is a need for specific intervention strategies directed towards the specific classes of depressive symptoms in men. Men should be counseled on the benefits of financially supporting their children without being compelled to do so by law.

Keywords: Depression, Trajectories, Symptoms, Fathers, Mental Health, Family Transition, Child Maintenance

1. Introduction

Men's mental health problems such as depression are increasing worldwide. Globally, studies have shown that depression is the greatest contributor to suicide among men (Affleck *et al.* 2018; Bantjes *et al*. 2018). In South Africa, men are four times more likely to commit suicide than women (World Health Organization, 2019). In the country, mental health problems are linked to poverty,

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unemployment and marital dissolution among others (Mnyango and Alpaslan, 2018). The country has seen families changing, giving rise to the necessity of payment of child maintenance in cases where children are involved. The study examines whether family changes and payment of child maintenance predict men's trajectories of depressive symptoms. These two factors have not been examined in relation to men's trajectories of depressive symptoms in South Africa.

It is important to focus on the trajectories of depressive symptoms among men in South Africa for several reasons. Mental health problems are a leading public health concern linked to an increase in suicide and cognitive functioning contributing to higher levels of mortality among men. The issues concerning mental health are still being viewed as taboo in the country leading to suicidal acts. Men affected with mental health problems turn to alcohol or drugs with some engaging in their work or hobbies as a way of hiding it from family and friends (Axinn *et al.* 2020). Despite the existence of various campaigns on mental health, men still have higher reports of suicide in the country.

Mental health problems among men are often concealed due to cultural practices, which often encourage men to be strong. The notion of masculinity renders men vulnerable, as they believe that they are not expected to show any signs of weakness. The fact that men have the desire to want to solve everything even without the means of doing so, has seen some men suffering from mental health illnesses in silence (Bilsker *et al.* 2018). The masculine nature of men contributes to a lack of health-seeking behaviors since they believe that depression is for the weak (Cole, 2013).

In South Africa, despite the considerable attention that mental health has received, men's mental health is inadequately studied. Not much is known concerning trajectories of depressive symptoms among men in the country. The existing studies have largely relied on cross-sectional data to highlight the determinants and prevalence of mental health (Bantjes *et al.* 2018; Tomita *et al.* 2015) This limits the estimation of the trajectories of depressive symptoms over time. Some studies which have used the NIDS have only used less than five waves of the data (Ohrnberger *et al.* 2020; Mungai and Bayat, 2019; Eyal *et al*. 2018). The use of longitudinal data drawn from several waves allows us to examine the intra and inter-individual differences in changes in men's depressive symptoms. The study is the first in the country to focus on men's trajectories of depressive symptoms. The paper makes two contributions: it provides the trajectories of depressive symptoms in men and it shows how family changes and payment of child maintenance predicts the trajectories of depressive symptoms among men in South Africa.

2. Method
2.1. Study design and sample

This study is a longitudinal study using data from the National Income Dynamics Study (NIDS), which keeps track of individuals within households every two years. The NIDS datasets are publicly and readily available online. The survey collects data on household compositions, individuals, migration, household income and expenditure in South Africa. The main aim of the survey is to provide detailed data on socio-economic issues such as the labor market, education, poverty, inequality, education, and health. The NIDS panel data reveal changes in the structure of households, living conditions and well-being of individuals in households over time in South Africa.

Longitudinal surveys are often characterized by missing data. One of the most common sources of missing data in longitudinal studies is sample attrition. Some individuals may drop out from a subsequent survey as a result of various reasons including death and other reasons. Since latent growth curve models and latent growth mixture models seek to measure the trajectories of a phenomenon over time, one precondition is that there should be at least two points of observation for each individual. To establish the existence of heterogeneous trajectories in the depressive symptoms of the men who formed part of the sample of this study, only the men who had data points for at least two waves formed part of the analysis. This ultimately led to 9,102 men being included in the analysis. The distribution of these men in terms of the number of occurrences in subsequent waves is shown in Table 1:

Table 1. Sample attrition

No. of Waves	Frequency	Cumulative F	Percentage	Cumulative %
2	2938	2938	32.28%	32.28%
3	2094	5032	22.97%	55.25%
4	2127	7159	23.57%	78.82%
5	1943	9102	21.35%	100.00%

As shown in Table 1, men who had data for only two waves constituted the majority of the men (32.28%) while the men who had available data for all the five waves constituted the least proportion of all the men (21.35%). The cumulative percentages show that the proportion of men who had available data for 2 and 3 waves was 55.25% while those who had data for 2, 3 and 4 waves was 78.82%.

2.2. Variables

The dependent variable is depression measured using a 10-item version of the Centre for Epidemiologic Studies Depression Scale (CES-D). The NIDS uses the CES-D scale, a shorter version which is a valid psychometric tool (Björgvinsson *et al.* 2013; Tomita *et al.* 2015). Family change is a dummy variable that is coded "1" if a man experienced a family change, which is defined as any change from being married, cohabitation, divorced or widowed or "0" if the man did not experience a family change. Child maintenance is a dummy variable that is coded as "1" if a man was paying child maintenance or "0" if not paying child maintenance.

2.3. Data analysis

The data was analyzed using the Latent Growth Curve Models (LGCM). The LGCM evaluate longitudinal change in terms of initial level (intercept) and change (slope, quadratic term, and/or cubic term) to describe individual differences in growth over time (Duncan and Duncan, 2009). A latent growth curve model estimates the trajectory of growth or change in variables over time. In its analysis, it identifies which variables might be explaining the changes and how the various trajectories of change might be associated (Bollen and Curran, 2006; Duncan *et al.* 2013; Preacher *et al.* 2008).

A single trajectory of depressive symptoms was modeled to describe how the depressive symptoms fluctuated across 2008-2017. Latent growth models were estimated to determine the shape that best fit the data, including no-growth, linear, quadratic, and cubic models. Once the latent growth model was established, it was used as a baseline model for comparison of the Growth Mixture Models. Fit indices included the root mean square error of approximation (RMSEA), comparative fit index (CFI), and the Tucker-Lewis index (TLI). RMSEA values less than 0.06 and CFI and TLI values above 0.95 are considered indicators of a good fit (Hu and Bentler, 1999).

To examine whether multiple heterogeneous trajectories of depressive symptoms exist among men across the five waves in this study, Growth Mixture Models (GMM) were utilized. In Growth Mixture Modeling, individuals are categorized based on common patterns of change while at the same time noting the existence of individual differences within the identified groups (Jung and Wickrama, 2008). To identify these groups with similar patterns of change, a series of GMMs were fitted to the data to determine if different classes of depressive symptoms could be identified among the men who formed part of this study. To this end, multiple GMMs were fitted to the data sequentially until no improvement was found and/or worsening was reported. The study hypothesized four classes of depressive symptom trajectory in line with existing literature. Thus, 2-class, 3-class, 4-class, and 5-class models were specified for the data and the shape of the trajectory (linear, quadratic, or cubic) were informed by the results of the LGCMs.

The process of choosing the appropriate number of classes of depressive symptom trajectories among the men involved comparing the increasing number of classes to the baseline model and each successive class. Various fit statistics were subsequently used to select the optimal number of classes from among the hypothesized classes plus one. The Akaike information criterion (AIC), Bayesian information criterion (BIC) and the Sample-Size Adjusted (SABIC) were used to select the optimal number of classes with the lowest values of the coefficients signaling a better fit. Additionally, higher entropy values signaled a better fit of the model together with the requirement that all proportions for the latent classes should be above 1% (Jung and Wickrama, 2008).

To identify the risk factors that distinguish amongst the trajectories of depressive symptoms among men, two dummy variables were created, one was coded "1" if a man experienced a family change or "0" otherwise and the other coded as "1" if a man was paying child maintenance or "0" otherwise. These two covariates were then included separately in a model that includes the identified depressive symptom classes to see the trajectories of the classes by family change as well as by child maintenance.

3. Results

3.1. Identifying the baseline model

Before determining whether multiple heterogeneous trajectories of depressive symptoms are present among the men sampled for this study, it was imperative to first establish the shape of the growth curve which best reflected the changes in depressive symptoms across the waves. The existence of missing data arising from sample attrition was handled with full information maximum likelihood analysis, which included all cases with at least two waves of data. The unconditional growth model with no covariates was used to compare the fit of various models that had distinct growth shapes and included the following: an intercept only model, a linear growth model, a quadratic model and the cubic model. The fit indices that were used to select the accurate shape for the growth include the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI) and the Root Mean Square Error of Approximation (RMSEA). CFI and TLI values exceeding 0.95 and RMSEA values less than 0.06 are considered indicators of good fit (Hu and Bentler, 1999). The information about the fit indices of the above-mentioned models are shown in Table 2:

Table 1. Summary of the Latent Growth Models

Model	χ^2	Df	p	CFI	TLI	RMSEA
Intercept only	246.24	13	<0.001	0.357	0.506	0.044
Linear	104.25	10	<0.001	0.740	0.740	0.032
Quadratic	52.47	6	<0.001	0.872	0.787	0.029
Cubic	7.22	1	<0.001	0.983	0.829	0.026

Notes: CFI=Comparative fit index; TLI=Tucker-Lewis index; RMSEA=Root Mean Square Error of Approximation

As shown in Table 2, the different fit indices support the cubic model as reflected by the improving TLI, CFI and RMSEA from the intercept, linear, quadratic and cubic models. The cubic model reflects the curvilinear pattern of increasing and decreasing depressive symptoms of the men across the five waves. To compare the different models, a likelihood ratio test was also conducted on the different pairs of the models to see whether each successive model improved the previous model.

Table 2. Likelihood ratio test for model fit

Model	df	AIC	BIC	χ^2	χ^2 diff	Diff df	$p > \chi^2$
Comparison of intercept only and linear model							
Linear	10	173641	173712	104.25			
Intercept only	13	173777	173826	246.24	141.99	3	<0.001
Comparison of the linear model and quadratic model							
Quadratic	6	173597	173697	52.47			
Linear	10	173641	173712	104.26	51.78	4	<0.001
Comparison of quadratic and cubic model							
Cubic	1	173562	173697	7.22			
Quadratic	6	173597	173697	52.47	45.25	5	<0.001

Notes: df=degrees of freedom, χ^2 diff = chi-square difference, Diff df=degrees of freedom of the chi-square difference, AIC=Akaike Information Criterion, BIC= Bayesian Information Criterion.

As shown in Table 3, the cubic growth parameter is chosen ahead of the intercept only, linear and quadratic models as the likelihood ratio tests are highly significant (<0.001).

3.2. Examining multiple heterogeneous trajectories of depressive symptoms

After identifying the optimal model fit for the growth in the depressive symptoms among men, Growth Mixture Models were used to examine whether there are multiple trajectories of depressive symptoms among the men who formed part of the sample of this study. With Growth Mixture models, individuals with identical patterns of change in depressive symptoms are grouped while changes in individual differences are also catered for in the models. To achieve this, a succession of models were fitted on the data to establish if separate groups could be identified for depressive symptoms across the five waves of the study. The optimal number of classes was derived from a series of GMMs, which were specified until no further improvement or worsening fit was found. The shape of the trajectory was informed from the LGCMs fitted in the previous section. Fit statistics used to identify the optimal number of classes include the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Sample Size Adjusted Bayesian Information Criterion (SABIC) where a better fit was signified by lower coefficients. Additionally, the entropy coefficient was also used to identify the optimal number of classes where higher entropy values were preferred, in line with the recommendations of Jung and Wickrama (2008). The comparisons from the cubic growth mixture model are shown in Table 4.

Table 3. Cubic Growth Mixture Model comparisons

Classes	AIC	BIC	SABIC	Entropy	Smallest class
2	173615	173646	173646	0.807	3.05%
3	173623	173666	173666	0.785	0.00%
4	173695	173750	173750	0.140	0.00%
5	173620	173687	173687	0.806	0.00%

Notes: AIC= Akaike Information Criterion, BIC= Bayesian Information Criterion, SABIC= Sample Size Adjusted Bayesian Information Criterion. The lowest values of the information criteria as well as the highest values of the entropy coefficients are shown in bold.

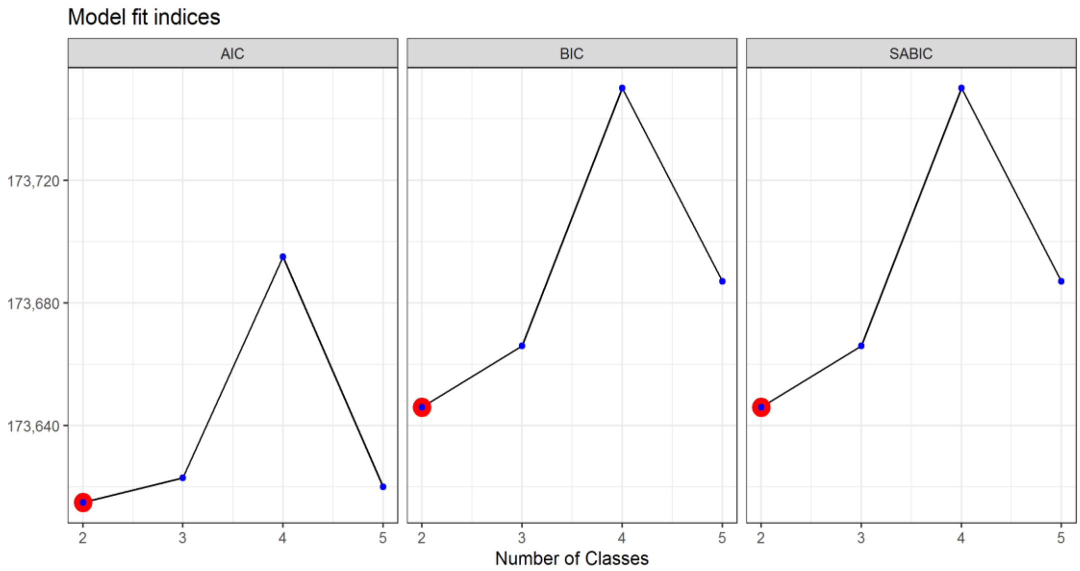

Figure 1. Fit indices for the linear growth model

Notes: AIC= Akaike Information Criterion, BIC= Bayesian Information Criterion, SABIC= Sample Size Adjusted Bayesian Information Criterion. The points highlighted in red indicate the information criteria with the lowest values.

As shown in Figure 1, the optimal number of classes for depressive symptoms among the men across the five waves was two. This is supported by the lowest information criteria values as well as the highest entropy value. Additionally, the other classes had the smallest classes constituting less than 1%, a departure from recommendations that indicate that the smallest class should be more than 1%. The two-class depressive symptom trajectory across the five waves of the study is visualized in Figure 2:

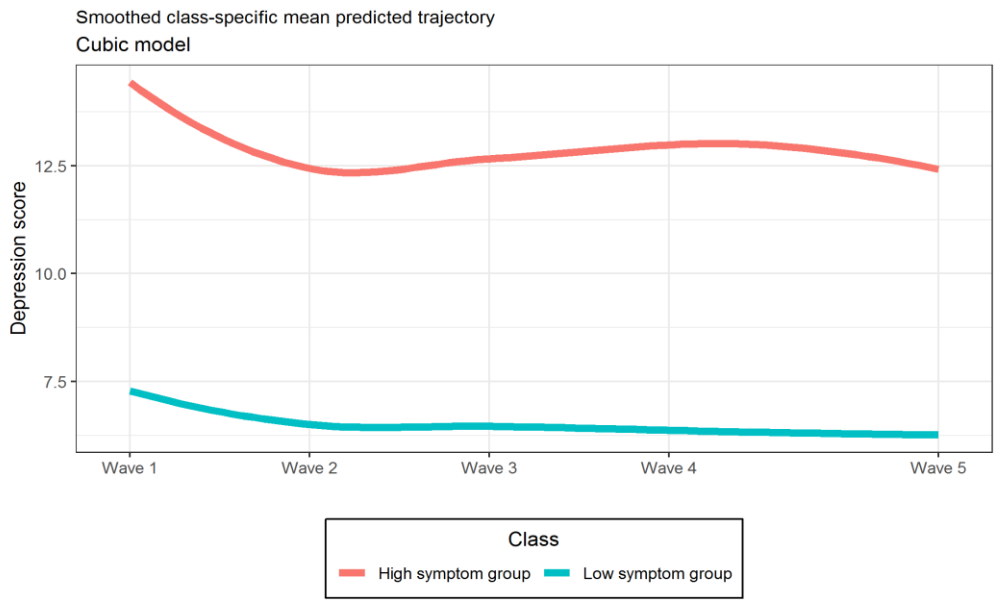

Figure 2. Derived latent trajectories using the cubic model

As shown in Figure 2, the two classes of depressive symptoms among men can be categorized into the low-symptom group as well as the high symptom group. The low symptom group is stable and is characterized by minute decreases over time from the baseline period. On the other hand, the high symptom group is characterized by chronically high levels of depressive symptoms, which seem not to be decreasing but fluctuating above a score of 12.5 across the five waves of the study. The two classes of depressive symptoms are consistent with the literature as there are studies that have reported classes with the same characteristics (Glasheen *et al.* 2013). The names given to the two classes of depressive symptoms are for discussion purposes only and do not reflect the clinical thresholds for the depressive symptoms.

3.3. Robustness

Though the fit indices used in this study selected the cubic model as the baseline model for the LCGM, some studies argue that a cubic model is not appropriate for a study with data points not exceeding five waves. To make sure that the trajectories in the two classes of depressive symptoms identified using a cubic baseline model are not driven by model misspecification, the growth mixture model is further estimated using a quadratic as well as a linear baseline specification to compare with the results from the cubic growth model. The fit indices for the linear as well as the quadratic growth models are visualized in Figure 3:

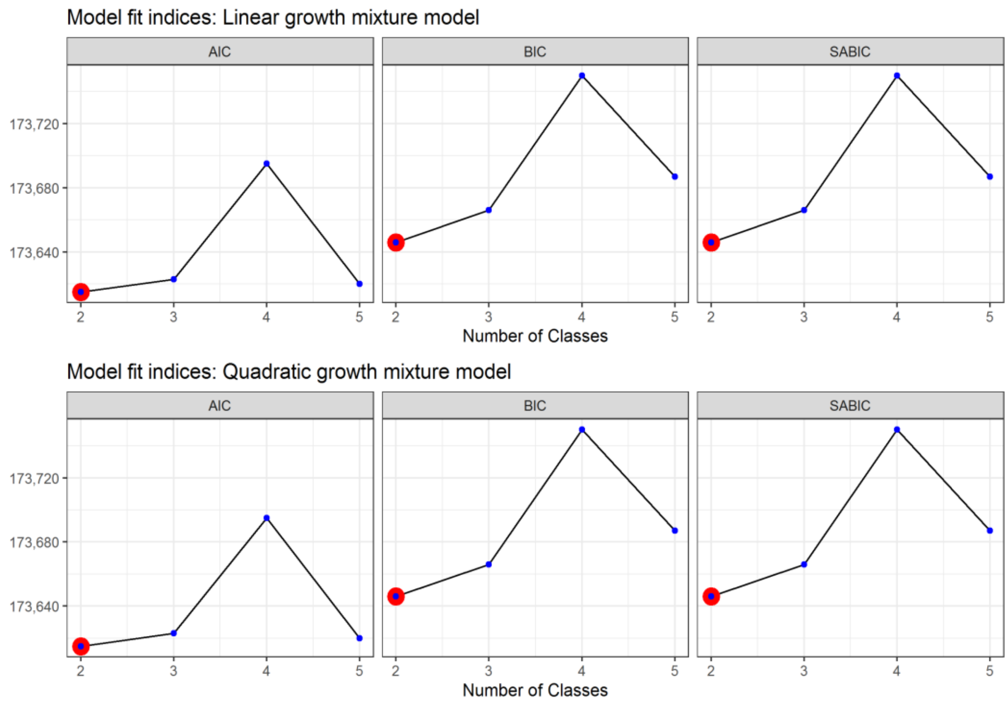

Figure 3. Fit indices for the linear growth and quadratic growth model

Notes: AIC= Akaike Information Criterion, BIC= Bayesian Information Criterion, SABIC= Sample Size Adjusted Bayesian Information Criterion. The points highlighted in red indicate the information criteria with the lowest values.

Figure 3 shows that even using the linear or quadratic growth model as the baseline model, the different information criteria, as well as the entropy coefficients still select a model with two classes for depressive symptoms among men. Additionally, only two classes for depressive symptoms had the smallest class constituting more than 1%. Higher classes of depressive symptoms had the smallest classes constituting less than 1% of all the classes, further confirming a two-class depressive symptom trajectory as the optimal model. The two-class depressive symptom trajectories selected by the linear as well as the quadratic growth models respectively are illustrated in Figure 4:

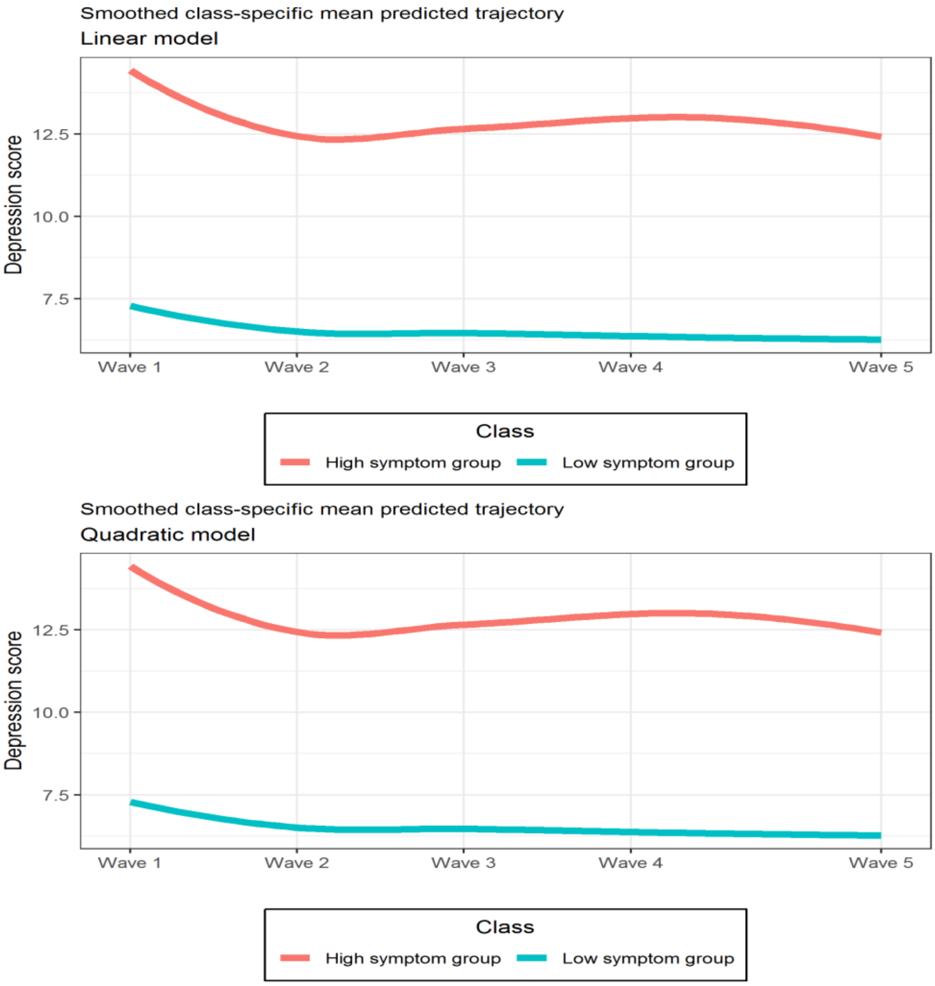

Figure 4. Derived latent trajectories using the linear and quadratic growth models

The top panel and the bottom panel of Figure 4 show the smoothed class-specific mean trajectories of depressive symptoms among the men using the linear and quadratic latent growth curve models. The smoothed class-specific mean trajectories of depressive symptoms visually look the same as the trajectories attained using the baseline cubic growth model. Thus, it can be asserted that the two-class depressive symptom trajectories are robust to different latent growth curve models.

3.4. Latent growth mixture models with covariates

To see the trajectories in the depressive symptoms by family change, a family change variable is created which is given a value of "0" if a man did not experience any family change across the waves of the study. If a man experienced a family change or a series of family changes, this was coded as "1". The latent growth mixture model using cubic growth change was utilized to assess the comparison between the trajectories of depressive symptoms between those men who experienced a family change and those who did not experience a family change. The predicted wave trajectories of depressive symptoms by the family change are visualized in Figure 5:

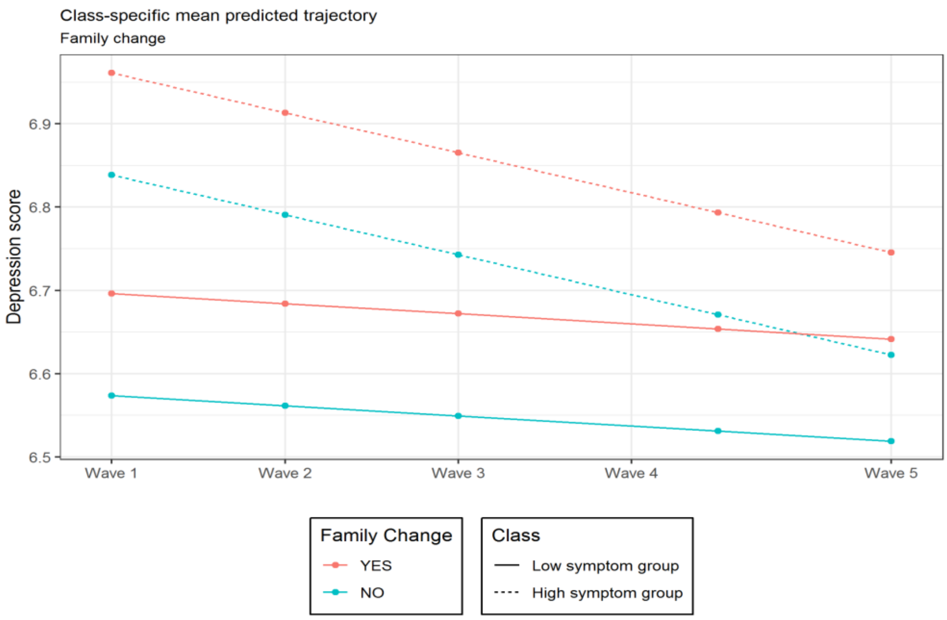

Figure 5. Wave trajectories of depressive symptoms by family change

As shown in Figure 5, though the class-specific mean predicted trajectories of the men who experienced a family change and those who did not experience a family change are decreasing both for the high symptom and the low symptom group, it can be noted that the depressive symptom trajectory for the men who experienced a family change was higher than those who did not experience a family change for both classes of depressive symptoms. It can also be noted that the trajectory of depressive symptoms for the man who experienced family changes was decreasing at a faster rate compared to the men who did not experience any family change. Another covariate added to the unconditional latent growth mixture model is the child maintenance variable. The variable was coded as “1” if a man was paying child maintenance or “0” if the man was not paying child maintenance. The wave trajectories of depressive symptoms by child maintenance are visualized in Figure 6.

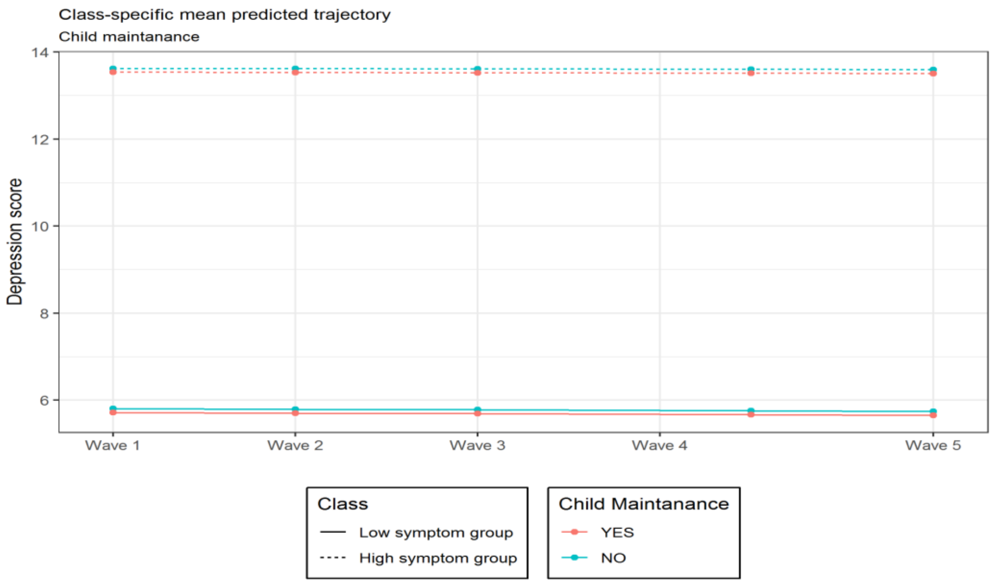

Figure 6. Wave trajectories of depressive symptoms by child maintenance

As shown in Figure 6, the mean trajectories of depressive symptoms were constant across the five waves for both the low symptom and high symptom groups. Surprisingly, the men who did not pay child maintenance had higher trajectories of depressive symptoms compared to the men who paid child maintenance for both the low symptom and the high symptom groups.

5. Conclusion

The study finds two heterogeneous classes of depressive symptoms among men in South Africa. This has several policy implications, especially from a government-intervention perspective. Using a general intervention strategy to curb mental health issues among men might not produce the desired effects. It is crucial that specific intervention strategies be directed towards the specific classes of depressive symptoms so that the specific needs of men are catered for. Secondly, family change is seen as predicting the trajectories in the levels of depressive symptoms. The men who experienced a family change had higher mean trajectories of depressive symptoms both for the high symptom group and the low symptom group compared to the men who did not experience a family change.

More work should therefore be done to give men more access to counselling services after going through a family change as well as devising strategies to circumvent other avoidable family changes like divorce. The men who did not pay child maintenance had high trajectories of depressive symptoms compared to the men who paid child maintenance for both the high symptom and the low symptom group. The high trajectories of depressive symptoms of men who did not pay child maintenance compared to the men who paid child maintenance reflect the peace of mind that comes with men paying child maintenance for their children. Men should therefore be counselled on the benefits of financially supporting their children rather than being compelled to do so by law. The depressive symptoms are self-reported which might be subject to recall bias or social desirability.

The changes in men’s depressive symptoms might not fully reflect the episodes of depression that occurred during the periods between the five waves as the CES-D scale might be subject to recall bias The study’s use of a novel analytic method, the latent growth curve modeling to understand the trajectories of men’s depressive symptoms is the first in mental health research among men in South Africa. Future studies could expand this study by untangling family change into its constituent parts like divorce, widowhood and other parts to reveal the trajectories of mental health problems for men experiencing a specific type of family change.

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