# **BMJ Open** Simulation study to demonstrate biases created by diagnostic criteria of mental illnesses: major depressive episodes, dysthymia, and manic episodes

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### ABSTRACT

**Objectives** Composite diagnostic criteria alone are likely to create and introduce biases into diagnoses that subsequently have poor relationships with input symptoms. This study aims to understand the relationships between the diagnoses and the input symptoms, as well as the magnitudes of biases created by diagnostic criteria and introduced into the diagnoses of mental illnesses with large disease burdens (major depressive episodes, dysthymic disorder, and manic episodes).

Settings General psychiatric care.

**Participants** Without real-world data available to the public, 100 000 subjects were simulated and the input symptoms were assigned based on the assumed prevalence rates (0.05, 0.1, 0.3, 0.5 and 0.7) and correlations between symptoms (0, 0.1, 0.4, 0.7 and 0.9). The input symptoms were extracted from the diagnostic criteria. The diagnostic criteria were transformed into mathematical equations to demonstrate the sources of biases and convert the input symptoms into diagnoses.

**Primary and secondary outcomes** The relationships between the input symptoms and diagnoses were interpreted using forward stepwise linear regressions. Biases due to data censoring or categorisation introduced into the intermediate variables, and the three diagnoses were measured.

**Results** The prevalence rates of the diagnoses were lower than those of the input symptoms and proportional to the assumed prevalence rates and the correlations between the input symptoms. Certain input or bias variables consistently explained the diagnoses better than the others. Except for 0 correlations and 0.7 prevalence rates of the input symptoms for the diagnosis of dysthymic disorder, the input symptoms could not fully explain the diagnoses.

**Conclusions** There are biases created due to composite diagnostic criteria and introduced into the diagnoses. The design of the diagnostic criteria determines the prevalence of the diagnoses and the relationships between the input symptoms, the diagnoses, and the biases. The importance of the input symptoms has been distorted largely by the diagnostic criteria.

# Strengths and limitations of this study

- The prevalence of three mental illnesses was determined by the prevalence of the input symptoms and modified by the diagnostic criteria and correlations between the input variables in simulated populations.
- Biases due to data censoring or categorisation were created by the diagnostic criteria and introduced into the intermediate variables and the three diagnoses of mental illnesses in simulated populations.
- The diagnostic criteria modified the importance of the input symptoms; certain input symptoms or bias variables were weighted more than expected in simulated populations.
- The design of diagnostic criteria influenced the diagnosis prevalence. With the same input symptom prevalence, dysthymic disorder was the most prevalent among three illnesses. Major depressive episodes were the least prevalent.
- This study is based on simulated data and needs to be verified with real-world data.

### BACKGROUND

The diagnoses of several mental illnesses in patients are often made based on a variety of criteria. These criteria often involve symptoms reported by the patients.<sup>1–3</sup> For example, the diagnosis of major depressive disorder defined in the Diagnostic and Statistical Manual of Mental Disorders, 4th o Edition, Text Revision (DSM-IV-TR) requires at least one major depressive episode.<sup>12</sup> For  $\overline{\mathbf{g}}$ each major depressive episode, the major criteria are 'depressive mood and/or loss of interest or pleasure in life activities for at least 2 weeks'.<sup>12</sup> In addition to the major criteria, the patients need to report at least five of the nine symptoms that 'cause clinically significant impairment in social, work or other important areas of functioning almost every day, 'including insomnia or hypersomnia and

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Correspondence to Dr Wei-Chih Chen; wiji.chen@gmail.com fatigue or loss of interest.<sup>12</sup> In other words, patients need to meet both the major and minor criteria before being diagnosed with a major depressive episode.

Historically this symptom-based diagnostic approach developed by Feighner et al has been widely accepted.<sup>45</sup> Since then, mental illnesses can be diagnosed through different sets of criteria. This approach is important clinicians become capable of screening because important symptoms before diagnosing and treating patients accordingly. In fact, these criteria can also be seen as composite measures that use multiple measures to capture disorders that may not be quantified with single variables.<sup>67</sup> Recent studies on composite measures have found composite diagnostic criteria problematic because biases can be introduced while aggregating information from input variables.<sup>7</sup> The biases emerge while the sums of input variables are censored or while input variables are transformed inadequately.<sup>7 8</sup> In other words, biases can be created when there is information in the composite measures that is not explained by and unrelated to the input variables.<sup>7</sup> For example, categorising continuous variables considers individuals in the same group homogenous and disregards the heterogeneity between individuals in the same categories.<sup>7</sup> Such practices induce biases and decrease measurement precision.78

Currently, there is no extensive review on the existence of these biases created by composite measures or medical diagnoses, and only selected diagnoses have been studied for such biases. These biases have been proven vital to another symptom-based composite measure, the diagnosis of frailty, a condition that often occurs in the elderly and is significantly associated with health outcomes, such as mortality, falls, and morbidity.<sup>7</sup> Frailty is diagnosed based on several symptoms and characterised by weakness and vulnerability to adverse health events.<sup>7</sup> While using one of the most widely used diagnostic criteria, the Biological Syndrome Model scores, to diagnose frailty,<sup>9</sup> biases alone can explain more than 71% of the variances of the frailty

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diagnosis.<sup>7</sup> The biases introduced by data censoring and data categorisation can better explain the frailty diagnosis than the input symptoms.

Mostly designed as symptom-based composite measures, it is possible that the diagnostic criteria of mental illnesses also create and introduce biases into diagnoses so that the diagnoses could not be fully explained by the input symptoms. In concern of the biases created by the diagnostic criteria alone, this study aims first to understand the relationships between mental symptoms and diagnoses and **\_** tionships between mental symptoms and diagnoses and then to quantify the potential role of the biases regarding the diagnoses by simulating populations with different prevalence rates and between-variable correlations of mental symptoms. **METHODS Assumptions and simulation parameters** A file containing R codes to reproduce the simulations was attached in the online supplemental file 1. Simu-lated populations with mental symptoms of different

lated populations with mental symptoms of different prevalence rates and between-variable correlations were created to interpret the diagnoses and understand the uses rela potential magnitudes of biases that could be introduced via data processing implied by the diagnostic criteriaonline supplemental file 1. Three diagnoses of mental illnesses were chosen for the leading associated disease burdens<sup>2</sup>: major depressive episodes for the diagnosis of đ major depressive disorder, dysthymic disorder, and manic text episodes for the diagnosis of bipolar disorder.<sup>1</sup>

There were assumptions made to simulate the populations (table 1). First, for each simulation, the prevalence rates of the input symptoms were assumed to be similar for the three diagnoses in this study. Second, the input  $\Xi$ symptoms for the diagnoses of major depressive episodes and dysthymic disorder correlated with the same correlation coefficients.<sup>10</sup> The symptoms for the diagnosis of manic episodes correlated to one another. Third, the

Syr car	ndrome Model scores, to diagnose frailty, <sup>9</sup> biases alone tion coefficients. <sup>10</sup> The sympt n explain more than 71% of the variances of the frailty manic episodes correlated to	oms for the diagnosis of one another. Third, the
Та	ble 1 The assumptions and parameters in the simulations	
	Assumptions	
1	Equal prevalence rates for the input symptoms of the same diagnosis; presence of input symptoms assigned randomly	
2	Same correlations between the input symptoms of the diagnoses of major depressive episodes and dysthymic disorder; same correlations between the input symptoms of manic episodes	
3	The input symptoms of manic episodes created independent of those of major depressive episodes and dysthymic disorder	
4	Diagnoses made accurately based on the diagnostic criteria and symptoms reported precisely by patients	
	Parameters of input symptoms of the same diagnosis for each simulation	
1	Population sizes	100000
2	Prevalence rates (uniform for all input symptoms in a simulation)	0.05, 0.1, 0.3, 0.5 and 0.7
3	Correlations (uniform between all input symptoms of the same diagnosis in a simulation)	0, 0.1, 0.4, 0.7 and 0.9
4	Number of simulations for each combination of the assumed prevalence rates and between- variable correlations of the input symptoms	100

input symptoms for the diagnosis of manic episodes were created independently of those for the diagnosis of the other two mental illnesses. The assumptions of the prevalence rates and between-variable correlations were made because there was no acceptable-quality data on the symptoms of mental illnesses published and we needed to examine various combinations of these epidemiological measures. There were studies on the prevalence of mental illnesses,<sup>11 12</sup> but the information on the prevalence of mental symptoms was very limited. There were variables about depression or anxiety collected in national surveys, such as the items collected through the Center for Epidemiologic Studies Depression Scale.<sup>7 13-19</sup> However, these variables were not the symptoms used in the DSM-IV-TR. Lastly, we assumed that the diagnoses were made accurately based on the input symptoms reported precisely by patients and the diagnostic criteria in the DSM-IV-TR were strictly followed. However, these assumptions did not hold in the real world.<sup>20</sup> For simplicity and practicality reasons, we assumed perfect diagnostic quality by physicians and accurate reporting of the input symptoms by patients in the simulated populations.

#### **Diagnostic criteria as mathematical functions**

The input symptoms were extracted from the major and minor criteria of the diagnoses and listed in tables 2-4. The input symptoms, major and minor criteria, and the diagnoses were assigned variable names. All input symptoms, items or domains in the major or minor criteria, and the diagnoses were binomial variables, presenting 0 and 1 for the absence and presence of the symptoms, criteria or the diagnoses, respectively. For example, two symptoms, 'insomnia' and 'hypersomnia', were extracted from one of the minor criteria for the diagnosis of major depressive episodes.<sup>1</sup> Two other symptoms, 'more talkative than usual' and 'pressure to keep talking', were extracted from one of the minor criteria for the diagnosis of manic episodes.

Mathematical functions were generated based on the diagnostic criteria to convert input symptoms into diagnoses. For example, one of the minor criteria of dysthymic disorder was 'poor appetite or overeating.' This required two input symptoms and one bias variable to generate the criterion.<sup>7</sup> In other words, 'poor appetite or overeating' equalling the sum of two input variables, 'poor appetite' and 'overeating,' and a bias variable to achieve censoring of the sum of both variables.<sup>7</sup> The sum of two binomial variables could be 0, 1 and 2 for the subjects. However, to derive a binomial variable (having at least one symptom) based on a distribution of 0 to 2, the bias variable had values of -1 for subjects with both symptoms to obtain values less than or equal to one in all subjects.<sup>7</sup> Therefore, the bias variable had values of -1 for the subject with both symptoms and 0 for the other subjects. In addition to adding variables together to derive an intermediate variable or a diagnosis, multiplication, categorisation, and other more complicated methods were used in the

diagnostic criteria to generate diagnosis variables and domain variables in the major or minor criteria.

For example, the diagnosis of dysthymic disorder required the confirmation of both the major criteria, 'depressed mood most of the day for more days than not, for at least 2 years' and the minor criteria, 'the presence of two or more of the following symptoms,' at the same time.<sup>1</sup> The diagnosis based on whether subjects meeting both the major and minor criteria of dysthymic disorder is the same as identifying those with a multiplicative product of 1 of two binomial variables (0 and 1 for absence and presence of the major or minor criteria). In the equations, two binomial variables were multiplied to confirm the diagnosis of dysthymic disorder among those with a multiplicative product of 1. Individuals could be assigned with 0 or 1 for whether they met both criteria, while the sum of major and minor criteria were 0, 1 or 2 for the individuals. Linearly, a bias variable with values of -1 or 0 was created and those meeting both the major or minor criteria were assigned with  $-1.^7$  For categorisation of continuous variables, bias variables were required to remove the variations between the subjects in the same categories.<sup>7</sup> Other equations to generate the intermediate variables and the diagnoses were listed and explained in tables 2–4. **Generation of bias variables** Bias variables could be generated while binomial input remove the variations between the subjects in the same

symptoms were summed or multiplied to obtain binomial intermediate or diagnosis variables (see the example in the previous two paragraphs).<sup>7</sup> A visual presentation of how bias variables were generated was published.<sup>7</sup> Therefore, the number of bias variables depended on a the complexity of how the diagnoses were made. For  $\blacksquare$ example, six of the nine items or domains in the minor criteria for the diagnosis of major depressive episodes were the censored sums of the input symptoms and six bias variables were derived along with the intermediate variables that represented the items in the minor criteria. All bias variables were described in tables 2–4.

### Simulation parameters and simulated populations

We simulated populations of 100000 subjects. There were five prevalence rates to simulate the input symptoms for the diagnosis of major depressive episodes, dysthymic disorder and manic episodes: 0.05, 0.1, 0.3, 0.5 and 0.7. The correlations between the input symptoms were hypothesised to be 0, 0.1, 0.4, 0.7 and 0.9. There were 25 combinations of the assumed prevalence rates **3** and between-variable correlations. The presence of the input symptoms was randomly assigned to the subjects after specifying the prevalence rates and between-variable correlations between the input symptoms.<sup>21 22</sup> The intermediate and diagnosis variables were derived according to the equations in tables 2-4. For each combination of prevalence rates and between-variable correlations, the populations were simulated for 100 times to obtain the mean values and 95% CIs of derived prevalence rates, as

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ssification of Criterion nptoms variable	ajor spressive bisode ariable= de)	lajor criteria, ssential for iagnosis				linor criteria mde_mi tt least 5 of symptoms celuding the
Domains in the majo or minor criteria			Depressed mood or a loss of interest or pleasure in daily activities for more than 2 weeks.	Depressed mood for more than 2 weeks.	Loss of interest or pleasure in daily activities for more than 2 weeks.	
or Domain variables				r mde_ma1	mde_ma2	
Symptoms						
Symptom variables						
Equations to derive diagnosis or domain variables	mde=mde_ma1 x mde_ma2 x (mde_mi3+ mde_mi5+mde_mi6+ mde_mi5+mde_mi8+ mde_mi7+mde_bias1) + (1-mde_ma1 x (me_ma1 x (me_ma2) x (mde_ mi3+mde_mi4+ mde_mi5+mde_mi6+ mde_mi7+mde_mi8+ mde_mi9+mde_mi8+					
Approximation by linear regression	mde=intercept + coef1 x mde_ma1+coef2x mde_ma2+coef3x mde_mi3+coef5 x mde_mi3+coef5 x mde_mi6+coef7 x mde_mi7+coef8 x mde_mi9+coef10 x mde_bias					
Mechanisms related to introducing biases	<ol> <li>Multiplication to create the situations when one or two symptoms in the major criteria confirmed and the bias (mde_bias) calculated by extracting the information of the diagnosis not explained by the input symptoms and two bias variables generated by censoring (mde_bias1 and mde_bias1 and mde_bias1 and the threshold of three or four (mde_bias1 and mde_bias2)</li> </ol>					

Table 2 Continu	ed							
Classification of Ci symptoms va	riterion ariable	Domains in the major or minor criteria	Domain variables	Symptoms	Symptom variables	Equations to derive diagnosis or domain variables	Approximation by linear regression	Mechanisms related to introducing biases
		Significant unintentional weight loss or gain	mde_mi3			mde_mi3=mde_mi3_1+ mde_mi3_2+ mde_mi3_bias		Censoring of the sum of multiple input variables
				Significant unintentional weight gain	mde_mi3_1			
				Significant unintentional weight loss	mde_mi3_2			
				Information of the domain not explained by the input variables	mde_mi3_bias			
		Insomnia or sleeping too much	mde_mi4			mde_mi4=mde_mi4_1+ mde_mi4_2+ mde_mi4_bias		Censoring of the sum of multiple input variables
				Insomnia	mde_mi4_1			
				Sleeping too much	mde_mi4_2			
				Information of the domain not explained by the input variables	mde_mi4_bias			
		Agitation or psychomotor retardation noticed by others	mde_mi5			mde_mi5=mde_mi5_1+ mde_mi5_2+ mde_mi5_bias		Censoring of the sum of multiple input variables
				Agitation	mde_mi5_1			
				Psychomotor retardation noticed by others	mde_mi5_2			
				Information of the domain not explained by the input variables	mde_mi5_bias			
		Fatigue or loss of energy	mde_mi6			mde_mi6=mde_mi6_1+ mde_mi6_2+ mde_mi6_bias		Censoring of the sum of multiple input variables
				Fatigue	mde_mi6_1			
								Continued

ible 2 Continu	ed							
ssification of Cr ptoms va	riterion ıriable	Domains in the major or minor criteria	Domain variables	Symptoms	Symptom variables	Equations to derive diagnosis or domain variables	Approximation by linear regression	Mechanisms related to introducing biases
				Loss of energy	mde_mi6_2			
				Information of the domain not explained by the input variables	mde_mi6_bias			
		Feelings of worthlessness or excessive guilt	mde_mi7			mde_mi7=mde_mi7_1+ mde_mi7_2+ mde_mi7_bias		Censoring of the sum of multiple input variables
				Feelings of worthlessness	mde_mi7_1			
				Feelings of excessive guilt	mde_mi7_2			
				Information of the domain not explained by the input variables	mde_mi7_bias			
		Diminished ability to think or concentrate, or indecisiveness	mde_mi8			mde_mi8=mde_mi8_1+ mde_mi8_2+ mde_mi8_bias		Censoring of the sum of multiple input variables
				Diminished ability to think or concentrate	mde_mi8_1			
				Indecisiveness	mde_mi8_2			
				Information of the domain not explained by the input variables	mde_mi8_bias			
		Recurrent thoughts of death	mde_mi9					
rmation m to sgorisation osing three nains in or criteria)	de_bias1							Bias introduced to categorise the sum of the number of confirmed symptoms in the minor criteria
rmation m to igorisation osing four aains in or criteria)	de_bias2							Bias introduced to categorise the sum of the number of confirmed symptoms in the minor criteria
								Continued

well as the adjusted R squared and p values derived by approximating the diagnosis variables.

# **Diagnosis approximation**

Due to the existence of the biases, the input symptoms were not likely to fully explain the diagnoses.<sup>7</sup> Therefore, the diagnoses were approximated by the input, bias and intermediate variables individually and collectively.<sup>7 13 15 17</sup> The approximation was conducted using forward-stepwise linear regressions.7 13 15 17 23 The interpretability of the diagnoses by the input symptoms and bias variables was assessed via adjusted R square ranging from 0 to 1: 0 suggested that the input symptoms were unrelated to the diagnosis, and 1 suggested that the input symptoms perfectly explained the diagnosis.<sup>15 16 24-27</sup>

copy All statistical analyses were conducted within the R environment (V.3.4.1)<sup>28</sup> and RStudio (V.1.0.153).<sup>29</sup> Twotailed p values less than 0.05 were considered statistical significant. including

### Patient and public involvement

This is a simulation study that did not involve patients or for uses rel human subjects.

### RESULTS

The derived prevalence rates of the input symptoms for the three mental illnesses matched the assumed rates in 6 the online supplemental file 1. The derived correlations between the input symptoms were close to assumed levels in the online supplemental file 1. The simulations were a successful and accurate based on the assumed prevalence rates and correlations.

### Prevalence of intermediate variables

The items in the major and minor criteria were the intermediate variables necessary to create the diagnoses. The methods used to generate the intermediate variables were important for the prevalence rates of the intermediate variables and the derived diagnoses in figure 1. For example, an intermediate variable, 'significant unintentional weight loss or gain, 'was created by summing and censoring two binomial variables with values of 0 and 1 (significant unintentional weight loss; significant unintentional weight gain). The prevalence rates of the intermediate variables were larger than those of the two input symptoms regardless of the assumed prevalence rates or between-variable correlations of the input symptoms.

In contrast, the diagnosis of dysthymic disorder was a multiplication product of two intermediate binomial variables, the major and minor criteria and the prevalence rates of dysthymic disorder were lower than those of the major or minor criteria under all combinations of the assumed correlations and prevalence rates of the input symptoms in figure 2.

# **Prevalence of mental illnesses**

The derived prevalence rates of three diagnoses were plotted against the assumed prevalence rates and

Table 2 Cont	inued							
Classification of symptoms	Criterion variable	Domains in the major or minor criteria	Domain variables	Symptoms	Symptom variables	Equations to derive diagnosis or domain variables	Approximation by linear regression	Mechanisms related to introducing biases
Information of diagnosis not explained by the domains	mde_bias							Information of the diagnosi not explained by the input variables and two bias variables generated due to data categorisation

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diate sistication symptoms symptoms variables	iable iable	Intervision     Intervision       Major or     Major or       Naior or     Interme       Depressed     dys_ma       mood most     dys_ma       more days     dys_mi       than not, for at     dys_mi       least 2 years     dys_mi       or overeating     dys_mi	diate Symptom diagnosis or domain Approximation introducing biases	dys=intercept Multiplication to create + coef1 x the situations where both dys_mat+coef2 x the major and minor dys_mit+coef3 x criteria met (union of dys_bias two binomial variables, made_ma x mde_m) and the bias variable (dys_bias) equivalent to the residual of the diagnosis not explained by the input symptoms and the bias variables due to censoring and categorisation			dys_mi=dys_mi1+dys_mi2+ Categorising of the sum dys_mi3+dys_mi4+dys_mi5+ of multiple input variables dys_mi6+dys_mi_bias	dys_mi1_dys_mi1_1+ Censoring of the sum of dys_mi1_2+dys_mi1_bias multiple input variables	Poor appetite dys_mi1_1	Overeating dys_mi1_2	Information dys_mi1_bias of the domain not explained by the input variables
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Mechanisms related to introducing biases	Censoring of the sum of multiple input variables				Censoring of the sum of multiple input variables					Censoring of the sum of multiple input variables		
Approximation												
Equations to generate diagnosis or domain variables	dys_mi2=mde_mi4= mde_mi4_1+ mde_mi4_2+mde_mi4_bias				dys_mi3=mde_mi6= mde_mi6_1+mde_mi6_2+ mde_mi6_bias					dys_mi5=mde_mi8= mde_mi8_1+mde_mi8_2+ mde_mi8_bias		
Symptom variables		mde_mi4_1	mde_mi4_2	mde_mi4_bias		mde_mi6_1	mde_mi6_2	mde_mi6_bias			mde_mi8_1	mde_mi8_2
Symptoms		Insomnia	Sleeping too much	Information of the domain not explained by the input variables		Fatigue	Loss of energy (low energy)	Information of the domain not explained by the input variables			Diminished ability to think or concentrate (Poor concentration)	difficulty making decisions (indecisiveness)
Intermediate variables	dys_mi2/mde_mi4				dys_mi3/mde_mi6				dys_mi4	dys_mi5/mde_mi8		
Major or minor criteria (domains)	Insomnia or sleeping too much*				Low energy or fatigue*				Low self- esteem	Poor concentration or difficulty making decisions*		
Criterion variable												
Classification of symptoms												

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	Equations to generate Symptom diagnosis or domain variables variables Approximation introducing biases	mde_mi8_bias		Bias introduced by categorising the number of input symptoms confirmed in the minor criteria	Information of the diagnosis not explained by the input symptoms and the bias variables generated due to data categorisation (dys_mi_ bias)
	Intermediate variables		dys_mi6	dys_mi_bias	
	Major or minor criteria (domains)		Feelings of hopelessness	Information of minor criteria not explained by input variables	
nued	Criterion variable				dys_bias
Table 3 Contil	Classification of symptoms				Information of diagnosis not explained by major or minor criteria

Table 4The inpuDisorders, Fourth I	it symptom Edition, Tex	s, intermediate va tt Revision	rriables and bias variables f	or the diagnosis	of manic episodes based on th	e Diagnostic and Statistical M	anual of Mental
Classification of symptoms	Criterion variable	Major or minor criteria (domains)	Domain variables Symptoms	Symptom variables	Equations	Mechan Approximation introduc	isms related to ing biases
Manic episode (variable=manic)					manic = (1 - man_ma1 x man_ma2) x	manic=intercept 1. Multip + coef1 x man_ the si	blication to create tuations where

	(man_ma1+man_ma2) x	ma1+coef2x	one of the symptom in
	man_ma3 x (man_mi1+man_	man_	the major criteria met
	mi2+	ma2+coef3 x	(union of three binomial
	man_mi3+man_mi4+	man_	variables, such as man_
	man_mi5+man_mi6+	ma3+coef4 x	ma1+man_ma2 and
	man_mi7+man_bias1) +	man_	man_ma1 x man_ma2),
	(1 - (1 - man_ma1 x	mi1+coef5x	2. multiplication for the
	man_ma2)(man_ma1+	man_	condition of presenting
	man_ma2))	mi2+coef6x	irritable mood ( x man
	x man_ma3 x (man_mi1+man_	man_	ma3), and
	mi2+	mi3+coef7 x	3. the bias variable (man_
	man_mi3+	man_	bias) equivalent to the
	man_mi4+man_mi5+	mi4+coef8x	residual of the diagnosis
	man_mi6+	man_	not explained by the
	man_mi7+man_bias2)	mi5+coef9 x	input symptoms and the
		man_	bias variables due to
		mi6+coef10 x	censoring;
		man_	4. the bias variables
		mi7+coef11 x	introduced by
		man_bias	catedorising the number
			of input symptoms
			confirmed in the minor
			criteria (man_bias1 and
			man_bias2)
Major criteria,			
essential for the diacnosis of a			
manic enisode			
(more than one			
bipolar episode			
required to			
diagnose			
bipolar disorder)			
			Continued

ted to s						um of ables			
Mechanisms rela introducing biase						Censoring of the s multiple input varia			
Approximation									
iquations						nan_mi1=man_mi1_1+ nan_mi1_2+ nan_mi1_bias			
Symptom variables E		man_ma1	man_ma2	man_ma3			man_mi1_1	man_mi1_2	man_mi1_bias
Symptoms		Elevated mood, lasting at least 1 week	Expansive mood, lasting at least 1 week	Irritable mood, lasting at least 1 week			Increased self- esteem	Grandiosity	Information of the domain not explained by the input variables
Domain variables						man_mi1			
Major or minor criteria (domains)	A distinct period of abnormally and persistently elevated, expansive or irritable mood, lasting at least 1 week (or any duration if hospitalisation is necessary)					Increased self-esteem or grandiosity			
of Criterion variable					<b>~ e ≍ ≥</b>				
Classification c symptoms					Minor criteria (three or more of the following symptoms have persisted; four the mood is onl irritable)				

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Table 4         Continued							
Classification of Criterion symptoms variable	Major or minor criteria (domains)	Domain variables	Symptoms	Symptom variables	<b>A</b> pp	oroximation	Mechanisms related to introducing biases
	Decreased need for sleep (eg, feels rested after only 3 hours of sleep)	man_mi2					
	More talkative than usual or pressure to keep talking	man_mi3			man_mi3=man_mi3_1+ man_mi3_2+ man_mi3_bias		Censoring of the sum of multiple input variables
			More talkative than usual	man_mi3_1			
			Pressure to keep talking	man_mi3_2			
			Information of the domain not explained by the input variables	man_mi3_bias			
	Flight of ideas or subjective experience that thoughts are racing	man_mi4			man_mi4=man_mi4_1+ man_mi4_2+ man_mi4_bias		Censoring of the sum of multiple input variables
			Flight of ideas	man_mi4_1			
			Subjective experience that thoughts are racing	man_mi4_2			
			Information of the domain not explained by the input variables	man_mi4_bias			
							Continued

chanisms related to oducing biases		nsoring of the sum of Itiple input variables				
Me Approximation intr		Cer				
Equations		man_mi6=man_mi6_1+ man_mi6_2+ man_mi6_bias				
Symptom variables			man_mi6_1	man_mi6_2	man_mi6_bias	
Symptoms			Increase in goal-directed activity	Psychomotor agitation	Information of the domain not explained by the input variables	
Domain variables	man_mi5	man_mi6				man_mi7
Major or minor criteria (domains)	Distractibility (ie, attention too easily drawn to unimportant or irrelevant external stimuli)	Increase in goal-directed activity (either socially, at work or school, or sexually) or psychomotor agitation				Excessive involvement in pleasurable activities that have a high potential for painful consequences (eg, engaging in unrestrained buying sprees, sexual indiscretions, or foolish business investments)
Classification of Criterion symptoms variable						

lable 4 Continu	eq							
Classification of symptoms	Criterion variable	Major or minor criteria (domains)	Domain variables	Symptoms	Symptom variables	Equations	Approximation	Mechanisms related to introducing biases
Information of diagnosis due to categorisation (choosing at least three symptoms)	man_bias1							Bias introduced by categorising the number of input symptoms confirmed in the minor criteria
Information of diagnosis due to categorisation (choosing at least four symptoms)	man_bias2							Bias introduced by categorising the number of input symptoms confirmed in the minor criteria
Information of diagnosis not explained by symptoms	man_bias							Information of the diagnosis not explained by the input symptoms and the bias variables generated due to data categorisation, man_ bias1 and man_bias2



Figure 1 The prevalence rates of an intermediate variable for the diagnosis of major depressive episodes by assumed input symptom prevalence and correlations. The intermediate variable is 'significant unintentional weight loss or gain' and the input symptoms are 'significant unintentional weight loss' and 'significant unintentional weight gain.' The black line represents the situation where the prevalence rates of the input symptoms are the same as that of the intermediate variable. Lines above the black lines have the prevalence rates of the intermediate variable larger than those of the input symptoms. CI, confidence interval.

correlations of the input symptoms in figures 2-4 and listed in table 5. None of the three diagnoses had prevalence rates exceeding those of the input symptoms. In general, higher prevalence rates or between-variable correlations of the input symptoms were associated with higher prevalence rates in the three diagnoses, except for manic episodes that had higher prevalence rates (0.692)assuming 0 correlations and 0.7 prevalence rates than the



Figure 2 The prevalence rates of dysthymic disorder by assumed input symptom prevalence and correlations. Dysthymic disorder is diagnosed when both the major (depressed mood most of the day for more days than not, for at least 2 years) and minor criteria (at least two of the six items) are met. The black line represents the situation where the prevalence rates of the input symptoms are the same as those of dysthymic disorder. Lines below the black lines have dysthymic disorder prevalence rates lower than those of the input symptoms. CI, confidence interval.



Figure 3 The prevalence rates of major depressive episodes by assumed input symptom prevalence and correlations. Major depressive episodes are diagnosed when both major and minor criteria are confirmed. The black line represents the situation where the prevalence rates of the input symptoms are the same as that of major depressive episodes. Lines below the black lines have the prevalence rates of major depressive disorder lower than those of the input symptoms. CI, confidence interval.

prevalence rate (0.679) assuming 0.1 correlations and 0.7 prevalence rates of the input symptoms. When compared across figures 2-4, given the same assumed prevalence rates and between-variable correlations of the input symptoms, the diagnostic criteria of dysthymic disorder consistently generated diagnoses of the highest prevalence rates and the criteria of major depressive episodes created diagnoses of the least prevalence rates (see table 5 for details).



Figure 4 The prevalence rates of manic episodes by assumed input symptom prevalence and correlations. Manic episodes are diagnosed when the symptoms present as described in the diagnostic manual. The black line represents the situation where the prevalence rates of manic episodes are the same as those of the input symptoms. Lines below the black lines have prevalence rates of manic episodes lower than those of the input symptoms. Cl, confidence interval.

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Table 5 The derived pre	and between-variable co	

Assumed correlations between input symptoms	Assumed prevalence of input symptoms	Major depressive episodes	Dysthymic disorder	Manic episodes
0	0.05	0 (95% CI 0 to 0)	0.004 (95% CI 0.004 to 0.004)	0 (95% CI 0 to 0)
0	0.1	0.001 (95% CI 0.001 to 0.001)	0.025 (95% CI 0.025 to 0.025)	0.002 (95% CI 0.002 to 0.002)
0	0.3	0.067 (95% CI 0.067 to 0.067)	0.249 (95% CI 0.249 to 0.249)	0.136 (95% CI 0.135 to 0.136)
0	0.5	0.245 (95% CI 0.244 to 0.245)	0.493 (95% CI 0.493 to 0.493)	0.436 (95% CI 0.436to 0.436)
0	0.7	0.49 (95% CI 0.49 to 0.49)	0.7 (95% CI 0.7 to 0.7)	0.692 (95% CI 0.692 to 0.693)
0.1	0.05	0.004 (95% CI 0.004 to 0.004)	0.018 (95% CI 0.018 to 0.018)	0.007 (95% CI 0.007 to 0.007)
0.1	0.1	0.011 (95% CI 0.011 to 0.011)	0.049 (95% CI 0.049 to 0.049)	0.022 (95% CI 0.021 to 0.022)
0.1	0.3	0.094 (95% CI 0.094 to 0.094)	0.25 (95% CI 0.25 to 0.25)	0.172 (95% CI 0.171 to 0.172)
0.1	0.5	0.267 (95% CI 0.267 to 0.268)	0.482 (95% CI 0.482 to 0.482)	0.425 (95% CI 0.425to 0.425)
0.1	0.7	0.51 (95% CI 0.509to 0.51)	0.697 (95% CI 0.697 to 0.697)	0.679 (95% CI 0.679to 0.679)
0.4	0.05	0.019 (95% CI 0.019to 0.019)	0.037 (95% CI 0.037 to 0.037)	0.029 (95% CI 0.029to 0.029)
0.4	0.1	0.042 (95% CI 0.042 to 0.042)	0.078 (95% CI 0.078 to 0.078)	0.062 (95% CI 0.062 to 0.062)
0.4	0.3	0.166 (95% CI 0.166 to 0.167)	0.267 (95% CI 0.267 to 0.267)	0.231 (95% CI 0.231 to 0.231)
0.4	0.5	0.344 (95% CI 0.344 to 0.344)	0.476 (95% CI 0.476 to 0.476)	0.44 (95% CI 0.44 to 0.441)
0.4	0.7	0.57 (95% CI 0.57 to 0.57)	0.689 (95% CI 0.688 to 0.689)	0.666 (95% CI 0.666 to 0.666)
0.7	0.05	0.035 (95% CI 0.035 to 0.035)	0.046 (95% CI 0.046 to 0.046)	0.042 (95% CI 0.042 to 0.042)
0.7	0.1	0.071 (95% CI 0.071 to 0.071)	0.092 (95% CI 0.092 to 0.092)	0.085 (95% CI 0.085 to 0.085)
0.7	0.3	0.233 (95% CI 0.233 to 0.234)	0.285 (95% CI 0.285 to 0.285)	0.27 (95% Cl 0.27 to 0.27)
0.7	0.5	0.422 (95% CI 0.421 to 0.422)	0.486 (95% CI 0.485 to 0.486)	0.469 (95% CI 0.468 to 0.469)
0.7	0.7	0.635 (95% CI 0.635 to 0.635)	0.69 (95% CI 0.69 to 0.691)	0.678 (95% CI 0.677 to 0.678)
0.9	0.05	0.042 (95% CI 0.042 to 0.042)	0.048 (95% CI 0.048 to 0.048)	0.046 (95% CI 0.046to 0.046)
0.9	0.1	0.085 (95% CI 0.085 to 0.085)	0.096 (95% CI 0.096to 0.097)	0.093 (95% CI 0.093to 0.093)
0.9	0.3	0.268 (95% CI 0.268 to 0.268)	0.293 (95% CI 0.293 to 0.293)	0.286 (95% CI 0.286to 0.287)
0.9	0.5	0.463 (95% CI 0.463 to 0.463)	0.493 (95% CI 0.492 to 0.493)	0.485 (95% CI 0.485to 0.486)
0.9	0.7	0.669 (95% CI 0.669 to 0.669)	0.695 (95% CI 0.694 to 0.695)	0.688 (95% CI 0.688 to 0.688)
Cl, confidence interval.				



R-squared. The diagnosis of dysthymic disorder is approximated by all variable, including input symptoms and bias variables, using forward-stepwise regression. The selection of the variables was determined by adjusted R-squared. Circles are the maximal adjusted R-squared achieved by the regression with input symptoms, bias variables, or both of them. See table 4 for the details in the input symptoms and the bias variables. The assumed correlations between the input symptoms are 0.4 and the assumed prevalence rates of the input symptoms are 0.7 in this figure.

# Associations between the diagnoses and input symptoms or bias variables

1.0

0.8

0.6

0.4

0.2

0.0

Adjusted R squared

The diagnoses were first interpreted with the input symptoms (including intermediate variables) and the bias variables individually. The diagnosis of dysthymic disorder, for example, was interpreted with the input symptoms, the bias variables, and both in figure 5. For each simulation, the diagnosis of dysthymic disorder was approximated with an increasing number of the input symptoms, the bias variables or both. After selecting the variables that best approximated the diagnosis based on adjusted R-squared, the input symptoms could explain a proportion of 0.956 of the diagnosis variance and the bias variables could explain at most a proportion of 0.405 of the diagnosis variance in figure 5. With all variables used in the regression, the diagnosis could be perfectly explained by the input symptoms and bias variables (adjusted R-squared=1). The individual input symptoms and the bias variables that individually best explained the diagnoses are listed in tables 6 and 7, respectively.

For the diagnosis of major depressive episodes, the first or second items in the major criteria (variable names: mde\_ma1 or mde\_ma2 in table 2) individually best explained the diagnosis depending on the assumed prevalence rates and correlations in table 6. For the diagnosis of dysthymic disorder, the major criteria (dys\_ma in table 3) consistently and individually explained the diagnosis

Protected by copyright, including for uses related to text and data the best. For the diagnosis of manic episodes, the third item of the major criteria (man ma3 in table 4) individually best explained the diagnosis in all combinations of assumed prevalence rates and correlations. However, the proportions of diagnosis variances best explained by indi-≥ vidual input symptoms varied widely between 0.001 and 0.974, depending on the assumed prevalence rates and between-variable correlations. Based on a high correlang, tion with the diagnoses, certain input variables or symptoms were more important than others, such as the major criteria for the diagnosis of dysthymic disorder. The <u>0</u> prevalence rates and between-variable correlations were important to determine the relationships between input symptoms and diagnoses.

Similarly, there were bias variables that consistently best explained the diagnoses in table 7. For the diagnosis of major depressive episodes, the biases due to categorisation of the numbers of confirmed input symptoms **g** (mde bias1 and mde bias2 in table 2) were the leading bias variable. The diagnosis of major depressive episodes not explained by the input symptoms or information censoring (mde\_bias in table 2) was the leading bias variable in two combinations of the assumed prevalence rates and correlations. For the diagnosis of dysthymic disorder, the residual of the diagnosis not explained by the major and minor criteria (dys\_bias in table 3) and the bias due to the categorisation of the confirmed input symptoms

Table 6The individual input symptoms that best explained the diagnoses based on adjusted R-squared: major depressiveepisodes, dysthymic disorder and manic episodes by assumed input symptom prevalence and correlations

Assumed correlations between input symptoms	Assumed prevalence of input symptoms	Major depressive episodes	Dysthymic disorder	Manic episodes
0	0.05	mde_ma1	dys_ma	man_ma3
0	0.05	0.001 (95% CI 0.001 to 0.001)	0.076 (95% CI 0.075to 0.077)	0.002 (95% CI 0.002 to 0.002)
0	0.1	mde_ma1	dys_ma	man_ma3
0	0.1	0.01 (95% CI 0.01 to 0.01)	0.228 (95% CI 0.227 to 0.229)	0.021 (95% Cl 0.02to 0.021)
0	0.3	mde_ma1	dys_ma	man_ma3
0	0.3	0.167 (95% CI 0.167 to 0.167)	0.774 (95% CI 0.773 to 0.774)	0.366 (95% CI 0.366 to 0.367)
0	0.5	mde_ma2	dys_ma	man_ma3
0	0.5	0.324 (95% Cl 0.324 to 0.325)	0.971 (95% CI 0.971 to 0.971)	0.773 (95% CI 0.772 to 0.773)
0	0.7	mde_ma2	dys_ma	man_ma3
0	0.7	0.412 (95% CI 0.412 to 0.412)	0.999 (95% CI 0.999to 0.999)	0.964 (95% CI 0.964 to 0.964)
0.1	0.05	mde_ma2	dys_ma	man_ma3
0.1	0.05	0.07 (95% CI 0.07 to 0.071)	0.353 (95% CI 0.352 to 0.355)	0.136 (95% CI 0.135 to 0.137)
0.1	0.1	mde_ma1	dys_ma	man_ma3
0.1	0.1	0.101 (95% CI 0.1 to 0.101)	0.462 (95% CI 0.461 to 0.463)	0.199 (95% CI 0.198 to 0.199)
0.1	0.3	mde_ma2	dys_ma	man_ma3
0.1	0.3	0.242 (95% CI 0.242 to 0.243)	0.777 (95% CI 0.777 to 0.778)	0.483 (95% CI 0.483 to 0.484)
0.1	0.5	mde_ma2	dys_ma	man_ma3
0.1	0.5	0.365 (95% CI 0.365 to 0.366)	0.932 (95% CI 0.931 to 0.932)	0.74 (95% Cl 0.74 to 0.741)
0.1	0.7	mde_ma2	dys_ma	man_ma3
0.1	0.7	0.445 (95% CI 0.445 to 0.446)	0.986 (95% CI 0.986to 0.986)	0.906 (95% CI 0.906 to 0.907)
0.4	0.05	mde_ma1	dys_ma	man_ma3
0.4	0.05	0.375 (95% Cl 0.373 to 0.376)	0.731 (95% Cl 0.729to 0.732)	0.561 (95% CI 0.559 to 0.562)
0.4	0.1	mde_ma1	dys_ma	man_ma3
0.4	0.1	0.395 (95% CI 0.394 to 0.396)	0.763 (95% CI 0.762 to 0.764)	0.595 (95% Cl 0.594 to 0.596)
0.4	0.3	mde_ma1	dys_ma	man_ma3
0.4	0.3	0.465 (95% CI 0.465 to 0.466)	0.851 (95% CI 0.85to 0.851)	0.701 (95% CI 0.701 to 0.702)
0.4	0.5	mde_ma2	dys_ma	man_ma3
0.4	0.5	0.525 (95% Cl 0.524 to 0.525)	0.908 (95% CI 0.908to 0.908)	0.787 (95% CI 0.786 to 0.787)
0.4	0.7	mde_ma2	dys_ma	man_ma3
0.4	0.7	0.568 (95% CI 0.568 to 0.569)	0.946 (95% CI 0.946to 0.947)	0.855 (95% CI 0.854 to 0.855)
0.7	0.05	mde_ma2	dys_ma	man_ma3

Continued

correlations between input symptoms	prevalence of input symptoms	Major depressive episodes	Dysthymic disorder	Manic episodes
0.7	0.05	0.688 (95% CI 0.687 to 0.69)	0.909 (95% CI 0.908 to 0.909)	0.831 (95% CI 0.83to 0.832)
0.7	0.1	mde_ma1	dys_ma	man_ma3
0.7	0.1	0.688 (95% CI 0.687 to 0.689)	0.912 (95% CI 0.911 to 0.913)	0.836 (95% CI 0.835 to 0.836)
0.7	0.3	mde_ma2	dys_ma	man_ma3
0.7	0.3	0.71 (95% CI 0.709 to 0.711)	0.93 (95% CI 0.93 to 0.93)	0.862 (95% CI 0.861 to 0.862)
0.7	0.5	mde_ma2	dys_ma	man_ma3
).7	0.5	0.729 (95% CI 0.728to 0.729)	0.944 (95% CI 0.943 to 0.944)	0.882 (95% CI 0.882 to 0.883)
0.7	0.7	mde_ma1	dys_ma	man_ma3
0.7	0.7	0.745 (95% CI 0.744 to 0.745)	0.954 (95% CI 0.954 to 0.955)	0.9 (95% CI 0.9 to 0.9)
0.9	0.05	mde_ma1	dys_ma	man_ma3
0.9	0.05	0.828 (95% CI 0.827 to 0.829)	0.958 (95% CI 0.957 to 0.958)	0.918 (95% CI 0.917 to 0.919)
0.9	0.1	mde_ma2	dys_ma	man_ma3
0.9	0.1	0.838 (95% CI 0.838to 0.839)	0.961 (95% CI 0.961 to 0.961)	0.925 (95% CI 0.924 to 0.925)
0.9	0.3	mde_ma2	dys_ma	man_ma3
0.9	0.3	0.856 (95% CI 0.856 to 0.857)	0.969 (95% CI 0.968 to 0.969)	0.937 (95% CI 0.936to 0.937)
0.9	0.5	mde_ma2	dys_ma	man_ma3
0.9	0.5	0.862 (95% CI 0.862 to 0.863)	0.972 (95% CI 0.972 to 0.972)	0.942 (95% CI 0.942 to 0.943)
0.9	0.7	mde_ma2	dys_ma	man_ma3
0.9	0.7	0.865 (95% CI 0.865 to 0.866)	0.974 (95% CI 0.974 to 0.974)	0.946 (95% CI 0.946 to 0.946)
See table 2 to 4 for variable with 95% confidence inter- correlations. CI, confidence interval.	e definitions. Adjusted R- vals (Cls) derived from 10	squared is derived from linear 0 simulations for each combina	regressions using individual inp ation of assumed input sympto	out symptoms as predictor m prevalence and

in the minor criteria (dys\_mi\_bias) were the leading bias variables. For the diagnosis of manic episodes, the bias due to the categorisation of the number of confirmed input symptoms in the minor criteria up to three (man bias1 in table 4) was the leading bias variables, except for two combinations of the assumed prevalence rates and correlations, in which the bias due to categorisation of the confirmed input symptoms in the minor criteria up to four (man\_bias2 in table 4) best explained the diagnosis. However, the proportions of diagnosis variances explained by individual bias variables varied widely from 0 to 0.87. Depending on the assumed prevalence rates and between-variable correlations of the input symptoms, certain bias variables were more important than other bias variables and even some input variables. The assumed prevalence rates and between-variable correlations were

important factors for the relationships between the bias variables and the diagnoses.

In general, the proportions of the diagnosis variance technologies. that could be explained by either individual input symptoms or single bias variables were low when the prevalence rates and between-variable correlations of the input symptoms were assumed to be low. With higher assumed prevalence rates or correlations, the proportions of the diagnoses explained by the single input symptoms or bias variables were higher. Across three diagnoses, the diagnosis of dysthymic disorder could be better explained by single input variables (higher adjusted R-squared), and the diagnosis of major depressive episodes was associated with the least adjusted R-squared. The bias variables of the diagnosis of manic episodes could explain the diagnosis

Assumed correlations between nput symptoms	Assumed prevalence of input symptoms	Major depressive episodes	Dysthymic disorder	Manic episodes
	0.05	mde_bias2	dys_bias	man_bias2
	0.05	0 (95% Cl 0 to 0)	0.028 (95% Cl 0.028 to 0.028)	0.001 (95% CI 0.001 to 0.001)
	0.1	mde_bias2	dys_bias	man_bias2
	0.1	0.004 (95% CI 0.004 to 0.004)	0.053 (95% CI 0.053 to 0.054)	0.011 (95% CI 0.011 to 0.011)
	0.3	mde_bias2	dys_bias	man_bias1
	0.3	0.015 (95% CI 0.015 to 0.015)	0.045 (95% Cl 0.045 to 0.045)	0.089 (95% CI 0.089 to 0.09)
	0.5	mde_bias	dys_bias	man_bias1
	0.5	0.013 (95% CI 0.013 to 0.014)	0.007 (95% CI 0.007 to 0.007)	0.035 (95% CI 0.034 to 0.035)
	0.7	mde_bias	dys_bias	man_bias1
	0.7	0.01 (95% CI 0.01 to 0.01)	0 (95% CI 0 to 0)	0.002 (95% CI 0.002 to 0.002)
1	0.05	mde_bias2	dys_bias	man_bias1
.1	0.05	0.037 (95% CI 0.037 to 0.037)	0.113 (95% CI 0.113to 0.114)	0.083 (95% CI 0.083 to 0.084)
1	0.1	mde_bias2	dys_bias	man_bias1
1	0.1	0.047 (95% CI 0.047 to 0.048)	0.122 (95% CI 0.121 to 0.122)	0.116 (95% CI 0.115to 0.116)
1	0.3	mde_bias2	dys_mi_bias	man_bias1
1	0.3	0.077 (95% CI 0.077 to 0.077)	0.105 (95% CI 0.105 to 0.106)	0.198 (95% CI 0.197 to 0.198)
.1	0.5	mde_bias2	dys_mi_bias	man_bias1
1	0.5	0.079 (95% Cl 0.079 to 0.08)	0.073 (95% Cl 0.073 to 0.073)	0.166 (95% CI 0.166 to 0.167)
1	0.7	mde_bias2	dys_mi_bias	man_bias1
1	0.7	0.065 (95% CI 0.065 to 0.065)	0.047 (95% Cl 0.046to 0.047)	0.094 (95% CI 0.093 to 0.094)
4	0.05	mde_bias1	dys_mi_bias	man_bias1
4	0.05	0.294 (95% CI 0.293 to 0.295)	0.415 (95% CI 0.413to 0.416)	0.432 (95% CI 0.431 to 0.433)
4	0.1	mde_bias1	dys_mi_bias	man_bias1
4	0.1	0.304 (95% CI 0.303 to 0.304)	0.419 (95% CI 0.418 to 0.42)	0.445 (95% CI 0.444 to 0.445)
4	0.3	mde_bias1	dys_mi_bias	man_bias1
4	0.3	0.335 (95% CI 0.334 to 0.335)	0.411 (95% CI 0.411 to 0.412)	0.473 (95% CI 0.472 to 0.473)
4	0.5	mde_bias1	dys_mi_bias	man_bias1
4	0.5	0.354 (95% CI 0.354 to 0.355)	0.395 (95% CI 0.395 to 0.396)	0.475 (95% Cl 0.474to 0.475)
4	0.7	mde_bias1	dys_mi_bias	man_bias1
4	0.7	0.356 (95% CI 0.355 to 0.356)	0.367 (95% CI 0.366 to 0.367)	0.451 (95% CI 0.45 to 0.451)
.7	0.05	mde_bias1	dys_mi_bias	man_bias1

Table 7 Continued

Assumed correlations between input symptoms	Assumed prevalence of input symptoms	Major depressive episodes	Dysthymic disorder	Manic episodes
0.7	0.05	0.616 (95% CI 0.615 to 0.617)	0.705 (95% CI 0.704 to 0.706)	0.723 (95% CI 0.722 to 0.724)
0.7	0.1	mde_bias1	dys_mi_bias	man_bias1
0.7	0.1	0.611 (95% CI 0.611 to 0.612)	0.699 (95% CI 0.698 to 0.699)	0.72 (95% CI 0.72 to 0.721)
0.7	0.3	mde_bias1	dys_mi_bias	man_bias1
0.7	0.3	0.623 (95% CI 0.623 to 0.624)	0.699 (95% CI 0.699 to 0.7)	0.728 (95% CI 0.728 to 0.729)
0.7	0.5	mde_bias1	dys_mi_bias	man_bias1
0.7	0.5	0.632 (95% CI 0.632 to 0.633)	0.696 (95% CI 0.696 to 0.697)	0.731 (95% CI 0.731 to 0.732)
0.7	0.7	mde_bias1	dys_mi_bias	man_bias1
0.7	0.7	0.639 (95% CI 0.638to 0.639)	0.693 (95% CI 0.692 to 0.693)	0.732 (95% CI 0.731 to 0.732)
0.9	0.05	mde_bias1	dys_mi_bias	man_bias1
0.9	0.05	0.777 (95% CI 0.776to 0.778)	0.835 (95% Cl 0.834to 0.835)	0.847 (95% CI 0.847 to 0.848)
0.9	0.1	mde_bias1	dys_mi_bias	man_bias1
0.9	0.1	0.788 (95% CI 0.788to 0.789)	0.842 (95% Cl 0.841 to 0.843)	0.855 (95% CI 0.854 to 0.855)
0.9	0.3	mde_bias1	dys_mi_bias	man_bias1
0.9	0.3	0.807 (95% CI 0.806 to 0.807)	0.854 (95% CI 0.853 to 0.854)	0.867 (95% CI 0.867 to 0.868)
0.9	0.5	mde_bias1	dys_mi_bias	man_bias1
0.9	0.5	0.811 (95% CI 0.811 to 0.811)	0.855 (95% CI 0.855to 0.856)	0.87 (95% CI 0.87 to 0.871)
0.9	0.7	mde_bias1	dys_mi_bias	man_bias1
0.9	0.7	0.812 (95% CI 0.811 to 0.812)	0.853 (95% CI 0.853 to 0.853)	0.869 (95% CI 0.869 to 0.87)

See table 2 to 4 for variable definitions. Adjusted R-squared is derived from linear regressions using individual bias variables as predictor with 95% confidence intervals (CIs) derived from 100 simulations for each combination of assumed input symptom prevalence and correlations. CI, confidence interval.

individually better than the bias variables of the other two diagnoses.

# Approximating the diagnoses with input symptoms

When the diagnoses were approximated by all of their own input symptoms (table 8), there were always some diagnosis variances that could not be explained by the input symptoms. In other words, the input symptoms together could not fully explain the diagnoses, except for the diagnosis of dysthymic disorder that could be fully explained by the input symptoms (adjusted R-squared=1) assuming 0 between-variable correlations and 0.7 prevalence rates for the input symptoms. In table 8, the proportions of diagnosis variances explained by input symptoms increased with higher assumed prevalence rates or between-variable correlations of the input symptoms in general. The input symptoms of dysthymic disorder explained the diagnosis better than those of the other two diagnoses under all combinations of assumed prevalence rates and between-variable correlations. However, the proportion of diagnosis variance explained by own input symptoms varied widely from 0.003 to 1.0. The assumed prevalence rates and between-variable correlations of the input symptoms and the design of the diagnostic criteria were all important for the relationships between input symptoms and diagnoses.

# Approximating the diagnoses with bias variables

The diagnoses were approximated with the bias variables of their own. The bias variables always explained some of the diagnosis variances, except for the diagnosis of dysthymic disorder assuming 0 between-variable correlations and 0.7 prevalence rates for the input symptoms (adjusted R-squared=0). With increasing assumed

Table 8 Approximating the	diagnoses using input sympto	ms and derived adjusted R-squared		
Assumed correlations between input symptoms	Assumed prevalence of input symptoms	Major depressive episodes	Dysthymic disorder	Manic episodes
0	0.05	0.003 (95% CI 0.002 to 0.003)	0.122 (95% CI 0.121 to 0.123)	0.004 (95% CI 0.004to 0.005)
0	0.1	0.024 (95% CI 0.023to 0.024)	0.305 (95% CI 0.304 to 0.306)	0.039 (95% CI 0.038to 0.039)
0	0.3	0.348 (95% CI 0.348 to 0.349)	0.842 (95% CI 0.841 to 0.842)	0.483 (95% CI 0.482 to 0.483)
0	0.5	0.649 (95% CI 0.649to 0.649)	0.986 (95% CI 0.986 to 0.986)	0.817 (95% CI 0.817 to 0.817)
0	0.7	0.823 (95% CI 0.823 to 0.823)	1 (95% CI 1 to 1)	0.967 (95% CI 0.967 to 0.967)
0.1	0.05	0.143 (95% CI 0.141 to 0.144)	0.435 (95% CI 0.433 to 0.436)	0.212 (95% CI 0.211 to 0.213)
0.1	0.1	0.198 (95% CI 0.197 to 0.199)	0.539 (95% CI 0.538 to 0.54)	0.29 (95% CI 0.289 to 0.291)
0.1	0.3	0.45 (95% CI 0.45 to 0.451)	0.826 (95% CI 0.826 to 0.827)	0.588 (95% CI 0.588 to 0.589)
0.1	0.5	0.663 (95% CI 0.663 to 0.664)	0.952 (95% CI 0.952 to 0.952)	0.799 (95% CI 0.799to 0.799)
0.1	0.7	0.809 (95% CI 0.809 to 0.809)	0.991 (95% CI 0.991 to 0.991)	0.922 (95% CI 0.922 to 0.922)
0.4	0.05	0.587 (95% CI 0.585 to 0.588)	0.782 (95% CI 0.781 to 0.783)	0.675 (95% CI 0.674 to 0.676)
0.4	0.1	0.607 (95% CI 0.606 to 0.608)	0.807 (95% CI 0.807 to 0.808)	0.698 (95% CI 0.697 to 0.698)
0.4	0.3	0.688 (95% CI 0.688 to 0.689)	0.878 (95% CI 0.877 to 0.878)	0.775 (95% CI 0.774 to 0.775)
0.4	0.5	0.761 (95% CI 0.761 to 0.762)	0.925 (95% CI 0.924 to 0.925)	0.838 (95% CI 0.838 to 0.838)
0.4	0.7	0.821 (95% CI 0.821 to 0.822)	0.956 (95% CI 0.956 to 0.956)	0.887 (95% CI 0.887 to 0.888)
0.7	0.05	0.813 (95% CI 0.812 to 0.814)	0.925 (95% CI 0.925 to 0.926)	0.877 (95% CI 0.877 to 0.878)
0.7	0.1	0.826 (95% CI 0.826 to 0.827)	0.928 (95% CI 0.927 to 0.928)	0.881 (95% CI 0.881 to 0.882)
0.7	0.3	0.86 (95% CI 0.86to 0.86)	0.942 (95% CI 0.942 to 0.942)	0.9 (95% CI 0.9to 0.9)
0.7	0.5	0.88 (95% CI 0.88 to 0.88)	0.953 (95% CI 0.953 to 0.953)	0.913 (95% CI 0.913 to 0.913)
0.7	0.7	0.895 (95% CI 0.895 to 0.895)	0.962 (95% CI 0.962 to 0.962)	0.925 (95% CI 0.925 to 0.925)
0.9	0.05	0.903 (95% CI 0.903 to 0.904)	0.965 (95% CI 0.965 to 0.966)	0.941 (95% CI 0.94to 0.941)
0.9	0.1	0.91 (95% CI 0.91 to 0.911)	0.968 (95% CI 0.968 to 0.968)	0.945 (95% CI 0.945 to 0.945)
0.0	0.3	0.923 (95% CI 0.923to 0.923)	0.974 (95% CI 0.974 to 0.974)	0.954 (95% CI 0.953 to 0.954)
0.9	0.5	0.928 (95% CI 0.928 to 0.928)	0.976 (95% CI 0.976 to 0.977)	0.958 (95% CI 0.957 to 0.958)
0.0	0.7	0.932 (95% CI 0.932 to 0.932)	0.978 (95% CI 0.978 to 0.978)	0.96 (95% CI 0.96to 0.96)
Adjusted R-squared is the maxin simulations for each combination	nal values from the forward-stepw of assumed input symptom prev	ise linear regressions using all input symp alence and correlations.	toms as candidate predictors with 95% c	onfidence intervals (Cls) derived from 100

Cl, confidence interval.

between-variable correlations for the input symptoms, the adjusted R-squared increased. However, given the same assumed between-variable correlations, the proportions of diagnosis variances explained by the bias variables might increase or decrease with the assumed prevalence rates. Compared with the adjusted R-squared in table 8, the proportion of the diagnosis variances explained by the bias variables was always smaller than that explained by the input symptoms in table 9. The proportions of the diagnosis variance explained by bias variables also varied widely from 0 to 0.89. The assumed prevalence rates and between-variable correlations of input symptoms and the design of the diagnostic criteria were important for the relationship between the bias variables and the diagnoses. Only when the input symptoms for the diagnosis of dysthymic disorder were randomly and independently prevalent to 70% of the simulated populations, the bias variables became irrelevant to the diagnosis.

#### DISCUSSION

This study is a first attempt to assess the biases created by mental illness diagnostic criteria, as well as understand the relationships between input symptoms and the diagnoses of three mental illnesses: major depressive episodes (at least one episode required for the diagnosis of major depressive disorder), dysthymic disorder and manic episodes. The diagnostic criteria of these three mental illnesses have been reviewed and rewritten as mathematical functions. Simulated populations of 100000 for each of 100 simulations, with input symptoms of the three diagnoses, were created. For simplicity and practicality, the presence of the input symptoms was randomly assigned, and the input symptoms were assumed to have uniform prevalence rates and between-variable correlations. There were 25 combinations of assumed prevalence rates and between-variable correlations simulated.

Mathematically, the diagnostic criteria are functions and composite measures to transform information from the input symptoms to diagnoses. There are bias variables created by the diagnostic criteria due to data processing.<sup>4</sup> There are three major mechanisms of introducing biases: censoring, data categorisation<sup>8</sup> and multiplication of input symptoms.<sup>7</sup> These mechanisms introduce information or biases that cannot be fully explained by the input symptoms.<sup>7</sup> The introduced biases can sometimes explain more than half of the variance in the diagnoses depending on the prevalence rates and between-variable correlations of the input symptoms. The findings show that the design of the diagnostic criteria is important for bias introduction and significant for the prevalence of the diagnoses in populations, the relationships between the input symptoms and the diagnoses, and the relationships between the bias variables and the diagnoses.

#### The role of the diagnostic criteria

With the same assumptions in the prevalence rates and between-variable correlations of the input symptoms, the

design of the diagnostic criteria of three mental illnesses can be compared with each other. The design of diagnostic criteria transform input symptoms into various diagnosis prevalence rates with implicit upper limits (ie, no more prevalent than the input symptoms), unacknowledged differential weights on the input symptoms (ie, certain input symptoms better explaining the diagnoses) and the introduction of biases (ie, due to censoring, data categorisation or multiplication).

We are the first to notice that the prevalence rates of **u** the three diagnoses are lower than those of the input symptoms if input symptoms are randomly distributed with uniform prevalence rates and correlations. Given similar assumed input symptom prevalence and correlations, dysthymic disorder is the most prevalent, and 8 major depressive episodes are the least. The diagnosis of dysthymic disorder can be better explained by its input symptoms individually or collectively than the other two diagnoses. The diagnosis of major depressive episodes is least explained by own input symptoms individually or collectively. As expected, the diagnosis of the three mental illness is similar to composite measures or indices and is subject to the biases introduced by data processing, given all combinations of the assumed prevalence rates and between-variable correlations of the input symptoms.<sup>7</sup> There is only one exception: dysthymic disorder with the input symptoms that are randomly and independently present in 70% of the population. This is because the diagnosis of dysthymic disorder is a multiplicative product of the major and minor criteria. Without correlations, everyone in the population is certain to qualify for the minor criteria (probability of 100% because having at least two out of the six items in the minor criteria: mathematically  $[C(2,6)+C(3,6)+C(4,6)+C(5,6)+C(6,6)] \times (0.7)^6$  $= 37 \times 0.117 = 4.35 > 100\%$ ). If 70% of the population were also randomly assigned with the major criteria and 100% were assigned with the minor criteria, 70% would be diagnosed with dysthymic disorder and the diagnosis of dysthymic disorder can be fully explained by the major criteria. In fact, without correlations between input symptoms, it only requires each of the six items in the minor criteria to be randomly assigned to 54.8%  $[(1/37)^{(1/6)}]$ of the population for everyone to qualify for the minor criteria, and the diagnosis can be fully explained by the minor and major criteria.

Distortion of the input symptoms
The importance of the input symptoms has been distorted g

due to the diagnostic criteria for the three mental illnesses. The same phenomenon has been proven in the diagnosis of frailty based on three of the most commonly used scoring methods.<sup>7</sup> In other words, based on the functions to generate the diagnoses, the input symptoms are differentially weighted, and weights are not explicitly acknowledged. The most prominent is the diagnosis of dysthymic disorder; more than 90% of the variance can be explained by its major criteria assuming 0.7 or 0.9 between-variable correlations for the input symptoms in table 6. Another

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Table 9 Approximating the	diagnoses using bias variables	and derived R-squared		
Assumed correlations between input symptoms	Assumed prevalence of input symptoms	Major depressive episodes	Dysthymic disorder	Manic episodes
0	0.05	0.003 (95% CI 0.002 to 0.003)	0.029 (95% CI 0.029 to 0.03)	0.004 (95% CI 0.004 to 0.004)
0	0.1	0.013 (95% CI 0.012to 0.013)	0.056 (95% CI 0.056to 0.056)	0.017 (95% CI 0.017to 0.017)
0	0.3	0.083 (95% CI 0.083 to 0.083)	0.047 (95% CI 0.047 to 0.047)	0.098 (95% CI 0.098to 0.099)
0	0.5	0.111 (95% CI 0.111 to 0.112)	0.007 (95% CI 0.007 to 0.007)	0.039 (95% CI 0.038to 0.039)
0	0.7	0.095 (95% CI 0.095 to 0.095)	0 (95% CI 0 to 0)	0.012 (95% CI 0.012to 0.013)
0.1	0.05	0.083 (95% CI 0.082 to 0.084)	0.145 (95% CI 0.144to 0.146)	0.126 (95% CI 0.125to 0.127)
0.1	0.1	0.096 (95% CI 0.095 to 0.097)	0.156 (95% CI 0.155to 0.156)	0.154 (95% CI 0.153 to 0.154)
0.1	0.3	0.145 (95% CI 0.144 to 0.145)	0.139 (95% CI 0.138to 0.139)	0.216 (95% CI 0.216to 0.216)
0.1	0.5	0.172 (95% CI 0.172 to 0.173)	0.097 (95% CI 0.097 to 0.097)	0.182 (95% CI 0.181 to 0.182)
0.1	0.7	0.175 (95% CI 0.175 to 0.175)	0.065 (95% CI 0.064 to 0.065)	0.115 (95% CI 0.115to 0.116)
0.4	0.05	0.421 (95% CI 0.419 to 0.423)	0.455 (95% CI 0.453 to 0.456)	0.505 (95% CI 0.504 to 0.506)
0.4	0.1	0.422 (95% CI 0.421 to 0.423)	0.454 (95% CI 0.453 to 0.455)	0.507 (95% CI 0.506to 0.508)
0.4	0.3	0.435 (95% CI 0.434 to 0.435)	0.442 (95% CI 0.442 to 0.443)	0.512 (95% CI 0.512 to 0.513)
0.4	0.5	0.452 (95% CI 0.452 to 0.453)	0.427 (95% CI 0.427 to 0.427)	0.506 (95% CI 0.505 to 0.506)
0.4	0.7	0.46 (95% CI 0.459to 0.46)	0.403 (95% CI 0.402 to 0.403)	0.481 (95% CI 0.481 to 0.482)
0.7	0.05	0.728 (95% CI 0.727 to 0.729)	0.729 (95% CI 0.728 to 0.731)	0.764 (95% CI 0.763 to 0.765)
0.7	0.1	0.722 (95% CI 0.721 to 0.723)	0.723 (95% CI 0.722 to 0.724)	0.76 (95% CI 0.759to 0.761)
0.7	0.3	0.726 (95% CI 0.726 to 0.727)	0.722 (95% CI 0.722 to 0.723)	0.761 (95% CI 0.761 to 0.762)
0.7	0.5	0.732 (95% CI 0.731 to 0.732)	0.72 (95% CI 0.719 to 0.72)	0.76 (95% CI 0.76 to 0.761)
0.7	0.7	0.737 (95% CI 0.736 to 0.737)	0.717 (95% CI 0.716 to 0.717)	0.758 (95% CI 0.758 to 0.759)
0.9	0.05	0.852 (95% CI 0.851 to 0.853)	0.85 (95% CI 0.849 to 0.851)	0.871 (95% CI 0.871 to 0.872)
0.9	0.1	0.86 (95% CI 0.859 to 0.861)	0.857 (95% CI 0.856 to 0.857)	0.876 (95% CI 0.876 to 0.877)
0.9	0.3	0.872 (95% CI 0.871 to 0.872)	0.867 (95% CI 0.867 to 0.868)	0.886 (95% CI 0.886 to 0.886)
0.9	0.5	0.874 (95% CI 0.874 to 0.875)	0.869 (95% CI 0.868 to 0.869)	0.888 (95% CI 0.887 to 0.888)
0.9	0.7	0.874 (95% CI 0.874to 0.875)	0.867 (95% CI 0.866 to 0.867)	0.886 (95% CI 0.886 to 0.886)
Adjusted R-squared is the maxin simulations for each combinatior CI, confidence interval.	al values from the forward-stepw of assumed input symptom prev	ise linear regressions using all bias variabl alence and correlations.	les as candidate predictors with 95% con	idence intervals (Cls) derived from 100

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example is that the third item of the major criteria for the diagnosis of manic episodes, 'irritable mood, 'individually predicts the diagnosis better than any other input symptoms or intermediate variables. This input symptom has been given more weight than others and can explain more than 91.8% of the diagnosis variance, assuming 0.9 correlations between input symptoms. Based on the texts in the DSM-IV-TR, we do not think this symptom should be emphasised to this degree. However, the diagnostic criteria impose implicit and unequal weights to the input symptoms, and introduce biases into the diagnoses.

### **Future directions**

We think it important to rethink the role and importance of the diagnostic system. Current approaches are embedded with implicit assumptions of the prevalence rates of the diagnoses (no higher than input symptoms if the prevalence of input symptoms are similar), unacknowledged weights to input symptoms (certain input symptoms explaining the diagnoses much better) and biases that are induced by data processing and could not be explained by the input symptoms. It is unclear whether the diagnosis of dysthymic disorder was intentionally designed to be more prevalent than those of major depressive episodes or manic episodes, given their input symptoms of the same prevalence rates.

In the real world, there are other important issues related to the diagnostic criteria. For example, diagnoses are not closely linked to treatment,<sup>20 30</sup> diagnoses are not well made particularly by non-psychiatrists,<sup>31</sup> and there are two diagnostic systems (the DSM and the International Classification of Disease) that require efforts to harmonise.<sup>32</sup> Amid these issues, we think the diagnostic criteria for mental illnesses should be reviewed and improved for interpreteability, clinical use without introducing biases, and better connection to clinical decisions. Certain measures and biomarkers have been proven useful to identify mental illnesses.<sup>33 34</sup> We are developing methods that better detect symptom-based conditions and applying syndrome mining techniques<sup>35</sup> to search for neglected mental illnesses.

### LIMITATIONS

The strength of this study is the use of simple assumptions in simulated populations that enables the comparison of the diagnostic criteria of three mental illnesses. However, the assumptions in the prevalence rates and betweenvariable correlations for the input symptoms might not be realistic. Some of the assumptions are unlikely to hold in the real world. However, simulations are the only option for us due to the lack of real-world data on the prevalence of the input symptoms. In addition, the translation from symptoms to diagnoses was assumed to be perfect based on the diagnostic criteria. The simulations in this study only reflect the problems in the design of the diagnostic criteria and are not designed to review the impact of how they are used in the real world.

To the best of our knowledge, there is no study on the relationships between the input symptoms and diagnoses. The input symptoms were extracted from the diagnostic criteria and the diagnostic criteria were transformed into mathematical functions. Without mental illness data available to the public, 100000 subjects were simulated with different assumptions on the prevalence rates (0.05,0.1, 0.3, 0.5 and 0.7) and correlations (0, 0.1, 0.4, 0.7 and 0.9) of the input symptoms. We found that biases were  $\underline{P}$ introduced into the diagnoses of three mental illnesses: major depressive episodes, dysthymic disorder, and manic episodes. The prevalence rates of the diagnoses were proportional to the assumed prevalence rates and between-variable correlations of the input symptoms. Certain input symptoms were more important than the others in explaining the diagnoses. However, the input a symptoms could not fully explain the diagnoses, except when the input symptoms independent of each other with 0.7 symptom prevalence rates were used for the diagnosis of dysthymic disorder. In conclusion, the criteria used to diagnose these three mental illnesses may fail to repre-₫ sent the concepts they are based on, in a similar manner r uses related to text and data mining, Al training, and similar technologies to three of the most commonly used scoring methods to diagnose frailty.

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