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The added value of daily diary data in 1- and 3-year prediction of psychopathology and psychotic experiences in individuals at risk for psychosis

S. van der Tuin [a,*], S.H. Booij [a,b], M.K. Muller [a,c], D. van den Berg [d,e], A.J. Oldehinkel [a], J.T.W. Wigman [a]

[a] Dept of Psychiatry, Interdisciplinary Centre Psychopathology and Emotion regulation, University of Groningen, University Medical Center Groningen, Hanzeplein 1 (Entrance 24- Triade), Groningen 9700 RB, the Netherlands
[b] Center for Integrative Psychiatry, Lentis, Groningen, the Netherlands
[c] Department of Psychiatry, Rijks Universiteit Groningen, University Medical Center Groningen, GGZ Drenthe Mental Health Institution, Assen, the Netherlands
[d] Department of Clinical Psychology, Amsterdam Public Health Research Institute, Vrije Universiteit Amsterdam, the Netherlands
[e] Department of Psychosis research and Innovation, Parnassia Psychiatric Institute, the Hague, the Netherlands

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ABSTRACT

This study aimed to assess whether adding information on psychological experiences derived from a daily diary to baseline cross-sectional data could improve short- (1-year) and long-term (3-years) prediction of psychopathology and positive psychotic experiences (PEs). We used 90-day daily diary data from 96 individuals in early subclinical risk stages for psychosis. Stepwise linear regression models were built for psychopathology and PEs at 1- and 3-years follow-up, adding: (1) baseline questionnaires, (2) the mean and variance of daily psychological experiences, and (3) individual symptom network density. We assessed whether similar results could be achieved with a subset of the data (7–14- and 30-days). The mean and variance of the diary improved model prediction of short- and long-term psychopathology and PEs, compared to prediction based on baseline questionnaires solely. Similar results were achieved with 7–14- and 30-day subsets. Symptom network density did not improve model prediction except for short-term prediction of PEs. Simple metrics, i.e., the mean and variance from 7 to 14 days of daily psychological experiences assessments, can improve short- and long-term prediction of both psychopathology and PEs in individuals in early subclinical stages for psychosis. Diary data could be a valuable addition to clinical risk prediction models for psychopathology development.

1. Introduction

Psychotic disorders are among the most disruptive mental disorders and come with huge impact on affected individuals, their direct environment and society (Fusar-Poli et al., 2017; Oud and Meyboom-de Jong, 2009; van Os et al., 2009). Psychosis usually develops gradually with psychotic experiences (PEs), defined as subclinical expressions of psychotic symptoms, being present prior to a first psychotic episode. The clinical staging model acknowledges this gradual development of psychosis and defines four stages through which individuals can, but not necessarily do, progress (McGorry et al., 2006). At the one end of the continuum (stage 0) are individuals with an increased risk to develop psychosis, and at the other end (stage 4) are individuals with chronic psychotic illness (McGorry et al., 2006). The early clinical stages for psychosis are characterized by a diffuse and transdiagnostic symptom pattern (Cross et al., 2014; Hickie et al., 2013). Therefore, in psychosis development prediction, it is important to also consider non-psychosis-specific symptoms like sad mood and anxiety. The ability to predict how psychosis develops from the early stages onwards can aid in identifying individuals who are most at risk to progress, and hence might benefit most from early intervention. However, the ability to predict who will progress to more severe illness can be improved (De Pablo et al., 2021; Yung and McGorry, 2007).

Most research on the prediction of psychosis in the context of the staging model has focused on predicting the onset of a first episode of psychosis in those considered at Ultra-High Risk (UHR; more recently

* Corresponding author.
E-mail address: s.van.der.tuin@umcg.nl (S. van der Tuin).

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also labeled as Clinical High Risk (CHR)) for psychosis. Several risk factors have been identified for individuals at CHR to progress into more established illness, including severity of symptoms or lower functioning at baseline, associated distress, comorbid psychopathology and cognitive deficits (Riecher-Rössler et al., 2009; Yung and McGorry, 2007). Furthermore, persistent negative or disorganized thoughts were found to predict the onset of psychotic experiences in the general population (Dominguez et al., 2010) and low baseline functioning was associated with psychosis onset in help-seeking young individuals (Yung et al., 2006). Factors that increase the risk of transitioning to psychosis have mostly been investigated using questionnaires, interviews or other cross-sectional assessment methods, which come with low patient and clinician burden but have demonstrated only moderate predictive capacity (Fusar-Poli et al., 2020; Rosen et al., 2021). Therefore, it is important to investigate whether other assessment methods, which take a different approach to conceptualizing and measuring risk, can improve predictive accuracy. One such different assessment method lies in ambulatory assessment, where PEs as potential risk factors are assessed in the context of daily life. Because the collection of such data, however, requires a much higher investment of participants, this effort must be justified.

Over the last decade, mental illness has been increasingly studied from a symptom network perspective. The network theory of psychopathology states that mental illness is better explained as the interaction between symptoms (i.e., as a network) than as a consequence of one underlying cause (Borsboom, 2017). Symptom networks visualize the associations (edges) between symptoms (nodes) (Epskamp et al., 2018). In addition to modeling networks of cross-sectional data, symptom networks can be constructed at the individual level using intensive longitudinal data, also known as diary data, Ambulatory Assessments (AA) or Ecological Momentary Assessments (EMA)). The symptom network approach to psychopathology has led to new hypotheses to explain and predict the development of mental illness. One hypothesis is the 'density hypothesis' (Borsboom, 2017), which states that more strongly connected networks are posing a vulnerability for more (severe) psychopathology, as one small perturbation to the network can activate all other nodes in the network. Hence, network indices such as density might be of added value to the prediction of psychosis.

Several studies used intensive longitudinal data to construct individual symptom networks and showed a positive association of individual symptom network density with depression diagnosis (Pe et al., 2014) and depressive scores (Lydon-Staley et al., 2019), but the findings are not highly robust. A study in which positive affect and negative affect were assessed with EMA (9 times per day, 8 days) and daily diary data (50 days) found that the network density of both positive affect and negative affect was cross-sectionally associated with anxiety and depression when using the EMA dataset, but not when using daily diary data (Shin et al., 2022). Furthermore, a previous study using the same sample as the current study did not reveal cross-sectional differences in individual network density between subgroups with different levels of risk for psychosis (van der Tuin et al., 2022). Groen et al. (2019) also found no differences in network density between young adults with persistent and those with reduced depressive symptoms at 6-month follow-up. Due to the contradicting results and weak associations between density and symptoms, the predictive value of network density remains unclear.

Recently, DeJonckheere et al. (2019) proposed that simple metrics from ILD may work better in the prediction of psychopathology than a complex metric like density. They analyzed data from 15 different studies ($n = 1777$) with time series data and found that the mean, and to a lesser extend the standard deviation, of positive affect and negative affect of the time series were better predictors of psychological well-being than complex affect dynamic measures like network density. This is in line with a study by Shin et al. (2022), who found that network density based on a daily diary was not related to anxiety and depression, but the mean score of positive affect and negative affect was. Likewise, Minaeva et al. (2021) found that a simple measure of morning negative affect predicted depression development one year later, while a more complex measure of negative affect inertia did not. In addition, Sperry et al. (2020) found that higher negative affect variance predicted bipolar spectrum psychopathology at three-year follow-up. These findings raise the question whether complex measures such as density should be considered as illness predictor or more simple metrics are equally good or even better predictors. Regardless of whether complex or simple metrics are used, one important disadvantage of intensive longitudinal data is its relatively high burden on participants. This higher burden is only justified if the assessments have *additive* predictive power on top of traditional, less burdensome measures such as single-time questionnaires. When intensive longitudinal data actually has additional value, a relevant next question is how many data points are sufficient to establish this effect (Kuranova et al., 2020). To the best of our knowledge, no study to date assessed the additive predictive power of (a) the mean and variance of diary data and (b) individual symptom network density based on diary data in the prediction of mental health in individuals at risk for psychosis.

In the current study, we aimed to assess whether the short-term (1-year) and long-term (3-years) prediction of psychopathology and PEs could be improved by adding information retrieved from 90-day daily diary data in addition to cross-sectional questionnaires in a sample of individuals in early subclinical stages of psychosis. We used a stepwise prediction model for each outcome, starting with (i) baseline questionnaire, then adding (ii) the mean and variance of the diary data and lastly (iii) density of individual symptom networks. As the early clinical stages for psychosis are characterized by a diffuse and transdiagnostic symptom pattern, both specific PEs and more general psychopathology levels could be predictive of future PEs. The Clinical High at Risk Mental State (CHARMS) approach incorporates this by including several transdiagnostic symptoms in the early clinical stages (McGorry et al., 2018). In addition, Shah et al. (2017) found that 32 % of individuals with a first episode of psychosis had broad early symptoms like depression, anxiety and low functioning rather than specific PEs before their psychosis diagnosis. This highlights that it is can be beneficial to assess, in addition to specific PEs, also more general psychopathology when predicting PEs. Therefore, we used diary metrics from both general psychopathology and PEs as predictors. The steps that we used to build our models reflect the increasing effort to collect the data as well as the complexity of the used metrics. The mean and variance of the diary data are both relatively simple measures; they are also often simultaneously computed and are therefore added at the same time in step 2. Network density is a more complex measure, both conceptually and computationally, and therefore should only be used when it outperforms more simple measures. The mean, variance and network density are partly related constructs, but also have their own predictive value (Dejonckheere et al., 2019). The mean and variance are statistically unrelated constructs when they come from a normal distribution, but are more correlated when the mean is low (and the variance is thus also often low). We expected the latter for PEs, but not psychopathology. Network density is based on how strongly fluctuation in one symptom is associated with fluctuations in other symptoms and is thus particularly associated with variance. Therefore, we expected a relatively high correlation of symptom network density with the variance of diary data, but not with the mean. We also assessed whether a shorter diary-period (30–14–7 days) would yield similar results. In terms of prediction, we hypothesized that short-term prediction of psychopathology and PEs would be better than long-term prediction. We also hypothesized that adding the mean and variance of the diary data would improve model prediction, but that adding network density would not. Lastly, we hypothesized that diary metrics of both PEs and psychopathology would improve model prediction.

2. Methods

2.1. Participants and study design

Data from the Mapping Individual Routes of Risk and Resilience (Mirorr) study was used. Mirorr combines daily diary data of 90 days with a three-year follow-up period in young adult individuals ($N = 96$) who are distributed along the early stages of the psychosis continuum (stage 0 – stage 1b). Mirorr consists of four subgroups, each representing a different early clinical stage for psychosis (stage 0–1b). Individuals in stage 0 (subgroup 1) were recruited from the general population and individuals in stage 1a-1b (subgroup 2–4) were recruited from mental health care institutions. Individuals from subgroup 1, reflecting stage 0, were individuals considered at psychometric risk (scoring high on a self-report questionnaire about PEs) for psychosis (Versmissen et al., 2008). Individuals in subgroups 2 and 3 both reflect stage 1a and capture individuals in mental health care with respectively low (subgroup 2) or mild (subgroup 3) levels of PEs. Individuals in subgroup 4 have moderate PEs and are considered at ultra-high risk for psychosis (stage 1b). As we did not use subgroups in the analysis for the current paper but instead investigate prognosis across all individuals and stages, these subgroups are not further described here, but details can be found in Booij et al. (2018) and supplementary figure 1. At baseline (T0), participants first completed several questionnaires on psychopathology, well-being, functioning and risk and protective factors and started with a 90-day daily diary consisting of 80 items that covered a broad range of transdiagnostic symptoms including PEs, depression, anxiety, mania, obsessive compulsive behavior and anger symptoms, functioning as well as risk and protective factors on their smartphone each evening. The daily diary was repeated at 1-year follow-up (T1) and the questionnaires were repeated at post-diary, 1-year (T1), 2-year (T2) and 3-year (T3) follow-up. For this study, diary data from T0 and questionnaire data from T0, T1 and T3 were used. Mirorr consists of four subgroups, each representing a different early clinical stage for psychosis (stage 0, stage 1a with mild symptoms, stage 1a with moderate symptoms, stage 1b). As we did not use subgroups in the analysis for the current paper but instead investigate prognosis across all individuals and stages, these subgroups are not further described here but details can be found in Booij et al. (2018).

Inclusion criteria were: (1) age between 18 and 35 years, (2) ability to read and speak Dutch fluently, (3) being capable of following the research procedures, and (4) providing informed consent. Exclusion criteria were: (1) history of or current psychotic episode according to the Diagnostic and Statistical Manual of Mental Disorders 4 (DSM-4) criteria, (2) significant hearing or visual problem impairments, and (3) pregnancy. For a more detailed description of the design and procedure of the Mirorr study, see Booij et al. (2018) and Wigman et al. (2022).

The study was approved by the medical ethical committee of the University Medical center Groningen, Groningen, the Netherlands (registration number MEC no. 2015/159, ABR no. NL52974.042.15). The study was conducted in accordance with the Helsinki Declaration. All participants provided written informed consent.

2.2. Instruments

2.2.1. Diary data

For this study, we selected a) items that reflect a more general and transdiagnostic measure of psychopathology and b) items that specifically reflect PEs. For psychopathology, we selected items belonging to five transdiagnostic domains (depression, anxiety, irritation, stress, and PEs). To calculate an overall mean and variance score we computed domain scores per person per day and next created a total score per person per day on these five domains. For PEs, we used only the 5 items of the PEs domain (Supplementary Table 1). To calculate an overall mean and variance, we created a total PE score per person per day and calculated an overall mean and variance per person. Item selection was in line with previous studies on this dataset (van der Tuin et al., 2021, 2022). All items were scored on a 100-point Visual Analogue Scale (VAS) ranging from 'not at all' to 'very much'. For all domains with more than one item, we calculated composite reliability scores to assess whether the items load on the same scale, taking the multilevel structure into account (Geldhof et al., 2014), through the R-package 'multilevelTools' (Wiley, 2020). The within-person omegas ranged between 0.60 and 0.86 and between-person omegas ranged between 0.90 and 0.99.

2.2.2. Questionnaires

General psychopathology. The total score of the Symptom Checklist Revised (SCL-90-R; Arrindell and Ettema, 2003) was used as a measure of general psychopathology. The SCL-90-R is a self-report questionnaire with 90 items covering a broad range of psychological symptoms during the past week scored on a 5-point Likert scale. The SCL-90-R has high reliability (Smits et al., 2015) and excellent internal consistency in our sample (Cronbach's Alfa = 0.98).

PEs. The Community Assessment of Psychic Experiences (CAPE; Konings et al., 2006) is a self-report questionnaire with 42 items that was used to measure subclinical PEs. The CAPE questionnaires has three subscales: positive symptoms (20 items), negative symptoms (14 items) and depressive symptoms (8 items). All questions are scored on frequency (1 = never to 4 = almost always) and distress (1 = not distressing, 4 = very distressing). The CAPE has good reliability and validity (Konings et al., 2006) and internal consistency in our sample (Cronbach's alfa = 0.89). We followed the recommendation by Jaya et al. (2021) to use weighted severity of the positive subscale by multiplying frequency and distress for all positive subscale items and dividing by 20 (i.e. the number of items in the subscale). The CAPE score after the first diary period (three months from the beginning of the study) was used as baseline measurement as this assessment had fewer missing values than the pre-diary assessment.

2.3. Statistical analyses

All analyses were performed in R version 4.1.0 (R core team, 2022), and alpha $p < 0.05$ was used as inference criterion.

Several preprocessing steps were taken to get all variables for the main analyses, as described in Appendix A. In short, two symptom networks were constructed per individual to obtain personalized symptom network densities, one based on psychopathology domains and one on PE items. Outcome data was not complete as not all participants completed all follow-up waves. We used the 'mice' package (van Buuren and Groothuis-Oudshoorn, 2011) for multiple imputation of the outcomes.

2.3.1. Multiple linear regressions

Eight multiple linear regression models were built. Two models were constructed to predict SCL-90 scores (general psychopathology): one short-term (T1) and one long-term (T3) prediction. Six models were constructed to predict CAPE scores (PEs): three short-term (T1) and three long-term (T3) predictions (*Fig. 1*).

Each regression model was built in the same three steps. *Step 1:* fitting a linear regression model with the baseline (T0) questionnaire of the outcome as predictor. *Step 2:* adding the mean and variance of diary items (respectively psychopathology and PEs, see specific models). *Step 3:* adding the network density (of respectively psychopathology and PEs). To test whether the models in step 2 and 3 better captured the data than the simple model from step 1, we used an ANOVA.

Regression assumptions were checked and when violated, variables were transformed with a parameter (lambda) that optimally approached normality, using the 'boxcox' function of the MASS package (Venables and Ripley, 2002)(Appendix B). In addition, we checked for multicollinearity by assessing the Variance Inflation Factor (VIF) with the 'vif' function from the 'car' package (Fox and Weisberg, 2019).

Predictors	*Outcome*
Model 1 SCL-90 (general psychopathology) short-term with diary PP:	
1. Baseline SCL-90 2. + Diary mean & variance PP 3. + Network density PP	SCL-90 T1
Model 2 SCL-90 (general psychopathology) long-term with diary PP:	
1. Baseline SCL-90 2. + Diary mean & variance PP 3. + Network density PP	SCL-90 T3
Model 3 CAPE (PEs) short-term with diary PP:	
1. Baseline CAPE 2. + Diary mean & variance PP 3. + Network density PP	CAPE T1
Model 4 CAPE (PEs) long-term with diary PP:	
1. Baseline CAPE 2. + Diary mean & variance PP 3. + Network density PP	CAPE T3
Model 5 CAPE (PEs) short-term with diary PEs:	
1. Baseline CAPE 2. + Diary mean & variance PEs 3. + Network density PEs	CAPE T1
Model 6 CAPE (PEs) long-term with diary PEs:	
1. Baseline CAPE 2. + Diary mean & variance PEs 3. + Network density PEs	CAPE T3
Model 7 CAPE (PEs) short-term with diary PP & PEs:	
1. Baseline CAPE 2. + Diary mean & variance PP & PEs 3. + Network density PP & PEs	CAPE T1
Model 8 CAPE (PEs) long-term with diary PP & PEs:	
1. Baseline CAPE 2. + Diary mean & variance PP & PEs 3. + Network density PP & PEs	CAPE T3

Fig. 1. overview of all linear regressions. For each model, the same steps were followed; step 1: using the baseline questionnaire to predict outcome, step 2: adding the mean and variance from diary measures, step 3: adding network density. Abbreviations: SCL-90: Symptom checklist 90, PP: psychopathology, CAPE: Community Assessment for Psychic Experiences, PEs: psychotic experiences.

While we constructed eight models for this paper, we deliberately did not correct for multiple testing. The reason for this is that we had clear hypotheses for each research question and made deliberate choices in which variables to conclude in each model.

2.3.2. Sensitivity analyses

We repeated the same analyses using only data from the first 7, 14, and 30 days to assess whether a shorter length of diary data collection would produce similar results. These numbers were based on commonly used periods of EMA studies. Because with shorter time periods the number of measurements is too low to construct reliable symptom networks, we omitted the step to add network density to the linear regression and only focused on mean and variances of the diary data.

2.3.3. Power

For a multiple regression with $N = 96$, a medium effect size and 4 predictors, the power to detect a true effect is 0.85. The power for the R^2 change in a linear multiple regression with a medium effect size ($f^2 = 0.15$), $N = 96$, 2 tested predictors and a total number of predictors of 3 is 0.92. For the last step of the model, the power for the R^2 change in a linear multiple regression with a medium effect size, $N = 96$, 1 tested predictor and a total number of 4 predictors is 0.96 (calculated with G*power). Thus, we had sufficient power for all analyses.

3. Results

Of the 96 individuals who completed baseline questionnaires and diary; 89 individuals completed the first follow-up and 77 the first and third follow-up. Because we used multiple imputation to impute missing datapoints, our final data set consisted of 96 individuals for all analyses. Table 1 shows descriptive statistics for the total sample and follow-up completers.

Table 1
Descriptive information for all waves, and for the total sample and follow-up completers.

	Baseline (T0)			One-year follow-up (T1)		Three-year follow-up (T3)	
	Completed T0 $N = 96$	*Completed T0 and T1* $N = 89$	*Completed T0, T1 and T3* $N = 77$	$N = 89$	*Imputed datasets* $N = 96$	$N = 77$	*Imputed datasets* $N = 96$
Age				–		–	
Gender, female% (absolute number)	76 % (73)	76 % (68)	77 % (59)	–		–	
SCL90, mean (sd)	186.71 (59.43)	186.34 (59.23)	182.69 (59.13)	162.93 (52.01)	162.78 (51.82)	152.60 (49.97)	156.68 (52.11)
CAPE, mean (sd)	1.67 (0.81)	1.69 (0.83)	1.68 (0.82)	1.47 (0.62)	1.47 (0.61)	1.36 (0.59)	1.38 (0.59)
Mean diary PP	27.42	28.18	27.81	–		–	
Variance diary PP	121.50	120.53	115.10	–		–	
Mean diary PEs	14.32	14.47	14.25	–		–	
Variance diary PEs	48.24	47.25	45.18	–		–	

Abbreviations: SCL-90: Symptom checklist 90, PP: psychopathology, CAPE: Community Assessment for Psychic Experiences, PEs: psychotic experiences.

Since we used the score on the CAPE after the diary period as the baseline measurement, the average follow-up time between CAPE T0 and CAPE T1 was 8.3 months and between CAPE T0 and CAPE T3 32.5 months (2.7 years), hence less than one and three years. The average follow-up time between SCL T0 and SCL T1 was 12.1 months and between SCL T0 and SCL T3 35.7 months (3 years).

For the first six regression models, multicollinearity was within a normal range (range VIF: 1.13–2.63). The last two models, which included diary predictors from both psychopathology and PEs, showed large multicollinearity and were therefore not further described. For full correlation matrixes with all variables, see Supplementary Table 2.

3.1. Linear regression models predicting psychopathology (SCL-90; Table 2)

The linear regressions with SCL-90 as outcome showed violations of homoscedasticity and outliers. Through the box-cox function of the MASS package (Venables and Ripley, 2002) we found that a lambda of −0.5 fitted with both SCL T1 and SCL T3. The transformation that fits with a lambda of −0.5 is 1/sqrt(x) and thus this was used. After the transformation of the outcome (respectively SCL-90 T1 and SCL-90 T3), the assumptions were met.

3.1.1. Step 1

Both short- and long-term SCL-90 was predicted by the scores on their baseline measurement (respectively $R^2 = 0.47$ and 0.38).

3.1.2. Step 2

Adding the mean and variance of daily psychopathology significantly improved prediction for short- and long-term prediction of the SCL90 (respectively R^2-change = 0.09 and 0.06), with the mean, but not the variance, being a significant predictor.

3.1.3. Step 3

Adding network density to the model did not improve short-term or long-term prediction of the SCL-90 (respectively R^2-change = −0.01 and 0.00).

3.2. Linear regression models predicting PEs (CAPE; Table 3)

The linear regressions with CAPE as outcome showed violations of the assumptions of a linear relationship, normality of residuals and homoscedasticity. The box-cox function showed that lambda of −1 was within the 96 % CI for both outcomes. The transformation that fits with the −1 lambda is 1/x, and thus this was used for model 3–6. After the transformation on both outcomes (CAPE T1 and T3) and baseline predictor (CAPE T0), the assumptions were met.

3.2.1. Step 1

Both short- and long-term CAPE was predicted by their scores at baseline (respectively $R^2 = 0.39$ and 0.31).

Table 2
Linear regressions predicting short- and long-term psychopathology (SCL90).

		Beta	SE Beta	F^2	*T*-value	*P*-value	R^2 adj	*F*-test
Model 1: short-term SCL-90 predicted by diary PP								
Step 1	SCL-90 T0	0.69	0.08	0.90	−8.88	0.00**	0.47	
Step 2	SCL-90 T0	0.43	0.10	0.23	−4.30	0.00**	0.56	$F = 7.82$
	Mean diary PP	0.38	0.10	0.18	−3.74	0.00**		$p = <0.001$
	Variance diary PP	0.04	0.08	−0.00	−0.55	0.59		
Step 3	SCL-90 T0	0.43	0.10	0.22	−4.23	0.00**	0.55	$F = 0.006$
	Mean diary PP	0.38	0.10	0.18	−3.72	0.00**		$p = 0.94$
	Variance diary PP	0.05	0.10	−0.01	−0.49	0.63		
	Network density PP	−0.01	0.09	−0.01	0.08	0.94		
Model 2: long-term SCL-90 predicted by diary PP								
Step 1	SCL-90 T0	0.62	0.09	0.60	−7.05	0.00**	0.38	
Step 2	SCL-90 T0	0.39	0.11	0.15	−3.37	0.00**	0.44	$F = 5.03$
	Mean diary PP	0.35	0.11	0.12	−3.10	0.00**		$p = 0.009$
	Variance diary PP	0.01	0.09	−0.01	−0.06	0.95		
Step 3	SCL-90 T0	0.38	0.12	0.14	−3.27	0.00**	0.44	$F = 0.23$
	Mean diary PP	0.35	0.11	0.12	−3.11	0.00**		$p = 0.63$
	Variance diary PP	0.04	0.12	−0.01	−0.33	0.74		
	Network density PP	−0.05	0.11	−0.01	0.48	0.63		

Abbreviations: SCL-90: Symptom Checklist 90, PP: psychopathology, Note: SCL-90 T1 and T3 were transformed (1/sqrt(x)), which changed the interpretation (i.e. a higher value indicated less psychopathology). For interpretation purposes, we transformed each Beta by multiplying it with −1. This way, for all variables a higher values indicated more psychopathology.

Table 3
Linear regressions predicting short- and long-term psychotic experiences (CAPE).

		Beta	SE Beta	F^2	*T*-value	*P*-value	R^2 adj	*F*-test
	Model 3: short-term CAPE predicted by diary PP							
Step 1	CAPE T0	0.63	0.08	0.65	7.60	0.00**	0.39	
Step 2	CAPE T0	0.52	0.09	0.34	5.57	0.00**	0.43	$F = 3.45$
	Mean diary PP	0.18	0.10	0.03	−1.79	0.08		$p = 0.04$
	Variance diary PP	0.12	0.09	0.01	−1.31	0.19		
Step 3	CAPE T0	0.51	0.09	0.36	5.63	0.00**	0.47	$F = 6.65$
	Mean diary PP	0.17	0.10	0.03	−1.74	0.09		$p = 0.01$
	Variance diary PP	0.29	0.11	0.08	−2.60	0.01*		
	Network density PP	−0.26	0.10	0.07	2.58	0.01*		
	Model 4: long-term CAPE predicted by diary PP							
Step 1	CAPE T0	0.56	0.09	0.45	6.07	0.00**	0.31	
Step 2	CAPE T0	0.44	0.10	0.21	4.20	0.00**	0.34	$F = 2.26$
	Mean diary PP	0.24	0.11	0.05	−2.14	0.04*		$p = 0.11$
	Variance diary PP	−0.04	0.10	−0.01	0.37	0.71		
Step 3	CAPE T0	0.44	0.11	0.21	4.17	0.00**	0.33	$F = 0.23$
	Mean diary PP	0.24	0.11	0.05	−2.11	0.04*		$p = 0.63$
	Variance diary PP	0.00	0.13	−0.01	−0.01	0.99		
	Network density PP	−0.06	0.12	−0.00	0.48	0.63		
	Model 5: short-term CAPE predicted by diary PEs[3]							
Step 1	CAPE T0	0.63	0.08	0.65	7.60	0.00**	0.39	
Step 2	CAPE T0	0.46	0.10	0.25	4.77	0.00**	0.46	$F = 6.78$
	Mean diary PEs	0.09	0.12	−0.00	−0.71	0.48		$p = 0.002$
	Variance diary PEs	0.26	0.11	0.05	−2.36	0.02*		
Step 3	CAPE T0	0.46	0.10	0.25	4.77	0.00**	0.46	$F = 0.61$
	Mean diary PEs	0.07	0.12	−0.01	−0.56	0.58		$p = 0.44$
	Variance diary PEs	0.29	0.12	0.06	−2.49	0.01*		
	Network density PE	−0.06	0.08	−0.00	0.78	0.44		
	Model 6: long-term CAPE predicted by diary PEs							
Step 1	CAPE T0	0.56	0.09	0.45	6.07	0.00**	0.31	
Step 2	CAPE T0	0.36	0.11	0.13	3.36	0.00**	0.37	$F = 4.54$
	Mean diary PEs	0.26	0.13	0.03	−1.96	0.05		$p = 0.01$
	Variance diary PEs	0.09	0.13	−0.00	−0.71	0.48		
Step 3	CAPE T0	0.37	0.11	0.13	3.35	0.00**	0.37	$F = 0.22$
	Mean diary PEs	0.25	0.13	0.03	−1.84	0.07		$p = 0.64$
	Variance diary PEs	0.11	0.14	−0.00	−0.81	0.42		
	Network density PE	−0.05	0.10	−0.01	0.47	0.64		

Abbreviations: CAPE: Community Assessment Psychic Experiences, PP: psychopathology, PE: psychotic experiences,. Note: CAPE T0, T1 and T3 were transformed (1/x), this changed the interpretation (i.e. a lower value on the CAPE indicates more PEs). To ease interpretation, we multiplied the Beta's of all predictors, except CAPE T0. This way, for all variables, a higher value indicates more symptoms.

3.2.2. Step 2 Diary psychopathology

Adding the mean and variance of daily psychopathology improved short-term prediction of the CAPE, but neither was a significant predictor (R^2-change = 0.04). Long-term prediction of the CAPE was not improved by adding the mean and variance of daily psychopathology (R^2-change = 0.03), although the mean was a significant predictor.

3.2.3. Step 3 Diary psychopathology

Adding network density of daily psychopathology improved short-term prediction of CAPE (R^2-change = 0.04) and density was a significant predictor. Long-term prediction of the CAPE was not improved by adding network density of daily psychopathology (R^2-change = −0.01).

3.2.4. Step 2 Diary PEs

Adding the mean and variance of daily PEs improved short- and long-term prediction of the CAPE (respectively R^2-change = 0.07 and 0.06). For short-term prediction, the variance was a significant predictor, with a higher variance predicting higher CAPE scores. For long-term prediction, neither was a significant predictor.

3.2.5. Step 3 Diary PEs

Adding network density of PE items did not improve short- or long-term prediction of the CAPE (respectively R^2-change = 0.00 and 0.00).

3.3. Sensitivity analyses 7–14–30 days of diary

Results showed that the R^2 of the models based on different lengths of diary periods were highly comparable, for both psychopathology and PE prediction, with a difference of at most 0.02 between the model based on 7 days and that on 90 days (Table 4; for full models see Supplementary Tables 3a-c and 4a-c).

4. Discussion

This study aimed to assess the added value of diary metrics in short- and long-term prediction of psychopathology and positive psychotic experiences (PEs) on top of baseline questionnaires in young adults in early clinical stages that index risk for psychosis (stage 0-stage 1b). With our stepwise approach we found that, in general, adding the mean and variance from a 90-day diary period improved short- and long-term

Table 4
The explained variances (R adjusted) for all models with as predictors: (i) baseline questionnaire and (ii) mean and variance of the diary period with 7–14–30–90 days diary periods.

	7 days *R adj*	14 days *R adj*	30 days *R adj*	90 days *R adj*
SCL-90 prediction				
Short-term SCL-90, diary PP	0.54	0.55	0.55	0.56
Long-term SCL-90, diary PP	0.43	0.43	0.43	0.44
CAPE prediction				
Short-term CAPE, diary PP	0.42	0.44	0.44	0.43
Long-term CAPE, diary PP	0.33	0.36	0.34	0.34
Short-term CAPE, diary PEs	0.44	0.47	0.48	0.46
Long-term CAPE, diary PEs	0.36	0.39	0.38	0.37

Abbreviations: SCL-90: Symptom Checklist 90, PP = psychopathology, CAPE: Community Assessment Psychic Experiences, PEs = psychotic experiences.

prediction of psychopathology and PEs on top of baseline questionnaires, whereas adding network density did not improve prediction, except psychopathology network density, which improved short-term prediction of PEs. For prediction of PEs, we distinguished between general psychopathology and specific PEs as diary predictors. We found that both psychopathology and PEs diary metrics improved prediction of PEs, with PEs predictors performing slightly better than psychopathology predictors.

The early clinical stages for psychosis, characterized by a broad and diffuse symptom pattern (Cross et al., 2014; Hickie et al., 2013), also pose a vulnerability for developing other mental disorders (Lin et al., 2015; McGorry et al., 2018). Therefore, we first focused the prediction of psychopathology. We found that baseline psychopathology predicted both short- and long-term psychopathology, with a better prediction of short-term than long-term outcomes. This prediction was improved by adding information from our 90-day daily diary data to the model, respectively from 47 % to 56 % explained variance (R^2) and from 38 % to 44 % explained variance (R^2). Individuals with higher mean values on daily psychopathology experienced more psychopathology 1- and 3-years later. This is in line with Dejonckheere et al. (2019), who found that especially the mean of positive affect and negative affect from time series predicted depressive symptoms. As hypothesized, network density did not improve our predictions; thus, we found no support for the density hypothesis.

Similar to psychopathology prediction, baseline PEs predicted PEs better after one year (explained variance, R^2=39 %) than after three years (explained variance, R^2=31 %). We assessed the added value of diary metrics of psychopathology as well as specific PEs. Short-term prediction of PEs was improved by adding the mean and variance of daily psychopathology as well as daily PE, with daily PE performing slightly better (46 % versus 43 %). We could not statistically compare these models as they are not nested. Therefore, we cannot conclude whether the difference between daily psychopathology and daily PEs as predictors was significant. The variance of PE items significantly improved prediction; individuals who fluctuated more in their daily PEs had more PEs one year later. This is in line with other studies that found an association between higher emotion/symptom variability and psychopathology (Dejonckheere et al., 2019; Houben et al., 2015; Koval et al., 2013; Sperry et al., 2020). While some form of reactivity to life is probably adaptive, higher fluctuations in PEs appear to be maladaptive (Houben et al., 2015). It has been suggested that whether fluctuations are adaptive is context specific; however, we were not able to control for this. Future research should therefore take context into account when researching the relationship between symptom variability and (future) levels of psychopathology and PEs.

In addition, short-term prediction of PEs was also improved by adding network density of daily psychopathology. In contrast to the density hypothesis, we found that lower density was predictive of more PEs one year later. A possible explanation for this unexpected result is that symptom associations (i.e. edges) in symptom networks are based on fluctuations rather than mean levels. Thus, it is possible that symptoms levels are high with low fluctuation, resulting in low network density. However, this was not reflected in the correlation between network density and mean diary scores in our study, showing a positive, although rather low, correlation ($r = 0.15$). Moreover, the correlation between network density of psychopathology and short-term PEs was low ($r = -0.04$) and thus our result might be due to a suppressor effect of network density. As we found this effect of network density in only one model, it is plausible that this is a chance finding and interpretation of this result is inconclusive. Furthermore, in addition, this result does not align with previous work on part of the same dataset in which we found no differences in network density between individuals in different clinical stages (van der Tuin et al., 2022). Although in all other models, the Beta coefficients of network density were also negative – thus all pointing to less dense networks being associated with more severe psychopathology, they were also all non-significant and we found an effect of network density only in one model. Thus, it is plausible that this is a chance finding and interpretation of this result is inconclusive.

Long-term prediction of PEs was only improved by adding diary metrics of PEs and not of psychopathology. It therefore seems that an optimal choice for predictors depends on one's aim; if the aim is to predict the development of PEs in individuals in the early clinical stages, daily diary assessments should focus specifically on PEs instead of on more transdiagnostic psychopathology.

In general, we found that baseline questionnaires were the best predictors of both psychopathology and PEs, followed by the mean of the diary period. Only in the prediction of short-term PEs, the variance of PEs was a better predictor than the mean. Keeping in mind that the correlation between the mean and variance of daily PEs was relatively high (0.73), it is possible that the variance was favored over the mean as the significant predictor in this model, while it could also have been the other way around. Our findings implicate that (i) daily diary metrics improve prediction of outcome on top of traditional measures, and (ii) complex diary metrics like network density do not outperform more simple diary metrics. Although we would, therefore, not recommend using network density to predict outcome, studying symptom networks can still be helpful to answer other relevant research questions (Dejonckheere et al., 2019). For example, creating symptom networks might aid understanding symptom dynamics of individuals (Riese et al., 2021) and help in advancing case conceptualization in clinical care (Scholten et al., 2022; von Klipstein et al., 2020).

For all models we observed that similar results could be achieved with diary periods as short as 7–14 days. Therefore, diary data from a short diary period could be a valuable addition to clinical risk prediction in clinical practice. As such a diary period is relatively short, the computational complexity low and the amount of diary items necessary relatively low (i.e. we used 14 items in total), the feasibility of this added diary component is high.

Strong points of this study include the combination of a relatively long daily diary period with a long term follow-up, the inclusion of analyses with shorter, potentially less burdensome diary period and the inclusion of relatively common and mild PEs, which is especially suited for our sample of individuals along the early clinical stages. We deliberately did not use more severe PEs like hallucinations as these were relatively rarely endorsed in our sample and are thus not suited for this target population.

Our results should be seen in the light of a number of limitations and considerations. First, as in most longitudinal studies, we had some loss to follow-up. However, we used the recommended strategy, i.e., multiple imputation, to deal with this (Moons et al., 2019). In addition, we had only 7 % missing individuals at 1-year follow-up and 20 % at 3-year follow-up. Although selective attrition may lead to biased estimates, the fact that 80 % of the sample still participated in the third wave gives us some confidence that the non-response did not strongly influenced our results. Second, our sample consisted of a heterogeneous group of individuals in different early clinical stages. We cannot exclude the possibility that predictors perform differently per clinical stage. However, the number of individuals in each stage was too low to perform separate analyses. Third, while there are several advantages of our design of one measurement per day, we cannot exclude the possibility that network density based on multiple measurements within one day would provide different results. For example, one study showed that network density of positive affect and negative affect from EMA data (9 times per day, 8 days) was cross-sectionally associated with anxiety and depression, while the network density from daily diary data (50 days) was not (Shin et al., 2022). As the optimal sampling frequency is currently unknown (Fried and Cramer, 2017), future research should focus on the effect of sampling frequency on prediction capacity. Fourth, we initially aimed to include both diary metrics of psychopathology and PEs in one model to directly compare their explanatory power with each other. However, due to multicollinearity between the measures, we were unable to do this. The sum score of daily psychopathology captured

multiple domains, including PEs, which could potentially explain the overlap in results with daily PEs and daily psychopathology as predictors. Post-hoc, we assessed the correlation between the mean and variance of psychopathology, both with and without PEs included. This showed very high correlations ($r = 0.99$ for both the mean and variance) for psychopathology measures with and without PEs. Therefore, we conclude that levels of daily PEs is not the driving force of daily psychopathology. Rather, they are conceptually related constructs and act rather similar as predictors. While we expected some overlap between daily PEs and daily psychopathology, the correlation of $r = 0.84$ was higher than expected. These post-hoc results underline that in the early clinical stages used in this study, symptoms expression indeed is very diffuse, with general psychopathology highly overlapping with PEs. Due to a procedural error, 13 individuals had no baseline pre-diary CAPE (PEs) measurement. In addition, the time between pre-diary measurements and the start of the daily diary, and thus also the follow-up measurements, varied largely per individual. Individuals who completed both pre- and post-diary assessments scored significantly lower post-diary ($t = 2.67$, $p = 0.01$) with a mean difference of 0.14. To use the most complete data as well as the most similar measurement timing for everyone, we decided to use post-diary measurements of CAPE instead of pre-diary measurements. In addition, we had no sufficient detailed information on treatment to take this into account in the analyses. The majority of our sample was in mental health care and thus received some form of treatment aimed to ameliorate psychopathology which may have influenced our results.

5. Conclusion

Our study shows that information from daily diary data can improve short-term and long-term prediction of both psychopathology and positive PEs on top of baseline questionnaires in individuals in early clinical stages, with a diary period as short as 7–14 days. We showed that simple metrics from diary data, i.e., the mean and variance, are better predictors than the more complex metric of symptom network density. Subsequently, we did not find evidence for the density hypothesis from the symptom network theory as we did not find that having a dense network posed a vulnerability for developing more severe psychopathology. When predicting future course of mental health, it is important to keep in mind the specific population and aim of the prediction; when specifically predicting future PEs, diary items concerning mild PEs have a better predictive capacity than transdiagnostic psychopathology items. Future research should focus on building and testing prediction models with diary data with internal and external validation, building prototype tools to implement prediction models and testing whether implementing these prediction tools work in clinical practice.

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Author agreement

All authors have seen and approved the final version of the manuscript being submitted. The article is the authors' original work, has not received prior publication and is not under consideration for publication elsewhere.

Declaration of Competing Interest

The authors have no conflicts of interest to declare.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psychres.2023.115546.

Appendix A. Preprocessing steps to get the variables for analyses

Symptom network density. First, individual symptom networks were constructed to obtain individual symptom network densities. Two networks per person were constructed, one containing five domains of general psychopathology, and one containing the PE items (see 'instruments'). For both networks, the approach was the same and thus we describe the approach once.

Symptom networks were estimated as graphical Vector Autoregressive Models (gVAR) models using version 0.10 of the 'psychonetrics' package (Epskamp, 2021). Before the diary data was entered in the gVAR models, for each individual we: (1) imputed missing data using exponential moving average, (2) transformed data with a nonparanormal transformation to approach normality (Fan et al. 2017), and (3) de-trended data. GVAR models can produce both a temporal (based on VAR coefficients) and a contemporaneous (based on VAR residuals) network. A temporal network shows the relationship between two variables from the previous time-point onto the next time-point while controlling for the temporal effect of all other variables. The contemporaneous network shows the unique associations among variables that occur on a different timescale than the sampling rate. Based on previous work on the same dataset, we found that most associations occur within days (van der Tuin et al., 2021; 2022) and thus we focused solely on contemporaneous networks in this study.

The individual networks were estimated using Full Information Maximum Likelihood estimation (FIML) with gVAR. After estimating a fully connected network, it was pruned using a recursive pruning technique at an alpha level of 0.05. This means that in each iteration, non-significant edges were removed from the network and the remaining edges were re-estimated. This technique works well when estimating sparse individual network structures as shown by simulation studies (Isvoranu & Epskamp, preprint; Mansueto et al. preprint).

As a last step, individual symptom network density was calculated by averaging the gVAR residuals. This provides an indication of how densely the individual networks were connected.

Multiple imputation of outcomes. Not all participants completed all follow-up waves and thus we had missing data for some individuals for some waves. As recommended by (Moons et al., 2019), we used multiple imputation to impute missing data for the individuals who did not complete all measurement waves ($n = 7$ at T1 and $n = 19$ at T3). We followed the recommendation by White et al. (2011), and created 19 imputed datasets, equal to the percentage of missing cases at T3. Based on van Buuren (2018), we used 10 iterations. As our data had a multilevel structure (multiple measurements per person per questionnaire), we used multilevel multiple imputation with the R-package "mice" (van Buuren and Groothuis-Oudshoorn, 2011) with the 2lpmm imputation method van Buuren (2018).

Appendix B

All linear regressions were constructed on the imputed datasets, meaning that all analyses were conducted on all 19 imputed datasets and

the result was pooled according to Rubin's rule (Van Buuren, 2018). Regression assumptions were checked on the complete data. When assumptions were violated, we used the MASS package (Venables and Ripley, 2002) and the 'boxcox' function to assess which transformation parameter (lambda) was optimal to approach normality. This transformation often improves the other assumptions as well. As we intended to compare models with each other, we assessed whether there was a lambda within the 95 % confidence interval for both the short-term and long-term outcomes, so that we could perform the same transformation for all models with the same outcome. Transformations were performed after multiple imputation on all 19 datasets. To get standardized Beta values we standardized all variables after transformation. After the transformation, we assessed the assumptions again to see whether the transformation successfully improved the model.

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