Asian Journal of Psychiatry RNA-sequencing of peripheral whole blood of individuals at ultra-high-risk for psychosis – a longitudinal perspective --Manuscript Draft--

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Abstract:	Background The peripheral blood is an attractive source of prognostic biomarkers for psychosis conversion. There is limited research on the transcriptomic changes associated with psychosis conversion in the peripheral whole blood. Study Design We performed RNA-sequencing of peripheral whole blood from 65 ultra-high-risk (UHR) participants and 70 healthy control participants recruited in the Longitudinal Youth-at-Risk Study (LYRIKS) cohort. 13 UHR participants converted in the study duration. Samples were collected at 3 timepoints, at 12-months interval across a 2-year period. We examined whether the genes differential with psychosis conversion contain schizophrenia risk loci. We then examined the functional ontologies and GWAS associations of the differential genes. We also identified the overlap between differentially expressed genes across different comparisons. Study results Genes containing schizophrenia risk loci were not differentially expressed in the peripheral whole blood in psychosis conversion. The differentially expressed genes in psychosis conversion are enriched for ontologies associated with cellular replication. The differentially expressed genes in psychosis conversion are associated with non- neurological GWAS phenotypes reported to be perturbed in schizophrenia and psychosis but not schizophrenia and psychosis phenotypes themselves. We found minimal overlap between the genes differential with psychosis conversion samples. Conclusion The associations between psychosis conversion and peripheral blood-based biomarkers are likely to be indirect. Further studies to elucidate the mechanism behind potential indirect associations are needed.
Suggested Reviewers:	Valeria Mondelli Professor, King's College London valeria.mondelli@kcl.ac.uk

	Prof Mondelli specializes in psychoimmunology, which is highly relevant in this manuscript.
Opposed Reviewers:	
Response to Reviewers:	

Dear Editors,

Thank you for the opportunity to revise and resubmit our manuscript titled "RNAsequencing of peripheral whole blood of individuals at ultra-high-risk for psychosis – a longitudinal perspective" by Tan et al. to be considered for publication as an Article in the Asian Journal of Psychiatry. Together with the revised manuscript, we have attached a document with our responses to the reviewer's comments as well an annotated version of the revised manuscript to where all changes have been marked. We hope the annotated version will help to facilitate evaluations of the revised manuscript.

The novelty of our study has been shifted slightly to reflect a change in the framing of the study as requested by the reviewer. We will describe our study and the revised novelty in this cover letter:

This study is part of the Longitudinal Youth at-Risk Study (LYRIKS) which is a Singapore-based longitudinal study for psychosis conversion in adolescents and early adults designated as ultra-high risk of psychosis conversion (Lee et al, Schizophr Res, 2013). Whole blood samples were collected over 2 years at 12 months interval including baseline and when the participant converted to psychosis. We were able to obtain blood samples of participants before and after they converted to psychosis respectively as well as samples from participants who were diagnosed as high-risk but did not convert to psychosis, and matched controls over the study duration.

Particular novelty of study are: 1) At the time of writing and to the best of our knowledge, we are the first study to conduct a gene ontology enrichment analysis on the genes differential in psychosis conversion using a longitudinal cohort. 2) Due to cohort inclusion criteria and strict drug laws in Singapore (the country of origin for this study), our findings are minimally confounded by cannabis use. This is significant as cannabis use has been shown to confer additional risk to psychosis conversion and over 50% of the individuals who converted to psychosis in comparable studies reported a use of cannabis which (Chaumette et al, Schizophr Bull, 2019) and (Mongan et al, Jama Psych, 2020). 3) By using a linear mixed-effect model-based method in our analysis, we were able to account for intra-individual correlations inherent to longitudinal data. This additional correlation was not accounted for in existing similar studies (Chaumette et al, Schizophr Bull, 2019) and (Mongan et al, Schizophr Bull, 2019) and (Mongan et al, Schizophr Bull, 2019) and analysis, we were able to account for intra-individual correlations inherent to longitudinal data. This additional correlation was not accounted for in existing similar studies (Chaumette et al, Schizophr Bull, 2019) and (Mongan et al, Jama Psych, 2020).

Using power analysis methods described in (Bi and Liu, BMC Bioinfo, 2016), we found that our study is sufficiently powered at 0.851. We performed RNA-sequencing of the whole blood samples. Key results include 1) The genes correlated with psychosis conversion are predominately immune related and while the genes are not associated with psychosis and schizophrenia phenotypes, they are associated many phenotypes reported to be perturbed in schizophrenia, including diseases and disorders such as "insomnia" and "coronary artery disease" and physiological parameters such as "fatty acid measurement" and "systolic blood pressure". Based on these findings, we hypothesize that that the relation between peripheral blood-based biomarkers and psychosis conversion is likely to be indirect. 2) We showed that there is minimal overlap between genes that are correlated with psychosis conversion and genes that correlate with labels useful for identifying participants likely to convert (i.e. pre-conversion versus non-conversion). Results indicating this distinction is important for any future biomarker studies.

We believe that the findings of this paper will be of interest to the readers of your journal and valuable in informing future clinical studies into potential biomarkers for psychosis conversion. We would like to thank the Editor and Reviewers for their advice and comments. It has been very helpful in improving our paper. Along with this letter and the revised manuscript, we also have included an annotated version of the revised manuscript where the locations of changes have been marked (strikethrough for deleted text and red for inserted text) together with comments justifying each change. Please find our responses to your comments and an overview of the changes made below.

Reviewer #1: This is an interesting study assessing RNA-sequencing in 65 UHR and 70 HC subjects. Though the findings are interesting, and authors appear to have a valuable set of data, some amendments need to be made.

Introduction is poorly written and should be reframed. It lacks a comprehensive review of the current literature in the topic of the proposed study. Also, some sentences are strangely inserted in the text, without a strong connection with the remaining of the text (e.g., the one about recreational drug use).

Response: Thank you for this suggestion. Key changes to the introduction include:

We described the current state of study in peripheral blood-based markers of psychosis conversion in UHR individuals, the limitations of existing studies, and the value of our study (page 4-6 in the annotated version). The sentence about recreational drug use has been modified to be more specific: "recreational drug" has been specified as "cannabis". The relevance of cannabis use has been more precisely defined: "over 50% of the individual who converted to psychosis in comparable studies Mongan et al. and Chaumette et al. reported a use of cannabis, representing a potential confounding factor."

Key points of the revised introduction include:

- 1. While there had been many studies that examined the transcriptomic changes associated with psychosis conversion, the majority are either cross-sectional or only involved a small set of candidate biomarkers.
- 2. Transition into psychosis is an evolving process and employing cross-sectional designs tend to introduce significant bias (Maxwell and Cole 2007)
- 3. Using a small set of candidate biomarkers precludes the discovery of novel candidate markers and the ability to perform gene set enrichment analysis.
- 4. We could only identify 2 studies that utilised high-throughput profiling on a longitudinal cohort study data, namely Chaumette et al. 2019 and Mongan et al. 2020.
- Neither Chaumette et al nor Mongan et al examined the gene ontologies of the gene differentially expressed with psychosis conversion. The methods utilised in the 2 studies (DESEQ and SVM respectively) were not designed to model intra-individual correlations inherent in longitudinal data.
- 6. over 50% of the individual who converted to psychosis in Mongan et al. and Chaumette et al. reported a use of cannabis. As cannabis has been reported to confer additional risk to psychosis transition, it represents a confounding factor.
- 7. Our study provides the following value:

- a. Utilised linear mixed-effect model-based method for identifying differentially expressed genes thereby accounting for intra-individual correlations in the data.
- b. We examined the gene ontology of the genes differentially expressed in psychosis conversion.
- c. We examined whether the genes that are differential with psychosis conversion are necessarily differential between pre-conversion and non-conversion participants.
- d. The drug free nature of our cohort allows for an analysis without confounding by cannabis and other illicit substances.
- e. As an additional opportunity, we were also able to examine whether the genes containing loci likely to confer significant risk of schizophrenia identified in a recent Psychiatric Genomic Consortium meta-analysis (Trubetskoy et al. 2022) were differentially expressed in the peripheral blood with psychosis conversion.

These changes have been worked into the introduction/background. We hope these are satisfactory, and now provides an improved framing of our research contribution.

In Table 1, the different comparisons should be ordered by increased adjusted p-value.

Response: Thank you for this comment. The rows in Table 1 and Table 2 have been reordered by ascending adjusted p-value

The second paragraph of the Discussion section should describe with much more detail the findings of the study. Which genes were correlated with mitosis? What are the roles of the genes found? Authors should also better explain why this pattern is indicative of immune upregulation, and other assumptions like "hematological phenotypes" found in their sample.

Please provide rationale for the arguments hypothesized, so that the findings make physiological sense to the reader.

Response:

Thank you for this comment, this comment brought to our attention that the 2nd paragraph of the discussion was lacking in elaboration. We have made the following changes:

- 1. The sections regarding the GO enrichment analysis has been reworked to explain why we believe the enriched ontologies is indicative of cellular replication/mitosis and consequently an immune upregulation.
 - a. GO terms were grouped by commonalities (e.g: mitotic spindle assembly, chromosomal segregation) in the results. Example: regulation of chromosome segregation (GO:0051983) and mitotic sister chromatid segregation (GO:0000070) were grouped into chromosomal segregation
 - b. The various commonalities in the terms namely: mitotic spindle assembly and organization, chromosomal segregation, and DNA replication and cell cycle regulation are all processes of cell replication. This pattern is highly suggestive of the source cells undergoing cellular replication.
 - c. Since the source of the RNA are leukocytes, a pattern of immune cell proliferation and thus immune upregulation.

Regarding the assumption of "haematological phenotypes", the term was intended to broadly describe phenotypes typically expected to be associated with SNPs located within genes expressed by cells in the peripheral blood (e.g. mean corpuscular volume and basophile count). We now realised that using this term may appear presumptuous. Hence, the 3rd paragraph of the discussion has been reworked to avoid is over generalising the enriched phenotypes. The changes made to the 3rd paragraph is described in greater detail below in response to the comment on the aptness of the term "co-morbidities".

English should be improved. E.g., the use of the word "terms" in line 239; line 82, "In total, 392 RNA libraries from the were collect from the..."

Response:

- 1. Thank you for the comment. Upon scrutinizing the text, we realised that in addition to the language, the term "RNA libraries" is not appropriate as at this stage, the RNA has not been extracted and the samples exist in venous whole blood. Line 82 has been rewritten to reflect this. It now reads as "In total, 392 venous whole blood samples were collected" (page 7 in annotated version). We greatly appreciate the opportunity to rectify this mistake.
- 2. The word "term" in line 239 has been replaced by the more appropriate "phenotype" (page 16 in annotated version).

We have also made language tweaks across the rest of the manuscript to improve readability and flow.

In the Discussion, use of term comorbidity might be inadequate, as authors did not investigate other illnesses in their sample. Nor were their findings related to comorbidities. Genes might be related to other physical entities but stating that they are related to comorbidities in schizophrenia is not quite right. As a matter of fact, immune response is possibly an integral component of disease pathophysiology, and not a comorbidity.

Response:

Thank you for this very astute comment. We understand that immune response is possibly an integral component of disease pathophysiology and not a comorbidity. Our original intention for the usage of the term "co-morbidity" was to group disorders/diseases such as insomnia and coronary artery diseases from the non-disorder/disease phenotypes such as systolic blood pressure.

Upon further consideration, we agree with the reviewer that the term "co-morbidities" is inappropriate. We now describe insomnia and coronary artery disease phenotypes as "disorders and diseases frequently observed in individuals with schizophrenia".

The interpretation we wish to convey was that while the differentially expressed genes were not enriched in SNPs associated with schizophrenia and psychosis GWAS phenotypes, many of the enriched phenotypes were reported to be perturbed in individuals with schizophrenia and psychosis.

Based on this pattern, we hypothesized that the connection between the peripheral blood and psychosis conversion is likely to be indirect.

Upon scrutiny, we understood that the writing is unsatisfactory and may cause confusion. Furthermore, while implied by its absence in Table 3, the result that the differentially expressed genes were not enriched in SNPs associated with GWAS phenotypes was not explicitly stated.

We apologize for these oversights.

We have made the following amendments to our text:

- 1. We have included a segment to explicitly state that the differentially expressed genes were not enriched in SNPs associated with GWAS phenotypes relating to psychosis and schizophrenia (annotated version page 13). We have also added a new supplementary table listing the number of overlap and adjusted p-value of the various GWAS phenotypes associated with psychosis and schizophrenia (Supplementary Table S6).
- We discussed the lack of enrichment for SNP associated in schizophrenia and psychosis in the discussion. This result is consistent with the recent meta-analysis by the Psychiatric Genomic Consortium (Trubetskoy et al. 2022) that revealed that most of the SNP conferring significant risk to schizophrenia were expressed neuronal cells in the CNS (page 16 in the annotated version)
- 3. Insomnia and coronary artery disease is now described as "disorders and diseases frequently observed in individuals with schizophrenia" (page 17 in the annotated version)
- 4. We rephrased our original hypothesis
 - a. Original: "neurological changes associated with psychosis conversion are accompanied by a range of non-neurological concomitant changes, many of which have been reported to be correlated with and or co-morbidities of schizophrenia"
 - b. New: "We hypothesize that the association between psychosis conversion and biomarkers readily observable in the peripheral whole blood is likely to be indirect" (page 17 in annotated version)
- 5. We elaborated upon the implications of our hypothesis to include important future research questions.
 - a. Original: "Consequently, using blood-based markers to detect co-morbidities and concomitant changes of psychosis and schizophrenia could represent a meaningful direction in predicting clinical outcomes in UHR individuals."
 - b. New: "Whether a differential expression of genes enriched for SNPs associated with these phenotypes necessarily indicate a perturbation of the phenotype, and how are these non-neurological phenotypes implicated in the pathophysiology of psychosis will be important research directions to evaluate this hypothesis. If positive evidence of both questions can be found, using blood-based markers to detect concomitant changes of psychosis and schizophrenia could represent a viable avenue for predicting clinical outcomes in UHR individuals." (page 17 in annotated version)

Please refrain from using the term "schizophrenic" as it is stigmatizing (line 240).

Response:

Thank you for pointing this out. We did not mean to offend any groups. This was an oversight on our part. Consistent with the remainder of the text, the line has been amended to read "individual with schizophrenia" (line 326 in the annotated version)

- Peripheral whole blood samples were collected from UHR individuals at 12 months intervals.
- Profiling by RNA-sequencing indicates that psychosis conversion in UHR individuals is associated with immune dysregulation.
- Genes differential in psychosis conversion are not associated with schizophrenia and psychosis phenotypes but are associated with many phenotypes reported to be perturbed in schizophrenia. We hypothesize an indirect connection between the peripheral blood and psychosis conversion.
- Uncovering mechanistic links between psychosis conversion and the perturbed phenotypes along with the connection between the perturbed phenotypes and the genes differentially expressed with psychosis conversion will be important research directions.
- Minimal overlap between gene differential for psychosis conversion and genes differential between pre-conversion sample from non-conversion samples.

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The computational work for this article was partially performed on resources of the National Supercomputing Centre, Singapore (<u>https://www.nscc.sg</u>).



	GWAS Phenotype	SHORT vs CVT	MEDIUM vs CVT
		adj.p-val	adj.p-val
Both SHORT vs	body height	2.65E-71	4.90E-07
CVT and			
MEDIUM vs CVT	systolic blood pressure	0.004808	2.74E-06
SHORT vs CVT	acute myeloid leukemia	0	-
only	neuroimaging measurement	2.31E-75	-
	insomnia	2.28E-45	-
	educational attainment	5.67E-25	-
	vaginal microbiome measurement	7.79E-16	-
	smoking initiation	6.80E-12	-
	rheumatic heart disease	3.92E-10	-
	lipid measurement	9.13E-07	-
	phospholipid measurement	1.95E-05	-
	response to tenofovir	4.47E-05	-
	mean corpuscular hemoglobin	0.000135	-
	brain measurement	0.000139	-
	gut microbiome measurement	0.000331	-
	basophil count	0.000412	-
	total cholesterol measurement	0.000431	-
	brain volume measurement	0.001301	-
	mean corpuscular volume	0.003454	-
	erythrocyte count	0.004056	-
	attention deficit hyperactivity disorder	0.005285	-
	coronary artery disease	0.007824	-
	mean reticulocyte volume	0.009638	-
	high density lipoprotein cholesterol		-
	measurement	0.028402	
	basophil percentage of leukocytes	0.029636	-
MEDIUM vs CVT	triglyceride measurement	-	2.03E-07
only	body mass index	-	5.64E-07

Table 3: Enriched GWAS phenotypes in SHORT vs CVT and MEDIUM vs CVT

	Term	Overlap	Adjusted P-value	Combined Score	Genes
	mitotic spindle organization (GO:0007052)	10/157	4.47E-05	187.6127	CDC20;TPX2;CENPF;KIF4A; BUB1B;BIRC5;KIF2C;BUB1;S KA1;DLGAP5
	microtubule cytoskeleton organization involved in mitosis (GO:1902850)	9/128	4.47E-05	198.4685	CDC20;CENPF;KIF4A;BUB1B ;BIRC5;KIF2C;BUB1;SKA1;D LGAP5
	regulation of mitotic cell cycle phase transition (GO:1901990)	9/188	5.52E-04	104.6555	CDC20;TPX2;ANLN;CENPF;C DK1;KIF14;BUB1B;HMMR;C DC6
	mitotic sister chromatid segregation (GO:0000070)	7/102	5.52E-04	149.2213	KIF18B;CDK1;KIF14;NCAPG; KIF2C;CEP55;DLGAP5
T vs CVT	regulation of chromosome segregation (GO:0051983)	4/18	5.52E-04	562.6262	KIF2C;CDC6;MKI67;BUB1
SHOR	hepatocyte differentiation (GO:0070365)	3/6	5.52E-04	1938.618	PROX1;E2F7;E2F8
	DNA replication (GO:0006260)	7/108	5.70E-04	136.0071	EXO1;PCLAF;CDK1;MCM10; CLSPN;CDC6;TICRR
	spindle assembly checkpoint signaling (GO:0071173)	4/21	5.78E-04	438.5553	CDC20;CENPF;BUB1B;BUB1
	mitotic spindle assembly checkpoint signaling (GO:0007094)	4/21	5.78F-04	438.5553	CDC20:CENPE:BUB1B:BUB1
	mitotic spindle checkpoint signaling (GO:0071174)	4/21	5.78F-04	438 5553	CDC20:CENPE-BUB1B-BUB1
	monovalent inorganic anion homeostasis (GO:0055083)	1/10	0.045367	1307.487	CA12
	mitotic DNA replication checkpoint signaling (GO:0033314)	1/10	0.045367	1307.487	ORC1
vs CVT	chloride ion homeostasis (GO:0055064)	1/10	0.045367	1307.487	CA12
MEDIUM v	mitotic nuclear membrane disassembly (GO:0007077)	1/12	0.045367	1032.951	CCNB2
	mitotic DNA integrity checkpoint signaling (GO:0044774)	1/13	0.045367	932.0597	ORC1
	nuclear membrane disassembly (GO:0051081)	1/14	0.045367	847.7047	CCNB2

Table 2: Top 10 enriched gene ontologies in SHORT vs CVT and MEDIUM vs CVT

DNA replication	1/17	0.047186	661.819	ORC1
checkpoint signaling				
(GO:0000076)				
positive regulation of	1/21	0.050957	506.0053	TEDC2
smoothened signaling				
pathway (GO:0045880)				
regulation of	1/32	0.061207	296.3194	ORC1
transcription involved in				
G1/S transition of mitotic				
cell cycle (GO:000083)				
bicarbonate transport	1/35	0.061207	264.3328	CA12
(GO:0015701)				

0.029279

0.034103

0.034103

0.034103

0.034103

0.042874

0.042963

0.042963

0.048307

2.25E-03

5.55E-03

5.77E-03

1.63E-02

1.80E-02

1.80E-02

1.98E-02

2.20E-02

3.23E-02

4.99E-02

3.027541

2.084801

2.405233

2.478262

2.660014

1.717976

1.531203

1.507651

1.306614

5.587628 4.679412

3.728576

2.135852

1.908368

2.111974

1.569783

1.530564

0.886514

-0.09548

	Gene symbol	log2FC	Avg Expr	adj.P.Val	Log-odds DE
	IGKV1-6	1.749106	2.151455	0.00223	6.270656
	PCOLCE2	2.446494	-3.358	0.004089	4.545012
∟	CYP51A1P1	1.8136	-2.89244	0.011334	0.954209
5	ITGA8	1.922005	-3.78934	0.017899	-0.271
VS	AC005220.1	-1.80242	-4.31701	0.022967	-0.7087
RT	EEF1A1P30	-1.91238	-3.86173	0.024979	-0.92225
Р	AP003419.3	-2.01198	-3.92194	0.032333	-1.41701
S	AC253536.3	1.709154	-2.73394	0.032544	-1.46671
	AC079331.2	-1.92406	-3.66073	0.034124	-1.51914
	AC136618.1	-1.94269	-3.90204	0.034201	-1.51579
⊢	AC106872.3	1.063223	-3.23106	0.005703	4.106383
Ş	UBE3AP2	-1.10486	-1.9454	0.019576	1.907311
nor	FAM27E4	1.414184	-4.00346	0.02079	1.97393
vs r	ENSG00000286996	-1.1608	-2.15429	0.023742	1.057269
RT	CYP51A1P1	-1.50222	-2.89244	0.026721	0.658721
SHO	ENSG00000286065	-1.04637	-2.17584	0.048531	-0.92696
	AC145423.3	-1.55434	-2.22482	0.02214	3.62668

2.632654

-0.45198

-1.87729

-0.97772

0.716462

-0.74495

-1.40456

0.766532

-3.34769

-3.34769

-3.24698

-2.22482

0.572607

-3.28153

-3.21542

-1.03113

-3.22812

-3.00218

-2.15429

-1.19849

2.204792

1.551655

-1.21044

-1.48894

-1.58104

1.436071

-1.95492

2.050455

2.100376

1.351728

2.204425

1.788875

1.427606

1.419754

1.3693

2.38041

-1.39376

1.1773

LINC02289

IGKV2D-24

AC027607.1

ENSG00000285966

ENSG0000285534

TEDC2

ORC1

CCNB2

CA12

CA12

LINC01629

DAAM2

ADGRB3

AC145423.3

ATP2C2-AS1

AC020703.1

ENSG0000286996

TMEM119

MAOA

MEDIUM vs CVT

MEDIUM vs non-CVT

Table 1: Top 10 differentially Expressed Genes Across Different Comparisons

e-Component/Supplementary Material

Click here to access/download e-Component/Supplementary Material Supplementary.docx

Financial Disclosure

The authors declare no financial conflict of interest.

Conflict of Interest

The authors declare no conflict of interest.

REVISED Manuscript (text UNmarked)

1 Abstract

2 Background

The peripheral blood is an attractive source of prognostic biomarkers for psychosis conversion. There is limited research on the transcriptomic changes associated with psychosis conversion in the peripheral whole blood.

6 Study Design

We performed RNA-sequencing of peripheral whole blood from 65 ultra-high-risk (UHR)
participants and 70 healthy control participants recruited in the Longitudinal Youth-at-Risk
Study (LYRIKS) cohort. 13 UHR participants converted in the study duration. Samples were
collected at 3 timepoints, at 12-months interval across a 2-year period. We examined whether
the genes differential with psychosis conversion contain schizophrenia risk loci. We then
examined the functional ontologies and GWAS associations of the differential genes. We also
identified the overlap between differentially expressed genes across different comparisons.

14 Study results

Genes containing schizophrenia risk loci were not differentially expressed in the peripheral whole blood in psychosis conversion. The differentially expressed genes in psychosis conversion are enriched for ontologies associated with cellular replication. The differentially expressed genes in psychosis conversion are associated with non-neurological GWAS phenotypes reported to be perturbed in schizophrenia and psychosis but not schizophrenia and psychosis phenotypes themselves. We found minimal overlap between the genes differential with psychosis conversion and the genes that are differential between pre-conversion and non-conversion samples.

23 Conclusion

The associations between psychosis conversion and peripheral blood-based biomarkers are likely to be indirect. Further studies to elucidate the mechanism behind potential indirect associations are needed.

27 Introduction

The ultra-high-risk (UHR) criteria was introduced to identify individuals likely in the 28 29 prodromal phase of psychosis (A. R. Yung et al. 1996). Accurate and early identification is 30 essential for targeted interventions to improve clinical outcomes (Fusar-Poli, McGorry, and 31 Kane 2017). Psychometric assessments such as the Comprehensive Assessment for At-Risk 32 Mental States (CAARMS)(Alison R. Yung et al. 2005) and the Structured Interview for Prodromal 33 Syndromes (SIPS)(Miller et al. 2003) have been shown to have high sensitivity but poor specificity(Oliver et al. 2022). There is thus motivation to supplement the UHR designation with 34 35 other measurements.

The peripheral blood is an attractive source for biomarker discovery (Liew et al. 2006). Many studies have been conducted in attempts to identify blood-based biomarkers of psychosis conversion (Ota et al. 2019; Demars et al. 2020; Chaumette et al. 2019; Mongan et al. 2020; English et al. 2018; Perkins et al. 2015; Laskaris et al. 2019). However, the majority of existing studies are either cross-sectional (Ota et al. 2019; Laskaris et al. 2019) or only assessed the expression changes of a selected list of candidate genes (English et al. 2018; Perkins et al. 2015;

42 Demars et al. 2020). Transition into psychosis is an evolving process and employing cross-43 sectional designs tend to introduce significant bias (Maxwell and Cole 2007). Additionally, 44 assessing a relatively small set of candidate genes precludes the possibility of discovering novel biomarkers and the characterization of transcriptomic changes using methods such as Gene Set 45 Enrichment Analysis (GSEA) (Subramanian et al. 2005). To date, only 2 studies profiled the 46 47 transcriptomic changes of psychosis conversion in a longitudinal study cohort using highthroughput methods (Chaumette et al. 2019; Mongan et al. 2020). 48 49 Existing studies are limited in a few aspects: First, at the time of writing, no studies have examined the gene ontologies of the genes differentially expressed in psychosis conversion. 50 Second, it is unknown if the genes differentially expressed in psychosis conversion are 51 52 necessarily differential between pre-conversion and non-conversion participants – a property that reflects the suitability and reliability of the genes as prognostic biomarker. Third, the intra-53 54 individual correlation inherent to longitudinal data were not accounted for in existing studies 55 (Chaumette et al. 2019; Mongan et al. 2020). Fourth, over 50% of converters in existing studies reported a history of cannabis use (Chaumette et al. 2019; Mongan et al. 2020) – this is a 56 potential confounding factor as cannabis use has been strongly evidenced to confers additional 57 58 risk in transition to psychosis (Gage, Hickman, and Zammit 2016). 59 We performed RNA-sequencing on whole blood samples from a subsample of the 60 LYRIKS cohort (Lee et al. 2013). Peripheral whole blood samples were collected from the LYRIKS 61 cohort at 12 months interval and individuals with a history of substance use (including 62 cannabis) were excluded from the study (Lee et al. 2013).

Using a linear-mixed effect model-based method (Hoffman and Roussos 2021), we 63 64 examined the differential expression of gene in psychosis conversion and the gene ontology enrichment of the differentially expressed genes. The linear-mixed effect model based method 65 allows us to model the intra-individual correlations within the data (Diggle 2013). Along with 66 67 the gene ontology enrichment analysis, the differential expression analysis also provides us an opportunity to examine whether a set of 120 genes containing high-risk loci identified by a 68 recent large scale meta-analysis are differentially expressed with psychosis conversion in the 69 70 peripheral blood (Trubetskoy et al. 2022). We then examined whether the genes that are 71 differential with psychosis conversion are necessarily differential between pre-conversion and non-conversion participants. The drug-free nature of our cohort also allows us to provide a 72 73 perspective into the transcriptomic changes of psychosis conversion with minimal confounding by cannabis and other illicit substances use. 74 75 This study aims to expand upon the existing understanding of blood-based biomarkers of psychosis conversion and provide directions for future studies in this domain.

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78 **Methods**

Participants 79

80 The Longitudinal Youth-at-Risk study (LYRIKS) was a prospective, observational study 81 conducted in Singapore on youths aged 14 to 29 to assess risk factors for psychosis (Lee et al., 2013). Briefly, participants were followed up over 2 years and were recruited from psychiatric 82 clinics, various community agencies including educational institutes and social services, or were 83

self-referred. Participants were excluded if they (i) had a past or current history of psychosis or
intellectual disability, (ii) were currently using illicit substances, (iii) were taking mood
stabilizers, (iv) had previous antipsychotic exposure of more than 5 mg haloperidol per day for 3
weeks (or equivalent) or were on an antipsychotic at the point of recruitment, or (iv) had
medical causes associated with their attenuated psychotic symptoms.

89 Ethics approval for this study was provided by the National Healthcare Group's Domain Specific Review Board (approval number 2009/00167). After complete description of the study 90 91 to the participants, written informed consent was obtained. The present study utilised whole blood samples from 135 participants (70 control (CTRL) and 65 UHR) from the original LYRIKS 92 cohort (Lee et al. 2013). All samples from participants who converted were included. Only 93 94 samples from participants with at least 2 follow-ups were included for control and participants 95 who did not convert. UHR designation and psychosis threshold were assessed using CAARMS. 96 Venous whole blood samples were collected from the participants at 12-month intervals. 97 Participants who converted at any point in the study were removed from the study following a final sample collection. Of the 65 UHR participants, 13 converted to psychosis (CVT) and 52 did 98 not (non-CVT). In total, 392 venous whole blood samples were collected (Supplementary Table 99 100 **S1**).

101 Demographic

The control group (CTRL) consist of 25 [35.7%] females with mean [SD] age of 21.1 [3.07] years and 45 [64.3%] males with mean [SD] age of 22.8 [3.51] years. The UHR group consist of 46 [70.8%] males with mean [SD] age of 21.4 [3.08] years and 19 [29.2%] females with mean

105	[SD] age of 21.9 [3.05] years. Of the 65 UHR participants, 52 participants did not develop
106	psychosis over the 2-year study period (non-CVT). Of the 52 non-CVT participants, 17 [32.7%]
107	are female with a mean [SD] age of 22.2 [3.3] years and 35 [67.3%] are male with mean [SD]
108	age of 21.4 [3.08] years. The remaining 13 [20%] UHR participants with mean [SD] age of 20.3
109	[3.13] years developed psychosis over the study period (CVT); 2 [15.4%] are females. The
110	median time to conversion from baseline was 11 months [IQR 19 - 5 = 14].
111	No statistically significant difference in sex proportion was found between CVT
112	participants and CTRL participants (Chi-squared = 2.06 , p = 0.205) or with non-CVT participants
113	(Chi-squared = 3.06; P= 0.080). No statistically significant difference in age was found between
114	CVT participants and CTRL participants (t = 1.05, 95% CI, [-1.05, 3.11]; P = 0.310) or non-CVT
115	participants (t = -0.48142; 95% Cl, [-2.58, 1.62]; P = 0.636).

116 Sequencing and pre-processing

117 A sample of venous whole blood was collected from all participants into Tempus[™] 118 Blood RNA tube (Thermo Fisher Scientific) and stored at -80°C. Total RNA was extracted with the Tempus[™] Spin RNA Isolation Kit (Thermo Fisher Scientific) according to manufacturer's 119 120 protocol. Quality and concentration of extracted RNA was measured with 2100 Bioanalyzer System (Agilent). The libraries were prepped and sequenced using 8 Illumina NovaSeq 121 (2x151bp) sequencing lanes. Sequencing quality was assessed using FastQC v0.11.9 (Schmieder 122 and Edwards 2011). Sequences are aligned to Ensembl GRCh38 using STAR 2.7.9a (Dobin et al. 123 2013). Aligned reads are quantified using featureCount from the Subread 2.0.3 R Package (Liao, 124 125 Smyth, and Shi 2019). Genes with zero variance and mean count < 1 were discarded yielding a

- total of 21810 genes. All processing and analysis were performed in the R Programming
- 127 language Version 4.0.3 (R Core Team 2013).

128 **Power analysis**

- We performed power analysis using ssizeRNA R package (Bi and Liu 2016). We defined our criteria at absolute log2 fold-change > 1 and false discover rate = 0.05. Following the low number of differentially expressed genes in similar studies (Mongan et al. 2020; Chaumette et al. 2019), we set our expected proportion of differentially expressed genes at 0.005. We found that a sample size of 11 is sufficient to achieve a statistical power of 0.81. At 13 converter
- 134 samples, our study has a power of 0.851.

135 Differential gene analysis

- 136 We divided the samples into 5 groups (**Figure 1**):
- 137 (1) Samples from participants who did not develop psychosis (non-CVT)
- 138 (2) Samples from participants post-conversion (CVT)
- (3) Samples collected less than, or equal to 12 months before conversion (SHORT)
- 140 (4) Samples collected more than 12 months before conversion (MEDIUM)
- 141 (5) Samples from participants healthy controls (CTRL)
- 142 Samples in SHORT and MEDIUM will be referred to as pre-conversion samples (pre-CVT).
- 143 *Sex* and *time* were included as model covariates where *time* is the month of sample collection.
- 144 Longitudinal data involves repeated measurements from the same participant across time

which introduces intra-individual correlation. Repeated measurements result in intra-individual
correlations that needs to be accounted for in the model. One method capable of modelling
such correlation is the linear mixed effect model (Diggle 2013). We modelled known co-variates
in the data via a linear mixed effect model using the DREAM model (Hoffman and Roussos
2021) from the voom-limma pipeline (Law et al. 2014). We modelled the slope of each sample
across time and sample intercept as random effects:

151
$$y = group + sex + time + (time|sample) + (0|sample)$$

p-value adjustment (adjusted p-value) for multiple testing was addressed via BenjaminiHochberg correction (Benjamini and Hochberg 1995). Threshold for differential expression was
defined at an absolute log fold-change of > 1 and an adjusted p-value of < 0.05. List of contrasts
used can be found in **Supplementary Notes.**

156 <Insert Figure 1>

157 Functional profiling via Gene Ontology analysis

- 158 Enrichment analysis for Gene Ontology (GO) functional terms was performed using
- 159 Enrichr (Chen et al. 2013) webtool (which employs a Fisher's exact test). We examined the top
- 160 10 enriched ontologies ranked by adjusted p-value for analysis and interpretation.

161 **Phenotype association analysis**

162 GWAS phenotype associations were queried from the Genecards database (Fishilevich 163 et al. 2017; Stelzer et al. 2016). GWAS phenotypes with less than 5 occurrences amongst the differential genes were dropped. We perform Fisher's exact tests with Bonferroni correction to
 determine if the differential genes are enriched for SNP associated with a particular phenotype
 found in the European Bioinformatics Institute (EBI) GWAS catalog (Buniello et al. 2019). The
 same EBI catalogue is used in Genecards (Stelzer et al. 2016). Further details on data processing
 procedure are detailed in Supplementary Notes.

- 169
- 170 <u>Results</u>

171 Differential gene expression analysis

172 We identified 12, and 130 genes differentially expressed in MEDIUM vs CVT, and SHORT 173 vs CVT respectively. The 10 differential genes with largest fold changes are listed in Table 1, the 174 full list of differential genes can be found in Supplementary Table S2-S3. No genes were found to be differential in MEDIUM vs SHORT. We also identified 6, and 22 genes differentially expressed in 175 176 MEDIUM vs non-CVT, and SHORT vs non-CVT respectively (Table 1) (full list in Supplementary 177 Table S4-S5). No differential genes were identified when comparing CTRL vs CVT. We then 178 examined whether the genes reported to contain high-risk loci in a recent large-scale metaanalysis were differentially expressed in our analysis (Trubetskoy et al. 2022). None of the 179 genes associated with those loci were differentially expressed in our analyses. 180

181

182 < Insert Table 1 >

183 Gene ontology enrichment analysis

184	We performed enrichment analysis of the differential genes found in SHORT vs CVT and
185	MEDIUM vs CVT to identify enriched gene ontologies. The enriched ontologies in SHORT vs CVT
186	contain commonalities namely: mitotic spindle assembly and organization (GO:0007052;
187	GO:0071173; GO:0007094; GO:0071174), chromosomal segregation (GO:0051983; GO:0000070), and
188	DNA replication and cell cycle regulation (GO:1901990; GO:0006260) (Table 2). Commonalities in the
189	enriched ontologies in MEDIUM vs CVT include: cell cycle checkpoint (GO:0044774; GO:0033314;
190	GO:0000076; GO:0000083), and nuclear membrane disassembly (GO:0007077; GO:0051081) (Table 2).
191	However, the overlap is minimal between the GO gene sets and the genes differential in
192	MEDIUM vs CVT, likely due to the small number of differential genes in this comparison.
193	< Insert Table 2 >
193 194	< Insert Table 2 > GWAS phenotypes enrichment analysis
193 194 195	< Insert Table 2 > GWAS phenotypes enrichment analysis We examined the GWAS phenotypes associated with SNPs within the differentially
193 194 195 196	< Insert Table 2 > GWAS phenotypes enrichment analysis We examined the GWAS phenotypes associated with SNPs within the differentially expressed genes for SHORT vs CVT and MEDIUM vs CVT. We found 25 and 4 GWAS phenotypes
193 194 195 196 197	< Insert Table 2 > GWAS phenotypes enrichment analysis We examined the GWAS phenotypes associated with SNPs within the differentially expressed genes for SHORT vs CVT and MEDIUM vs CVT. We found 25 and 4 GWAS phenotypes that are enriched amongst the GWAS phenotypes of genes differential in SHORT vs CVT and
193 194 195 196 197 198	< Insert Table 2 > GWAS phenotypes enrichment analysis We examined the GWAS phenotypes associated with SNPs within the differentially expressed genes for SHORT vs CVT and MEDIUM vs CVT. We found 25 and 4 GWAS phenotypes that are enriched amongst the GWAS phenotypes of genes differential in SHORT vs CVT and MEDIUM vs CVT respectively (Table 3). The differentially expressed genes were not enriched
193 194 195 196 197 198 199	< Insert Table 2 > GWAS phenotypes enrichment analysis We examined the GWAS phenotypes associated with SNPs within the differentially expressed genes for SHORT vs CVT and MEDIUM vs CVT. We found 25 and 4 GWAS phenotypes that are enriched amongst the GWAS phenotypes of genes differential in SHORT vs CVT and MEDIUM vs CVT respectively (Table 3). The differentially expressed genes were not enriched for any schizophrenia and psychosis GWAS phenotypes (Supplementary Table S6).

200 < Insert Table 3 >

201 Comparison between genes differential in psychosis conversion and genes differential in pre 202 conversion and non-conversion

203	We examined whether the genes differential in psychosis conversion are also
204	differential between pre-conversion and non-conversion participants. We identified the
205	intersection (denoted by the symbol \cap) between the set of genes differential in psychosis
206	conversion and the set of genes differential between pre-conversion and non-conversion. We
207	found 2 genes in SHORT vs CVT \cap SHORT vs non-CVT and 5 gene in both MEDIUM vs CVT \cap
208	MEDIUM vs non-CVT. CYP51A1P1 and UBE3AP2 were differential in both SHORT vs CVT and
209	SHORT vs non-CVT. CA12, COL9A2 and pseudogenes ENSG00000285966, ENSG00000248936,
210	ENSG00000278112 were differential in both MEDIUM vs CVT and MEDIUM vs non-CVT.
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220 Discussion

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221 Our study possesses several properties that allow for unique perspectives into the nuances of peripheral blood-based transcriptomic changes in UHR and psychosis conversion. 222 First, at the time of writing, we are the first to conduct a gene ontology enrichment 223 224 analysis on the genes differential in psychosis conversion using a longitudinal cohort. Second, 225 we employed a mixed-effect model to account for the intra-individual correlation within a 226 longitudinal data – a factor unaccounted for in previous studies (Chaumette et al. 2019; Mongan et al. 2020). Third, owing to the recruitment criteria, our study cohort is minimally 227 confounded by substance use. Fourth, at the time of writing, this study is the first to examine 228 229 whether the gene differential in psychosis conversion is also differential between pre-230 conversion and non-conversion participants. The genes identified in recent whole exome (Singh et al. 2022) and large scale GWAS 231 232 (Trubetskoy et al. 2022) analyses to confer high risk of schizophrenia were not differentially 233 expressed in our analyses. This is consistent with the finding that the genes were mostly 234 expressed in synaptic junctions rather than the peripheral blood (Trubetskoy et al. 2022). This finding highlights the difficulty of employing schizophrenia genetic risk loci as a basis of 235 identifying biomarkers in the peripheral blood. 236 The commonalities in the enriched gene ontologies include 1) mitotic spindle assembly 237

cycle checkpoint, and 4) nuclear membrane disassembly – all processes of cellular replication.

and organization, 2) chromosomal segregation, 3) DNA replication and cell cycle regulation cell

240 This pattern suggests that the source cells are proliferating. Considering that nucleated cells in

the whole blood are generally leukocytes, the source cells are predominately leukocytes and
this observation is consistent with a pattern of immune upregulation widely observed in
schizophrenia and psychosis conversion (Gardiner et al. 2013; Tomasik et al. 2016; Xu et al.
2012). Disentangling biomarkers specific to psychosis conversion from markers of general
immune responses will be a crucial step in the identification of peripheral blood-based
biomarkers of psychosis.

247 Gene differential with psychosis conversion were not enriched with SNPs associated 248 with schizophrenia or psychosis phenotypes. This is consistent with a recent finding that found that the genes containing the SNPs conferring substantial risk to schizophrenia were 249 predominately expressed by neuronal cells in the central nervous system (Trubetskoy et al. 250 251 2022). Several of the enriched phenotypes have been reported to be perturbed in individuals 252 with schizophrenia, these include cell population ratios such as neutrophil to lymphocyte ratio (Karageorgiou, Milas, and Michopoulos 2019), physiological measurements such as fatty acid 253 measurement and systolic blood pressure (Andreassen et al. 2013), disorders and diseases 254 255 frequently observed in individuals with schizophrenia such as insomnia and coronary artery 256 disease (Palmese et al. 2011; Ifteni et al. 2014), and variations in the gut microbiome (Nguyen 257 et al. 2019; Zhu et al. 2020). We hypothesize that the association between psychosis conversion 258 and biomarkers readily observable in the peripheral whole blood is likely to be indirect. 259 Whether a differential expression of genes enriched for SNPs associated with these phenotypes 260 necessarily indicate a perturbation of the phenotype, and how are these non-neurological 261 phenotypes implicated in the pathophysiology of psychosis will be important research 262 directions to evaluate this hypothesis. If positive evidence of both questions can be found,

using blood-based markers to detect concomitant changes of psychosis and schizophrenia could
represent a viable avenue for predicting clinical outcomes in UHR individuals.

Genes differential with psychosis conversion are not necessarily differential between 265 pre-conversion and non-conversion individuals. Of the genes that exist in the overlaps, 266 267 CYP51A1P1 and UBE3AP2 were differential in both SHORT vs CVT and SHORT vs non-CVT. 268 CYP51A1P1 is a pseudogene for cytochrome P450 family 51 subfamily A member 1 (CYP51A1). 269 The cytochrome P450 family proteins are predominantly involved in lipids and cholesterol 270 metabolism (Stelzer et al. 2016). UBE3AP2 is a pseudogene for ubiquitin protein ligase 3A (UBE3A) and was reported to associate with hypertension (Stelzer et al. 2016). While certain 271 rare variants in UBE3A has been proposed to confer risks to schizophrenia (Singh et al. 2022; 272 273 Trubetskoy et al. 2022), it is unclear if this correlation might extend to pseudogenes of UBE3A 274 and to psychosis conversion. Genes CA12, COL9A2 were differential in both MEDIUM vs CVT and MEDIUM vs non-CVT. CA12 is a carbonic anhydrase which catalyzes the reversible 275 hydration of carbon dioxide. GWAS associated studies reported that CA12 is associated with a 276 277 large range of phenotypes including schizophrenia symptom severity (Stelzer et al. 2016). COL9A2 codes for an alpha chain subunit in type IX collagen. Associations between COL9A2 and 278 279 schizophrenia are indirect, via phenotypes such as cognitive measurements (Lam et al. 2018), 280 testosterone measurements (Moore et al. 2013), and waist-hip-ratio (Andreassen et al. 2013). 281 At the time of writing, the functions of ENSG00000285966, ENSG00000248936, and ENSG00000278112 are unknown and will not be discussed. Based on our study design, these 282 283 genes and pseudogenes are theoretical candidate biomarkers for psychosis conversion. 284 However, the lack of robust links to pathways linked to the pathology of schizophrenia

dampens our confidence in the ability of these genes and pseudogenes to serve as biomarkersof psychosis conversion.

287 Limitation

288	Our study contains several limitations. Firstly, the sample size of 392 used in this study is
289	relatively small especially since samples are distributed into multiple time-points across various
290	groups. Hence, the inferential statistical analyses performed in this study may be
291	underpowered. However, we opine that a reliable (and useful) biomarker should be robust and
292	detectable, even against the backdrop of small sample sizes. Secondly, we did not distinguish
293	non-CVT participants who remitted from the UHR status from non-CVT participants who
294	maintained UHR status to avoid further reducing sample sizes across groups. Thirdly, the
295	etiology of psychosis conversion is inherently heterogenous (Zwicker, Denovan-Wright, and
296	Uher 2018) and without a basis for pre-defining all medically relevant subtypes, our study
297	design was unable to account for the heterogenous nature of psychosis conversion. Finally, the
298	overlaps in our gene ontology enrichment analysis are small especially in MEDIUM vs CVT, we
299	advise the readers to exercise discretion when considering the results.

300 Conclusion

The identification of peripheral blood-based biomarkers for psychosis is an area of great clinical value. Our study expanded upon existing studies by illustrating various important nuances in the identification of peripheral blood-based biomarkers of psychosis conversion and establishes directions for future investigations. We identified differentially expressed genes in

psychosis conversion, which were consistent with a pattern of immune upregulation. The SNPs 305 306 in the genes differential in psychosis conversion were associated with a range of phenotypes reported to be perturbed in schizophrenia and psychosis but are not associated with 307 308 schizophrenia and psychosis phenotypes themselves. We also showed that the genes correlated 309 with psychosis conversion are not necessarily differential between pre-conversion and nonconversion individuals. The genes containing risk loci for schizophrenia were not differentially 310 expressed in the peripheral whole blood in psychosis conversion. From these findings, we 311 312 hypothesize that the associations between psychosis conversion and peripheral blood 313 biomarkers are indirect. Mechanistic studies to examine such indirect associations will be a 314 valuable research direction.

315 Data availability

The results of each contrast in the differential genes analysis can be found in the Supplementary section. Supplementary information is available at the journal website. Raw transcripts counts are not available due to patient confidentiality requirements. Analysis code is available on request from the authors.

320 Author contribution

321	S.M.X.T., Y.J.Y., J.L	., and W.W.B.G	conceptualized a	and designed the	e research; S.M.X.T., Y.J.	.Y.
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322 performed the research; S.M.X.T. performed that statistical analysis; S.M.X.T. and Y.J.Y. wrote

323 the manuscript; Y.J.Y. and J.L. were responsible for the acquisition of the data; S.M.X.T., B.S.,

324 S.B., Z.D., M.D., N.K., E.L., A.S, Y.J.Y., J.L., and W.W.B.G interpretated the results; B.S., S.B., Z.D.,

325	M.D., N.K., E.L., A.S, Y.J.Y., J.L., and W.W.B.G reviewed the work. All authors approve of the
326	submitted version of the manuscript.
327	Transparency declaration
328	We affirm that the manuscript is an honest, accurate, and transparent account of the
329	study being reported; that no important aspects of the study have been omitted; and that any
330	discrepancies from the study as planned have been explained.
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- 521

522

1 Abstract

2 Background

- 3 The peripheral blood is an attractive source of prognostic biomarkers for psychosis
- 4 conversion. It is also unclear whether genes correlated with psychosis conversion can reliably
- 5 identify patients who will eventually experience psychosis and schizophrenia in the future.
- 6 There is limited research on the transcriptomic changes associated with psychosis conversion in
- 7 the peripheral whole blood.

8 Study Design

- 9 We performed RNA-sequencing of peripheral whole blood from 65 ultra-high-risk (UHR)
- 10 participants and 70 healthy control participants recruited in the Longitudinal Youth-at-Risk
- 11 Study (LYRIKS) cohort. 13 UHR participants converted in the study duration. Samples were
- 12 collected at 3 timepoints, at 12-months interval across a 2-year period. We examined the
- 13 functional ontologies and genetic associations of the differential genes correlated with
- 14 psychosis conversion. We then compared the sets of differentially expressed genes across
- 15 different comparisons. We examined whether the genes differential with psychosis conversion
- 16 contain schizophrenia risk loci. We then examined the functional ontologies and GWAS
- 17 associations of the differential genes. We also identified the overlap between differentially
- 18 expressed genes across different comparisons.
- 19 Study results

Commented [ST2]: Changes made to reflect the addition of whether "genes differential with psychosis conversion contain schizophrenia risk loci"

1

20

Commented [ST1]: This change has been made to better reflect the revised framing of the research; the lack of highthroughput longitudinal studies into the transcriptomic changes in psychosis conversion

21	The differentially expressed genes are enriched for ontologies associated with cellular
22	replication. GWAS phenotypes associated with co-morbidities of schizophrenia such as
23	"insomnia" and "coronary artery disease" as well as physiological parameters associated with
24	schizophrenia such as "fatty acid measurements", "body height", "systolic blood pressure", and
25	"gut microbiome measurements" were also observed. Genes containing schizophrenia risk loci
26	were not differentially expressed in the peripheral whole blood in psychosis conversion. The
27	differentially expressed genes in psychosis conversion are enriched for ontologies associated
28	with cellular replication. The differentially expressed genes in psychosis conversion are
29	associated with non-neurological GWAS phenotypes reported to be perturbed in schizophrenia
30	and psychosis but not schizophrenia and psychosis phenotypes themselves. We found minimal
31	overlap between the genes differential with psychosis conversion and the genes that are
32	differential between pre-conversion and non-conversion samples.
33	Conclusion
34	Our findings are consistent with theories of immune dysregulation in psychosis. Using
35	blood-based markers to detect co-morbidities and concomitant changes of psychosis might
36	represent a viable direction in prognosis in UHR individuals. Our results also illustrate the
37	distinction between genes differential with psychosis conversion with genes useful as biomarkers
38	of psychosis conversion.
39	The associations between psychosis conversion and peripheral blood-based biomarkers
40	are likely to be indirect. Further studies to elucidate the mechanism behind potential indirect

41 associations are needed.

Commented [ST3]: This change reflects the changes made in the discussion section

42 Introduction

43	The ultra-high-risk (UHR) criteria was introduced to <mark>define patients in the prodrome of</mark>
44	psychosis identify individuals likely in the prodromal phase of psychosis (A. R. Yung et al. 1996).
45	Accurate and early identification is essential for potential targeted interventions to improve
46	clinical outcomes (Fusar-Poli, McGorry, and Kane 2017). Psychometric assessments such as the
47	Comprehensive Assessment for At-Risk Mental States (CAARMS)(Alison R. Yung et al. 2005) and
48	the Structured Interview for Prodromal Syndromes (SIPS)(Miller et al. 2003) have been shown
49	to have high sensitivity but poor specificity(Oliver et al. 2022). There is thus motivation to
50	supplement the UHR designation with other measurements.
51	Attempts have been made to identify candidate blood-based biomarkers of psychosis
52	conversion in UHR using high-throughput methods such as high-throughput proteomic(Mongan
53	et al. 2020) and RNA-sequencing(Chaumette et al. 2019). However, large proportions of
54	participants in comparable cohorts studies such as North American Prodrome Longitudinal
55	Study (NAPLS) and the EUropean network of national schizophrenia networks studying Gene-
56	Environment Interactions (EU-GEI) reported recreational drug use which is highly correlated
57	with positive symptom severity(Addington et al. 2012; Quattrone et al. 2021). Furthermore,
58	existing studies only included blood samples collected at baseline and at conversion. This
59	design likely to result in large variations in the latency to conversion between samples collected
60	before conversion and could mask changes only observable in the few months before
61	conversion.

62

Commented [ST4]: Changes made to improve precision of wording

63	The peripheral blood is an attractive source for biomarker discovery (Liew et al. 2006).
64	Many studies have been conducted in attempts to identify blood-based biomarkers of psychosis
65	conversion (Ota et al. 2019; Demars et al. 2020; Chaumette et al. 2019; Mongan et al. 2020;
66	English et al. 2018; Perkins et al. 2015; Laskaris et al. 2019). However, the majority of existing
67	studies are either cross-sectional (Ota et al. 2019; Laskaris et al. 2019) or only assessed the
68	expression changes of a selected list of candidate genes (English et al. 2018; Perkins et al. 2015;
69	Demars et al. 2020). Transition into psychosis is an evolving process and employing cross-
70	sectional designs tend to introduce significant bias (Maxwell and Cole 2007). Additionally,
71	assessing a relatively small set of candidate genes precludes the possibility of discovering novel
72	biomarkers and the characterization of transcriptomic changes using methods such as Gene Set
73	Enrichment Analysis (GSEA) (Subramanian et al. 2005). To date, only 2 studies profiled the
74	transcriptomic changes of psychosis conversion in a longitudinal study cohort using high-
75	throughput methods (Chaumette et al. 2019; Mongan et al. 2020).
76	Existing studies are limited in a few aspects: First, at the time of writing, no studies have
77	examined the gene ontologies of the genes differentially expressed in psychosis conversion.
78	Second, it is unknown if the genes differentially expressed in psychosis conversion are
79	necessarily differential between pre-conversion and non-conversion participants – a property
80	that reflects the suitability and reliability of the genes as prognostic biomarker. Third, the intra-
81	individual correlation inherent to longitudinal data were not accounted for in existing studies
82	(Chaumette et al. 2019; Mongan et al. 2020). Fourth, over 50% of converters in existing studies

reported a history of cannabis use (Chaumette et al. 2019; Mongan et al. 2020) – this is a

84	potential confounding factor as cannabis use has been strongly evidenced to confers additional
85	risk in transition to psychosis (Gage, Hickman, and Zammit 2016).
86	In this study, we performed RNA-sequencing on whole blood samples from the
87	Longitudinal Youth at-Risk Study (LYRIKS) cohort(Lee et al. 2013). The LYRIKS cohort was
88	recruited in Singapore, which have one of the lowest substance abuse rate in the world(United
89	Nations Office on Drugs and Crime 2006) and participants with history of substance or anti-
90	psychotic use were excluded(Lee et al. 2013). Blood samples were collected from the LYRIKS
91	cohort at 12 months interval: allowing for additional stratification of samples collected before
92	conversion. We performed differential gene expression analysis to identify gene ontology
93	enrichment analysis to examine the transcriptomic changes in the peripheral blood as a
94	participant convert to psychosis. We also examined whether the gene that are differential with
95	psychosis conversion are necessarily useful in identifying samples collected before conversion
96	from samples from patients who do not convert to psychosis.
97	We performed RNA-sequencing on whole blood samples from a subsample of the
98	LYRIKS cohort (Lee et al. 2013). Peripheral whole blood samples were collected from the LYRIKS
99	cohort at 12 months interval and individuals with a history of substance use (including
100	cannabis) were excluded from the study (Lee et al. 2013).
101	Using a linear-mixed effect model-based method (Hoffman and Roussos 2021), we
102	examined the differential expression of gene in psychosis conversion and the gene ontology
103	enrichment of the differentially expressed genes. The linear-mixed effect model based method
104	allows us to model the intra-individual correlations within the data (Diggle 2013). Along with

105 the gene ontology enrichment analysis, the differential expression analysis also provides us an

106	opportunity	y to examine whether a set of 120 genes	containing high-risk loci identified by a	a
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- 107 recent large scale meta-analysis are differentially expressed with psychosis conversion in the
- 108 peripheral blood (Trubetskoy et al. 2022). We then examined whether the genes that are
- 109 differential with psychosis conversion are necessarily differential between pre-conversion and
- 110 non-conversion participants. The drug-free nature of our cohort also allows us to provide a
- 111 perspective into the transcriptomic changes of psychosis conversion with minimal confounding
- 112 by cannabis and other illicit substances use.
- 113 This study aims to expand upon the existing understanding of blood-based biomarkers
- 114 of psychosis conversion and provide directions for future studies in this domain.

Commented [ST5]: Revision of the introduction to better frame the study

115

116 <u>Methods</u>

- 117 Participants
- 118 The Longitudinal Youth-at-Risk study (LYRIKS) was a prospective, observational study
- 119 conducted in Singapore on youths aged 14 to 29 to assess risk factors for psychosis (Lee et al.,
- 120 2013). Briefly, participants were followed up over 2 years and were recruited from psychiatric
- 121 clinics, various community agencies including educational institutes and social services, or were
- 122 self-referred. Participants were excluded if they (i) had a past or current history of psychosis or
- 123 intellectual disability, (ii) were currently using illicit substances, (iii) were taking mood
- 124 stabilizers, (iv) had previous antipsychotic exposure of more than 5 mg haloperidol per day for 3
- 125 weeks (or equivalent) or were on an antipsychotic at the point of recruitment, or (iv) had
- 126 medical causes associated with their attenuated psychotic symptoms.

127	Ethics approval for this study was provided by the National Healthcare Group's Domain
128	Specific Review Board (approval number 2009/00167). After complete description of the study
129	to the participants, written informed consent was obtained. The present study utilised whole
130	blood samples from 135 participants (70 control (CTRL) and 65 UHR) from the original LYRIKS
131	cohort (Lee et al. 2013). All samples from participants who converted were included. Only
132	samples from participants with at least 2 follow-ups were included for control and participants
133	who did not convert. UHR designation and psychosis threshold were assessed using CAARMS.
134	Venous whole blood samples were collected from the participants at 12-month intervals.
135	Participants who converted at any point in the study were removed from the study following a
136	final sample collection. Of the 65 UHR participants, 13 converted to psychosis (CVT) and 52 did
137	not (non-CVT). In total, 392 venous whole blood samples were collected RNA libraries were
-	
138	collected from the 135 participants across 5 timepoints namely: Baseline, 6 months, 12 months,
138 139	collected from the 135 participants across 5 timepoints namely: Baseline, 6 months, 12 months, 18 months, and 24 months (or conversion in CVT) (Supplementary Table S1).
138 139 140	collected from the 135 participants across 5 timepoints namely: Baseline, 6 months, 12 months, 18 months, and 24 months (or conversion in CVT) (Supplementary Table S1). Demographic
138 139 140 141	collected from the 135 participants across 5 timepoints namely: Baseline, 6 months, 12 months, 18 months, and 24 months (or conversion in CVT) (Supplementary Table S1). Demographic The control group (CTRL) consist of 25 [35.7%] females with mean [SD] age of 21.1 [3.07]
138 139 140 141 142	collected from the 135 participants across 5 timepoints namely: Baseline, 6 months, 12 months, 18 months, and 24 months (or conversion in CVT) (Supplementary Table S1). Demographic The control group (CTRL) consist of 25 [35.7%] females with mean [SD] age of 21.1 [3.07] years and 45 [64.3%] males with mean [SD] age of 22.8 [3.51] years. The UHR group consist of
138 139 140 141 142 143	collected from the 135 participants across 5 timepoints namely: Baseline, 6 months, 12 months, 18 months, and 24 months (or conversion in CVT) (Supplementary Table S1). Demographic The control group (CTRL) consist of 25 [35.7%] females with mean [SD] age of 21.1 [3.07] years and 45 [64.3%] males with mean [SD] age of 22.8 [3.51] years. The UHR group consist of 46 [70.8%] males with mean [SD] age of 21.4 [3.08] years and 19 [29.2%] females with mean
 138 139 140 141 142 143 144 	collected from the 135 participants across 5 timepoints namely: Baseline, 6 months, 12 months, 18 months, and 24 months (or conversion in CVT) (Supplementary Table S1). Demographic The control group (CTRL) consist of 25 [35.7%] females with mean [SD] age of 21.1 [3.07] years and 45 [64.3%] males with mean [SD] age of 22.8 [3.51] years. The UHR group consist of 46 [70.8%] males with mean [SD] age of 21.4 [3.08] years and 19 [29.2%] females with mean [SD] age of 21.9 [3.05] years. Of the 65 UHR participants, 52 participants did not develop
 138 139 140 141 142 143 144 145 	collected from the 135 participants across 5 timepoints namely: Baseline, 6 months, 12 months, 18 months, and 24 months (or conversion in CVT) (Supplementary Table S1). Demographic The control group (CTRL) consist of 25 [35.7%] females with mean [SD] age of 21.1 [3.07] years and 45 [64.3%] males with mean [SD] age of 22.8 [3.51] years. The UHR group consist of 46 [70.8%] males with mean [SD] age of 21.4 [3.08] years and 19 [29.2%] females with mean [SD] age of 21.9 [3.05] years. Of the 65 UHR participants, 52 participants did not develop psychosis over the 2-year study period (non-CVT). Of the 52 non-CVT participants, 17 [32.7%]

age of 21.4 [3.08] years. The remaining 13 [20%] UHR participants with mean [SD] age of 20.3

147

Commented [ST6]: This change was made in response to the comment "English should be improved. E.g., the use of the word "terms" in line 239; line 82, "In total, 392 RNA libraries from the were collect from the...""

As explained in the accompanying letter, "RNA libraries" is replaced by "venous whole blood samples"

The portion relating to the various timepoint has been deleted as it is redundant to the information in Supplementary Table S1 and disrupts the flow of the sentence.

148	[3.13] years developed psychosis over the study period (CVT); 2 [15.4%] are females. The
149	median time to conversion from baseline was 11 months [IQR 19 - 5 = 14].
150	No statistically significant difference in sex proportion was found between CVT
151	participants and CTRL participants (Chi-squared = 2.06, p = 0.205) or with non-CVT participants
152	(Chi-squared = 3.06; P= 0.080). No statistically significant difference in age was found between
153	CVT participants and CTRL participants (t = 1.05, 95% CI, [-1.05, 3.11]; P = 0.310) or non-CVT
154	participants (t = -0.48142; 95% CI, [-2.58, 1.62]; P = 0.636).
155	Sequencing and pre-processing
156	A sample of venous whole blood was collected from all participants into Tempus [™]
157	Blood RNA tube (Thermo Fisher Scientific) and stored at -80 °C. Total RNA was extracted with
158	the Tempus [™] Spin RNA Isolation Kit (Thermo Fisher Scientific) according to manufacturer's
159	protocol. Quality and concentration of extracted RNA was measured with 2100 Bioanalyzer
160	System (Agilent). The libraries were prepped and sequenced using 8 Illumina NovaSeq
161	(2x151bp) sequencing lanes. Sequencing quality was assessed using FastQC v0.11.9 (Schmieder
162	and Edwards 2011). Sequences are aligned to Ensembl GRCh38 using STAR 2.7.9a (Dobin et al.
163	2013). Aligned reads are quantified using featureCount from the Subread 2.0.3 R Package (Liao,
164	Smyth, and Shi 2019). Genes with zero variance and mean count < 1 were discarded yielding a
165	total of 21810 genes. All processing and analysis were performed in the R Programming
166	language Version 4.0.3 (R Core Team 2013).

167 Power analysis

168	We performed power analysis using ssizeRNA R package (Bi and Liu 2016). We defined	
169	our criteria at absolute log2 fold-change > 1 and false discover rate = 0.05. Following the low	
170	number of differentially expressed genes in similar studies (Mongan et al. 2020; Chaumette et	
171	al. 2019), we set our expected proportion of differentially expressed genes at 0.005. We found	
172	that a sample size of 11 is sufficient to achieve a statistical power of 0.81. At 13 converter	
173	samples, our study has a power of 0.851.	
174	Differential gene analysis	
175	We divided the samples into 5 groups (Figure 1):	
176	(1) Samples from participants who did not develop psychosis (non-CVT)	
177	(2) Samples from participants post-conversion (CVT)	
178	(3) Samples collected less than, or equal to 12 months before conversion (SHORT)	
179	(4) Samples collected more than 12 months before conversion (MEDIUM)	
180	(5) Samples from participants healthy controls (CTRL)	
181	Samples in SHORT and MEDIUM will be referred to as pre-conversion samples (pre-CVT).	
102	number of months for follow-up since the sample was collected <i>time</i> is the month of sample	
105	collection Longitudinal data involves repeated measurements from the same participant across	Commented IST71. This shares use made to improve
104	time which introduces intra-individual correlation. Repeated measurements result in intra-	sentence flow
185	individual correlations that needs to be accounted for in the model. The approach we chose is	
180	to deal with longitudinal data One method capable of modelling such correlation is the linear	Commented [ST8]: This change was made to improve sentence flow
	9	

188	mixed effect model (Diggle 2013). We modelled known co-variates in the data via a linear	
189	mixed effect model using the DREAM model (Hoffman and Roussos 2021) from the voom-	
190	limma pipeline (Law et al. 2014). We modelled the slope of each sample across time and	
191	sample intercept as random effects:	
192	y = group + sex + time + (time sample) + (0 sample)	
193	p-value adjustment (adjusted p-value) for multiple testing was addressed via Benjamini-	
194	Hochberg correction (Benjamini and Hochberg 1995). Threshold for differential expression was	
195	defined at an absolute log fold-change of > 1 and an adjusted p-value of < 0.05. List of contrasts	
196	used can be found in Supplementary Notes.	
197	<insert 1="" figure=""></insert>	
198	Functional profiling via Gene Ontology analysis	
198 199	Functional profiling via Gene Ontology analysis Enrichment analysis for Gene Ontology (GO) functional terms was performed using	
198 199 200	Functional profiling via Gene Ontology analysis Enrichment analysis for Gene Ontology (GO) functional terms was performed using Enrichr (Chen et al. 2013) webtool (which employs a Fisher's exact test). We examined the top	
198 199 200 201	Functional profiling via Gene Ontology analysis Enrichment analysis for Gene Ontology (GO) functional terms was performed using Enrichr (Chen et al. 2013) webtool (which employs a Fisher's exact test). We examined the top 10 enriched ontologies ranked by adjusted p-value for analysis and interpretation.	
198 199 200 201 202	Functional profiling via Gene Ontology analysis Enrichment analysis for Gene Ontology (GO) functional terms was performed using Enrichr (Chen et al. 2013) webtool (which employs a Fisher's exact test). We examined the top 10 enriched ontologies ranked by adjusted p-value for analysis and interpretation. Phenotype association analysis	
198 199 200 201 202 202	Functional profiling via Gene Ontology analysis Enrichment analysis for Gene Ontology (GO) functional terms was performed using Enrichr (Chen et al. 2013) webtool (which employs a Fisher's exact test). We examined the top 10 enriched ontologies ranked by adjusted p-value for analysis and interpretation. Phenotype association analysis GWAS phenotype associations were queried from the Genecards database (Fishilevich	
198 199 200 201 202 203 203	Functional profiling via Gene Ontology analysis Enrichment analysis for Gene Ontology (GO) functional terms was performed using Enrichr (Chen et al. 2013) webtool (which employs a Fisher's exact test). We examined the top 10 enriched ontologies ranked by adjusted p-value for analysis and interpretation. Phenotype association analysis GWAS phenotype associations were queried from the Genecards database (Fishilevich et al. 2017; Stelzer et al. 2016). GWAS phenotypes with less than 5 occurrences amongst the	
198 199 200 201 202 203 203 204 205	Functional profiling via Gene Ontology analysis Enrichment analysis for Gene Ontology (GO) functional terms was performed using Enrichr (Chen et al. 2013) webtool (which employs a Fisher's exact test). We examined the top 10 enriched ontologies ranked by adjusted p-value for analysis and interpretation. Phenotype association analysis GWAS phenotype associations were queried from the Genecards database (Fishilevich et al. 2017; Stelzer et al. 2016). GWAS phenotypes with less than 5 occurrences amongst the differential genes were dropped. We perform Fisher's exact tests with Bonferroni correction to	

207	found in the European Bioinformatics Institute (EBI) GWAS catalog (Buniello et al. 2019). The	
208	same EBI catalogue is used in Genecards (Stelzer et al. 2016). Further details on data processing	
209	procedure are detailed in Supplementary Notes.	
210		
211	<u>Results</u>	
212	Differential gene expression analysis	
213	We identified 12, and 130 genes differentially expressed in MEDIUM vs CVT, and SHORT	
214	vs CVT respectively. The 10 differential genes with largest fold changes are listed in Table 1, the	
215	full list of differential genes can be found in Supplementary Table S2-S3. No genes were found to	
216	be differential in MEDIUM vs SHORT. We also identified 6, and 22 genes differentially expressed in	
217	MEDIUM vs non-CVT, and SHORT vs non-CVT respectively (Table 1) (full list in Supplementary	
218	Table S4-S5). No differential genes were identified when comparing CTRL vs CVT. We then	
219	examined whether the genes reported to contain high-risk loci in a recent large-scale meta-	
220	analysis were differentially expressed in our analysis (Trubetskoy et al. 2022). None of the	
221	genes associated with those loci were differentially expressed in our analyses.	Commented [ST9]: This segment was originally intended as a supplementary analysis. With the reframing of the
222		study, we believe it is more appropriate to merge it with this analysis
223	< Insert Table 1 >	
224		

225

226 Gene ontology enrichment analysis

- 227 We performed enrichment analysis of the differential genes found in SHORT vs CVT and 228 MEDIUM vs CVT to identify enriched gene ontology terms ontologies. The enriched ontologies 229 in SHORT vs CVT The genes differential in SHORT vs CVT are mostly enriched for GO terms 230 associated with mitosis **(Table 2)**. The enriched GO terms in MEDIUM vs CVT are also consistent 231 with the theme of mitosis observed in SHORT vs CVT **(Table 2)**. contain commonalities namely: 232 mitotic spindle assembly and organization (GO:0007052; GO:0071173; GO:0007094; GO:0071174),
- 233 chromosomal segregation (GO:0051983; GO:0000070), and DNA replication and cell cycle regulation
- 234 (GO:1901990; GO:0006260) (Table 2). Commonalities in the enriched ontologies in MEDIUM vs
- 235 CVT include: cell cycle checkpoint (GO:0044774; GO:0033314; GO:0000076; GO:0000083), and nuclear
- 236 membrane disassembly (GO:0007077; GO:0051081) (Table 2). However, the overlap is minimal
- 237 between the GO gene sets and the genes differential in MEDIUM vs CVT, likely due to the small
- 238 number of differential genes in this comparison.
- 239 < Insert Table 2 >
- 240 GWAS phenotypes enrichment analysis

We examined the GWAS phenotypes associated with SNPs within the differentially expressed genes for SHORT vs CVT and MEDIUM vs CVT. We found 25 and 4 GWAS phenotypes that are enriched amongst the GWAS phenotypes of genes differential in SHORT vs CVT and MEDIUM vs CVT respectively **(Table 3)**. The enriched GWAS phenotypes are largely associated with relative abundance of leukocyte populations and related cellular measurements. Our **Commented [ST10]:** This change was made in response to the comment:

"The second paragraph of the Discussion section should describe with much more detail the findings of the study. Which genes were correlated with mitosis? What are the roles of the genes found? Authors should also better explain why this pattern is indicative of immune upregulation, and other assumptions like "hematological phenotypes" found in their sample. Please provide rationale for the arguments hypothesized, so that the findings make physiological sense to the reader."

The ontologies are grouped based on their commonalities

246	observation is consistent with prior observations that psychosis conversion is associate with	
247	immune response (Tomasik et al. 2016). We also noted well known co-morbidities of	
248	schizophrenia such as "insomnia" and "coronary artery disease" (Palmese et al. 2011; Ifteni et al.	
249	2014). Enrichment in GWAS phenotypes relating to physiological measurements such as "fatty	
250	acid measurements", "body height", "systolic blood pressure", and "gut microbiome	
251	measurements" were also observed. The differentially expressed genes were not enriched for	
252	any schizophrenia and psychosis GWAS phenotypes (Supplementary Table S6).	Con
253	< Insert Table 3 >	"In inac the
254	Comparison between genes differential in psychosis conversion and genes differential in pre-	ent
255	conversion and non-conversion	pat
256	We examined whether the genes differential in psychosis conversion are also	The phe sup
257	differential between pre-conversion and non-conversion participants. We identified the	
258	intersection (denoted by the symbol \cap) between the set of genes differential in psychosis	
259	conversion and the set of genes differential between pre-conversion and non-conversion. We	
260	found 2 genes in SHORT vs CVT \cap SHORT vs non-CVT and 5 gene in both MEDIUM vs CVT \cap	
261	MEDIUM vs non-CVT. CYP51A1P1 and UBE3AP2 were differential in both SHORT vs CVT and	
262	SHORT vs non-CVT. CA12, COL9A2 and pseudogenes ENSG00000285966, ENSG00000248936,	
263	ENSG00000278112 were differential in both MEDIUM vs CVT and MEDIUM vs non-CVT.	
264		

Commented [ST11]: This change was made in response of the comment:

"In the Discussion, use of term comorbidity might be inadequate, as authors did not investigate other illnesses in their sample. Nor were their findings related to comorbidities. Genes might be related to other physical entities but stating that they are related to comorbidities in schizophrenia is not quite right. As a matter of fact, immune response is possibly an integral component of disease pathophysiology, and not a comorbidity."

The result that schizophrenia and psychosis GWAS phenotypes were not enrich was explicitly stated, a new supplementary table (S6) was added.

264

266 Discussion

267	Our study possesses several properties that allow for unique perspectives into the
268	nuances of peripheral blood-based transcriptomic changes in UHR and psychosis conversion.
269	First, to our knowledge, our study is the first to partition pre-conversion samples based
270	on their time-to-conversion. Second, owing to strict anti-drug laws in Singapore and the
271	exclusion of participants with a history substance or anti-psychotic use, the LYRIKS cohort is
272	minimally contaminated by substance use(Lee et al. 2013). We showed that the genes
273	correlated with psychosis conversion are predominantly enriched for immune related biological
274	functions and that many of the GWAS phenotypes enriched those genes related to both
275	immunological phenotypes and known co-morbidities of schizophrenia. We also showed that
276	genes correlated with psychosis conversion are not necessarily the same as those useful for
277	prognosis. First, at the time of writing, we are the first to conduct a gene ontology enrichment
278	analysis on the genes differential in psychosis conversion using a longitudinal cohort. Second,
279	we employed a mixed-effect model to account for the intra-individual correlation within a
280	longitudinal data – a factor unaccounted for in previous studies (Chaumette et al. 2019;
281	Mongan et al. 2020). Third, owing to the recruitment criteria, our study cohort is minimally
282	confounded by substance use. Fourth, at the time of writing, this study is the first to examine
283	whether the gene differential in psychosis conversion is also differential between pre-
284	conversion and non-conversion participants.

- 285 The genes identified in recent whole exome (Singh et al. 2022) and large scale GWAS
- 286 (Trubetskoy et al. 2022) analyses to confer high risk of schizophrenia were not differentially

Commented [ST12]: This section described the novelty of our study. It has been amended to reflect changes made to the framing of the study in the introduction

287	expressed in our analyses.	This is consistent with the finding that the genes were mostly	Ľ
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- 288 expressed in synaptic junctions rather than the peripheral blood (Trubetskoy et al. 2022). This
- 289 finding highlights the difficulty of employing schizophrenia genetic risk loci as a basis of
- 290 identifying biomarkers in the peripheral blood.

291	Our GO enrichment analysis showed that genes correlated with psychosis conversion
292	are largely enriched for ontologies relating for mitosis. Considering that nucleated cells in the
293	whole blood are generally leukocytes, this pattern is indicative of a general immune
294	upregulation widely observed in schizophrenia and psychosis conversion (Gardiner et al. 2013;
295	Tomasik et al. 2016; Xu et al. 2012). However, the low number of differential genes in MEDIUM
296	vs CVT also meant that the overlaps with GO terms are small, we advise discretion when
297	considering the GO analysis results of MEDIUM vs CVT. The commonalities in the enriched gene
298	ontologies include 1) mitotic spindle assembly and organization, 2) chromosomal segregation,
299	3) DNA replication and cell cycle regulation cell cycle checkpoint, and 4) nuclear membrane
300	disassembly – all processes of cellular replication. This pattern suggests that the source cells are
301	proliferating. Considering that nucleated cells in the whole blood are generally leukocytes, the
302	source cells are predominately leukocytes and this observation is consistent with a pattern of
303	immune upregulation widely observed in schizophrenia and psychosis conversion (Gardiner et
304	al. 2013; Tomasik et al. 2016; Xu et al. 2012). Disentangling biomarkers specific to psychosis
305	conversion from markers of general immune responses will be a crucial step in the

306 identification of peripheral blood-based biomarkers of psychosis.

Commented [ST13]: This is a discussion of a result added in page 11 regarding whether the genes containing schizophrenia risk loci were differentially expressed in psychosis conversion

Commented [ST14]: This change was made in response to the comment

"The second paragraph of the Discussion section should describe with much more detail the findings of the study. Which genes were correlated with mitosis? What are the roles of the genes found? Authors should also better explain why this pattern is indicative of immune upregulation, and other assumptions like "hematological phenotypes" found in their sample. Please provide rationale for the arguments hypothesized, so that the findings make physiological sense to the reader."

307	Our GWAS phenotype enrichment analysis found that the genes correlated with
308	psychosis conversion are generally associated with haematological GWAS phenotypes rather
309	than neurological GWAS phenotypes. GWAS phenotypes relating to leukocyte percentages are
310	of interest as cell population ratios such as neutrophil to lymphocyte ratio has been shown to
311	be increased in chronic schizophrenia and psychosis conversion (Karageorgiou, Milas, and
312	Michopoulos 2019). Many terms describing physiological measurements such as fatty acid
313	measurement and systolic blood pressure are also reported to be different schizophrenic
314	patients(Andreassen et al. 2013). We also observed some GWAS phenotypes describing known
315	comorbidities of schizophrenia, such as insomnia and coronary artery disease (Palmese et al.
316	2011; Ifteni et al. 2014). And lastly, there is increasing attention into the role of the gut
317	microbiome in mental disorders including schizophrenia and psychosis (Nguyen et al. 2019; Zhu
318	et al. 2020). These observations suggest that the neurological changes associated with
319	psychosis conversion are accompanied by a range of non-neurological concomitant changes,
320	many of which have been reported to be correlated with and or co-morbidities of
321	schizophrenia. How these non-neurological concomitant changes can be used to determine
322	psychosis conversion risk should be a valuable research direction. Consequently, using blood-
323	based markers to detect co-morbidities and concomitant changes of psychosis and
324	schizophrenia could represent a meaningful direction in predicting clinical outcomes in UHR
325	individuals. Gene differential with psychosis conversion were not enriched with SNPs associated
326	with schizophrenia or psychosis phenotypes. This is consistent with a recent finding that found
327	that the genes containing the SNPs conferring substantial risk to schizophrenia were
278	predominately expressed by neuropal cells in the central pervous system (Trubetckoy et al.

329	2022). Several of the enriched phenotypes have been reported to be perturbed in individuals
330	with schizophrenia, these include cell population ratios such as neutrophil to lymphocyte ratio
331	(Karageorgiou, Milas, and Michopoulos 2019), physiological measurements such as fatty acid
332	measurement and systolic blood pressure (Andreassen et al. 2013), disorders and diseases
333	frequently observed in individuals with schizophrenia such as insomnia and coronary artery
334	disease (Palmese et al. 2011; Ifteni et al. 2014), and variations in the gut microbiome (Nguyen
335	et al. 2019; Zhu et al. 2020). We hypothesize that the association between psychosis conversion
336	and biomarkers readily observable in the peripheral whole blood is likely to be indirect.
337	Whether a differential expression of genes enriched for SNPs associated with these phenotypes
338	necessarily indicate a perturbation of the phenotype, and how are these non-neurological
339	phenotypes implicated in the pathophysiology of psychosis will be important research
340	directions to evaluate this hypothesis. If positive evidence of both questions can be found,
341	using blood-based markers to detect concomitant changes of psychosis and schizophrenia could
342	represent a viable avenue for predicting clinical outcomes in UHR individuals.
343	Genes differential with psychosis conversion are not necessarily differential between
344	pre-conversion and non-conversion individuals. Of the genes that exist in the overlaps,
345	CYP51A1P1 and UBE3AP2 were differential in both SHORT vs CVT and SHORT vs non-CVT.
346	CYP51A1P1 is a pseudogene for cytochrome P450 family 51 subfamily A member 1 (CYP51A1).
347	The cytochrome P450 family proteins are predominantly involved in lipids and cholesterol
348	metabolism (Stelzer et al. 2016). UBE3AP2 is a pseudogene for ubiquitin protein ligase 3A
349	(UBE3A) and was reported to associate with hypertension (Stelzer et al. 2016). While certain

350 rare variants in UBE3A has been proposed to confer risks to schizophrenia (Singh et al. 2022;

Commented [ST15]: This change was made in response to the comment

"In the Discussion, use of term comorbidity might be inadequate, as authors did not investigate other illnesses in their sample. Nor were their findings related to comorbidities. Genes might be related to other physical entities but stating that they are related to comorbidities in schizophrenia is not quite right. As a matter of fact, immune response is possibly an integral component of disease pathophysiology, and not a comorbidity."

The discussion of the GWAS phenotypes has been reframed. We begin by discussing the result that we did not observe enrichment in genes containing schizophrenia risk loci. We then discuss that many of the enriched phenotypes have been reported to be perturbed in schizophrenia. Based on these findings, we hypothesize that this pattern suggest that the link between psychosis transition and blood-based biomarkers is indirect.

Commented [ST16]: This segment has been added to improve sentence flow

351	Trubetskoy et al. 2022), it is unclear if this correlation might extend to pseudogenes of UBE3A
352	and to psychosis conversion. Genes CA12, COL9A2 were differential in both MEDIUM vs CVT
353	and MEDIUM vs non-CVT. CA12 is a carbonic anhydrase which catalyzes the reversible
354	hydration of carbon dioxide. GWAS associated studies reported that CA12 is associated with a
355	large range of phenotypes including schizophrenia symptom severity (Stelzer et al. 2016).
356	COL9A2 codes for an alpha chain subunit in type IX collagen. Associations between COL9A2 and
357	schizophrenia are indirect, via phenotypes such as cognitive measurements (Lam et al. 2018),
358	testosterone measurements (Moore et al. 2013), and waist-hip-ratio (Andreassen et al. 2013).
359	At the time of writing, the functions of ENSG00000285966, ENSG00000248936, and
360	ENSG00000278112 are unknown and will not be discussed. Based on our study design, these
361	genes and pseudogenes are theoretical candidate biomarkers for psychosis conversion.
362	However, the lack of robust links to pathways linked to the pathology of schizophrenia
363	dampens our confidence in the ability of these genes and pseudogenes to serve as biomarkers
364	of psychosis conversion.
365	Lastly, a recent large-scale meta-analysis identified a set of loci likely to confer
366	substantial risk of schizophrenia (Singh et al. 2022; Trubetskoy et al. 2022). None of gene
367	associated with those loci were differentially expressed in any of our analysis. This is
368	unsurprising as most of those genes were reported to be expressed in synaptic junctions rather
369	than the peripheral blood(Trubetskoy et al. 2022). This discrepancy further highlights the
370	difficulty of generalizing findings based on schizophrenia cohorts to UHR cohorts and from
371	schizophrenia to psychosis.

Commented [ST17]: This segment originally intended as a supplementary analysis had been merged with the differential gene expression analysis

372 Limitation

373	Our study contains several limitations. Firstly, the sample size of 392 used in this study is
374	relatively small especially since samples are distributed into multiple time-points across various
375	groups. Hence, the inferential statistical analyses performed in this study may be
376	underpowered. However, we opine that a reliable (and useful) biomarker should be robust and
377	detectable, even against the backdrop of small sample sizes. Secondly, we did not distinguish
378	non-CVT participants who remitted from the UHR status from non-CVT participants who
379	maintained UHR status to avoid further reducing sample sizes across groups. Thirdly, the
380	etiology of psychosis conversion is inherently heterogenous (Zwicker, Denovan-Wright, and
381	Uher 2018) and without a basis for pre-defining all medically relevant subtypes, our study
382	design was unable to account for the heterogenous nature of psychosis conversion. Finally, the
383	overlaps in our gene ontology enrichment analysis are small especially in MEDIUM vs CVT, we
384	advise the readers to exercise discretion when considering the results.
385	Conclusion
505	

386	The identification of peripheral blood-based biomarkers for psychosis is an area of great
387	clinical value. Our study expanded upon existing studies by illustrating various important
388	nuances in the identification of peripheral blood-based biomarkers of psychosis conversion and
389	establishes directions for future investigations. We identified differentially expressed genes in
390	psychosis conversion, which were consistent with a pattern of immune upregulation. The SNPs
391	in the genes differential in psychosis conversion were associated with a range of phenotypes
392	reported to be perturbed in schizophrenia and psychosis but are not associated with

393	schizophrenia and	psychosis	phenotypes themselves.	We also showed that the g	genes correlated
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- 394 with psychosis conversion are not necessarily differential between pre-conversion and non-
- 395 conversion individuals. The genes containing risk loci for schizophrenia were not differentially
- 396 expressed in the peripheral whole blood in psychosis conversion. From these findings, we
- 397 hypothesize that the associations between psychosis conversion and peripheral blood
- 398 biomarkers are indirect. Mechanistic studies to examine such indirect associations will be a
- 399 valuable research direction.

400 Data availability

- 401 The results of each contrast in the differential genes analysis can be found in the
- 402 Supplementary section. Supplementary information is available at the journal website. Raw
- 403 transcripts counts are not available due to patient confidentiality requirements. Analysis code is
- 404 available on request from the authors.

405 Author contribution

- 406 S.M.X.T., Y.J.Y., J.L., and W.W.B.G conceptualized and designed the research; S.M.X.T., Y.J.Y.,
- 407 performed the research; S.M.X.T. performed that statistical analysis; S.M.X.T. and Y.J.Y. wrote
- 408 the manuscript; Y.J.Y. and J.L. were responsible for the acquisition of the data; S.M.X.T., B.S.,
- 409 S.B., Z.D., M.D., N.K., E.L., A.S, Y.J.Y., J.L., and W.W.B.G interpretated the results; B.S., S.B., Z.D.,
- 410 M.D., N.K., E.L., A.S, Y.J.Y., J.L., and W.W.B.G reviewed the work. All authors approve of the
- 411 submitted version of the manuscript.

412

Commented [ST18]: We have added conclusion to provide a summary to the study

413 Transparency declaration

- 414 We affirm that the manuscript is an honest, accurate, and transparent account of the
- study being reported; that no important aspects of the study have been omitted; and that any
- 416 discrepancies from the study as planned have been explained.

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RNA-sequencing of peripheral whole blood of individuals at ultra-high-risk for psychosis – a longitudinal perspective

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