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Research paper

Network of positive affect and depression in older adults

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ABSTRACT

Background: Depression in older adults poses significant health challenges, yet the protective role of positive affect remains understudied. This research examined the complex network of positive affect and depression in older adults using advanced network analysis techniques to identify potential targets for intervention.
Methods: Bayesian Gaussian Graphical Models and Directed Acyclic Graph modelling were used to analyse associations between ten positive affect variables and depression. Exploratory and confirmatory network analyses ensured stability and node predictability quantified variable influence. Stepwise linear regression confirmed whether specific positive affective variables identified in the networks predicted lower depression scores.
Results: Enthusiasm emerged as a key ancestral node with the highest predictability (R^2 = 0.65), initiating cascades of positive affect. A primary pathway to depression was identified through feeling *active* (strength = 1.00, direction = 0.79), with an indirect pathway from feeling *enthusiastic* via *active* (strength = 0.98, direction = 0.79) to depression (strength = 1.00, direction = 0.79). Confirmatory longitudinal analysis showed that feeling *active* and *enthusiastic* consistently predicted lower depression scores ($p < 0.001$). The network structure remained stable across analyses.
Conclusions: Enthusiasm was identified as a central catalyst in the positive affect network, revealing clear pathways through which positive affect may protect against depression in older adults. Enhancing enthusiastic and active emotional experiences emerged as potential effective, nonpharmacological strategies for preventing and treating depression in older adults.

1. Introduction

Continuous advancement in science and medicine has increased human lifespan over the past 200 years (Brooks-Wilson, 2013; Strulik and Vollmer, 2013) – a result of many factors including better environments, access to healthcare, and our improved knowledge of well-being. However, living longer does not equate to living better, as the "later life" period (defined as 70+ years of age) is often associated with significant challenges to mental health and well-being, depression being a major contributor to these challenges (Reynolds 3rd et al., 2022; Robine, 2021; Senra and McPherson, 2021). Recent evidence suggests that depression effects approximately 35.1 % of adults aged 60 and older globally (Cai et al., 2023). Depression, and the symptoms associated with it, negatively impacts multiple areas of human functioning including physical health, cognitive functioning, quality of life, and correlates with increased mortality risk and healthcare spending (Alexopoulos, 2019; Fiske et al., 2009; Hu et al., 2022). These associated effects can compound the difficulty of managing age-related disability, causing an increased risk to aging populations (Moreno-Agostino et al., 2021; Senra and McPherson, 2021). With depression rates rising worldwide, this raises a crucial question: What is the value of extending life if those additional years don't improve in quality?

Positive feelings such as enthusiasm, interest, and excitement, operationally defined as positive affect (PA) (Watson et al., 1988) are incompatible with feelings of sadness (Garland et al., 2010) and have potential to enhance well-being in general populations (Carpenter et al., 2013; Craske et al., 2019; Fredrickson, 2004, 2001; Tugade and Fredrickson, 2004). To date, most research has treated PA as an overall measure of positive feelings (Diener and Chan, 2011; Gross and John, 2003; Heekerens and Eid, 2021; Pressman and Cohen, 2005)

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overlooking specific aspects of PA (Revord et al., 2021) that might play distinct protective role against depression symptoms. Research has also suggested that higher self-esteem, which is predictive of PA (Joshanloo, 2022), reduces depression risk in the general population (Hilbert et al., 2019) and in later life (T. Tang et al., 2022; X. Tang et al., 2022). This oversimplified approach may have limited our understanding of how distinct positive emotional experiences could enhance mental health in aging populations, as understanding the unique links between specific components of PA and depression in older adults is key to harness the protective potential of PA against depression.

Currently, late-life depression is treated using pharmacological treatment and evidence based psychological therapies, including cognitive behavioural therapy and behavioural activation (Alexopoulos, 2019; Hu et al., 2022). Unfortunately, older adults are less likely to seek professional psychological treatments despite their elevated risk of depression. This is due to internal barriers including stigma, normalising depressive symptoms as a symptom of aging, lack of perceived need, and underreporting by individuals due to the co-occurrence of other mental and physical health issues, leading to a lack of treatment (Barry et al., 2012; Elshaikh et al., 2023; Kok and Reynolds, 2017). External barriers can also impact treatment seeking, such as the related costs and other accessibility issues. Pharmacological treatment, while widely effective, is often associated with side effects and some limited effectiveness in older populations (Alexopoulos, 2019; Casey, 2017; Rodda et al., 2011). Understanding how different aspects of PA protect against depression may inform development of accessible, targeted, non-pharmaceutical interventions that enhance quality of life in aging populations both with and without symptoms of depression (Senra and McPherson, 2021).

Essentially, positive emotional experiences expand our attention and accumulate psychological resources over time (Fredrickson, 2013, 2004). In older adults, this process is particularly significant, as PA has been linked to enhanced cognitive flexibility (Carpenter et al., 2013), improved social connections (Mikels et al., 2014), reduced symptoms of depression (Alexander et al., 2021; Chakhssi et al., 2018; Huppert, 2006), and greater resilience (Ong et al., 2006; Tugade and Fredrickson, 2004) which may mitigate many age-related challenges. However, the precise mechanisms by which various facets of PA interact and potentially buffer against depression remain unclear, particularly in older adults, where emotional regulation processes may differ significantly from those in younger populations (Senra and McPherson, 2021).

The present study aims to investigate the interactive network of depression and positive affect in older adults to uncover potential protective mechanisms of PA against depression. Using network analytic approaches (Chalmers et al., 2022), the mechanisms of variable associations can be understood in a human context (Borsboom, 2017), through the influence (predictability) of network variables (nodes) on one another (Chalmers et al., 2022; Williams and Mulder, 2020). Methods such as Bayesian Gaussian Graphical Modelling (BGGM) (Williams and Mulder, 2020) and Directed Acyclic Graphs (DAG) (Lipsky and Greenland, 2022; Williams et al., 2018) not only reveal the structural dynamics of complex relationships between variables, but also point to actionable targets for intervention (T. Tang et al., 2022; X. Tang et al., 2022). As a method of confirming the results found within the networks, stepwise linear regression was used to clarify whether a relationship exists between higher scores on positive affect variables and lower scores on depression across time. This study specifically focuses on understanding how different aspects of PA may buffer against depressive symptoms, with potential implications for developing non-pharmaceutical interventions to enhance mental well-being in aging populations.

2. Method

2.1. Participants

Participants ($n = 997$) were selected from The Sydney Memory and Ageing Study (Sachdev et al., 2010) (MAS) dataset to complete this research (Fig. 1). The MAS is a longitudinal cohort study that recruited older adults (range = 70–90 years, $M = 78.77$ years, $SD = 4.82$) from the Eastern suburbs of Sydney, Australia between 2005 and 2007 (Sachdev et al., 2010). Participants in this dataset aged between 70 and 90 years were randomly selected from the New South Wales Kingsford Smith and Wentworth electoral rolls and invited to participate in the study via a letter (Sachdev et al., 2010). Data collection occurred at 2-year intervals, each collection creating a "wave" of the data. Exclusion criteria in this study included major psychological or neurological disorder, prior diagnosis of dementia, any medical or psychological conditions that may have prevented them from completing assessments and lack of proficiency in English. Participants were also excluded if initial assessments indicated a diagnosis of dementia, or they scored under 24 on the Mini-Mental State Examination (Folstein et al., 1975).

The Sydney MAS examined the representativeness of the original dataset through comparing the participants in the study with those who declined to participate using publicly available census data – no difference existed between groups on age or sex. Comparing the participant group to a representative sample of the general population from the same geographical area obtained from the census data of the Australian Bureau of Statistics, it was revealed that the participant group was more educated - 56.4 % of the participants had secondary education and 30.4 % had tertiary education compared to the census group having 42.2 % and 10.1 % respectively. The participant group also had a lower proportion of individuals in the 70–74 age group (26.0 % v. 32.3 %), and a higher proportion of individuals in the 75–80 age group (34.8 % v. 29.9 %) with other age groups having no significant difference, and the overall age distribution being comparable (Sachdev et al., 2010). The participant group also had a higher proportion of individuals living in private homes (97.5 %) compared to the census group (92.1 %) (Sachdev et al., 2010). More information on demographics and exclusion criteria of participants in the MAS has previously been published (Sachdev et al., 2010).

In the current research, participants with more than three missing answers on the positive scale of the Positive and Negative Affect Schedule (Watson et al., 1988), and/or no measurable Geriatric Depression Scale total score (Yesavage and Sheikh, 1986) were also excluded. This was investigated for the participants at each wave of the data. Attrition at each wave of the data included participants who did not complete the required assessments, participants who were non-contactable, participants who declined to participate and participants who were deceased(Fig. 1). Wave 3 data was not used in the Network Analyses due to Positive and Negative Affect Schedule data not being present in the MAS dataset, however Geriatric Depression Scale total score was collected at Wave 3 and was included in stepwise linear regression analysis (Fig. 1).

2.2. Measures

2.2.1. Positive affect (PA)

The Positive and Negative Affect Schedule (PANAS) (Watson et al., 1988) was used to measure participant's experienced positive affect. Specific positive affect items were *enthusiastic*, *active*, *inspired*, *strong*, *proud*, *alert*, *determined*, *attentive*, *interested*, and *excited*. Negative items were not used as a part of this current research. Participants self-reported their score on each item according to the question “to what extent have you felt each of the following emotions during the past week.” on a scale from 1 (*very slightly or not at all*) to 5 (*extremely*). Data from this measure was collected at Wave 1 and Wave 2 of the MAS and included in the current research. In this study, PA was conceptualised as

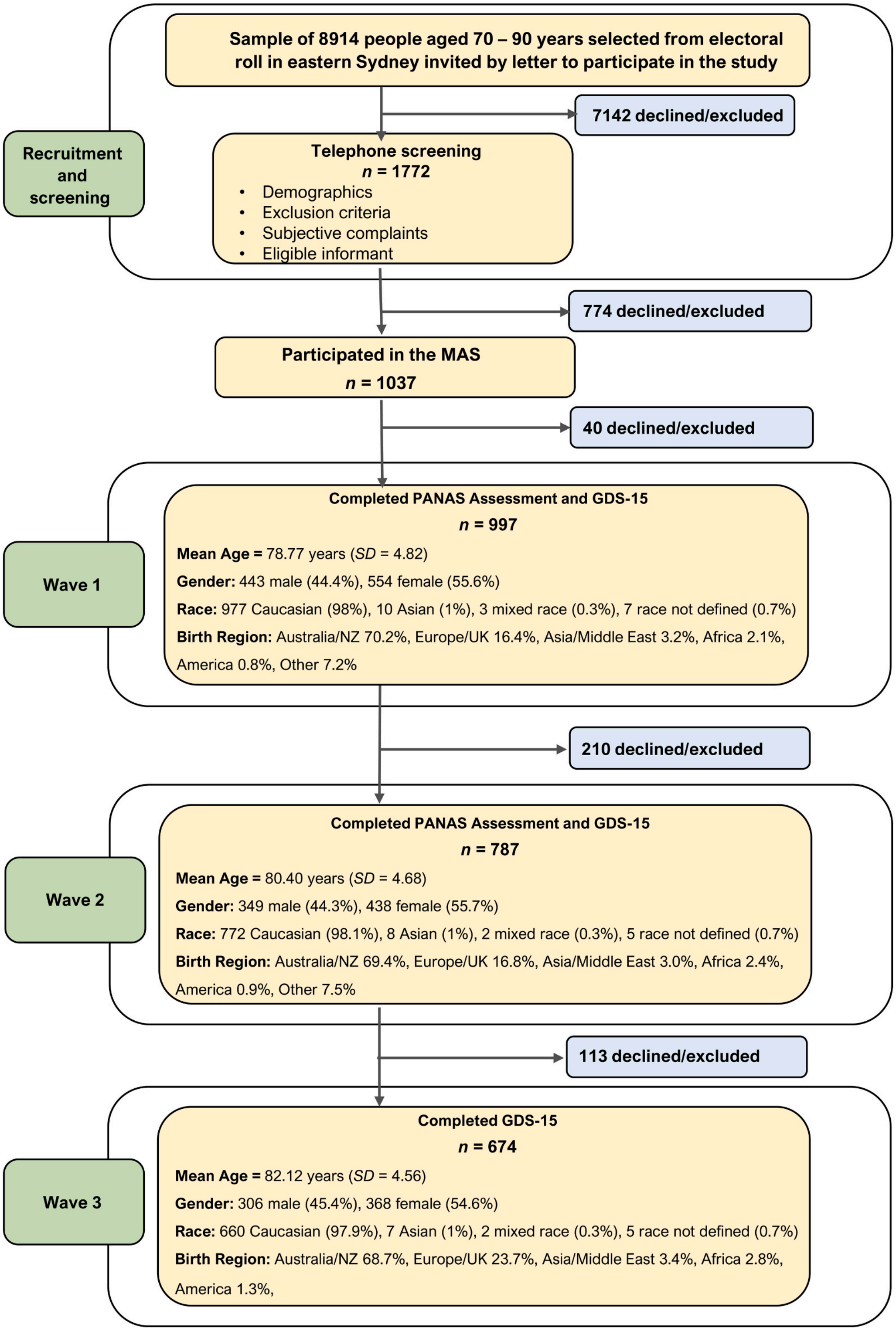

Fig. 1. Recruiting information and demographics of participants used in the current research.

state-level affect, capturing transient positive emotional experiences reported over the past week, rather than enduring trait-like dispositions of individuals.

2.2.2. Depression

Depression was measured using participants total score on the 15-item Geriatric Depression Scale, a shortened version of the original 30-item questionnaire (GDS-15) (Yesavage and Sheikh, 1986) The GDS-15 consists of 15 yes/no questions about how the participant has felt over the past week, the shortened version was specifically designed for use in older adults to reduce testing fatigue. Examples of items include “Do you often feel helpless?” and “Have you dropped many of your activities and interests?” The scale includes both positively and negatively worded items to reduce response bias. Scoring is dichotomous, with 1 point assigned for each answer indicating depressive symptoms. The total score is calculated by summing these points, resulting in a score range of *0–15*. Higher scores indicate more severe depressive symptoms, with scores of *0–4* considered normal, *5–8* indicating mild depression, *9–11* indicating moderate depression, and *12–15* indicating severe depression. Data from this measure was collected at Wave 1, Wave 2 and Wave 3 of the MAS and included in the current research.

2.3. Data analyses

An analysis of missing data was conducted to assess the overall level of missingness and to determine if the data was missing completely at random (MCAR). Across all variables, the overall percentage of missing data was found to be low, at approximately 1.59 %. To examine potential patterns in the missingness, logistic regression analyses were performed using missingness indicators for each variable. The results indicated weak predictability of missingness for most variables from the missingness of others, with low log-loss values suggesting limited systematic relationships. This lack of strong associations supports the assumption that missingness is independent of both observed and unobserved data, consistent with an MCAR mechanism.

Given the low level of missingness and the evidence for an MCAR pattern, Multiple Imputation by Chained Equations (MICE) was chosen as the most appropriate imputation method. MICE generated multiple imputations for each missing value based on the relationships observed in the data, preserving variability and avoiding the biases that single-value imputation methods might introduce. MICE's iterative process, which models each variable conditionally on others, also offered robust handling of potential dependencies, further ensuring that imputed values were well-aligned with observed data patterns.

We employed BGGM to examine the relationships between PA and depression. The analyses included network estimation, stability evaluation, and the DAG modelling. To evaluate the structure of associations among variables, we divided the dataset into exploratory and confirmatory samples (50/50 split). Networks for both samples were estimated using the BGGM with a continuous data type and weakly informative priors. Partial correlation matrices for each network were computed, and visualized using graphs. Significant partial correlations were identified as those whose 95 % credible intervals did not include zero. The exploratory and confirmatory networks were compared to assess stability. For each pairwise partial correlation, it was examined whether the 95 % credible intervals of the differences between the exploratory and confirmatory correlations included zero. Correlations with non-overlapping credible intervals were interpreted as unstable or unconfirmed associations, whereas those with overlapping intervals were considered stable and likely to represent reliable relationships. Predictability for each node in the networks was computed to quantify the proportion of variance explained by its neighbours. This metric provides insights into the influence of other variables on a given node and the overall connectedness of the network. Nodes with higher predictability suggest stronger interdependence within the network.

To infer causal relationships among variables, we employed the DAG modelling using the Hill Climbing (HC) algorithm. This approach uses a score-based method to identify the most probable causal structure, optimized via Bayesian Information Criterion (BIC). To ensure robustness, we applied network averaging with 10,000 bootstraps. The strength of connections (arcs) between variables was assessed, and the DAG was visualized with edge strengths reflecting the confidence of relationships. A threshold for significant arc strengths was determined using established guidelines, and edges below this threshold were excluded from the visualization. Edge strength represents the likelihood that a relationship exists between two variables in the dataset, ranging between 0 and 1. Values closer to 1 indicate a high probability that the edge exists and values near 0 suggest weak or no evidence for the presence of a relationship. The direction of the edge quantifies the proportion of estimations or bootstraps, where the direction of the relationship occurs from one node to another, also measured from 0 to 1. A value closer to 1 implies consistent directional flow from node A to node B across iterations of the DAG, while a value closer to 0 implies the reverse. Values close to 0.5 indicate a lack of a clear dominant direction in the relationship. Only edges with strength greater than 0.80 are interpreted and discussed. This criterion reflects a high probability that the edge represents a stable and replicable association across the estimations in the DAG (Williams and Mulder, 2020). Only edges with directionality greater than 0.70 were retained, balancing the need for directional confidence while also allowing for minor variation due to sampling variability. These thresholds prioritised robustness of the results over sensitivity of the methods, particularly given the results of this research yield some clinical implications.

Stepwise multiple linear regression analyses were conducted to examine the predictive relationships between positive affect variables and depression across different time points. This method combines forward and backward variable entry, where predictors are sequentially added based on their unique contribution to explaining variance in depression scores. The predictor explaining the most variance enters the model first, followed by subsequent predictors that contribute significant additional variance after controlling for previously entered variables. The model is continuously reassessed, with redundant predictors removed if they no longer meet significance criteria. The statistical threshold for variable entry was $p < 0.05$, and the threshold for removal was $p \geq 0.10$. This approach was applied to examine the relationship between baseline positive affect variables and depression scores at baseline, 2-year follow-up, and 4-year follow-up.

3. Results

The exploratory analysis of the MAS sample indicated that a direct negative association occurred between *active* and *depression* (−0.18). Nodes within the network that influenced *active* included *strong* (0.32), *enthusiastic* (0.15), *determined* (0.16), and *attentive* (0.17) (Fig. 2; Supplementary Table S1). The node with the most associations within the network was *enthusiastic*, with links to *interested* (0.22), *excited* (0.24), *strong* (0.16), *proud* (0.12), *inspired* (0.21), and *active* (0.15) (Supplementary Table S1). The strongest association within the exploratory sample was found to be *alert – attentive* (0.42) (Fig. 2).

Further network analysis using the confirmatory sample at baseline supported the direct negative association between *active* and *depression* (−0.25) (Fig. 2, Supplementary Table S2). This association was also confirmed to be stable across both samples using 95 % credible intervals (95 % CIs) of differences in partial correlations not excluding zero (Fig. 3). Additionally in this analysis, *strong* also had a significant negative partial correlation with *depression* (−0.12). Nodes that had significant influence on *active* included *interested* (0.13) and *strong* (0.19). Within this confirmatory sample, *inspired – excited* was found to be the strongest association (0.37) (Fig. 2, Supplementary Table S2). *Alert* and *enthusiastic* had the highest number of associations within this network, with *enthusiastic* being the most central node (Fig. 2).

All associations within networks were confirmed to be stable through examination of partial correlations, where 95 % confidence intervals (95 % CIs) included zero (Fig. 3). All remaining associations did not significantly differ between exploratory and confirmatory groups. The optimized nature of the network is further validated by Bayesian Information Criterion scores for MAS data networks of −14,073.75, and an optimal significance threshold of 0.50, indicating a good fit.

Predictability analyses for the exploratory and confirmatory networks of PA and depression are visualized in Fig. 4. High predictability indicates a variable with high influence on other nodes within the network. *Enthusiasm* ($R^2 = 0.65$) was found to have the highest predictability, followed by *alert* and *attentive* ($R^2 = 0.60$). *Depression* had the lowest predictability in the network ($R^2 = 0.25$), while moderate predictability was observed in the cases of *inspired*, *excited*, *strong*, *active* and *determined* ($R^2 = 0.45$–0.55).

Fig. 5 shows the DAG representing the directional links between PA variables and depression. The strength of the associations is represented

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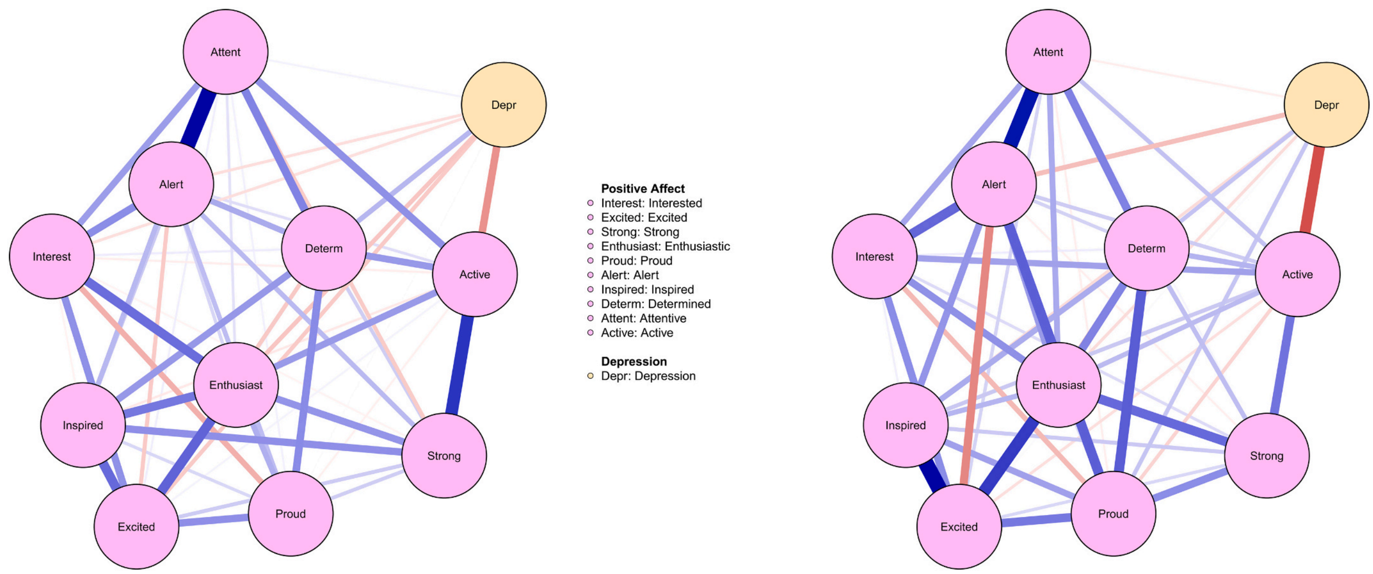

Fig. 2. Network associations between positive affect variables and depression in the exploratory and confirmatory groups of older adults at baseline (wave 1).

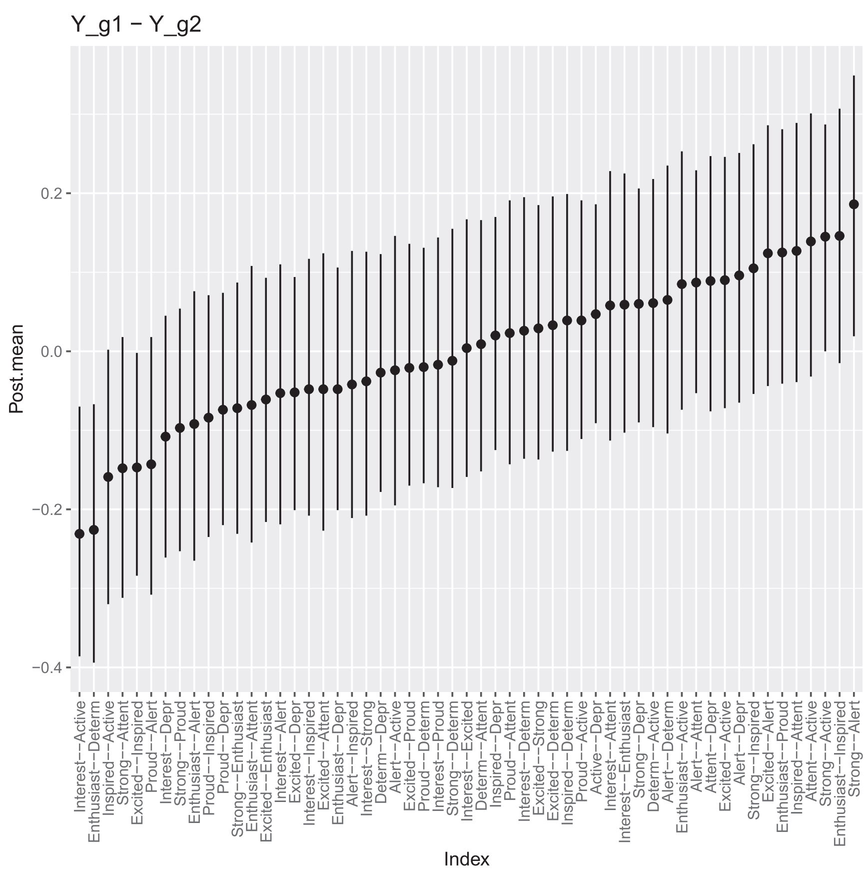

Fig. 3. Posterior distributions and 95 % Credible Intervals of differences in partial correlations between exploratory and confirmatory samples at baseline (wave 1). The differences considered as significant if 95 % CIs are not including zero.

by the density of the arrows, and the direction of the arrows indicates a plausible causal link between nodes. *Enthusiastic*, *excited*, *alert* and *inspired* appear as highly influential PA nodes in the older adult sample (Fig. 5). The strongest directed associations occur from *enthusiastic* to *excited*, *enthusiastic* to *alert*, *enthusiastic* to *inspired*, and *enthusiastic* to *strong*. The directed network originates with *enthusiastic* as the ancestral node, which influences the expression of all other nodes. *Depression* and *proud* both appear as descendants that are influenced by the interactions of other nodes.

The DAG analysis revealed several strong and directional relationships, with edge strengths (probability of edge presence) and directions (probability of specific direction) providing insights into the network's causal structure included in Supplementary Table S3. The strongest associations (strength >0.99) included the associations between *excited*

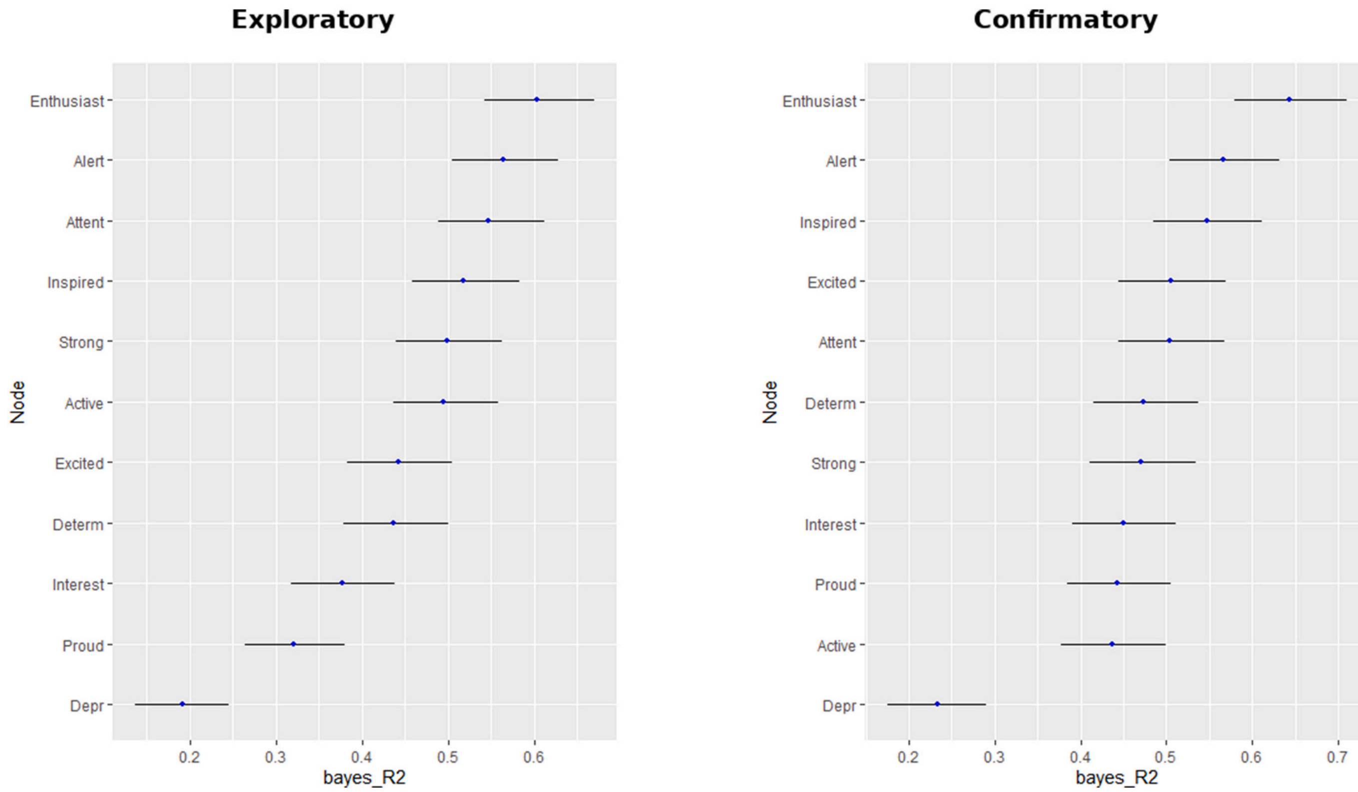

Fig. 4. Predictability plots of positive affect and depression for older adults' sample, exploratory group A and confirmatory group B across wave 1 (baseline), including 95 % CIs.

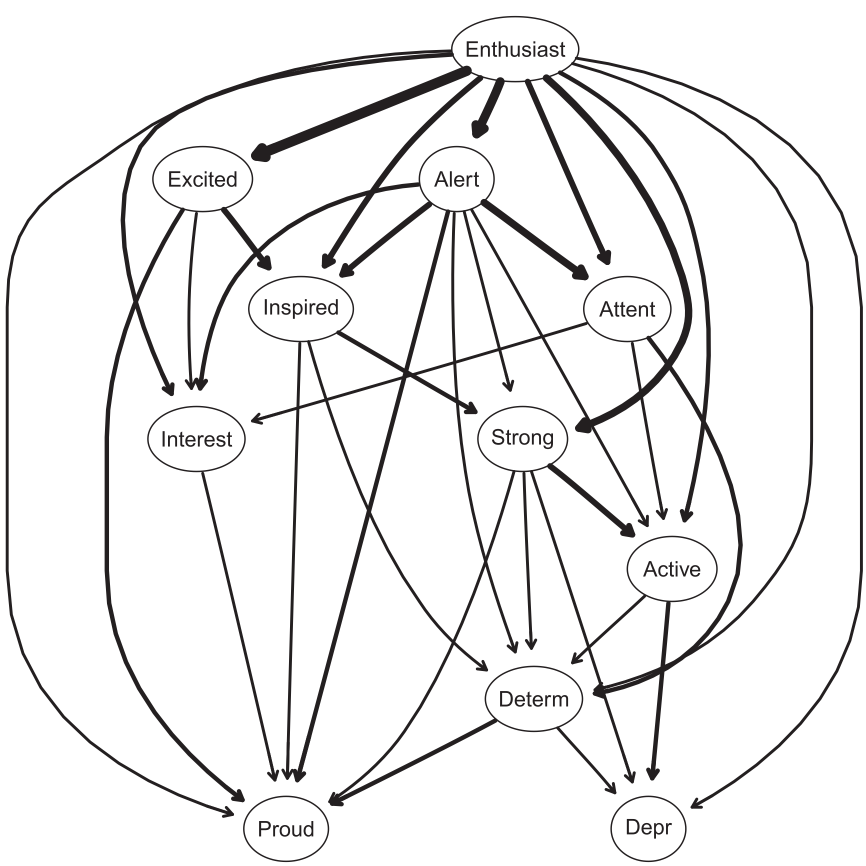

Fig. 5. Directed Acyclic Graph representing the directional association between positive affect variables and depression in older adults at baseline (wave 1).

and *enthusiastic* (strength = 1.00), *interested* and *enthusiastic* (strength = 1.00), *strong* and *active* (strength = 1.00), and *alert* and *active* (strength = 1.00). Strong directional effects (direction probability >0.80) found within the DAG were from *excited* to *proud* (direction = 0.88), *enthusiastic* to *interested* (direction = 0.86), *proud* to *alert* (direction = 0.85) and *active* to *depression* (direction = 0.79).

Enthusiastic emerged as a central node with multiple strong outgoing connections including to *interest* (strength = 1.00, direction = 0.86), *excited* (strength = 1.00, direction = 0.57), and *active* (strength = 0.98, direction = 0.81). *Alert* served as a mediator between several variables such as between *enthusiastic* and *attentive* (strengths >0.97) and between *proud* and *active* (strengths >0.72). These findings suggest a hierarchical structure where the PA facet *enthusiasm* appears to initiate cascades of other PA, while *active* shows the most direct relationship with *depression* levels. The high strength but varying directional probabilities of many associations indicate complex bidirectional relationships within the PA network, with some clear causal pathways emerging particularly in relation to *depression* (Fig. 5). A pathway to *depression* existed from *active* (strength = 1.00, direction = 0.79). As an ancestral node, having influence across PA variables in the network, *enthusiastic* showed an indirect effect on *depression* through the influence of *active* (Fig. 5). Enthusiastic → active (strength = 0.98, direction = 0.81) and active → depression (strength = 1, direction = 0.79). Additional indirect routes demonstrating the influence of enthusiastic on depression included *enthusiastic* → *strong* → *depression*, and *enthusiastic* → *determined* → *depression* (Fig. 5). Strengths and direction of associations can be found in supplementary materials (Supplementary Table S3).

Through stepwise linear regression, it was confirmed that higher scores on *active* and *enthusiastic* were consistent predictors of lower levels of *depression* in the MAS sample across baseline and two follow-up conditions. *Enthusiastic* and *active* occurred as a significant predictor in all waves ($p < 0.001$) (Table 1). At baseline, *active* accounted for 16 % of variance in *depression* ($R^2 = 0.16$, $\beta = -0.40$, $p < 0.001$), followed by *enthusiastic* which explained an additional 2 % of variance ($\Delta R^2 = 0.02$, $\beta = -0.18$, $p < 0.001$). *Strong* ($\Delta R^2 = 0.01$, $\beta = -0.10$, $p < 0.001$), *determined* ($\Delta R^2 = 0.01$, $\beta = 0.10$, $p < 0.001$), and *alert* ($\Delta R^2 = 0.01$, $\beta = -0.10$, $p < 0.001$) each contributed smaller but significant additional variance, bringing the total explained variance to 20 %.

At the second wave (follow-up after 2 years) a similar pattern was observed where *active* emerged as the strongest predictor ($R^2 = 0.11$, $\beta = -0.33$, $p < 0.001$), and after controlling for variance explained by *active*;*enthusiastic*, *strong*, *determined*, and *alert* were still significant predictors collectively explaining 15 % of the variance in *depression* scores. At 4-year follow-up (Wave 3), *enthusiastic* emerged as the primary predictor ($R^2 = 0.09$, $\beta = -0.31$, $p < 0.001$), with *active* ($\Delta R^2 = 0.03$, $\beta = -0.19$, $p < 0.001$) and *strong* ($\Delta R^2 = 0.01$, $\beta = -0.12$, $p < 0.001$) adding significant additional variance, explaining a total of 13 % of variance in *depression* scores. These longitudinal findings underscore the consistent predictive roles of *active* and *enthusiastic* experiences in relation to depression scores over time.

Table 1
Summary of the stepwise linear regression analyses predicting depression in participants of the MAS at 2-year intervals using baseline positive affect variables from the PANAS.

Outcome	Block and predictors		R^2	R^2 change	Standardized β
Depression at baseline	Positive affect variables				
	1	Active	0.16	0.16	−0.40*
	2	Enthusiastic	0.18	0.02	−0.18*
	3	Strong	0.18	0.01	−0.10*
	4	Determined	0.19	0.01	0.10*
	5	Alert	0.20	0.01	−0.10*
Depression after 2 years	Positive affect variables				
	1	Active	0.11	0.11	−0.33*
	2	Enthusiastic	0.13	0.02	−0.18*
	3	Strong	0.14	0.01	−0.12*
	4	Determined	0.15	0.01	0.09*
	5	Alert	0.15	0.01	−0.11*
Depression after 4 years	Positive affect variables				
	1	Enthusiastic	0.09	0.09	−0.31*
	2	Active	0.12	0.03	−0.19*
	3	Strong	0.13	0.01	−0.12*

* $p < 0.001$.

4. Discussion

This research aimed to explore the potential protective effect of PA against depression in an older adult population and the unique associations between these variables that contribute to this protective property. The exploratory and confirmatory networks highlighted specific affective pathways that could inform the development of targeted interventions for later life depression and revealed important findings that advance our understanding of the relationship between PA and depression in older adults. The network analyses revealed a remarkably stable structure of relationships between PA and depression. This stability provides strong support for the robustness of the results and suggests that the identified relationships are likely to be reliable targets for developing interventions against depression (Rodda et al., 2011). The use of state-level measures of PA suggests that the emotional experiences identified in this study may be more amenable to short term, low risk interventions. This enhances the practical relevance of the findings as it suggests that targeted activities to increase specific positive emotions could yield measurable benefits in reducing symptoms of depression, even in individuals who do not consistently report high trait positive affect.

Most notably, the directional analyses identified enthusiasm as an ancestral node that initiates cascades of other PA and a key catalyst in our network analyses, demonstrating the highest predictability (R^2 = 0.65). The high predictability of this variable indicates that being enthusiastic influences many nodes within the generated networks and individuals' experience of other PA. These findings support Fredrickson's (2004) theory broaden-and-build theory, which posits that moments of PA broaden the though-action repertoire of individuals and build psychological resilience to negative experiences. In the current research several facets of PA particularly enthusiasm, appear to function as influential nodes within the broader network, suggesting that specific PA experiences initiate experiences of PA through the activation of other PA states. Furthermore, the centrality of the enthusiasm node within the network suggests that certain PA experiences may scaffold more experiences of PA over time. This finding also supports prior research highlighting enthusiasm as a significant component of vitality and engagement in older adults, both of which are inversely associated with depressive symptoms (Forgeard et al., 2011; Fredrickson, 2013; Ong et al., 2006).

GDS scores (depression) emerging as an outcome of the interactions between PA nodes indicates that these affective experiences buffer a person's experience of depressive symptoms. Two primary protective associations to depression emerged through feeling active and strong, with the active pathway showing particularly robust inverse connection. These pathways remained stable in our longitudinal analyses, with both active and enthusiastic consistently predicting lower depression levels across multiple time points. The identification of active engagement as a key pathway to reduced depression also aligns with previous research by Gross and John who found that active engagement showed stronger protective effects against depressive symptoms compared to other aspects of PA (Gross and John, 2003). The network structure observed in this research suggests that individuals with higher levels of PA, particularly enthusiasm, may possess or more effectively utilise regulatory strategies that reduce the impact of depressive symptoms. It may enable individuals to reappraise life events in more positive ways, interrupting the negative thought cycles or rumination that contribute to depression.

The predictability analyses further reinforced the central role of enthusiasm, while also highlighting the importance of alert and attentive states in the network. Interestingly, depression showed the lowest predictability in the network, suggesting that experiencing depression symptoms may have a limited impact on individual's ability to experience PA, which is promising for developing new intervention approaches involving PA. For instance, interventions focusing on enhancing enthusiasm and promoting physical and mental activity might be particularly effective in preventing and treating depression in older adults, as suggested by recent research (Craske et al., 2019; Santos et al., 2013; van Steenbergen et al., 2021). The results support the idea that enhancing or supporting the experience of specific positive affective states could provide a feasible approach to improving mental health in older adults, including those who may not meet diagnostic criteria for depression but still experience emotional distress. Interventions that target momentary affective experiences may offer meaningful psychological benefits without requiring long term therapy or pharmacological treatment or could be used alongside these interventions to improve outcomes.

A major strength of this study lies in its methodological robustness. The use of both exploratory and confirmatory network analyses, combined with directed acyclic graph modelling and longitudinal regression analyses, provides multiple lines of evidence supporting our findings. The stability of our results between different analytical approaches and across time points further strengthens their reliability. Additionally, our large sample size and the use of advanced statistical techniques like Bayesian Gaussian Graphical Models with conservative thresholds for what was interpreted as significant results enabled us to identify subtle but important relationships that might have been missed with more traditional approaches. The DAG analysis, based on extensive bootstrapping across a large sample, provides strong evidence of meaningful associations within the PA network. However, as these findings are based on observational data, they should be viewed as indicative of potential pathways rather than definitive causal associations.

4.1. Limitations and future directions

Despite these strengths, several limitations should be noted. First, our sample was drawn from a specific geographic region, potentially limiting generalizability. Second, while our longitudinal analyses spanned four years, more frequent measurements might have captured shorter-term dynamics in the relationship between PA and depression symptoms. The PANAS measure used in this research assesses state positive affect, which captures recent emotional experiences rather than long-term affective dispositions. While this approach aligns with the research aim of identifying immediately modifiable mechanisms of affect, it limits the extent to which the findings can be generalised to trait-level positive affect.

Another limitation exists within the measurement of positive affect, as the PANAS includes only 10 positive affect items. This may not fully represent the breadth of positive emotions that could impact on symptoms of depression. Future research should consider using or developing more comprehensive positive affect measures to broaden the coverage of the positive affect domain of emotional experiences.

Future research should examine relationships between positive affect and depression symptoms in more diverse populations and investigate whether enthusiasm remains an initiating node over a longer period. It should also be noted that although certain PA variables (e.g. feeling enthusiastic, feeling interested) were identified as predictors of lower depression scores within the network and regression analyses, these results do not confirm that they function as protective factors in a clinical sense. Protective factors are typically defined as characteristics that protect individuals from developing a disorder and must demonstrate consistent effects over time and across populations. The current research provides preliminary support for their potential role, but further longitudinal and intervention studies are required to establish true protective status.

Although DAG modelling suggests potential directional pathways between affect variables and measured depression symptoms, the observational nature of this data precludes definitive causal interference. Unmeasured factors such as social support, physical health, and life experiences may contribute to the observed associations.

5. Conclusions

This study provides compelling evidence that enthusiasm serves as a central catalyst in the PA network, with specific pathways through active and strong states having a measurable relationship to reduced depression in older adults. These findings suggest that interventions targeting enthusiasm and promoting activity could be particularly effective in preventing and treating depression in older adults, offering a promising alternative or complement to traditional approaches. The identification of these specific pathways provides concrete targets for developing more effective, non-pharmaceutical interventions to enhance mental well-being in aging populations.

With more strategies to buffer against depression in older adults, the high prevalence of depressive symptoms found within this population may be lowered, reducing the healthcare burden and improving the life experience of those who are aging. The results suggests that positive affect, particularly enthusiasm, not only co-occurs with lower depression but may play an initiating role within PA networks. These findings contribute to a growing body of literature emphasising the functional and regulatory significance of PA experiences in older adults. Interventions that focus on cultivating enthusiasm, for example through behavioural activation, meaningful goal setting or engagement in intrinsically rewarding activities, may offer a promising avenue for promoting psychological resilience and preventing or reducing later life depression.

Clinical trial registration

This is an exploratory study and preregistration is not required.

CRediT authorship contribution statement

Ella G. Hopkins: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Patrick J. Leman:** Writing – review & editing, Supervision. **Matti Cervin:** Writing – review & editing, Methodology. **Katya Numbers:** Writing – review & editing, Data curation. **Henry Brodaty:** Writing – review & editing, Data curation. **Perminder S. Sachdev:** Writing – review & editing, Data curation. **Oleg N. Medvedev:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Ethics approval and patient consent statement

The Sydney Memory and Ageing Study was approved by the University of New South Wales Human Research Ethics Committee (HC 05037, 09382, 14327) and all participants provided written consent to participate in the study.

Declaration of competing interest

None.

Data availability

The data that support the findings of this study are available from the Centre for Healthy Brain Ageing (CHeBA) Research Bank following a standardized request process. Access requests can be directed to CHebaData@unsw.edu.au or to the corresponding author. Data access is

restricted due to participant consent terms requiring Older Australian Twins Study (OATS) investigators' review and approval of proposed secondary uses, regardless of data de-identification status.

Analysis code in R is available in the supplemental materials at the end of the manuscript. We report all data exclusions, manipulations, measures, and sample size determinations in the Method section.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2025.120529.

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