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RESEARCH ARTICLE **OPEN ACCESS**

Leveraging Network Insights into Positive Emotions and Resilience for Better Life Satisfaction

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Abstract:

Introduction/Objective: Within a network analysis framework, this study explored the relationships between positive emotions, resilience, and life satisfaction. Positive emotions and resilience are critical to enhancing psychological well-being, but their complex interplay requires further investigation, particularly in a Greek adult population.

Methods: We conducted a cross-sectional study with 1,230 Greek adults (67.6% females, 32.4% males), using a network analysis to assess the relationships among positive emotions, resilience, and life satisfaction. Data were collected through the Scale of Positive and Negative Experience (SPANE-8), the Brief Resilience Scale (BRS), and the Satisfaction with Life Scale (SWLS). Network structures were constructed using the graphical LASSO technique for partial correlation analysis, and Bayesian networks were applied to generate Directed Acyclic Graphs (DAGs) to identify directional pathways. Centrality metrics were used to determine critical variables in the network.

Results: Happiness, pleasure, and contentment are examples of positive emotions that are central nodes in the network that are highly correlated with higher levels of life satisfaction. Resilience, primarily as a recovery mechanism from stress, showed weaker direct associations with life satisfaction. The DAG revealed that positive emotions significantly influenced life satisfaction, suggesting their pivotal role in improving well-being.

Conclusion: The findings underscore the importance of positive emotions in enhancing life satisfaction, suggesting that interventions targeting emotional well-being may be more effective than those focused solely on resilience. These insights offer a foundation for developing psychological interventions to improve life satisfaction.

Keywords: Positive emotions, Resilience, Life satisfaction, Network analysis, Directed acyclic graphs, Satisfaction with life scale.

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1. INTRODUCTION

1.1. Context and Significance

The interplay between positive emotions, resilience, and life satisfaction is a central focus of study within well-being and positive psychology [1-4]. Research has shown that these elements are highly significant and have a significant impact on overall happiness. Positive emotions, such as joyfulness, happiness, and contentment, are linked to enhanced subjective well-being and sustained life satisfaction. These emotions go beyond transient pleasure; they foster a lasting sense of fulfillment by shaping an optimistic worldview and facilitating adaptive inter-

pretations of life's events [5-7].

Furthermore, resilience, the ability to recover from adversity and adapt to changes, is crucial in maintaining and enhancing life satisfaction. Resilient individuals exhibit robust psychological strengths and coping mechanisms that effectively confront and surmount stress, setbacks, and obstacles. Resilience is linked to emotional well-being and optimism, which may contribute to higher overall life satisfaction. Also, previous studies have shown that sex/gender differences can influence the experience and impact of positive emotions and resilience on life satisfaction [8-12].

The dynamic interrelation among positive emotions, resilience, and life satisfaction is synergistic, creating a mutually reinforcing cycle where each element supports and amplifies the others. Positive emotions enhance resilience by providing psychological resources needed to cope with adversity, while resilience helps maintain and cultivate positive emotions, even under challenging circumstances. This reciprocal relationship significantly contributes to higher levels of life satisfaction, forming a beneficial feedback loop that propels individuals toward greater well-being [6]. This foundational understanding underscores the importance of exploring these constructs individually and in their interconnected forms, using advanced methodological approaches to capture the nuances of their relationships. However, this cycle may not function consistently across all contexts. Chronic stress, socioeconomic conditions, culture, personality, or mental health can disrupt the relationship between positive emotions, resilience, and life satisfaction [13]. This suggests that while the interplay is significant, it may not apply universally, warranting further research.

By employing a network analysis framework, this study elucidates the complex dynamics within these variables, offering insights into broader implications for enhancing individual well-being.

1.2. Identification of Research Gaps and Methodological Choices

While foundational research highlights the influence of positive emotions and resilience on life satisfaction [3, 14, 15], there remains a nuanced gap regarding how these constructs interact within complex network systems. Most studies have treated these elements in isolation or simplistic relational dynamics without fully exploring intricate network interactions and the specific contributions of different types of positive emotions [16]. Limited exploration exists into how interconnectedness and centrality measures within network structures—such as strength, betweenness, and closeness—can inform our understanding of the most influential factors in life satisfaction [17, 18].

Furthermore, there is a noticeable lack of differentiation in the roles of various forms of resilience within these networks, mainly regarding how resilience as a recovery mechanism from stress compares to the influence of diverse positive emotions in the network dynamics of life satisfaction. While universally acknowledged as beneficial, resilience appears to exert its influence differently across various contexts within the network, suggesting a more complex role than traditionally understood [19, 20].

These gaps highlight the need for a detailed examination using sophisticated network analysis techniques to discern the specific pathways and interactions among positive emotions, resilience, and life satisfaction.

In addressing these gaps, this study used network analysis to explore the relationship between Positive Emotions, Resilience, and Life satisfaction. The network perspective considers interconnectedness rather than latent factors. Also, it extends beyond psychopathology research [21]. Network approaches have enhanced our understanding of psychological phenomena in studying personality, intelligence, and attitudes [22-24].

In this research, we applied two different algorithms to construct and analyze network structures to study relationships between variables. The initial step involved employing the graphical LASSO algorithm, which facilitated the creation of a partial correlation network [25]. This network accurately portrayed the strength of direct correlations between variables while eliminating misleading or spurious connections [26]. The graphical LASSO technique addresses multicollinearity issues and is scalable to diverse data types, including continuous, ordinal, and binary. This flexibility and robustness are essential for effectively managing varied data in psychological research [27, 28].

However, it should be noted that one limitation of this network is its lack of directionality, as it does not provide information about influence-and-effect relationships between variables [29].

To overcome this limitation, we constructed a directed acyclic graph (DAG) using a Bayesian network technique [30]. Bayesian networks and DAGs provide a method to explore potential directional pathways within intricate systems. DAGs, as probabilistic models, excel in discerning underlying relational structures based on available data [31]. These models are depicted as networks with directed connections and have gained recognition in network literature [32]. DAGs are characterized by edges with arrowheads indicating the direction of prediction and potential related effects, unlike edges in correlation and partial correlation networks [33].

Moreover, DAGs offer a structured way to explore directional pathways that are theoretically and empirically grounded, avoiding common pitfalls such as reverse relativity and confounding variables [34]. Using cross-sectional data with DAGs is effective in our study as DAGs investigate directional relationships among variables and do not establish causality [35]. Consequently, it is adequate to explore these directional relationships through DAGs initially. Furthermore, DAGs have been applied in various fields beyond epidemiology [15, 36, 37].

We adapted the DAG in a data-driven manner by allowing the algorithm to build a network structure

through a "learning network." As our data consisted of metric measurements, we constructed a Gaussian network, where independence assumptions were tested using partial correlation coefficient tests [38]. Throughout this study, we favored the term "direction" over "influence" to avoid unwarranted causality claims [32].

Ultimately, the DAG analysis excluded the possibility of feedback loops among the variables, while the graphical LASSO algorithm allowed for bidirectional edges. Consequently, both methods complemented each other [39]. Combining these techniques, we aimed to comprehensively understand the complex relationships and dynamics within the studied variables.

1.3. Theoretical Framework and Research Questions

Our study is grounded in the Broaden-and-Build Theory of positive emotions, developed by Barbara Fredrickson, which provides a crucial framework for understanding how positive emotions contribute to an individual's well-being [40]. This theory posits that experiencing positive emotions broadens an individual's momentary thought-action repertoires, which, over time, build their enduring personal resources, both psychological and physical. These expanded cognitive and emotional resources are believed to enhance an ability of the individual to develop resilience and achieve sustained life satisfaction.

Additionally, our study incorporates elements from resilience theory, particularly concepts related to recovery from stress. Resilience theory emphasizes the capacity to return to a baseline state after adversity and the ability to use such challenges as opportunities for personal growth and development. This aspect of resilience is particularly relevant in understanding how individuals maintain or enhance their life satisfaction despite facing stressful or adverse circumstances [41, 42].

Building on this theoretical backdrop, our study articulates specific research questions that seek to dissect the nuances of how different types of positive emotions and resilience interact within a network setting to enhance life satisfaction. The questions are formulated as follows:

1. How do positive emotions interact within a psychological network to influence life satisfaction?

2. How does resilience, particularly as a recovery mechanism from stress, affect life satisfaction in a network of psychological constructs?

3. What are the key interactions among central life satisfaction variables within the network?

4. What do the DAG-derived directional relationships reveal about the pathways among positive emotions, resilience, and life satisfaction?

5. What are the patterns of interaction among positive emotions, resilience, and life satisfaction in the network?

These research questions aim to probe deeper into the dynamics and interactions revealed by our network analysis, guiding further research and the development of interventions based on a detailed understanding of how positive emotions, resilience, and life satisfaction interact.

2. METHOD

2.1. Participants and Procedure

The study included 1,230 Greek adults (67.6% females, 32.4% males) aged 18–80 (M = 29.21, SD = 13.29). High school graduates comprised the largest proportion at 21.54%, followed by students of private colleges, technological educational institutes, or universities at 49.59%. The remaining categories, including primary school graduates, middle school graduates, master's degree holders, and doctorate holders, accounted for smaller percentages in the sample. The largest percentage, 46.59%, corresponded to individuals with no income. Those earning a monthly income below €600 accounted for 16.75%, while the income ranges of €600 - €1200, €1201 - €1800, €1801 - €2500, €2501 - €4000, and above €4000 made up 23.17%, 8.13%, 2.2%, 0.89%, and 2.28%, respectively according to the SAGER guidelines. A detailed breakdown of participant age ranges, education levels and income brackets can be found in Table **S1**. Recruitment occurred online between Nov. 2021 and Feb. 2022 using a network sampling approach facilitated by psychology undergraduates who recruited participants from their social networks. Participants provided informed consent, and no incentives were given. This study adopted the revised Declaration of Helsinki of 1975 on the ethical standards of the relevant national and institutional committees for human experimentation [43].

The questionnaire was distributed online, and informed consent was obtained from all participants. Data collection followed a network sampling approach, in which psychology students, adult and non-student participants from their social circles. Participants were not incentivized directly, but students received course credit for completing the recruitment. Recruitment guidelines allowed students to gather data from their social environments, though students themselves were excluded from completing the questionnaire. Factors such as age, gender, socioeconomic status, and education level were considered in the analysis to account for potential confounders. This ensured that these variables appropriately provided reliable interpretations of the relationships between positive emotions, resilience, and life satisfaction.

2.2. Measures

2.2.1. The Scale of Positive and Negative Experience 8 (SPANE-8)

The SPANE-8 is an adaptation of the SPANE-12, streamlined to enhance efficiency by condensing the number of items per factor from three to one, as detailed by Diener *et al*. [44] and Kyriazos *et al*. [45]. This modification results in a concise instrument comprising items such as "Pleasant" and "Bad," evaluated on a 5-point Likert scale from 1 (Very Rarely or Never) to 5 (Very Often or Always). SPANE-8 displayed strong internal consistency in a Greek cohort, with reliability coefficients of α = .86 for the positive domain and α = .79 for the negative domain. In our current investigation, the positive domain similarly

exhibited a reliability of α = .86.

2.2.2. The Brief Resilience Scale (BRS)

The BRS is a succinct measure of resilience, focusing specifically on an individual's capacity to bounce back from stress [46, 47]. This scale includes six items, such as "I tend to bounce back quickly after hard times," rated on a 5-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The scoring of the BRS allows for an assessment range from minimal to maximal resilience, with half of the items requiring reverse scoring. In this study, the BRS confirmed good internal consistency with a reliability score of α = .80. It is important to note that the resilience assessed by the BRS pertains strictly to the recovery aspect, a more specific focus compared to broader resilience measures like the Connor-Davidson Resilience Scale (CD-RISC), which encompasses a wider array of adaptive traits [48].

2.2.3. Satisfaction with Life Scale (SWLS)

The SWLS, developed by Diener *et al*. [49], gauges overall life satisfaction through five items, such as "I am satisfied with my life." These items are rated on a 7-point Likert scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). Historical data suggest that the SWLS consistently demonstrates high reliability, with coefficients ranging from .79 to .89. In more recent research involving a Greek sample, the scale achieved reliability of α = .87, underscoring its robustness in measuring life satisfaction.

The SPANE-8, BRS, and SWLS are widely validated and reliable tools, extensively used across multiple cultural and demographic contexts, including in Greece. Their application in this study is supported by their well-documented validity and reliability in previous research [45-49].

2.3. Network Construction and Analysis

2.3.1. Graphical LASSO Algorithm

We utilized a graphical Gaussian model, as advocated by Fried *et al*. [50], to map out our initial network analysis, focusing on the conditional independence among nodes under the simultaneous influence of their peers. To mitigate the occurrence of false-positive connections commonly associated with high-dimensional parameter estimates, we employed the graphical LASSO method, incorporating an L1 penalty to yield a streamlined inverse covariance matrix, a technique further developed by Carter *et al*. [51]. This approach curbs insignificant partial correlations and ensures that only the most robust associations, suggestive of true links, are considered. Two R packages supported our computational framework, qgraph [52] and glasso [53]. We adopted an extended Bayesian information criterion (EBIC) for model selection as delineated by Beard *et al*. [2], setting the sparsity tuning parameter, γ, at 0.5 and evaluating 100 different sparsity levels. This allowed us to optimize the balance between authenticity and sparsity in the network connections, following the principles outlined by Fried *et al*. [50]. Additionally, the network's nodes were analyzed for their centrality—strength, betweenness, and closeness—using methodologies from Bringmann *et al*. [54], and their stability was assessed *via* 1000 bootstrapped samples in the bootnet package [55], which provided a solid basis for evaluating the reliability and influence of each node.

2.3.2. Bayesian Network and Directed Acyclic Graph (DAG)

Advancing to the construction of a Bayesian network, or DAG, we adopted a structured learning approach using both constraint- and score-based methods to ascertain variable dependencies, followed by parameter estimation through maximum likelihood or Bayesian approaches, as outlined by Scutari *et al*. [56]. The hill-climbing algorithm from the bnlearn package [57] was instrumental in refining our network structure. We enhanced the network's stability and reliability through bootstrap methodologies described by Heeren *et al*. [58], retaining edges in our final DAG that demonstrated a consistent presence and directional probability in bootstrapped samples, as per Bringmann *et al*. [54].

Finally, the directionality and significance of each edge in the DAG were established based on their prevalence and Bayesian Information Criterion (BIC) scores, provided by the bnlearn package, which also dictated the visual representation of each connection's strength [59].

3. RESULTS

3.1. Network Structure and Centrality Measures

As illustrated in Fig. (**1**), the constructed network comprises 15 nodes with an average edge weight of 0.061 and is characterized by a median-low density. Of a potential 105 connections, 63 were established, capturing 60% of all possible interactions. Stability analysis of the edge weights indicated robust connections across all central measures with a Correlation Stability (CS) coefficient exceeding 0.75, suggesting that these findings are likely generalizable to the broader population.

Notably, the significant connections identified predominantly appeared within individual questionnaires rather than between them. Within the SPANE questionnaire, prominent links were evident between several items: SP_2 (Pleasant) and SP_3 (Happy), SP_2 (Pleasant) and SP_6 (Joyful), and between SP_3 (Happy) and SP_6 (Joyful). These associations underline a coherent internal structure in the SPANE that captures various facets of positive affect.

In the Brief Resilience Scale (BRS) context, meaningful connections emerged between resilience and stress recovery items. Specifically, strong links were observed between BRS_1 (I tend to bounce back quickly after hard times) and BRS_3 (It does not take me long to recover from a stressful event). Additionally, connections were noted between BRS_4 (It is hard for me to snap back when something bad happens) with both BRS_6 (I tend to take a long time to get over setbacks in my life) and BRS_2 (I have a hard time making it through stressful events), indicating a consistent pattern in responses related to challenges in resilience.

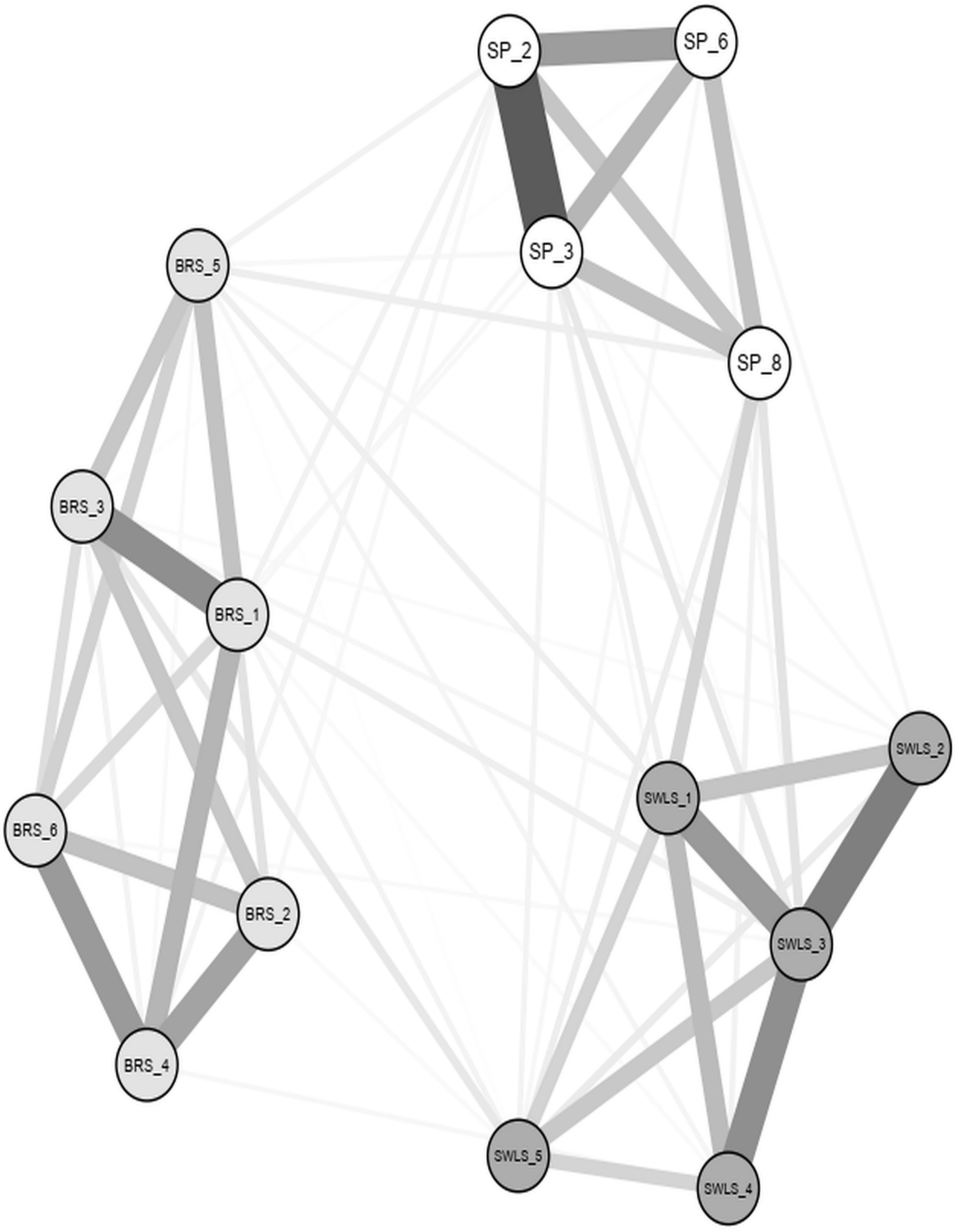

Fig. (1). The LASSO graphical technique was utilized to construct a network diagram, showcasing the interconnections among the questionnaire variables from SPANE-8 (positive emotions), BRS (resilience), and SWLS (life satisfaction). The thickness of the edges represents the strength of the partial correlations between variables, with thicker lines indicating stronger associations.

Within the Satisfaction with Life Scale (SWLS), significant relationships were identified that underscore satisfaction aspects, notably between SWLS_3 (I am satisfied with my life) and several other items: SWLS_2 (The conditions of my life are excellent), SWLS_4 (So far I have obtained the important things I want in life), and SWLS_1 (In most ways my life is close to my ideal). These findings suggest a strong interconnection among various perceptions of life satisfaction within the SWLS.

Across the datasets from the three questionnaires, the variables were clustered distinctly, showing limited interrelationships between different measures, highlighting the unique dimensions each scale probes within the psychological construct space.

3.2. Centrality Analysis

In our network analysis, the concept of centrality is pivotal for assessing the influence and connectivity of individual nodes within the network, as illustrated in Fig. (**2**). One key metric, strength centrality, evaluates the centrality of a node based on its connections. From our analysis, several variables demonstrated significant strength centrality, notably SWLS_3 (I am satisfied with my life), SP_3 (Happy), SP_2 (Pleasant), and SWLS_1 (In most ways my life is close to my ideal). These variables, deriving from different questionnaires, hold substantial influence within the network, primarily connecting more intensely with variables within the same questionnaire, which somewhat limits broader inter-questionnaire interactions. Psychologically, these variables are central to life satisfaction and emotional well-being, directly influencing numerous other factors.

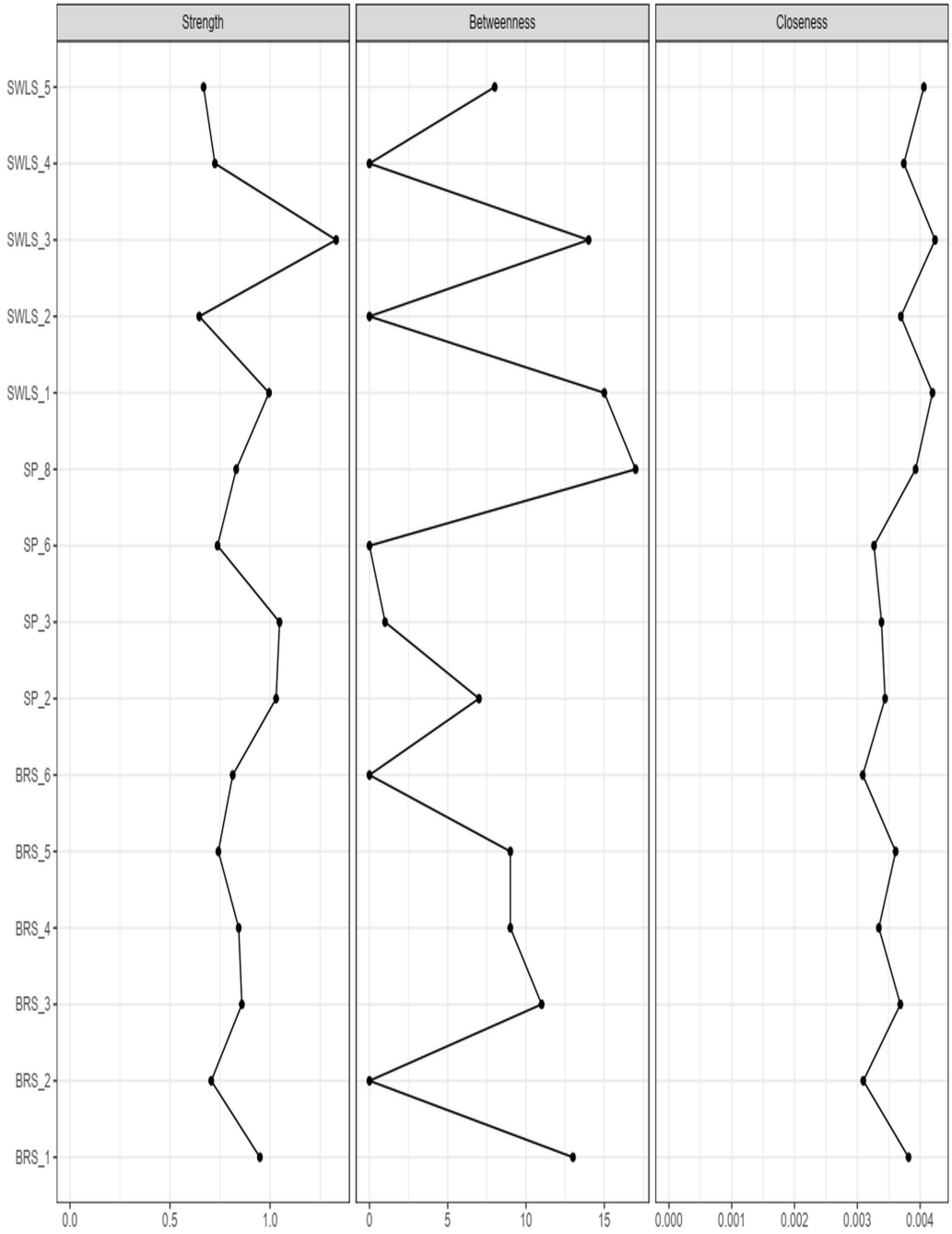

Fig. (2). Three standardized centrality metrics: strength, betweenness, and closeness

Another critical centrality measure, betweenness centrality, quantifies a node's role as a bridge along the shortest paths between other nodes, thus facilitating communication and information flow. Nodes that scored high in betweenness centrality include SP_8 (Contented), SWLS_1 (In most ways, my life is close to my ideal), SWLS_3 (I am satisfied with my life), and BRS_1 (I tend to bounce back quickly after hard times). These nodes play crucial roles in enhancing the efficiency of communication and information dissemination across the network, underscoring their strategic importance in linking various parts of the network effectively. Psychologically, this suggests that these variables help integrate and connect distinct psychological components, such as linking different aspects of positive emotions and life satisfaction.

Also, closeness centrality is a critical measure in network analysis, focusing on how swiftly a node can connect to all other nodes within the network by quantifying the average shortest path length from one vertex to all others. Among the vertices analyzed, those standing out in terms of closeness centrality include SWLS_3 (I am satisfied with my life), SWLS_1 (In most ways my life is close to my ideal), SWLS_5 (If I could live my life over, I would change almost nothing), and SP_8 (Contented). These vertices demonstrate the least average distance to all other nodes, indicating their strategic positioning within the network. Psychologically, these variables can be seen as crucial drivers of life satisfaction, spreading their influence more rapidly throughout the network.

Remarkably, the item SWLS_3 (I am satisfied with my life) features prominently across all three centralities discussed—strength, betweenness, and closeness—highlighting its pivotal role in the network's structure. Similarly, items such as SWLS_1 (In most ways, my life is close to my ideal), SP_8 (Contented), and BRS_1 (I tend to bounce back quickly after hard times) also exhibit significant influence. These nodes are integral to the overall communication dynamics, facilitating efficient information flow across the network. As such, they are central to disseminating information and play crucial roles in maintaining the cohesiveness and functionality of the network.

3.3. Directional Pathways in the Network

It is crucial to recognize that the strength of the variables identified in our analysis does not imply the directionality of their relationships with other variables. We conducted a Bayesian network analysis to elucidate the directional dynamics among these variables, illustrated in the Directed Acyclic Graph (DAG) as shown in Fig. (**3**). The DAG reveals several critical features, including forming two distinct “regions” or clusters within the network, facilitated by applying a sparsity parameter that retains only the most robust connections.

The first region encapsulates the “SPANE8-P” and “SWLS” variables, where SP_2 (Pleasant) and SP_3 (Happy) are prominent, indicating their significant influence within this cluster. The second region is predominantly composed of “BRS” variables, with BRS_1 (I tend to bounce back quickly after hard times) positioned as a key node, suggesting its central role in this subset of the network.

The overall directional patterns in the network suggest that variables related to positive affect predominantly influence other variables within the same category and, to a lesser degree, certain life satisfaction variables. Notably, SWLS_1 (In most ways, my life is close to my ideal) and SWLS_3 (I am satisfied with my life) are crucial links between the SPANE8-P and life satisfaction clusters. Their strategic positions suggest that they play a pivotal role in initiating connections to and from the contented-related variables.

Additionally, connections like SP_3 (Happy) with SWLS_1 and SP_8 (Contented) with both SWLS_1 and SWLS_3 underline significant interactions that bridge positive affect and life satisfaction domains. However, the variables associated with psychological resilience, such as BRS_1, appear to function independently within the network, asserting minimal influence on the interplay between positive emotions and life satisfaction.

This directed network structure was derived using the methodology developed by Scutari and Nagarajan [56], confirming the robustness and consistency of our findings across different analytical approaches. The DAG maps out the directional interactions and highlights the influential roles of specific variables in mediating the relationships within the network, emphasizing the complex dynamics that govern the associations between positive emotions, resilience, and life satisfaction.

4. DISCUSSION

4.1. Interpretation of Findings and Theoretical Implications

Our network analysis has provided insights into the dynamics between positive emotions, resilience (specifically in its role as a mechanism for recovery from stress), and life satisfaction, uncovering potential interconnections and the unique roles these elements may play within the network. This analysis highlighted the potential influence of certain positive emotions — specifically “Pleasant” (SP_2), “Happy” (SP_3), and “Joyful” (SP_6) from the Scale of Positive and Negative Experience 8 (SPANE-8). These emotions are strongly interlinked, exerting a substantial effect on life satisfaction. This finding reveals a synergistic effect where one positive emotion can enhance the effect of others, collectively elevating well-being (Research Question 1). This insight effectively addresses our first research question by demonstrating how these specific emotions contribute to life satisfaction and how their interrelationships may amplify overall well-being [60].

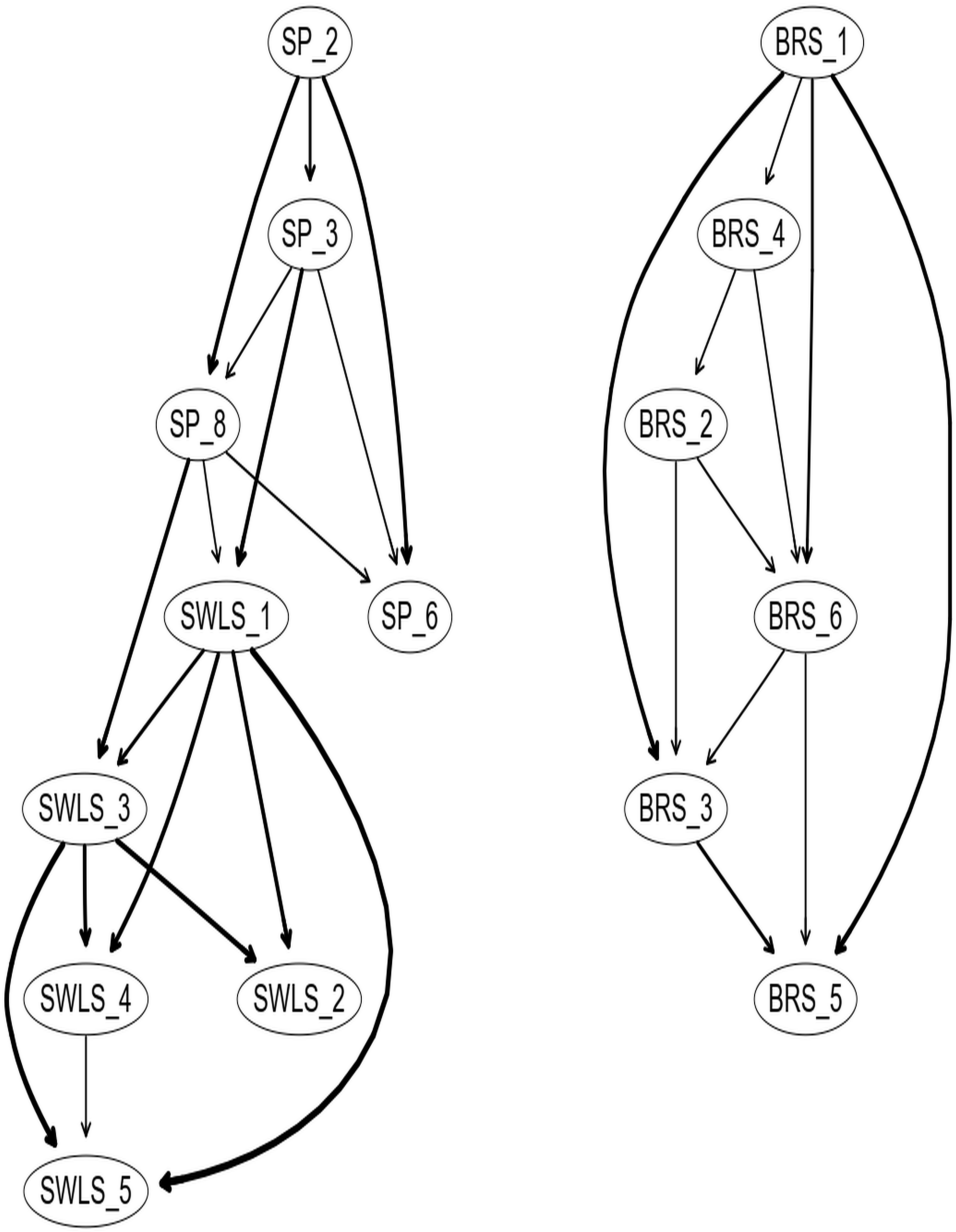

Fig. (3). A Bayesian network (Directed Acyclic Graph) displaying the directional relationships among variables from SPANE-8 (positive emotions), SWLS (life satisfaction), and BRS (resilience). The nodes represent individual items from each scale, with arrows indicating the direction of influence between variables. This diagram helps illustrate the potential pathways through which positive emotions and resilience influence life satisfaction.

In contrast to theories suggesting resilience and positive emotions have similar effects on life satisfaction, our findings reveal a clearer distinction between the two. Resilience, defined as the ability to recover from stress (measured by the Brief Resilience Scale), indirectly impacts life satisfaction more than positive emotions. Positive emotions, such as happiness and contentment, directly influence life satisfaction more immediately and significantly (Research Question 2). While resilience is important for emotional recovery and managing stress, it does not boost life satisfaction as directly as positive emotions. This challenges traditional views and suggests that interventions to improve life satisfaction should focus more on enhancing positive emotions, with resilience supporting well-being, particularly during adversity. This finding addresses our second research question by clarifying the distinct roles of resilience and positive emotions. It suggests that while resilience is valuable for recovery, focusing on positive emotions may lead to quicker improvements in life satisfaction [61].

The centrality analysis in our study has emphasized

the significant roles of certain life satisfaction variables, notably “I am satisfied with my life” (SWLS_3) and “In most ways, my life is close to my ideal” (SWLS_1). These findings are crucial as they underline their pivotal positions within the network (Research Question 3). They support our third research question about how significant connections within and between scales like the Satisfaction with Life Scale (SWLS) elucidate mechanisms that enhance life satisfaction. The central roles of these variables suggest they may be key nodes through which interventions could be strategically targeted to boost life satisfaction.

Furthermore, the Directed Acyclic Graph (DAG) analysis has provided vital insights into the directional relationships among the variables, particularly illustrating how 'Happy' (SP_3) exerts a direct and significant influence on life satisfaction measures such as 'I am satisfied with my life' (SWLS_3) (Research Question 4). This analysis delivers important data supporting our fourth research question by clarifying potentially related pathways. Practically, this suggests that positive psychology interventions focusing on increasing happiness and contentment may directly impact improving life satisfaction. For example, therapeutic strategies like mindfulness, gratitude exercises, and activities promoting joyfulness can be designed to target these influential emotional states specifically. Additionally, this finding highlights the value of differentiating between various positive emotions and tailoring interventions to enhance those emotions that have the strongest effect on life satisfaction [62].

Our research also unveils a complex pattern of interactions among positive emotions, resilience, and life satisfaction, which extends beyond the traditional linear models typically seen in psychological research. This complexity reveals more profound, intricate dependencies among these constructs, indicating a nuanced network of influences that could be harnessed to design more effective psychological interventions (Research Question 5). This approach addresses our fifth research question and adds a layer of sophistication to our understanding of these interactions.

While our findings emphasize the significant role of positive emotions in enhancing life satisfaction, it is important to consider alternative theories. For instance, hedonic adaptation theory suggests that individuals tend to return to a baseline level of happiness over time, regardless of the accumulation of positive emotional experiences [63]. Set-point theory posits that life satisfaction is largely determined by stable personality traits rather than transient emotional states [64]. Additionally, while resilience showed a more subdued role in our analysis, other models of resilience might argue for its centrality in contexts of extreme adversity, which may not be as prominent in our sample [40]. These alternative frameworks provide important context for understanding the scope of our findings and highlight areas for further research to explore the boundary conditions of these relationships.

4.2. Practical Implications and Applications

Our network analysis sheds light on the intricate relationships between positive emotions, resilience in stress recovery, and overall life satisfaction, offering valuable insights into psychology, mental health, and well-being practices. By using focused interventions to increase positive emotions, such as mindfulness, gratitude exercises, and positive psychology approaches, these findings can be immediately utilized in therapeutic settings. These interventions could significantly benefit therapeutic programs to boost feelings of happiness, joyfulness, and contentment, thereby improving life satisfaction. Mental health practitioners can use this network approach to identify the most impactful areas in a patient's psychological network, enabling more personalized care focusing on the most influential elements contributing to well-being. Additionally, well-being programs in schools and workplaces can implement these strategies to cultivate positive emotions among students and employees, enhancing overall satisfaction and productivity [65, 66].

The nuanced understanding of resilience, particularly its role in recovery from stress, suggests a need for reevaluating traditional resilience training. By integrating strategies enhancing positive emotional states, resilience training could become more comprehensive and effective. The central role of certain network variables indicates that interventions could be customized to target these key areas, potentially increasing the effectiveness of mental health programs. This approach allows mental health practitioners to craft personalized care plans that concentrate on the most impactful elements of an individual's psychological network, optimizing the benefits of therapy [67-69].

Furthermore, these insights have practical applications in educational and workplace settings. Well-being programs that enhance positive emotions could significantly improve life satisfaction among students and employees, contributing to a more vibrant, productive environment. At a broader societal level, the findings from our study could inform the development of community-based mental health and well-being initiatives. Implementing policies that promote and support positive emotional experiences at the community level could profoundly affect public health and societal well-being, aligning with strategies proposed in recent research [70, 71].

4.3. Limitations and Directions for Future Research

Employing a sample solely from Greece represents a limitation in our study concerning the generalizability of the results. The unique socio-cultural environment of Greece may influence the relationships between positive emotions, resilience, and life satisfaction in ways that are not necessarily applicable to other contexts. Thus, the findings from this study may predominantly reflect the specific dynamics of the Greek cultural setting, and extrapolation to other populations should be cautiously approached [72, 73].

It is important to remember that while DAGs can suggest likely directional connections, definitive causation can only be established through additional, rigorous experimental or longitudinal studies [74].

Future research should aim to replicate and expand upon this study by incorporating more diverse populations to enhance the external validity and generalizability of the findings. It is important to include participants from various cultural, ethnic, and socioeconomic backgrounds, as these factors could introduce different dynamics in the relationships among the psychological constructs under study [75]. Additionally, future studies should adopt longitudinal designs and experimental methodologies to strengthen causal inferences and explore the temporal dynamics of these relationships. Such approaches would allow researchers to understand better how these variables interact over time, providing insights into their long-term effects [76]. Considering the complexity of the interactions observed among the study variables, upcoming research could benefit from employing more sophisticated analytical models. These models should account for potential bidirectional influences and feedback loops, offering a more nuanced understanding of how positive emotions, resilience, and life satisfaction influence one another [77]. Finally, it is also crucial for future research to identify and control for potential confounding variables, such as individual personality traits, past life experiences, or environmental factors. Addressing these variables is essential for a clearer and more precise interpretation of the relationships observed, ensuring a more accurate and comprehensive understanding of the dynamics at play.

CONCLUSION

In conclusion, our network analysis has provided significant insights into the relationships among positive emotions, resilience, and life satisfaction in both males and females. The study revealed that positive emotions like 'Pleasant,' 'Happy,' and 'Joyful' are strongly associated with higher life satisfaction, suggesting a reevaluation of the traditional understanding of resilience's role. Furthermore, our findings emphasize the importance of certain life satisfaction variables as central nodes within the network, highlighting their potential as focal points for targeted interventions. The directed relationships identified through the analysis also suggest the possibility of designing more effective interventions by understanding the directional pathways between these variables. This comprehensive view challenges simpler models and suggests a more nuanced approach to enhancing life satisfaction.

AUTHORS' CONTRIBUTIONS

All authors contributed to the study's conception and design. They have accepted full responsibility for the manuscript's content, meticulously reviewed all results, and unanimously approved the final version for submission.

LIST OF ABBREVIATIONS

SPANE-8	=	Scale of Positive and Negative Experience (8-item version)
BRS	=	Brief Resilience Scale
SWLS	=	Satisfaction with Life Scale
DAG	=	Directed Acyclic Graph
LASSO	=	Least Absolute Shrinkage and Selection Operator
EBIC	=	Extended Bayesian Information Criterion

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Ethical approval was obtained from the Ethics Committee of the University of Western Macedonia, Greece (Approval No. Kyria2021zos).

HUMAN AND ANIMAL RIGHTS

This study was conducted following the institutional and national research committees' ethical standards, per the 1964 Helsinki Declaration and its later amendments.

CONSENT FOR PUBLICATION

All participants provided informed consent for their data to be used in this publication, and no incentives were given for participation.

STANDARDS OF REPORTING

The study adhered to the STROBE and SAGER guidelines for observational studies.

AVAILABILITY OF DATA AND MATERIALS

The datasets generated and analyzed during the current study are not publicly available due to privacy and ethical restrictions but are available from the corresponding author [T.K] upon reasonable request.

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None.

CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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Declared none.

SUPPLEMENTARY MATERIALS

Supplementary material is available on the Publisher's website.

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