revista de EDUCACIÓN
2025 408(5)
ISSN: 0034-8082

DOI Link: https://doi.org/10.59671/XQXd0
Vol.408, Issue.5, Part.1, May 2025, PP.154-167

Factor Structure of Subjective Well-Being Among Ukrainians

Valerii Olefir[1], Valerii Bosniuk[2], Marat Kuznietsov[3], Daria Kasiianenko[1]

[1]V. N. Karazin Kharkiv National University, Ukraine
[2]National University of Civil Protection of Ukraine, Ukraine
[3]H.S. Skovoroda Kharkiv National Pedagogical University, Ukraine

Abstract: Despite longstanding theoretical and practical interest in subjective well-being (SWB), its structural composition remains debated. Life satisfaction, along with positive and negative affect, is widely recognized as a core component of SWB; however, the nature of their interrelationships within a unified construct is still unclear. This study examined the factor structure of SWB using data from a sample of Ukrainian university students (N = 1111; age range = 18–26 years; 59.0% women). Participants completed the Ukrainian versions of the *Satisfaction with Life Scale* (SWLS) and the *Scale of Positive and Negative Experiences* (SPANE). Confirmatory factor analysis (CFA), bifactor CFA, exploratory structural equation modeling (ESEM), and bifactor ESEM were employed to evaluate competing theoretical models. Model selection was based on Akaike's Information Criterion (AIC) weights, balancing model fit and parsimony. While four models demonstrated adequate fit, the bifactor ESEM model showed the best overall performance. This model accounted for cross-loadings and identified a strong general SWB factor along with three specific components. Measurement invariance across gender was confirmed at the configural, metric, and scalar levels. Findings support the bifactor ESEM as a comprehensive and robust framework for conceptualizing the multidimensional structure of subjective well-being in emerging adults.

Keywords: subjective well-being, life satisfaction, positive and negative affect, bifactor model, ESEM, measurement invariance.

Introduction

Since the 1960s, the conceptualization of subjective well-being (SWB) has emerged as a central focus in psychological research (Maddux, 2018). A major contribution to this field was made by Diener (1984), who introduced a comprehensive framework for understanding how individuals evaluate and experience their lives. His widely accepted three-component model defines SWB as comprising life satisfaction, positive affect, and negative affect. This model has served as a foundation for operationalizing SWB in both theoretical and empirical studies.

Extensive research has demonstrated that individuals who report higher life satisfaction and a greater frequency of positive relative to negative emotions tend to experience a range of benefits, including improved physical health, stronger social relationships, and enhanced socioeconomic outcomes (Diener & Biswas-Diener, 2008; Diener et al., 2017; Lyubomirsky et al., 2005). Despite the substantial body of evidence supporting the importance of SWB, several critical questions regarding its underlying structure remain unresolved.

Specifically, it is still unclear whether SWB should be conceptualized as a construct composed of three distinct but related components or as a single, unified latent factor. Furthermore, it remains an open question whether a general assessment of SWB can adequately capture the essence of the construct. Additionally, the nature of the relationship between the cognitive dimension (life satisfaction) and the affective dimensions (positive and negative emotions) continues to be debated. In sum, the structural composition of subjective well-being warrants further empirical investigation.

Research on the Structure of Subjective Well-Being

Considerable scholarly attention has been directed toward understanding the structural organization of subjective well-being (SWB) – that is, how its core components are theoretically and empirically arranged. This interest is rooted in the recognition that structural clarity is essential for capturing the essence of the construct, guiding the interpretation of empirical findings, informing practical applications, and supporting the theoretical development of SWB (Olefir & Bosniuk, 2023). Busseri and Sadava (2011) conducted a comprehensive review of empirical studies on SWB and identified five distinct models that highlight both the conceptual complexities and operational challenges of the construct. The first model treats life satisfaction, positive affect, and negative affect as three separate and independent components. In contrast, a second, hierarchical model conceptualizes SWB as a higher-order latent factor that emerges from the intercorrelations among the three first-order components. A third model views SWB as a causal system in which positive and negative affect function as predictors of life satisfaction. The fourth approach is a composite model, in which SWB is represented as an aggregate of its three constituent components. Finally, the fifth, configurational model treats SWB as a pattern of individual differences across life satisfaction, positive affect, and negative affect, with individuals classified into specific types based on their unique profile.

Each of these conceptualizations presents limitations. The independent-components model treats SWB not as a unified psychological construct, but as a thematic grouping of separate variables, failing to account for their shared variance. The hierarchical model, while acknowledging a general SWB factor, obscures the unique contributions of each component, as all variance is attributed to the higher-order construct. The causal model presumes unidirectional influence – specifically, that positive and negative affect predict life satisfaction – yet this assumption lacks consistent empirical support and oversimplifies the interplay among components. The composite score model, which sums the three elements into a single index, is criticized for disregarding the distinct cognitive and affective modalities involved, thereby offering a conceptually inadequate representation (Jovanović, 2015). Lastly, the configurational model does not offer a theoretical explanation of SWB's structure, instead functioning primarily as a typology for classifying individuals based on their scores across components (Busseri & Sadava, 2011).

These varying approaches underscore the ongoing need for integrative frameworks that reconcile the complexity of SWB's multidimensional nature with methodological rigor and theoretical clarity.

To address limitations inherent in traditional models for assessing the structure of subjective well-being (SWB), researchers have increasingly adopted the bifactor measurement model (Chen et al., 2013; Jovanović, 2015; Lapuente et al., 2018). This model, developed for the study of multidimensional constructs, allows for the simultaneous estimation of a general factor – capturing the shared variance across all components – and specific factors that represent the unique variance of particular subcomponents after accounting for the general factor (Reise, 2012).

Findings from studies employing this approach have been mixed. For example, Jovanović (2015) provided partial support for the bifactor structure of SWB, reporting that approximately 50% of the variance in life satisfaction, positive affect, and negative affect was independent of the general factor. In contrast, Daniel-González et al. (2020) found that the general factor accounted for nearly two-thirds of the total variance, with the remaining variance attributable to three specific factors. However, from a psychometric standpoint, the three-correlated-factors model demonstrated superior fit. Conversely, Lapuente et al. (2018) concluded that the bifactor model offered better overall model fit, despite the general factor explaining only 15.9% of the variance.

One potential explanation for these divergent findings is the use of the Positive and Negative Affect Schedule (PANAS), which was employed in many of these studies. The affective dimensions measured by PANAS typically show only weak to moderate correlations (Schmukle et al., 2002; Busseri, 2018; Daniel-González et al., 2020), which may limit the suitability of the bifactor model in this context (Reise et al., 2018). As a result, recent research has favored the Scale of Positive and Negative Experience (SPANE). Unlike PANAS, SPANE captures the qualitative aspects of emotional experience and excludes items associated with high-arousal states (Daniel-González et al., 2020; Kaufman et al., 2022), making it more appropriate for use in bifactor modeling of SWB.

A notable advancement in the analysis of complex psychological constructs was the integration of the bifactor model within the framework of exploratory structural equation modeling (ESEM; Jennrich & Bentler, 2011, 2012; Myers et al., 2014; Morin et al., 2016). This development enabled researchers to simultaneously account for two key sources of construct-relevant psychometric multidimensionality: (a) the hierarchical structure of psychological constructs, characterized by the coexistence of general and specific factors within a single measurement model; and (b) the cross-loadings of observed indicators, which often show associations with non-target constructs (Morin et al., 2016).

To adequately address the hierarchical structure, the use of bifactor models is essential, while ESEM is preferable to traditional confirmatory factor analysis (CFA) when managing the presence of cross-loadings (Morin et al., 2016). Within this context, the bifactor-ESEM approach appears particularly well-suited for examining the structure of subjective well-being (SWB) for two primary reasons. First, the items comprising the Satisfaction with Life Scale (SWLS) and the Scale of Positive and Negative Experience (SPANE) are likely to reflect a hierarchically organized construct, encompassing both a general well-being factor and several specific dimensions. Second, the items assessing affective and cognitive aspects of life may exhibit cross-loadings, reflecting associations not only with their intended dimensions but also with non-target components of SWB.

Recent studies examining and comparing structural models of subjective well-being (SWB) using advanced statistical techniques have yet to reach a consensus regarding its conceptualization (Daniel-González et al., 2020; Jovanović et al., 2024; Kaufman et al., 2022). While some researchers argue that the bifactor model demonstrates superior fit to empirical data, others support the three-factor exploratory structural equation modeling (ESEM) approach. Still others suggest that the traditional three-factor confirmatory factor analysis (CFA) performs comparably to the ESEM framework. These divergent findings underscore the need for further empirical research guided by clearly defined criteria for selecting among competing structural models of SWB.

Despite the theoretical and practical importance of accurately modeling the structure of SWB, no consensus has been established among researchers. Moreover, the aforementioned models have yet to be tested within a Ukrainian context. This gap highlights the necessity of expanding the geographical and cultural scope of research, as subjective well-being is known to be influenced by national and cultural factors (Suh & Choi, 2018; Veenhoven, 2018). Accordingly, the present study aimed to examine the factor structure of subjective well-being among young adults in Ukraine. It was hypothesized that the bifactor ESEM model would provide a superior representation of the underlying structure of SWB compared to the traditional three-factor model.

Method

Participants

The sample consisted of 1,111 undergraduate students from higher education institutions across Ukraine, aged between 18 and 26 years. The gender distribution was 59.0% women and 41.0% men.

Variables

Three core components of subjective well-being (SWB) were assessed: life satisfaction, positive affect, and negative affect. In addition, measurement invariance of the best-fitting model was tested across gender.

Procedures and Instruments

The study employed a non-experimental, cross-sectional design using self-report questionnaires.

Life satisfaction was measured using the *Satisfaction with Life Scale* (SWLS; Diener et al., 1985), adapted for a Ukrainian-speaking population by Olefir and Bosniuk (2024). The scale includes five items (e.g., "Overall, my life is close to my ideal," "I have what I really need in my life"), with responses rated on a 7-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). The internal consistency in the present sample was satisfactory: Cronbach's α = .828, 95% CI [.811, .843]; McDonald's ω = .835, 95% CI [.819, .850].

Positive and negative affect were assessed using the *Scale of Positive and Negative Experiences* (SPANE; Diener et al., 2010), adapted into Ukrainian by Olefir et al. (2021). The SPANE comprises 12 items – six measuring positive experiences (e.g., "good," "happy," "joyful") and six measuring negative experiences (e.g., "sad," "scared," "angry"). Respondents rated the frequency of these experiences over the past four weeks on a 5-point scale ranging from 1 ("very rarely or never") to 5 ("very often or always"). The internal consistency coefficients for the current sample were as follows:

- Positive experiences: α = .872, 95% CI [.860, .883]; ω = .875, 95% CI [.863, .886]
- Negative experiences: α = .821, 95% CI [.803, .837]; ω = .827, 95% CI [.811, .843]

Research Procedure

Participants were invited to participate via email, which included an explanation of the study's aims and a link to an online survey hosted on Google Forms. Prior to participation, individuals were required to provide informed consent electronically. The consent form detailed the purpose of the study, estimated duration, the voluntary nature of participation (including the option to withdraw at any time), and information regarding the confidentiality, storage, and future use of the collected data.

revista de eDUCACIÓN
2025 408(5)
ISSN: 0034-8082

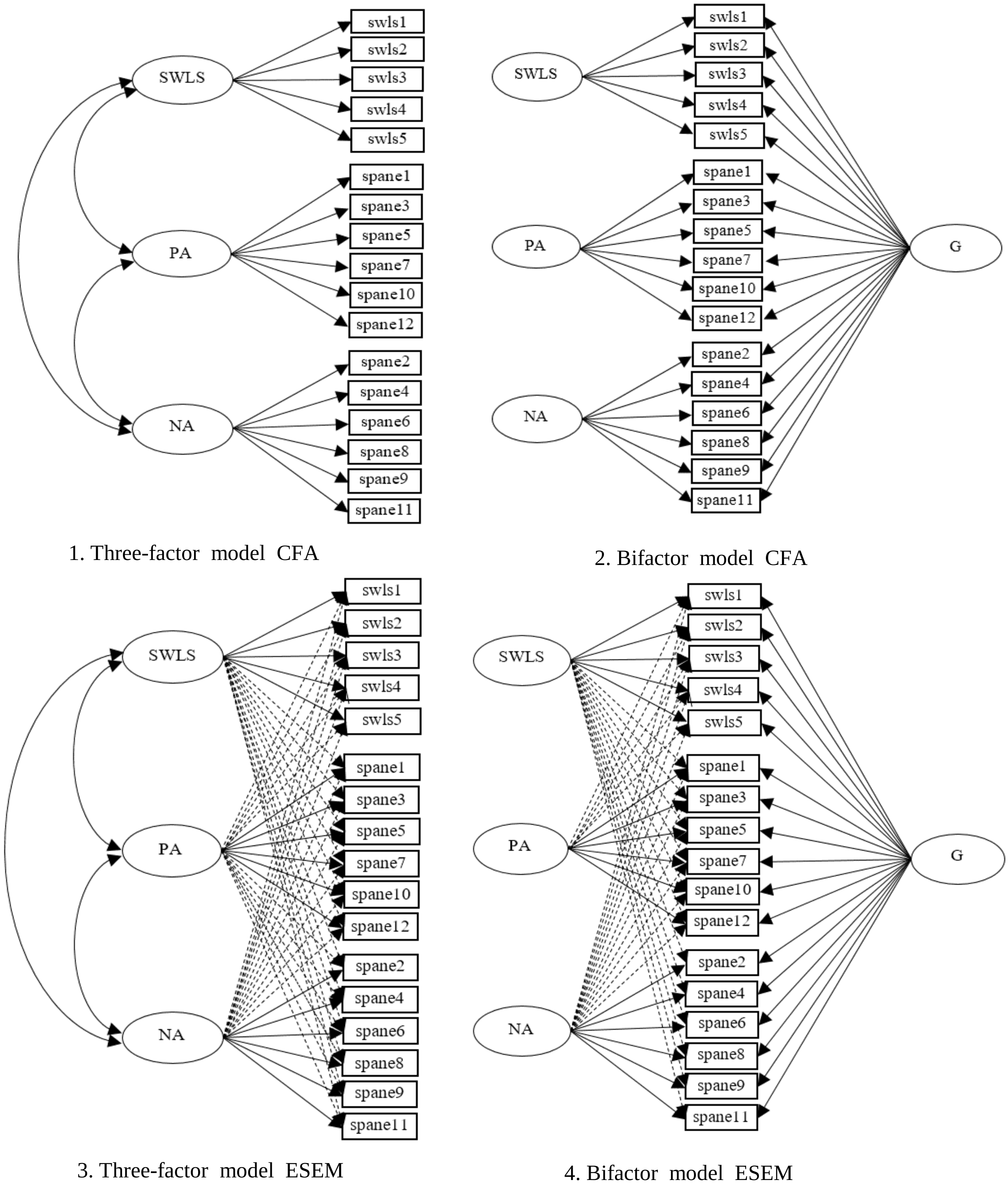

Figure 1 *Structure of the Models of Subjective Well-Being*
Note: SPANE = Scale of Positive and Negative Experiences; SWLS = Satisfaction with Life Scale; PA = Positive Affect; NA = Negative Affect; G = General Factor; CFA = Confirmatory Factor Analysis; ESEM =

ISSN: 0034-8082

Exploratory Structural Equation Modeling. Solid lines represent primary factor loadings; dashed lines represent potential cross-loadings; bidirectional arrows indicate covariances among latent variables.

Statistical Analysis

In line with contemporary approaches to modeling complex latent constructs, this study employed multiple structural models to examine the underlying structure of subjective well-being (SWB) and evaluate the proposed hypothesis. Specifically, we compared four competing models to determine which provided the best empirical representation of SWB.

Model 1 was a traditional three-factor confirmatory factor analysis (3F-CFA) model (Nye, 2023), which specified three correlated latent factors: life satisfaction, positive affect, and negative affect (see Figure 1). Each item was constrained to load solely on its designated factor, with no cross-loadings permitted. **Model 2**, referred to as the bifactor CFA model (BF-CFA), included a general SWB factor onto which all items from the Satisfaction with Life Scale (SWLS) and the Scale of Positive and Negative Experiences (SPANE) were simultaneously loaded. In addition, three orthogonal group-specific factors were specified – life satisfaction, positive affect, and negative affect – capturing variance not explained by the general factor. This bifactor structure allowed for the decomposition of shared versus unique variance while maintaining interpretability by ensuring orthogonality among factors. **Model 3**, the three-factor exploratory structural equation modeling model (3F-ESEM), extended the traditional CFA by allowing all items to load on all factors, with primary loadings guided by target rotation (Asparouhov & Muthén, 2009; Morin, 2023). This model maintained correlated factors but introduced flexibility by estimating potential cross-loadings, which are common in psychological data. **Model 4**, the bifactor ESEM model (BF-ESEM), combined features of the bifactor and ESEM frameworks. This model included one general factor and three specific factors, along with estimated cross-loadings, thereby integrating hierarchical structure with flexible item-factor associations. Target rotation was again used to guide estimation while minimizing non-primary loadings.

Analysis Strategy

The analysis followed a multi-stage approach. First, the fit of each model to the empirical data was assessed using conventional fit indices. A model was considered to demonstrate acceptable fit if the Comparative Fit Index (CFI) exceeded .90, and both the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR) were below .08. Good model fit was defined by more stringent criteria: CFI > .95 and RMSEA and SRMR < .05 (Brown, 2015). A threshold of .32 was used for interpreting salient factor loadings, in line with established guidelines (Tabachnick & Fidell, 2019).

In addition to global fit indices, model selection criteria were evaluated, including the Akaike Information Criterion (AIC) and the sample-size adjusted Bayesian Information Criterion (aBIC). The AIC is advantageous because it does not assume any model is a priori true but instead estimates Kullback-Leibler divergence to assess how closely each model approximates the data-generating process. To further facilitate model comparison, Akaike weights were computed based on the raw AIC values. These weights provide the relative probability that a particular model is the best among the set of competing alternatives (Wagenmakers & Farrell, 2004).

For bifactor models, additional indices were used to evaluate the extent and quality of the general and specific factor structure. These included the explained common variance (ECV),

ISSN: 0034-8082

percentage of uncontaminated correlations (PUC), hierarchical omega (ωH), and item-level explained common variance (I-ECV), as recommended by Rodriguez et al. (2016).

Second, the final model selected based on fit and parsimony was subjected to a test of measurement invariance across gender using Chen's (2007) criteria. Metric invariance was established if the change in CFI (ΔCFI) was less than −.01, accompanied by a change in RMSEA (ΔRMSEA) < .015 and a change in SRMR (ΔSRMR) < .03. Scalar invariance was confirmed when ΔCFI < −.01 was accompanied by either ΔRMSEA < .015 or ΔSRMR < .01 (Millsap, 2012).

All structural models were estimated using Mplus 7.0 (Muthén & Muthén, 1998–2015), employing the robust maximum likelihood estimator (MLR), which is appropriate for analyzing Likert-scale data and accounts for potential deviations from multivariate normality. ESEM models were constructed using syntax generated by the ESEM Code Generator (De Beer & Morin, 2022).

All statistical computations were carried out in R version 4.2.3 (R Development Core Team, 2014) using the RStudio environment (RStudio Team, 2020). Akaike weights were computed using the *AICcmodav* package (Mazerolle, 2023), and bifactor-specific indices (ECV, ωH, PUC, I-ECV) were calculated using the *BifactorIndicesCalculator* package (Dueber, 2025).

Results

Comparison of Competing Factor Models: CFA and BF-CFA Models of Subjective Well-Being

The evaluated models demonstrated a good overall fit to the data, as indicated by the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) values (see Table 1). Among the tested models, the straightforward three-factor confirmatory factor analysis (CFA) model showed particularly strong alignment with the data. All standardized factor loadings were substantial and statistically significant, with values exceeding .32 (see Table 2).

Table 1. Model Fit Indices for the Subjective Well-Being Structures

Model	**Fit indices and model selection criteria**						**Correlation between latent factors**		
	χ^2 (df)*	CFI	RMSEA [90% CI]	SRMR	AIC	aBIC	LS-PA	LS-NA	PA-NA
3F-CFA	320.78 (16)	.969	.044 [.039 - .050]	.034	46979.85	47047.81	.67	-.62	-.68
BF-CFA	262.01 (102)	.977	.042 [.035 - .048]	.027	46933.70	47027.37			
3F-ESEM	211.52 (88)	.982	.040 [.033 - .047]	.021	46907.71	47027.10	.62	-.59	-.63
BF-ESEM	158.44 (74)	.989	.034 [.027 - .042]	.016	46850.45	46995.55			

Note: 3F-CFA – three-factor confirmatory factor analysis model; 2F-CFA – bifactor confirmatory factor analysis model; 3F-SEM – three-factor exploratory structural equation modeling; 2F-SEM – bifactor exploratory structural equation modeling. SWB – satisfaction with life; PA – positive affect; NA – negative affect.

*All χ^2 values are significant at $p < .001$.

aBIC – Bayesian Information Criterion adjusted for sample size.

ISSN: 0034-8082

Inter-factor correlations were moderate and aligned with theoretical expectations. Specifically, life satisfaction was positively correlated with positive affect (r = .67) and negatively correlated with negative affect (r = –.62). Additionally, positive and negative affect were inversely related (r = –.68).

The standard bifactor CFA model also demonstrated a good fit to the data, meeting all established evaluation criteria. However, model fit indices showed minimal improvement over the basic three-factor CFA model, with changes in fit indices remaining below conventional thresholds (ΔCFI = |.008|; ΔRMSEA = |.002|; ΔSRMR = |.064|). Importantly, item-level Explained Common Variance (I-ECV) values for all indicators were below the .80 threshold, suggesting that a strictly unidimensional interpretation of the subjective well-being construct is not supported. This multidimensionality is further confirmed by the proportion of explained common variance (ECV = .62), the percentage of uncontaminated correlations (PUC = .70), and the hierarchical omega coefficient (ω_h = .32). With the exception of item SPANE9, all items loaded significantly onto the general factor, exceeding the conventional threshold of .32. After accounting for the general factor, all factor loadings on the three group-specific dimensions remained statistically significant. These ranged from .33 to .62 (M = .45) for life satisfaction, .29 to .49 (M = .39) for positive affect, and .28 to .47 (M = .43) for negative affect (see Table 2).

Table 2. Standardized Factor Loadings of the Models of Subjective Well-Being Structure

Items	3F-CFA			BF-CFA				3F-ESEM			BF-ESEM			
	LS	PA	NA	G	LS	PA	NA	LS	PA	NA	G	LS	PA	NA
SWLS1	**.81**			**.57**	**.62**			**.90**	-.11	.00	**.61**	**.56**	-.13	.01
SWLS2	**.70**			**.56**	**.42**			**.65**	.04	-.04	**.55**	**.42**	-.00	-.04
SWLS3	**.87**			**.67**	**.53**			**.83**	.01	-.03	**.64**	**.56**	.01	-.05
SWLS4	**.58**			**.47**	**.33**			**.53**	.15	.09	**.41**	**.43**	.17	-.01
SWLS5	**.61**			**.50**	**.35**			**.56**	.04	-.05	**.47**	**.38**	.02	-.05
SPANE1		**.76**		**.66**		**.37**		-.04	**.72**	-.10	**.65**	.03	**.47**	-.11
SPANE3		**.65**		**.54**		**.37**		-.01	**.68**	-.03	**.56**	.04	**.50**	-.09
SPANE5		**.70**		**.57**		**.42**		-.06	**.72**	-.03	**.58**	.11	**.30**	.05
SPANE7		**.75**		**.69**		**.29**		.01	**.61**	-.02	**.57**	.02	**.16**	.12
SPANE10		**.78**		**.62**		**.49**		-.05	**.82**	.06	**.17**	.02	**.42**	.06
SPANE12		**.78**		**.67**		**.39**		.03	**.74**	.02	**.46**	.04	**.38**	.02
SPANE2			**.80**	**-.68**			**.41**	.17	-.13	**.70**	**-.61**	-.01	-.06	**.45**
SPANE4			**.78**	**-.61**			**.47**	-.02	-.03	**.76**	**-.48**	-.04	-.06	**.53**
SPANE6			**.76**	**-.59**			**.47**	-.04	-.06	**.74**	**-.65**	.01	-.02	**.48**
SPANE8			**.73**	**-.55**			**.49**	.01	.01	**.74**	**-.77**	-.00	.04	**.47**
SPANE9			**.36**	**-.25**			**.28**	-.02	.07	**.39**	**-.66**	-.15	-.11	**.37**
SPANE11			**.58**	**-.41**			**.45**	.07	.13	**.66**	**-.67**	.04	.17	**.38**

Note: 3F-CFA – Three-Factor Confirmatory Factor Analysis; BF-CFA – Bifactor Confirmatory Factor Analysis; 3F-ESEM – Three-Factor Exploratory Structural Equation Modeling; BF-ESEM – Bifactor Exploratory Structural Equation Modeling; LS – Life Satisfaction; PA – Positive Affect; NA – Negative Affect; G – General Factor; SWLS1–5 – items from the Satisfaction with Life Scale; SPANE1–12 – items from the Scale of Positive and Negative Experiences.

ESEM and Bifactor ESEM Models of Subjective Well-Being

The examined three-factor Exploratory Structural Equation Modeling (3F-ESEM) model demonstrated a good fit to the data, free of statistical artifacts or anomalies. Correlations between the latent factors were moderate, directionally consistent with theoretical expectations, and closely aligned with those observed in the 3F-CFA model. Standardized factor loadings followed the expected pattern, with primary loadings exceeding .32 for their respective factors and cross-loadings near zero, supporting a theoretically coherent factor structure. In the subsequent analysis, the bifactor ESEM (BF-ESEM) model also exhibited an excellent fit to the data. Its fit indices did not differ significantly from those of the 3F-ESEM model (ΔCFI = |.006|, ΔRMSEA = |.007|, ΔSRMR = |.005|). Sixteen out of seventeen items demonstrated standardized loadings above .32 on the general factor, indicating a dominant latent dimension of subjective well-being. The general explained common variance (ECVGen) was .63, suggesting that 63% of the common variance in the item responses was accounted for by the general factor. The hierarchical omega coefficient (ωH) was .72, reflecting strong general factor saturation. Additional ECV values indicated that the specific factors – life satisfaction, positive affect, and negative affect – explained 51%, 15%, and 19% of the residual common variance, respectively. These results point to a prominent general factor with relatively weak but still distinguishable subdimensions. Target factor loadings exceeded .32 in 88% of cases, while cross-loadings were minimal, with only one value reaching .17, further confirming the model's structural clarity.

Model Selection and Justification

To determine the best-fitting model, the Akaike Information Criterion adjusted for small sample size (AICc) was applied. This measure balances model accuracy and parsimony. As shown in Table 3, the BF-ESEM model yielded the lowest AICc value (46862.71), indicating the best trade-off between model fit and complexity among the compared models. To quantify model superiority, Akaike weights (AICcWt) were calculated. The BF-ESEM model had an AICcWt of 1.00, meaning it holds a 100% probability of being the most plausible model in the candidate set for representing the structure of subjective well-being.

Table 3. Comparison of Subjective Well-Being Models Based on AICc

Candidate models	K	AICc	Delta_AICc	AICcWt	Cum.Wt	LL
BF-ESEM	79	46862.71	.00	1	1	-23346.22
3F-ESEM	65	46915.92	53.22	0	1	-23388.86
BF-CFA	51	46938.71	76.00	0	1	-23415.85
3F-CFA	37	46982.47	119.77	0	1	-23452.93

Note: K – number of estimated parameters in the model; AIC – Akaike Information Criterion (AICc – sample size-corrected AIC); Delta_AICc – difference in AICc between the best-fitting model and the compared model; AICcWt – AICc weight; Cum.Wt – cumulative AICc weight; LL – log-likelihood.

Measurement Invariance of the BF-ESEM Model by Gender

Measurement invariance of the bifactor ESEM (BF-ESEM) model across gender was evaluated in three steps. The first step tested configural invariance, which assessed whether the overall factor structure was similar for men and women. The second step examined metric invariance by imposing equality constraints on factor loadings across groups. In the final step, scalar invariance was tested by constraining both factor loadings and intercepts to be equal across gender. Results indicated no meaningful deterioration in model fit at any stage of testing. Specifically, for the metric invariance model, none of the fit indices suggested a lack of invariance (ΔCFI = –.009; ΔRMSEA = .006; ΔSRMR = .005). Similarly, scalar invariance showed no decline in fit (ΔCFI = .001; ΔRMSEA = –.003; ΔSRMR = .015). Although the χ^2 and $\Delta\chi^2$ values were statistically significant (p < .001), changes in approximate fit indices remained within acceptable thresholds. These findings suggest that the BF-ESEM model of subjective well-being demonstrates configural, metric, and scalar invariance across gender.

Table 4. Measurement Invariance Tests of the BF-ESEM Model by Gender

Model	χ^2	df	CFI	RMSEA [90% CI]	SRMR	AIC	aBIC
Configural	227.65	148	.988	.031 [.023 - .039]	.019	46798.10	47150.76
Metric	306.29	176	.979	.037 [.030 - .043]	.024	46848.65	47670.79
Scalar	348.89	213	.980	.034 [.027 - .040]	.039	46797.54	47030.80
Model comparison							
Configural vs. Metric	78.64	28	-.009	.006	.005	50.55	520.03
Metric vs. Scalar	42.60	37	.001	-.003	.015	-51.11	-639.99

Note: df – degrees of freedom; CFI – Comparative Fit Index;RMSEA – Root Mean Square Error of Approximation; CI – confidence interval; SRMR – Standardized Root Mean Square Residual; AIC – Akaike Information Criterion; aBIC – sample-size adjusted Bayesian Information Criterion. All χ^2 values are significant at p < .001.

Discussion

The primary aim of this study was to examine the factor structure of subjective well-being (SWB) using psychometrically validated assessment tools in a Ukrainian sample. To accomplish this, four competing structural models were evaluated: a three-factor confirmatory factor analysis (3F-CFA), bifactor confirmatory factor analysis (BF-CFA), three-factor exploratory structural equation modeling (3F-ESEM), and bifactor ESEM (BF-ESEM). From a psychometric standpoint, all tested models demonstrated good fit to the data. However, the objective was not simply to identify models that fit statistically, but to determine which model most accurately represents the empirical structure of SWB. The comparison between the 3F-CFA and 3F-ESEM models was designed to detect construct-relevant multidimensionality, particularly that which may arise from measurement artifacts such as item overlap or conceptual similarities among the components of SWB. These models exhibited moderate correlations between latent factors, which were nearly identical across both models. This finding suggests that the increased flexibility of the 3F-ESEM model did not result in a more refined differentiation of SWB components. Comparable levels of inter-factor correlation have been consistently observed in prior research using the SWLS and SPANE scales (Daniel-González et al., 2020; Jovanović et al., 2020, 2024), supporting the idea of a stable association among life satisfaction, positive affect, and negative affect.

The consistency of these correlations implies the presence of an overarching general factor underlying subjective well-being. However, neither the 3F-CFA nor 3F-ESEM frameworks are capable of evaluating the simultaneous influence of both general and specific factors on observed variables. These models presuppose distinct components of SWB but do not formally include a higher-order construct. Consequently, the next stage of analysis focused on models based on the bifactor approach (BF-CFA and BF-ESEM), which allow for the disentanglement of general and domain-specific variance. This hierarchical modeling provides a more comprehensive understanding of the structure of SWB by accounting for the shared variance across items as well as the unique contributions of individual components.

Both bifactor models of subjective well-being confirmed the existence of a robust general factor that accounted for approximately one-third of the total variance. Among the competing models, the bifactor ESEM (BF-ESEM) model provided the best fit across all evaluated indices. Its allowance for cross-loadings among items led to a more precise and nuanced representation of the latent structure of subjective well-being. These findings are consistent with a growing body of literature supporting the multidimensional nature of subjective well-being with a strong overarching general factor (Busseri, 2018; Busseri & Quoidbach, 2022; Daniel-González et al., 2020; Kaufman et al., 2022). Importantly, we emphasize that this general factor should not be interpreted as a composite score, a practice that has been criticized on theoretical grounds (Jovanović, 2015; Chen et al., 2016). Rather, it should be viewed as a latent construct that can be meaningfully modeled and interpreted within the framework of structural equation modeling (SEM). This latent factor allows researchers to examine subjective well-being as both a predictor and an outcome variable, enabling richer and more flexible theoretical models.

The gender invariance testing of the BF-ESEM model revealed consistent model fit across male and female groups, indicating that the structure of subjective well-being, as captured by this model, operates similarly across gender. This supports the model's applicability in diverse gender groups and reinforces its utility for broader psychological research and practice.

Notably, this study is the first to compare competing structural models of subjective well-being within the Ukrainian cultural context. However, several limitations should be acknowledged. First, our assessment focused solely on general life satisfaction; future research should examine satisfaction across distinct life domains (e.g., work, family, health) to test the generalizability of our findings. Second, the sample consisted of university students aged 18–25, which limits the generalizability of results to other age cohorts whose subjective well-being profiles may differ. Third, measurement invariance was assessed only with respect to gender. Future studies should consider other potential sources of variability, such as age, socioeconomic status, or regional differences, to enhance the robustness and external validity of the findings.

Conclusion

This study provides important insights into the factor structure of subjective well-being (SWB) by evaluating four competing models – 3F-CFA, BF-CFA, 3F-ESEM, and BF-ESEM – within a Ukrainian sample. While all models demonstrated acceptable psychometric fit, the bifactor ESEM model emerged as the most accurate representation of the data. This model captured both a strong general factor of SWB and meaningful specific dimensions of life satisfaction, positive affect, and negative affect.

Our findings underscore the value of modeling subjective well-being as a multidimensional construct with a hierarchical structure. The presence of a general latent factor allows for more sophisticated theoretical modeling and empirical testing, especially in research seeking to understand SWB as a predictor or outcome variable. Additionally, the demonstrated measurement invariance across gender supports the broader applicability of the BF-ESEM model in diverse populations.

This research contributes to the growing literature advocating for more nuanced models of SWB and extends this work into the underrepresented cultural context of Ukraine. Future studies should aim to replicate these findings using broader and more diverse samples, include domain-specific satisfaction indicators, and explore invariance across other demographic variables. By refining our understanding of the structure of subjective well-being, we enhance our ability to assess and promote mental health and quality of life across populations.

References

Asparouhov, T., & Muthén, B. (2009). Exploratory structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 16*(3), 397–438. https://doi.org/10.1080/10705510903008204

Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). The Guilford Press.

Busseri, M. A. (2018). Examining the structure of subjective well-being through meta-analysis of the associations among positive affect, negative affect, and life satisfaction. *Personality and Individual Differences, 122*, 68–71. https://doi.org/10.1016/j.paid.2017.10.003

Busseri, M. A., & Quoidbach, J. (2022). The structure of everyday happiness is best captured by a latent subjective well-being factor. *Journal of Research in Personality, 96*, 1–13. https://doi.org/10.1016/j.jrp.2021.104177

Busseri, M. A., & Sadava, S. W. (2011). A review of the tripartite structure of subjective well-being: Implications for conceptualization, operationalization, analysis, and synthesis. *Personality and Social Psychology Review, 15*(3), 290–314. https://doi.org/10.1177/1088868310391271

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Chen, F. F., Bai, L., Lee, J. M., & Jing, Y. (2016). Culture and the structure of affect: A bifactor modeling approach. *Journal of Happiness Studies, 17*(5), 1801–1824. https://doi.org/10.1007/s10902-015-9671-3

Daniel-González, L., de la Rubia, J. M., Valle de la O. A., & García-Cadena, C. H. (2020). Structure analysis of subjective well-being. *Salud Mental, 43*(3), 119–127. https://doi.org/10.17711/SM.0185-3325.2020.017

De Beer, L. T., & Morin, A. J. S. (2022). (B)ESEM invariance syntax generator for Mplus. https://doi.org/10.6084/m9.figshare.19360808

Diener, E. (1984). Subjective well-being. *Psychological Bulletin, 95*(3), 542–575. https://doi.org/10.1037/0033-2909.95.3.542

Diener, E., & Biswas-Diener, R. (2008). *Happiness: Unlocking the mysteries of psychological wealth.* Wiley/Blackwell. https://doi.org/10.1002/9781444305159

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment, 49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D.-w., Oishi, S., & Biswas-Diener, R. (2010). New well-being measures: Short scales to assess flourishing and positive and negative feelings. *Social Indicators Research*, *97*(2), 143–156. https://doi.org/10.1007/s11205-009-9493-y

Dueber, D. (2025). *BifactorIndicesCalculator: Bifactor Indices Calculator* (R package version 0.2.2). https://github.com/ddueber/bifactorindicescalculator

Jennrich, R. I., & Bentler, P. M. (2011). Exploratory bi-factor analysis. *Psychometrika, 76*(4), 537–549. https://doi.org/10.1007/s11336-011-9218-4

Jennrich, R. I., & Bentler, P. M. (2012). Exploratory bi-factor analysis: The oblique case. *Psychometrika*, *77*(3), 442–454. https://doi.org/10.1007/s11336-012-9269-1

Joshanloo, M. (2016). Factor structure of subjective well-being in Iran. *Journal of Personality Assessment*, *98*(4), 435–443. https://doi.org/10.1080/00223891.2015.1117473

Jovanović, V. (2015). A bifactor model of subjective well-being: A re-examination of the structure of subjective well-being. *Personality and Individual Differences, 87*, 45–49. https://doi.org/10.1016/j.paid.2015.07.026

Jovanović, V., Rudnev, M., Aryanto, C. B., et al. (2024). A cross-cultural evaluation of Diener's tripartite model of subjective well-being across 16 countries. *Journal of Happiness Studies*, *25*(6), 1–25. https://doi.org/10.1007/s10902-024-00781-4

Kaufman, V. A., Horton, C., Walsh, L. C., & Rodriguez, A. (2022). The unity of well-being: An inquiry into the structure of subjective well-being using the bifactor model. *International Journal of Applied Positive Psychology, 7*, 461–486. https://doi.org/10.1007/s41042-022-00077-z

Lapuente, L., Dominguez-Lara, S., Flores-Kanter, P. E., & Medrano, L. A. (2018). Estructura del bienestar subjetivo mediante análisis bifactor: Unidimensional o multidimensional? *Avaliação Psicológica, 17*(2), 252–259. https://doi.org/10.15689/ap.2018.1702.14521.11

Lyubomirsky, S., King, L., & Diener, E. (2005). The benefits of frequent positive affect: Does happiness lead to success? *Psychological Bulletin, 131*(6), 803–855. https://doi.org/10.1037/0033-2909.131.6.803

Maddux, J. E. (2018). Subjective well-being and life satisfaction: An introduction to conceptions, theories, and measures. In J. E. Maddux (Ed.), *Subjective well-being and life satisfaction* (pp. 3–31). Routledge. https://doi.org/10.4324/9781351231879-1

Mazerolle, M. J. (2023). *AICcmodavg: Model selection and multimodel inference based on (Q)AIC(c)* (R package version 2.3.3). https://cran.r-project.org/package=AICcmodavg

Millsap, R. E. (2012). *Statistical approaches to measurement invariance.* Routledge/Taylor & Francis Group. https://doi.org/10.4324/9780203821961

Morin, A. J. S. (2023). Exploratory structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (2nd ed., pp. 503–524). Guilford.

Morin, A. J. S., Arens, A. K., & Marsh, H. W. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling, 23*(1), 116–139. https://doi.org/10.1080/10705511.2014.961800

Muthén, L. K., & Muthén, B. O. (1998–2012). *Mplus User's Guide: Statistical analysis with latent variables* (7th ed.). Muthén & Muthén.

Myers, N. D., Martin, J. J., Ntoumanis, N., Celimli, S., & Bartholomew, K. J. (2014). Exploratory bifactor analysis in sport, exercise, and performance psychology: A substantive-methodological synergy. *Sport, Exercise, and Performance Psychology, 3*(4), 258–272. https://doi.org/10.1037/spy0000015

Nye, C. D. (2023). Reviewer resources: Confirmatory factor analysis. *Organizational Research Methods, 26*(4), 608–628. https://doi.org/10.1177/10944281221120541

Olefir, V., & Bosniuk, V. (2024). Adaptation of Ukrainian version of the Satisfaction With Life Scale by E. Diener. *Nauka i osvita – Science and Education, 2*, 64–72. https://doi.org/10.24195/2414-4665-2024-2-9

Olefir, V., Bosniuk, V., & Malofeikina, K. (2021). Validation and measurement invariance of the Ukrainian version of the Scale of Positive and Negative Experiences (SPANE). *The Journal of V. N. Karazin Kharkiv National University. A Series of Psychology, 71*, 34–42. https://doi.org/10.26565/2225-7756-2021-71-04

R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research, 47*(5), 667–696. https://doi.org/10.1080/00273171.2012.715555

Reise, S. P., Bonifay, W., & Haviland, M. G. (2018). Bifactor modelling and the evaluation of scale scores. In P. Irwing, T. Booth, & D. J. Hughes (Eds.), *The Wiley handbook of psychometric testing* (pp. 675–707). https://doi.org/10.1002/9781118489772.ch22

RStudio Team. (2020). *RStudio: Integrated development for R*. RStudio, PBC. http://www.rstudio.com/

Schmukle, S. C., Egloff, B., & Burns, L. R. (2002). The relationship between positive and negative affect in the Positive and Negative Affect Schedule. *Journal of Research in Personality, 36*(5), 463–475. https://doi.org/10.1016/S0092-6566(02)00007-7

Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson.

Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review, 11*(1), 192–196. https://doi.org/10.3758/BF03206482?