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Effects of Personal Characteristics on Satisfaction with Life and Subjective Happiness: Estimates of Single Mediator Models Using SEM

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Abstract

Since the onset of the COVID-19 pandemic, there has been an increased focus on research concerning individual well-being and its global impact. Understanding the factors that contribute to or detract from subjective well-being can enable practitioners to better support individuals affected by life events and crises. This study employs a single mediator model through structural equation modeling to explore the relationship between subjective happiness, life satisfaction, and subjective well-being. Furthermore, the model assesses whether these relationships are mediated by individual characteristics such as gender, social class, and relationship satisfaction. The paper presents the results of testing eight hypotheses related to Subjective Well-being, utilizing data from the Subjective Happiness Scale, the Satisfaction with Life Scale, the Brief Resilience Scale, the Relationship Assessment Scale, the Adverse Childhood Events inventory, the Adult Attachment Scale, and demographic information provided by the research participants.

JEL classification numbers: C1, C3, C4, C9.
Keywords: Structural equation modeling, Mediator model, Subjective well-being, Satisfaction with life, Resiliency, Adult attachment.

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1. Introduction

Events such as the COVID-19 pandemic represent a once-in-a-lifetime experience for most of the global population. The pandemic, along with the associated shutdowns, transitions in work environments, loss of employment and income, bereavement, and mental health challenges, has adversely affected many individuals (Grondal, Ask, Luke & Winblad, 2021). Grondal et al. (2021) identified that COVID-19 and its subsequent consequences negatively impacted an individual's subjective well-being, which correlated with increased frustration, impulsivity, and anger. Conversely, individuals who experienced a positive effect on their subjective well-being in response to COVID-19 were found to engage in emotional regulation and utilize the "crisis" as an opportunity to reassess various aspects of their lives. Similarly, Safiye, Vukcevic, and Cabarkapa (2021) concluded that subjective well-being remained stable among healthcare workers who exhibited higher levels of resilience. This research indicated that individuals with elevated levels of subjective well-being were less likely to experience burnout during the crisis.

Beyond the impact of a pandemic, researchers have explored how individuals navigate various life circumstances, whether health-related (Diener, Pressman, Hunter, Delgadillo Chase, 2017; Jebb, Morrison, Tay, Diener, 2020; Kushlev, Drummond, Diener, 2020), relationship-related (Tay, Chan, Diener, 2014), culturally influenced (Steel, Taras, Uggersley, & Bosco, 2018), or related to professional or personal goals (Klug & Maier, 2014; Mocoso &Salgado, 2021). These responses are specific to the meaning each person attributes to their current life narrative. Diener (1984) defined Subjective Well-being (SWB) as "how a person evaluates his or her own life" (p.2). SWB comprises three components: positive affect (positive emotions such as confidence, pride, and joy), negative affect (emotions such as rage, hate, and sadness), and life satisfaction (the cognitive component). An individual's evaluations can be more specific (e.g., marital satisfaction or satisfaction with one's car) or broader (e.g., life satisfaction or satisfaction with the self). The broader cognitive aspects of SWB, including Satisfaction with Life (SWL) and the Subjective Happiness Scale (SHS), are the focus of this investigation.

Satisfaction with Life (SWL) evaluates an individual's overall life satisfaction and indicates global life satisfaction. The Satisfaction with Life Scale (SWLS), developed by Diener, Larsen, and Griffin (1985), comprises five items rated on a 7-point Likert scale designed to be unidimensional. The validity and reliability of the SWLS have been confirmed across diverse socio-economic contexts and cultures (Busing & West, 2016; Diener, 2013; Diener et al., 1985; Tay et al., 2014; Vela et al., 2017). This scale demonstrates stability and outperforms single-variable measures (Andrews & Withey, 1976; Eid & Diener, 2004; Krueger & Schkade, 2008).

Happiness is defined as well-being and contentment, synonymous with joy. Numerous self-report scales assess subjective happiness (Andrews & Withey, 1976;

Bradburn & Noll, 1969; Cantril, 1966; Lyubomirsky & Lepper, 1999). The four-item Subjective Happiness Scale, developed by Lyubomirsky and Lepper (1999), measures "an individual's overall subjective happiness: a global, subjective assessment of whether one is happy or unhappy. Such a measure would reflect a broader and more molar category of well-being and tap into more global psychological phenomena" (Lyubomirsky & Lepper, 1999, p. 139). Despite its brevity, this scale exhibits strong psychometric properties, characterized by "high internal consistency, a unitary structure, and stability over time" (Lyubomirsky & Lepper, 1999, p. 128). This scale provides an overall subjective barometer of one's happiness.

These two components of Subjective Well-Being (SWB) are interrelated. For instance, religion is significantly associated with SHS and SWL (Ferriss, 2002; Greeley & Hout, 2006; Hadaway, 1978; Inglehart, 2010). The relationship between SWL and SHS is bidirectional: Subjective happiness (SHS) directly predicts Satisfaction with Life (SWL), and SWL directly predicts SHS. Saricam (2015, p. 281) reported "significant correlations between dimensions of authenticity and life satisfaction. Moreover, subjective happiness positively correlates with life satisfaction ($r = .64$)." Similarly, Yan, Su, Zhu, and He (2013) identified relationships between self-evaluations, subjective happiness, life satisfaction, and loneliness. Another model linking life satisfaction to subjective happiness was proposed and tested by Uysal, Satici, Satici, and Akin (2014).

Emmons and Diener (1985) asserted that "Demographic variables fail to account for substantial variance in individuals' perceptions of their subjective well-being" (p.1). However, more recently, Geerling and Diener (2020) reiterated that "demographic variables such as income, sex, age, and education account for less than 15% of the observed variability in SWB scores" (p. 168). Nonetheless, the results of recent studies have been mixed (Mayungbo, 2017). Similarly, Ng, Tey, and Asadullah (2017) investigated the determinants of life satisfaction among the oldest (80 or over) in China. They concluded that "health and economic status are the most significant predictors of life satisfaction" (p. 1). Most investigations of the relationship between individual covariates (COV) and SWB have involved the use of individual manifest variables. Our analysis is conducted at the latent variable level, with each construct converging on at least three measured variables.

In their 2020 study, Larwin, Harvey, and Constantinou expanded the concept of Subjective Well-Being (SWB) by integrating additional subjective scales, specifically "two scales measuring how individuals cope with personal challenges (The Brief Resilience Scale, BRS) and the nature of their social and personal networks (Perceived Relationship Quality, RAS)" (Larwin et al., 2020, pp. 27-28). Furthermore, they employed two additional self-administered scales to assess the residual effects of childhood and family dysfunction. These included the Adverse Childhood Experience Scale (ACE), which reflects adverse adolescent experiences, and the Adult Attachment Scale (AAS), which provides an overall evaluation of adult experiences. Two of these four mediating scales converged on single dimensions. The goodness of fit indices reported were CFI (> 0.95), TLI (>0.95),

Cronbach's Alpha (>0.80), and RMSEA< 0.09. Second-order confirmatory models were applied to the eighteen-item AAS scale and the ten-item ACE scale data.
The present study investigates the direct relationship between individual attributes, such as individual covariates (COV), and an individual's satisfaction with life (SWL). Indirectly, the effect of COV on SWL is mediated through RAS, BRS, ACE, and AAS. The theoretical framework underpinning this study is statistical mediation. A mediator is "a variable that accounts for all or part of the relation between a predictor and an outcome because the mediator is intermediate in the causal pathway from the independent variable to the dependent variable" (MacKinnon, 2000, p. 141). Specifically, statistical mediation seeks to elucidate the relationship between an independent variable, X, and a dependent construct, Y, when a third variable, M, intervenes.

2. Methods

The paper is structured as follows: first, the hypotheses tested are presented; second, relevant aspects of statistical mediation for testing these hypotheses are summarized; third, since a minimum of three manifest variables measure these constructs, they are transformed into single latent variables; and fourth, single mediator models are formulated and estimated using Mplus. The results are evaluated, and conclusions are drawn using null hypothesis significance tests (NHSTs) and p-values. However, as p-values do not convey the magnitude or importance of effects, several effect size measures are examined in the final section. "Effect sizes allow researchers to move away from the simple identification of statistical significance and toward a more generally interpretable, quantitative description of an effect size. They describe the size of observed effects independent of the possibly misleading influences of sample size" (Fritz et al., 2011, p. 2).
This study is guided by two categories of hypotheses: Total Effect Hypotheses (TEH) and Single Mediating Hypotheses (SMH).

- TEH1: Personal Covariates (COV) do not exert a significant influence on an individual's satisfaction with life (SWL).
- TEH2: Personal Covariates (COV) do not exert a significant influence on an individual's subjective happiness (SHS).
- SMH1: An individual's score on the Relationship Assessment Scale (RAS) does not mediate the relationship between Personal Covariates (COV) and satisfaction with life (SWL).
- SMH2: An individual's score on the Relationship Assessment Scale (RAS) mediates the relationship between Personal Covariates (COV) and subjective happiness (SHS).
- SMH3: An individual's resilience, as measured by the Brief Resilience Scale (BRS), does not mediate the relationship between Personal Covariates (COV) and satisfaction with life (SWL).

- SMH4: An individual's resilience, as measured by the Brief Resilience Scale (BRS), does not mediate the relationship between Personal Covariates (COV) and subjective happiness (SHS).
- SMH5: An individual's adverse childhood experiences, as measured by the Adverse Childhood Experiences Scale (ACE), do not mediate the relationship between Personal Covariates (COV) and satisfaction with life (SWL).
- SMH6: An individual's adverse childhood experiences, as measured by the Adverse Childhood Experiences Scale (ACE), do not mediate the relationship between Personal Covariates (COV) and subjective happiness (SHS).
- SMH7: An individual's relationship quality, as measured by the Adult Attachment Scale (AAS), does not significantly mediate the relationship between Personal Covariates (COV) and satisfaction with life (SWL).
- SMH8: An individual's relationship quality, as measured by the Adult Attachment Scale (AAS), does not significantly mediate the relationship between Personal Covariates (COV) and subjective happiness (SHS).

TEH1 and TEH2 evaluate total effects, while SMH1 through SMH8 assess direct and indirect effects. The interpretation of these indirect effects forms the basis for inferences regarding single mediation hypotheses.

2.1 Participants

This study draws upon data from a survey research project comprising n=851 participants from Northeast Ohio, who responded to an email invitation to complete a series of inventories. The sample consisted of students, recent graduates, and faculty members, who were encouraged to share the survey link with colleagues and acquaintances. The demographic profile of respondents was predominantly white (91.2%), female (89.1%), under the age of 50 (72.6%), and mostly married (73.4%). A substantial portion of the participants reported having attained higher education, with 58.6% possessing post-undergraduate education and 21.2% holding an undergraduate degree. Geographically, 47.4% resided in urban areas and villages, while 52.6% lived in suburban regions.

2.1.1 Instrumentation

The current investigation incorporates six scales: the Adverse Childhood Experiences scale, the Adult Attachment Scale, the Brief Resiliency Scale, the Relationship Assessment Scale, the Satisfaction with Life inventory, and the Subjective Happiness Scale. Basic demographic information, including relationship status, education, and current socio-economic status, was also collected. The Adult Attachment Scale (Collins, 1996) consists of 18 items that measure three factors of attachment: Close, Depend, and Anxiety. Responses are recorded on a five-point scale, with one representing "Not at all characteristic of me" and five representing "Very characteristic of me." For the AAS, the following items were reverse-coded: 2, 3, 8, 9, 15, 16, 17, and 18, as recommended by Collins. The reliability of the factor is consistently stable, with Cronbach's α ranging from .60 to .88 (Teixeira, Ferreira, & Howat-Rodrigues, 2019).

The Adverse Childhood Experiences inventory consists of ten items with a "Yes" or "No" response option to measure childhood trauma. The ten questions include five personal experience items and five family member behavior items (Felitti et al., 1998). The ACE is a reliable, valid, and economical screen for retrospective assessment of adverse childhood experiences, demonstrating adequate internal consistency (Cronbach's alpha = .88).

The Brief Resiliency Scale (BRS) consists of six items on a 5-point Likert-type scale ranging from strongly disagree (1) to strongly agree (5). It asks respondents how well they have dealt with different adversities (Tansey et al., 2017). Based on Rodríguez-Rey et al. (2020), the reliability estimates for the scale are α=.89.

The Relationship Assessment Scale (RAS), consisting of seven items on a 5-point Likert-type scale, has exhibited high internal reliability (Tansey et al., 2017). This instrument shows good internal consistency (α=.73 to .92) across different demographic groups and when administered in other languages (Dinkel & Balck, 2005). Even when applied to multiple types of relationships, the RAS provides a stable measure when completed with regard to romantic partners, parents, friends, and other types of relatives (Renshaw et al., 2011).

The Satisfaction with Life (SWL) scale comprises five items evaluated on a 7-point Likert scale, ranging from strongly disagree (1) to agree (7) strongly. This scale is designed to serve as a unidimensional measure of life satisfaction. The validity and reliability of the SWL have been confirmed across various socio-economic contexts and cultures (Busing & West, 2016; Diener et al., 1985; Diener, Inglehart, & Tay, 2013; Tay, Ng, Kuykendall, & Diener, 2014; Vela, Lerma, & Ikonomopoulos, 2017) as well as among diverse demographic groups (López-Ortega, Torres-Castro, & Rosas-Carrasco, 2016; Lucas-Carrasco, Den Oudsten, Eser, & Power, 2014).

In the SHS, two items evaluate ratings of absolute (self) and relative (to peers). In comparison, the remaining two items inquire about the extent to which scenarios of happy and unhappy individuals describe the respondents. Responses are recorded on a seven-point scale from "Not at all (1)" to "A great deal (7)." Despite its brevity, the SHS demonstrates robust psychometric properties, characterized by "high internal consistency, a unitary structure, and stability over time" (Lyubomirsky, 2008). According to Lyubomirsky (2008), the reliability estimates for the scale range from α = .79 to α = .94.

2.1.2 Procedures

In single statistical mediation, the objective is to elucidate the relationship between an independent variable, X, and a dependent construct, Y, when a third variable, M, mediates between them. Danner, Hagemann, & Fiedler (2015) delineated the various roles that M may assume between X and Y. This study concentrates solely on the mediational aspect: X → M → Y and X → Y. If X → M is denoted as a, and M → Y as b, then ab (a*b) represents the indirect effect of X on Y. In single mediational analyses, the focus is on the magnitude of a*b relative to either ĉ (the direct effect of X on Y, controlling for the effect of M) or c, the total effect of X on Y(Yzerbyt et al., 2018). For mediation to be established, three conditions must be met: the effect of the independent construct, COV, on the mediating construct, SWL or SHS, must be significantly different from zero; the effect of this mediator construct, RAS, BRS, ACE, or AAS, on the dependent construct SWL or SHS must also be significantly different from zero; and the mediation effect (COV on RAS, BRS, ACE, or AAS [a] x RAS, BRS, ACE, or AAS on SWL or SHS [b]) must be significant.

As Mascha, Dalton, Kurz, and Saager(2013) elaborated, "although evidence of mediation can be claimed if both effects a … and b … are significant, it is more convincing if the mediation effect itself, the product a × b, is also significantly different from 0. We and others thus make this a third requirement for claiming mediation" (p.984). Two issues pertinent to concluding this product coefficient involve computation and certainty. The former involves transforming categorical items into factors (the measurement model) and utilizing those results in the hypothesized mediation model.

Muthén (2006, n.p.) clarified the connection between categorical items and the scale of factors thus: there are two things here. First, the fact that your Likert scale items are skewed does not mean the factor must be skewed. Take the example of very extreme attitude items where most people disagree. This gives skewed items, but the factor may still be normal. The observed non-normality may be due to the extremeness of the item wording. Second, the default assumption in Mplus is that the factor is normal. However, it does not have to be normal if you work with mixture modeling. You may be interested in the following statement from our short courses: By assuming normal factors and using probit links, ML uses the same model as WLSMV. This is because normal factors and probit links result in multivariate normal u* variables. For model estimation, WLSMV uses the limited information of first- and second-order moments, thresholds, and sample correlations of the multivariate normal u* variables (tetrachoric, polychoric, and polyserial correlations). In contrast, ML uses complete information from all moments of the data.

Tofighi, MacKinnon, and Yoon (2009) present calculations of covariances and variances among parameter estimates for a, b, c, and ĉ within single mediation models. Given the non-symmetric distribution of these products, bootstrap procedures were employed to generate numerous samples, thereby estimating bias-corrected confidence intervals for these products. The coefficient is statistically significant at a specified alpha level if the confidence interval does not encompass zero. Furthermore, the bootstrap resampling procedure generated 5,000 samples, which were utilized to compute the 95% bias-corrected confidence intervals for both unstandardized and standardized coefficients. The lower and upper confidence intervals for each estimate are reported. Weighted least squares with robust standard errors and mean- and variance-adjusted Chi-square (WLSMV) served as the default estimator when categorical variables were present (Muthén & Muthén, 2012).

Given that all scales are ordinal, Mplus is deemed the optimal structural equation modeling software. In addition to producing these results, each execution of an Mplus model generates a global statistical diagram of the results. Hayes (2018) characterizes a statistical diagram as “a set of equations, in visual form. … A statistical diagram visually depicts how the effects represented in a conceptual diagram would be estimated by a mathematical model” (p. 19).

The final diagram complements the analysis and results by retaining only pertinent information. A statistical diagram is transformed into a conceptual diagram by omitting all results. For illustrative purposes, two statistical diagrams are included: one for a simple single mediation model and another for a second-order mediation model. Since the provided tables for each mediation model include unstandardized and standardized coefficients, the statistical diagram reports only standardized results. In Mplus, the graphics tool, Diagrammer, “can be used to draw an input diagram, to view a diagram created from an analysis, and to view a diagram created using an input without an analysis” (Mplus Diagrammer Version 1 September 2012).

3. Background Analyses of the Constructs

3.1 Covariances of Constructs

The data utilized in this study are primarily ordinal, with each construct comprising a minimum of three measured variables. The TECH4 option in Mplus was employed to transform the data into constructs: "the TECH4 option is used to request estimated means, covariances, and correlations for latent variables…. In addition to the means, covariances, and correlations, standard errors and p-values are given"(Muthén & Muthén, 2012, pp. 752-753). The estimated inter-construct correlations are presented in Table 1.

Table 1: Estimated Correlation Matrix for the Latent Variables and Subscales

	COV	SWL	SHS	RAS	BRS	ACE_1	ACE_2	AAS_1	AAS_2	AAS_3	AAS	ACE
COV	1.00											
SWL	0.51	1.00										
SHS	0.35	0.66	1.00									
RAS	0.46	0.60	0.43	1.00								
BRS	0.34	0.42	0.64	0.19	1.00							
ACE_1	0.13	0.33	0.35	0.24	0.25	1.00						
ACE_2	0.10	0.25	0.27	0.19	0.19	0.71	1.00					
AAS_1	0.32	0.37	0.48	0.32	0.41	0.48	0.37	1.00				
AAS_2	0.30	0.34	0.45	0.30	0.38	0.44	0.34	0.67	1.00			
AAS_3	0.30	0.34	0.44	0.29	0.38	-0.43	-0.33	-0.66	-0.61	1.00		
AAS	0.38	0.44	0.57	0.38	0.49	0.56	0.43	0.85	0.79	-0.78	1.00	
ACE	0.13	0.33	0.35	0.24	0.25	1.00	0.77	0.48	0.44	-0.43	0.56	1.00

COV = Personal Attributes; RAS = Relationship Assessment Scale; SWL = Satisfaction with Life; BRS = Brief Resilience Scale; SHS = Subjective Happiness Scale; ACE = Adult Childhood Experiences;
ACE_1 = Person-related; ACE_2 = Other People-related; AAS = Adult Assessment Scale; AAS_1 = CLOSE;
AAS_2 = ANXIETY; and AAS_3 = DEPEND.

To test the above hypotheses, a structural equation modeling approach consisting of two interrelated models—a measurement model and a structural equation model—is adopted.
Except for the correlation between COV and AAS_H, all other correlations are statistically significantly different from zero, with a p-value greater than 0.001.

3.2 Measurement Models: Ordinal to Constructs

The measurement model is typically formalized through mathematical or statistical models to elucidate the causal relationships between empirical data and latent constructs. This process results in a model-implied covariance or implied covariances, which are then compared to the sample data covariances. The differences, often called discrepancies, form the basis of a fit or discrepancy function. Bandalos (2018, p. 376) notes that these discrepancies will be zero if the model perfectly fits the data. Due to the highly restrictive nature of Confirmatory Factor Analysis (CFA) models, where each variable loads on a single factor only, varying degrees of misspecification are anticipated. A poor model fit indicates that the formulated model fails to explain inter-item or inter-construct covariations, leading to misspecified models that result in biased estimates (Bandalos, 2018, p. 376).
Global fit indices have been proposed for measurement models to assess the model's fit(Barrett, 2007; Kline, 2005; Miles & Shevlin, 2007). Three indices are selected that exhibited some variability among the measurement models tested in this paper: RMSEA, which attempts to balance model fit as measured by the non-centrality parameter with parsimony, operationalized as the model degrees of freedom

(Bandalos, 2018, p. 379), and two incremental fit indices (TLI and CFI). Although these indices may be highly correlated, they and RMSEA are widely used as measures of fit in Structural Equation Modeling (SEM) studies. Recently, Xia and Yang (2019) conducted a detailed investigation using categorical data, evaluating cut values for different estimation methods: maximum likelihood (ML), diagonally weighted least squares (DWLS), and unweighted least squares (ULS). They concluded that ULS and DWLS produced over-optimistic unscaled and scaled fit indices compared with ML, especially for CFI and TLI (Xia & Yang, 2019, p. 428). Commonly adopted levels are used because specific cutoff numbers could not be endorsed: an RMSEA value of < .05 indicates a close fit, and < .08 suggests a reasonable model. For each of the hypotheses proposed earlier, a measurement model is fitted using Mplus. As expected, the model fits the data with RMSEA < .06, CFI > .95, and TLI > .95. If any of these criteria are not met, model modification indices (MI) procedures are employed to relax the model specifications by either including additional links or freeing residuals between pairs of model constructs. The MI reports the decrease in $\chi 2$ for a degree of freedom for each parameter not included in the model. Assisting in the decision measures the associated expected parameter change (EPC). The results are reported in Table 2 and discussed briefly:
COV: As previously noted by Bandalos (2018) "If the model fits the data perfectly, these discrepancies will be zero (p. 379)," exemplified by COV, comprising three manifest variables, with RMSEA = 0, CFI = 1.00, and TLI = 1.00.
SWL: This construct converged as unidimensional across all five measures. The standardized coefficients differ significantly from zero, with p-values less than 0.05. The three global measures of model fit fall within the expected ranges.
SHS: This construct also converged as unidimensional across four measures. The standardized coefficients differ significantly from zero, with p-values less than 0.05. Although the two incremental fit indices exceed the 0.95 thresholds, the
RMSEA exceeds 0.09. Consequently, the construct was recomputed, incorporating the residual covariance between SHS3 ("Some people are generally very happy. They enjoy life regardless of what is going on, getting the most out of everything") and SHS4 ("Some people are generally not very happy. Although they are not depressed, they seem as happy as they might be") based on the highest MI and its EPC.
RAS: The seven manifest items converged on this unidimensional construct. The standardized coefficients differ significantly from zero, with p-values less than 0.05. It exhibits the following reliability attributes: Cronbach α = 0.944, Standardized α = 0.947, and Reliability Coefficient ρ = 0.947, along with Goodness-of-fit indices: Taylor-Lewis Index (TLI) = 0.990, Comparative Fit Index (CFI) = 0.993. These indices indicate excellent psychometric properties, although the
RMSEA exceeds 0.090. Following the MI and EPC procedure, the residual covariance between RAS4 ("How often do you regret this relationship?") and RAS7 ("Many problems in your relationship?") was incorporated into the measurement model. In this revised model, the RMSEA is reduced to 0.084.
BRS: This construct converged as unidimensional across six measures. The

standardized coefficients differ significantly from zero, with p-values less than 0.05. It demonstrates the following reliability attributes: Cronbach $\alpha = 0.888$, Standardized $\alpha = 0.889$, and Reliability Coefficient $\rho = 0.898$, along with Goodness-of-fit indices: Taylor-Lewis Index (TLI) = 0.982 and Comparative Fit Index (CFI) = 0.989. However, the RMSEA exceeds 0.090. Based on the MI and EPC procedure, the residual covariance between BRS1 ("I bounce back quickly after hard times") and BRS3 ("I recover fast from a stressful event") was included in the measurement model. In this augmented model, the RMSEA is reduced to 0.036.

ACE (Adverse Childhood Experience) is divided into two subscales: PERSON-related and OTHER-related. The PERSON-related subscale converged as a unidimensional construct, with standardized coefficients significantly different from zero and p-values less than 0.05. However, the variances explained by ACE3 and ACE5 are comparatively low, at 0.098 and 0.138, respectively. The model fits the data for the OTHER-related subscale, but two other items exhibit low variances explained: ACE9 at 0.194 and ACE10 at 0.139, respectively.

AAS: The eighteen items were categorized into three subscales: closeness, anxiety, and dependence. These subscales are discussed prior to their overarching second-order construct, AAS. The closeness subscale comprises six items, with all standardized coefficients significantly differing from zero ($p < 0.05$). As indicated in Table 2, this subscale demonstrates robust psychometric properties, evidenced by an RMSEA of 0.087 and positive lower and upper confidence intervals. Both the CFI and TLI exceed 0.95. Excluding AAS1, which was fixed at unity, the subscale exhibited the highest loadings on two items: AAS10 ("I often worry that my partner will not want to stay with me"), with an explained variance of 72.8%, and AAS4 ("In relationships, I often worry that my partner does not really love me"), with an explained variance of 66.7%.

As presented in Table 2, the second subscale, anxiety, did not satisfy the three minimum criteria for a valid subscale or scale: CFI = 0.905, TLI = 0.896, and RMSEA = 0.195. Consequently, the MI and EPC procedure was applied, and the model was adjusted by incorporating the residual covariance between AAS11 ("I want to merge completely with another person") and AAS12 ("My desire to merge sometimes scares people away"). The RMSEA decreased to 0.072 in this revised model, with CFI = 0.988 and TLI = 0.998. The third subscale is dependence, with an RMSEA exceeding 0.09 and a TLI below 0.95. The recalibrated measurement model incorporated results from the MI analysis, including the residual covariance between AAS3 ("I find it difficult to allow myself to depend upon others.") and AAS13 ("I am comfortable having others depend on me."). This revised subscale model was employed to calibrate the second AAS second-order construct. This second-order construct is hypothesized to converge on these subscales, and it significantly converged on each subscale (Table 2).

Table 2: The Transformation of Measurements to Constructs

Items	Subconstruct to Construct	Fit Indices
Cov3, cov4, cov5	***COV all by COV3 COV4 COV5***	*RMSEA 0.000 90% CI 0.000 – 0.000*
		CFI = 1.000, TLI = 1.000
swl1, … , swl5	***SWL all by SWL1 SWL2 SWL3 SWL4 SWL5 SWL6***	*RMSEA 0.064 90% CI0.039 – 0.092*
		CFI = 0.999, TLI = 0.998
shs1, … , shs4	*SHS all by SHS1 SHS2 SHS3 SHS4*	*RMSEA 0.169 90% CI 0.131 – 0.211*
		CFI = 0.996, TLI = 0.989
	With SHS3 and SHS4 correlated (MI = 45.419, EPC = 0.064)	*RMSEA 0.084 90% CI 0.034 – 0.147*
		CFI = 1.000, TLI = 0.997
	SHS all by SHS1 SHS2 SHS3 SHS4 [SHS3 with SHS4]	
ras1, … , ras7	*RAS all by RAS1 RAS2 RAS3 RAS4 RAS5 RAS6 RAS7*	*RMSEA 0.152 90% CI 0.137 – 0.167*
		CFI = 0.993, TLI = 0.990
	With RAS4 and RAS7 correlated (Mi = 207.379, EPC = 0.233)	*RMSEA 0.084 90% CI 0.068 – 0.101*
		CFI = 0.998, TLI = 0.997
	RAS_all by RAS1 RAS2 RAS3 RAS4 RAS5 RAS6 RAS7 [RAS4 with RAS7]	
brs1, … , brs6	*BRS_all by BRS1 BRS2 BRS3 BRS4 BRS5*	*RMSEA 0.036 90% CI 0.095 – 0.133*
		CFI = 0.989, TLI = 0.982
	With BRS3 and BRS1 correlated (MI=93.128, EPC=0.107)	*RMSEA 0.036 90% CI 0.011 – 0.060*
		CFI = 0.999, TLI = 0.998
	BRS_all by BRS1 BRS2 BRS3 BRS4 BRS5 [BRS4 with BRS7]	
ace1, … , ace10	*ACE_1 by ACE1 ACE2 ACE3 ACE4 ACE5*	*RMSEA 0.032 90% CI 0.011 – 0.063*
		CFI = 0.998, TLI = 0.996
	ACE_2 by ACE6 ACE7 ACE8 ACE9 ACE1	*RMSEA 0.002 90 % CI 0.001 - 0.044*
		CFI = 0.999, TLI = 0.999
	ACE_all by ACE_1, ACE_2	*RMSEA 0.040 90 % CI 0.028 - 0.051*
		CFI = 0.997, TLI = 0.983
Aas1, … , aas18	*CLOSE by AAS1 AAS7 AAS9 AAS13 AAS15 AAS17*	*RMSEA 0.087 90 % CI 0.068 - 0.107*
		CFI = 0.981, TLI = 0.969
	ANXIETY by AAS2 AAS4 AAS5 AAS10 AAS11 AAS12	*RMSEA 0.195 90 % CI 0.176 - 0.214*
		CFI = 0.905, TLI = 0.842
	With AAS11 and AAS12 correlated (MI=93.128, EPC=0.107)	*RMSEA 0.072 90 % CI 0.052 - 0.094*
		CFI = 0.988, TLI = 0.978
	DEPEND by AAS3 AAS6 AAS8 AAS14 AAS16 AAS18	*RMSEA 0.198 90 % CI 0.179 - 0.217*
		CFI = 0.937, TLI = 0.890
	With AAS3 and AAS13 correlated (MI=93.128, EPC=0.107)	*RMSEA 0.122 90 % CI 0.102 - 0.142*
		CFI = 0.979, TLI = 0.960
	AAS_all by AAS_1 AAS_2 AAS_3 [AAS3 with AAS13]	

Note: Final Constructs are in bold face.

SHS(3): Some people are generally very happy. They enjoy life regardless of what is going on getting the most out of everything; SHS(4): Some people are generally not very happy. Although they are

not depressed, they seem as happy as they might be;
RAS(4) How often do you wish you hadn't gotten into this relationship?; RAS(7) How many problems are there in your relationship?;
BRS(1) I tend to bounce back quickly after hard times; BRS(3) It does not take me long to recover from a stressful event;
AAS(11) I want to merge completely with another person; and AAS(12) My desire to merge sometimes scares people away.
AAS(3) I find it difficult to allow myself to depend upon others; AAS(13) My desire to merge sometimes scare people away.

4. Main Results

4.1 Total Effects of COV (H1 and H2) on SWL and SHS

Analyzing total effects in a mediation study is a crucial initial step, as significant total effects between the independent and dependent constructs are essential preconditions for mediation (Klein et al., 2006). Table 3 summarizes the total effects of respondents' socio-economic attributes on SWL (H1) and SHS (H2).

Table 3: Total Effects of Personal Attributes (COV) on SWL and SHS

Fit Measures	**SWL**		**SHS**	
RMSEA: Estimate 90% CI	0.05 [0.04, 06]		0.03 [0.01, 0.05]	
CFI	0.998		0.999	
TLI	0.996		0.940	
Coefficients	Estimate	SE	Estimate	SE
Unstandardized	0.76	0.13	0.67	0.16
95% CI	[0.55, 0.83]		[0.44, 1.04]	
Standardized	0.52	0.60	0.34	0.06
95% CI	[0.41, 0.63]		[0.22, 0.45]	
Covariates				
Unstandardized				
Marital	1.00	0.00**	1.00	0.00**
Education	0.80	0.11**	0.31	0.95**
SES	1.66	0.12**	0.54	0.11**
Standardized				
Marital	0.79	0.08**	0.84	0.10**
Education	0.39	0.07**	0.26	0.07**
SES	0.59	0.07**	0.46	0.11**
R^2	0.27		0.12	

Note. *p≤ .05. **p≤ .01

Based on the three measures of fit employed in this study—TLI, CFI, and RMSEA—the alternative hypotheses that the models adequately fit the data are accepted. Specifically, the RMSEA values of 0.047 [CI: 0.037, 0.062] and 0.033 [CI: 0.012, 0.052] for SWL and SHS, respectively, fall within the 'close fit' category as defined by Browne and Cudeck (1993). Furthermore, the CFI and TLI indices, which compare the empirically derived model to the null model, are within the acceptable range. Additionally, the variance in SWL and SHS explained by COV significantly differs from zero, with 27.1 percent (p = 0.013) for SWL and 11.6 percent (p > 0.001) for SHS. To further investigate the sources of the effects of the COV construct on SWL and SHS, the unstandardized, standardized, and p-values for the three items constituting this independent construct are reported (see Table 3). SES is the most substantial effect for both dependent constructs, with standardized scores of 0.786 for SWL and 0.688 for SHS. In both models, the marital status item (coded as 0 for not married and 1 for married) is the second most significant contributor to the effect of COV. Relationship Assessment Scale (RAS) as Mediator (H3 and H4). These results are summarized in Table 4 for the two dependent constructs, SWL and SHS.

Table 4: Total Effects of Personal Attributes (COV) on SWL and SHS through RAS

Fit Measures	SWL		SHS	
RMSEA: Estimate 90% C.I.	0.07 0.065 - 0.077		0.07 0.064 - 0.072	
CFI	0.992		0.993	
TLI	0.990		0.942	
Coefficients	Estimate	SE	Estimate	SE
Unstandardized				
COV on RAS	0.55	0.10**	0.51	0.11**
COV on SWL/SHS	0.29	0.10**	0.16	0.07*
RAS on SWL/SHS	0.46	0.04**	0.36	0.04**
Standardized				
COV on RAS	0.47	0.05**	0.46	0.05**
COV on SWL/SHS	0.26	0.07**	0.15	0.07**
RAS on SWL/SHS	0.49	0.05**	0.36	0.05**
R^2				
SWL/SHS	0.42	0.04**	0.20	0.04**
RAS	0.22	0.05**	0.21	0.05**
Covariates				
Unstandardized				
Marital	1.00	0.00**	1.00	0.00**
Education	0.39	0.11	0.31	0.95
SES	0.59	0.12	0.54	0.11
Standardized				
Marital	0.79	0.08**	0.84	0.10**
Education	0.31	0.07**	0.26	0.07**
SES	0.47	0.07**	0.46	0.07**

Note. *p≤ .05. **p≤ .01

Both models adequately fit the data, as evidenced by the fact that the lower- and upper-90 percent confidence intervals do not encompass zero. Additionally, the CFI and TLI indices exceed the acceptable threshold of 0.95. As previously reported by Yzerbyt et al. (2018), three conditions are required to conclude that a mediation effect is significantly different from zero: COV on RAS, COV on SWL, and RAS on SWL. The associated unstandardized coefficients, 0.548, 0.293, and 0.461, respectively, are significantly different from zero, with p-values less than 0.001. Typically, these coefficients are employed to assess the change in RAS and SWL for a unit increase in the COV construct; comparisons can be made by multiplying them by their standard deviations(Muthén et al., 2017, pp. 15-16). These constructs involve at least three measured variables, so Tech4 in Mplus can compute estimated inter-construct covariances and correlations. The construct standard deviations are derived as the square roots of the diagonal values of the covariance matrix. The standardized coefficients corresponding to the three unstandardized coefficients are 0.465, 0.262, and 0.485 for COV on RAS, COV on SWL, and RAS on SWL, respectively. For a one standard deviation change in the COV score, the SWL in standard deviation score, calculated by TECH4 as 0.888, is expected to increase by 0.262.

Alternatively, the standardized results generated by Mplus, which was utilized for this analysis, may be employed. For SHS as the predictor, the unstandardized coefficients are all significant and comparable to those for SWL, with the effect of COV on RAS being the most pronounced. A two-unit increase in an individual's attribute score results in approximately a one-unit increase in that individual's subjective happiness score. The associated standardized coefficient is also the largest; for a one standard deviation change in the COV score, the SHS score is expected to increase by 0.459 of an SHS standard deviation, calculated (by TECH4) as 0.931. In summary, H3 and H4 are validated; the RAS construct serves as a significant mediator between COV and SWL and COV and SHS. The mediator effects, COV→ RAS * RAS → SWL and COV→ RAS * RAS → SHS, of 0.252 and 0.184, respectively, are statistically different from zero (Table 4). Brief Resilience Scale (BRS) as Mediator (H5 and H6) The results of BRS as a mediator between COV and SWL or SHS are summarized in Table 5.

The fundamental inquiry in any structural equation analysis is whether the model adequately fits the data. For both dependent constructs examined, the model demonstrates a robust fit. Specifically, for the model with a mediator effect of 0.151, represented as COV→BRS * BRS → SWL, the fit indices are CFI=0.99, TLI=0.99, and RMSEA=0.046 with a 95% confidence interval ranging from 0.039 to 0.054. Similarly, for the COV→BRS * BRS → SHS model, which exhibits a mediator effect of 0.385, the fit indices are CFI=0.99, TLI=0.99, and RMSEA=0.057 with a 95% confidence interval from 0.049 to 0.064. Given that both models are single mediation models, two structural equation models are calibrated concurrently: one for the dependent construct and another for the mediating construct. For instance, in the COV→BRS → SWL model, the explained variance is 33.3 percent for the SWL equation and 12.1 percent for the BRS equation. The explained variances in the COV→BRS → SHS model are 42.6 percent for SHS, the dependent construct, and 11.2 percent for BRS, the mediating construct. In all four instances, the confidence intervals do not encompass zero, thereby validating the models and confirming their support by the data.

Table 5: Total Effects of Personal Attributes (COV) on SWL and SHS through BRS

Fit Measures	SWL		SHS	
RMSEA: Estimate	0.05		0.06	
90% CI	[0.039, 0.054]		[0.049, 0.064]	
CFI	0.99		0.99	
TLI	0.99		0.99	
Coefficients	Estimate	SE	Estimate	SE
Unstandardized				
COV on BRS	0.33	0.08**	0.38	0.09**
COV on SWL/SHS	0.66	0.13**	0.28	0.10**
BRS on SWL/SHS	0.46	0.04**	1.02	0.04**
Standardized				
COV on BRS	0.34	0.06**	0.34	0.06**
COV on SWL/SHS	0.42	0.06**	0.14	0.05**
BRS on SWL/SHS	0.28	0.04**	0.59	0.03**
R^2				
SWL/SHS	0.33	0.05**	0.43	0.03**
BRS	0.12	0.04**	0.11	0.04
Covariates				
Unstandardized				
Marital	1.00	0.00	1.00	0.00
Education	0.71	0.12**	0.76	0.23**
SES	1.13	0.21**	1.49	0.77*
Standardized				
Marital	0.64	0.08**	0.50	0.10**
Education	0.40	0.07**	0.38	0.07**
SES	0.84	0.07**	0.74	0.12**

Note. *p≤ .05. **p≤ .01

In both models, the mediating effects of BRS are quantified as 0.151 (COV →BRS * BRS →SWL) with a standard error of 0.036, and 0.385 (COV →BRS * BRS →SHS) with a standard error of 0.086 for SWL and SHS, respectively (Table 5). Both effects yield p-values less than 0.001, with positive lower and upper confidence limits. Consequently, the BRS construct significantly mediates the relationship between COV and SWL or SHS, while controlling for the direct effects of COV → SWL and COV → SHS. The three paths constituting the 'mediation triangle' (COV → SWL, COV → BRS, and BRS → SWL) are all statistically

significant, with p-values less than 0.001. The direct effects of COV on SWL or SHS, while controlling for the effect of BRS, suggest that a unit increase in a respondent's socio-economic status (COV) corresponds to an increase of approximately 0.60 in Satisfaction With Life (SWL) and approximately 0.28 in SHS. Although the loadings for the three items are comparable across both models, minor differences are observed. For instance, the loadings for education (0 = less and 1 = more) and socio-economic status (SES) (0 for less and 1 for higher) are lower for SWL compared to SHS.
The above report of COV's mediation on SHS mediated by BRS resulted from the interaction among three constructs that converged on a minimum of three manifest variables. Diagrammer, the graphics routine in Mplus, graphically prints this complex interlinkage pattern. As shown in Figure 1, the trimmed statistical diagram includes COV, BRS, and SHS loadings.

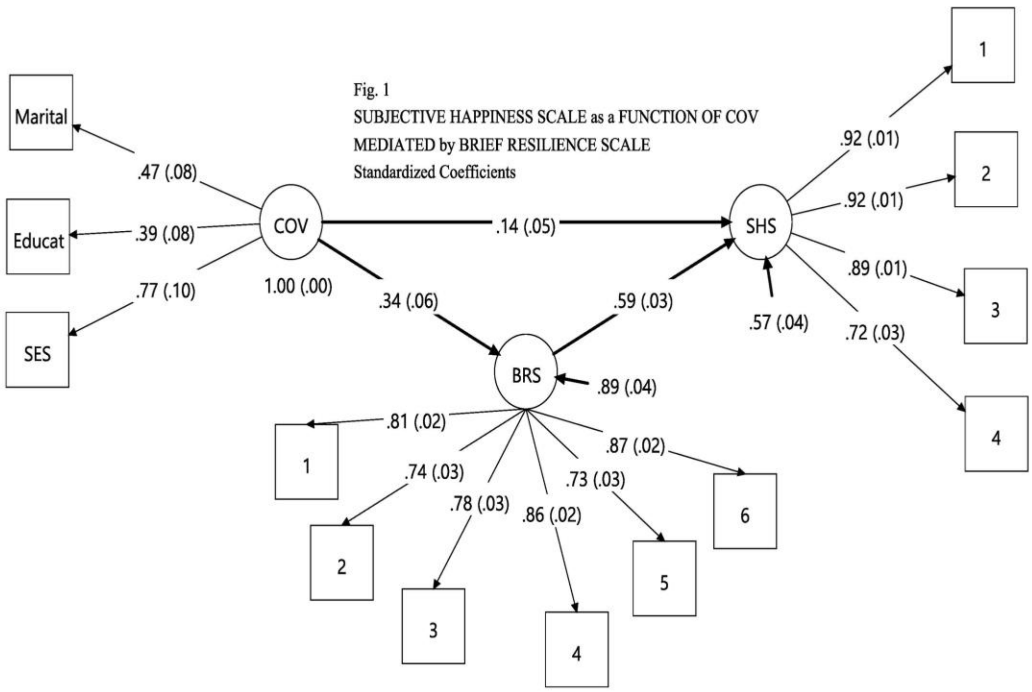

Figure 1: Subjective Happiness Scale

In descending order, they are COV (SES, Marital, and Education), BRA (the highest are BRS6, BRS4, and BRS1), and SHS (SHS1, SHS2, SHS3, and SHS4). In addition, there is a mediating triangle. All lines are positive and significant, especially COV → BRS and BRS → SHS

4.2 Adverse Childhood Experience (ACE) Scale as Mediator (H7 and H8)

The results for SWL and SHS-dependent constructs with second-order mediator construct, ACE, are summarized in Table 6.

Table 6: Total Effects of Personal Attributes (COV) on SWL and SHS through ACE

Fit Measures	SWL		SHS	
RMSEA	0.028		0.026	
90% CI	[0.021, 0.034]		[0.019, 0.032]	
CFI	0.995		0.996	
TLI	0.994		0.985	
Coefficients	Estimate	SE	Estimate	SE
First Order				
Unstandardized				
ACE by Self	1.00	0.00	1.00	0.00
ACE by Others	0.60	0.07**	0.64	0.06**
Standardized				
ACE by Self	0.88	0.02**	0.853	0.033**
ACE by Others	0.85	0.04**	0.917	0.046**
R^2				
ACE by Self	0.80	0.04**	0.73	0.04**
ACE by Others	0.73	0.06**	0.84	0.08**
Second Order				
Unstandardized				
ACE on COV	0.15	0.12	0.17	0.15
SWL/SHS on COV	0.71	0.10**	0.58	0.21**
SWL/SHS on ACE	0.30	0.07**	0.40	0.06**
Standardized				
ACE on COV	0.15	0.087**	0.109	0.061
SWL/SHS on COV	0.49	0.04**	0.31	0.03
SWL/SHS on ACE	0.27	0.07**	0.34	0.05
R^2				
SWL/SHS	0.35	0.05**	0.23	0.05**
ACE	0.02	0.02	0.01	0.02
Covariates				
Unstandardized				
Marital	1.00	0.00**	1.00	0.00
Education	0.65	0.15**	0.76	0.23**
SES	0.95	0.18**	1.486	0.77*
Standardized				
Marital	0.61	0.00	0.50	0.09**
Education	0.40	0.07**	0.38	0.07**
SES	0.58	0.07**	0.74	0.12
R^2				
SWL/SHS	0.35	0.05**	0.23	0.05**
ACE	0.02	0.02	0.01	0.03

Note. *$p \leq .05$. **$p \leq .01$

The findings reveal the mediating role of Adverse Childhood Experiences (ACE), conceptualized as a second-order factor model comprising two subscales: ACE_one and ACE_two. The ACE_one subscale encompasses five items that capture the individual's negative experiences, while the ACE_two subscale reflects the impact of adverse experiences on family members. In the model, the unstandardized coefficient for ACE_one was fixed at one, allowing the model to freely estimate the coefficient for ACE_two, which was determined to be 0.615, approximately two-thirds of that for ACE_one.

The standardized coefficients demonstrate that the direct effect of COVID-19 (COV) is twice as strong for personally experienced negative childhood encounters (ACE_one) compared to the antisocial acts of family members (ACE_two). The unstandardized direct effect of COV on ACE, the second-order construct, is 0.189, with confidence limits ranging from -0.033 to 0.405, indicating a lack of statistical significance. However, the direct effect of COV on Satisfaction with Life (SWL), while controlling for the effect of ACE, and the effect of ACE on SWL, while controlling for the direct effect, are statistically significant. These results suggest that ACE does not mediate the relationship between COV and SWL. The direct effect accounts for over ninety percent of the total effect of COV on SWL. The ratios of total effect to direct effects are notably low; for SWL, both effects are approximately six percent, and for the Subjective Happiness Scale (SHS), they are slightly higher, at about nine percent for the total effect and ten percent for the direct effect. These findings further indicate that ACE does not mediate the COV and SWL or SHS relationship. Consequently, the null hypotheses, H7 and H8, are accepted.

4.2.1 Adult Attachment Scale (AAS) as Mediator (H9 and H10)

The Adult Attachment Scale (AAS) was modeled as a second higher-order construct consisting of three subscales: Depend, Anxiety, and Close. The three global fit indices employed in this study indicate that this second-order model of the AAS fits both cognitive components (SWL and SHS) of Subjective Well-being (SWB). For SWL, the indices are 0.068 for RMSEA, 0.995 for CFI, and 0.994 for TLI; for SHS, they are 0.08 for RMSEA, 0.94 for CFI, and 0.93 for TLI, respectively (Table 7).

Table 7: Total Effects of Personal Attributes on SWL and SHS through AAS

Fit Measures	SWL		SHS	
RMSEA: Estimate 90% CI	0.07 [0.06, 0.07]		0.08 [0.07, 0.08]	
CFI	0.95		0.94	
TLI	0.94		0.93	
Coefficients	Estimate	SE	Estimate	SE
First Order				
Unstandardized				
AAS by Close	1.00	0.00**	1.00	0.00**
AAS by Anxiety	0.51	0.08**	0.49	0.08**
AAS by Depend	-0.94	0.09**	-0.86	0.08**
Standardized				
AAS by Close	0.89	0.03**	0.998	0.00**
AAS by Anxiety	0.70	0.03**	0.68	0.03**
AAS by Depend	-0.81	0.03**	-0.77	0.03**
R^2				
Close	0.80	0.05**	0.996	0.00**
Anxiety	0.48	0.05**	0.46	0.04**
Depend	0.65	0.06**	0.59	0.04**
Second Order				
Unstandardized				
COV on AAS	0.30	0.06**	0.35	0.06**
COV on SWL/SHS	0.61	0.06**	0.19	0.06**
AAS on SWL/SHS	0.49	0.05**	0.47	0.04**
Covariates				
Unstandardized				
Marital	1.00	0.00**	1.00	0.00**
Education	0.65	0.15**	0.65	0.22**
SES	0.95	0.18**	0.95	0.34**
Standardized				
Marital	0.61	0.00**	0.55	0.09
Education	0.40	0.07**	0.38	0.08**
SES	0.58	0.07**	0.68	0.09**
Standardized				
COV on AAS	0.37	0.06**	0.35	0.06**
COV on SWL/SHS	0.42	0.06**	0.19	0.05**
AAS on SWL/SHS	0.27	0.05**	0.47	0.04**
R^2				
SWL/SHS	0.33	0.05**	0.32	0.04**
AAS	0.14	0.04**	0.13	0.04**

Note1. *p≤ .05. **p≤ .01

The AAS exhibits a positive loading on the Depend and Anxiety subscales, while it loads negatively on the Close subscale. Given that the confidence intervals in these models do not encompass zero, both models demonstrate a good fit to the data. In both models, the direct effect of COV on SWL or SHS, while controlling for the effect of AAS, is significantly different from zero. Specifically, a two-unit increase in a respondent's socio-economic status (COV) results in an increase of over one unit in SWL. Although significant, the increase in SHS is approximately half of that observed in SWL. The mediation effects, quantified as 0.149 (COV → AAS * AAS → SWL) and 0.306 (COV → AAS * AAS → SHS), are significant, with p-values less than 0.001. It is concluded that both models adequately fit the data, as per the mediation effect criteria discussed earlier. In the SWL model, the total and direct effects account for 19.6 percent and 24.3 percent of the variance in COV, respectively. In contrast, the SHS model accounts for higher percentages: 51.4 and 52.1 percent, respectively. The contributions of individual items to the covariate (COV) vary, with marital status being significant for SWL and socio-economic status (SES) for SHS. The linkages calculated in a second-order factor are graphically represented in the statistical diagram (Figure 2).

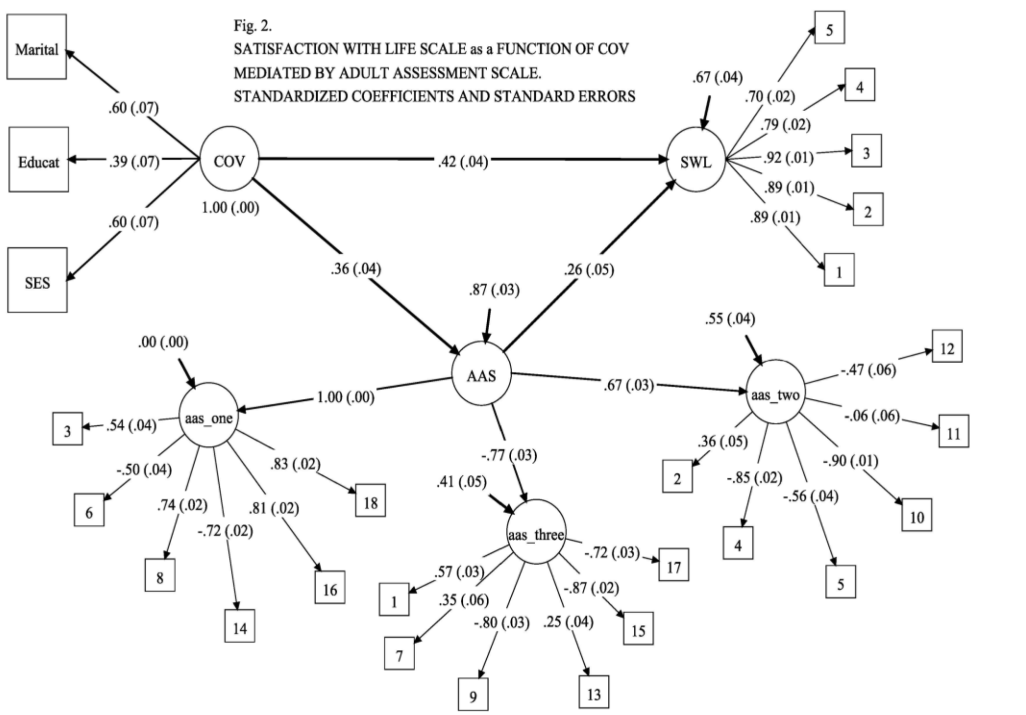

Figure 2: Satisfaction With Life Scale

The diagram illustrates that the personal attribute construct (AAS) converges on three subordinate constructs: Depend (AAS_one), Anxiety (AAS_two), and Close (AAS_three). The second-order AAS construct, along with COV and SWL, forms the vertices of the mediation triangle; the relationships COV → AAS, COV → SHS/SWL, and AAS → SHS/SWL are positive and significantly different from zero.

4.2.2 Effect Size Assessments

The criteria for rejecting the null hypotheses were RMSEA, NNFI, and CFI for the abovementioned ten hypotheses. In all three cases, the basis for rejecting the null hypothesis depends on the size of the p-value. However, as Lachowicz, Preacher, and Kelly(2018)stated, “p values provide no information about the size or importance of effects, only the likelihood of obtaining an effect as large or larger than that obtained (p.244).” Commenting on the limitations of p-values, Jose(2013)wrote, "You are able to answer that it was statistically significant, but you are not able to say whether the amount of mediation … was small, medium or large (p. 57).” To convey the size or importance of the result, the American Psychological Association (APA) also recommended reporting “effect size” as the magnitude of treatment effects. Additionally, it recommended the calculation and reporting of confidence bands. Later, in 2010, the APA Publication Manual strongly recommended reporting confidence intervals. “For the reader to appreciate the magnitude or importance of a study’s findings, it is almost always necessary to include some measure of effect size in the Results section” (American Psychological Association, 2010, p. 34).

Numerous effect size metrics have been proposed and evaluated across various disciplines, including the natural, physical, and social sciences (Preacher & Kelley, 2011). As early as the 1990s, Kirk (1996) identified over forty such indices. In the same year, Richardson (1996) categorized the research and practical applications of effect size measures into two primary categories: comparisons of means and between variance components. Ferguson (2009) further classified effect sizes into four categories: group differences (e.g., Cohen’s d), association measures (e.g., Pearson’s r), corrected estimates such as adjusted R^2, and risk estimates such as odds ratio. Synthesizing from MacKinnon (2008, pp. 79-102) and Jose (2013, p. 58), three methods for measuring the effect size of the mediated effect were identified: ratio and proportion, R^2 measures, and standardized values. In this study, MacKinnon’s proposed measures are employed for the entire mediated effect, as well as others that calculate effect size measures for individual paths. Specifically, the procedure involves computing ratio and proportion effect sizes for the eight single mediation models. Subsequently, partial correlations are used to measure effect size for the individual paths. In Mplus, the options for calculating p-values and implementing the bias-corrected bootstrap procedure were utilized for a 5 percent confidence band. Proportion and Ratio Effect Sizes: Table 8 summarizes the results for the eight single mediation models.

The initial three rows for each model present the mediated effects, encompassing the indirect, direct, and total effects. The magnitude of the mediated effects (first row) exhibits considerable variation, ranging from a maximum of 0.385 to a minimum of 0.048. All mediating effects are statistically significant, except in the two instances where ACE is the mediator. The final two rows of each of the eight single mediator models summarize the mediated effect as a ratio of direct and total effects; larger ratios indicate a more substantial mediated effect. This ratio surpasses one if the indirect effect exceeds the direct effect, as observed in the case of COV on SHS through RAS. However, in most instances, the lower and upper confidence intervals are positive, validating these ratios as effect size measures. Despite criticisms of both methods, they offer straightforward and easily interpretable effect size indicators relative to the direct or total effects. For the former, as the mediated effect increases relative to the direct effect, this index approaches 1.0, and in some instances, it exceeds one. Among the eight single-mediated effects examined, this was observed in two models (COV on SWL through RAS and COV on SHS through BRS).

Table 8: Effect Size Measures (Ratios and Proportions) for Eight Single Mediation Models, a*b Using Bias Corrected Bootstrap

Effect	Estimate	SE	Est./SE	p-value	L2.5%	U2.5%
COV on SWL through RAS						
Proportions						
INDIRECT (a*b)	0.25	0.04	6.55	<.001	0.19	0.34
DIRECT	0.29	0.10	3.10	.002	0.13	0.50
TOTAL	0.55	0.01	5.04	<.001	0.35	0.77
Ratios						
a*b/DIRECT	0.86	0.44	1.95	.051	0.50	1.97
a*b/TOTAL	0.46	0.08	5.59	<.001	0.33	0.66
COV on SHS through RAS						
Proportions						
INDIRECT (a*b)	0.18	0.04	4.85	<.001	0.12	0.27
DIRECT	0.16	0.09	1.72	.086	0.01	0.37
TOTAL	0.34	0.10	3.41	<.001	0.16	0.56
Ratios						
a*b/DIRECT	1.15	32.26	0.04	.972	0.41	7.97
a*b/TOTAL	0.53	0.17	3.14	<.001	0.31	0.92
COV on SWL through BRS						
Proportions						
INDIRECT (a*b)	0.15	0.04	4.27	<.001	0.10	0.24
DIRECT	0.66	0.13	5.12	<.001	0.45	0.94
TOTAL	0.81	0.14	5.95	<.001	0.58	1.11
Ratios						
a*b/DIRECT	0.23	0.07	3.40	<.001	0.13	0.41
a*b/TOTAL	0.19	0.04	4.33	<.001	0.13	0.29

COV on SHS through BRS						
Proportions						
INDIRECT (a*b)	0.39	0.10	3.87	<.001	0.24	0.61
DIRECT	0.28	0.11	2.55	.011	0.09	0.52
TOTAL	0.67	0.16	4.06	<.001	0.42	1.04
Ratios						
a*b/DIRECT	1.37	14.64	0.09	.925	0.72	4.52
a*b/TOTAL	0.58	0.10	5.71	<.001	0.42	0.82
COV on SWL through ACE (Second Order)						
Proportions						
INDIRECT (a*b)	0.05	0.03	1.89	.058	0.00	0.09
DIRECT	0.71	0.13	5.62	<.001	0.49	0.97
TOTAL	0.75	0.13	5.93	<.001	0.53	1.03
Ratios						
a*b/ DIRECT	0.07	0.04	1.80	.072	0.00	0.15
a*b/ TOTAL	0.06	0.03	1.92	.055	0.00	0.13
COV on SHS through ACE (Second Order)						
Proportions						
INDIRECT (a*b)	0.06	0.04	1.47	.142	-0.03	0.14
DIRECT	0.59	0.16	3.78	<.001	0.35	0.94
TOTAL	0.65	0.16	4.18	<.001	0.41	0.99
Ratios						
a*b/ DIRECT	0.10	0.08	1.31	.189	-0.04	0.28
a*b/ TOTAL	0.09	0.06	1.47	.141	-0.04	0.22
COV on SWL through AAS (Second Order)						
Proportions						
INDIRECT (a*b)	0.14	0.03	4.29	<.001	0.09	0.22
DIRECT	0.63	0.13	4.97	<.001	0.42	0.92
TOTAL	0.77	0.13	5.91	<.001	0.55	1.06
Ratios						
a*b/ DIRECT	0.22	0.07	3.20	<.001	0.12	0.40
a*b/ TOTAL	0.18	0.05	4.04	<.001	0.11	0.29
COV on SHS through AAS (Second Order)						
Proportions						
INDIRECT (a*b)	0.28	0.07	4.28	<.001	0.17	0.43
DIRECT	0.32	0.12	2.75	.006	0.12	0.58
TOTAL	0.60	0.14	4.24	<.001	0.37	0.52
Ratios						
a*b/ DIRECT	0.89	41.24	0.02	.983	0.46	2.38
a*b/ TOTAL	0.47	0.10	4.66	<.001	0.32	0.71

Table 8 presents the outcomes of dividing the product of a*b by the total effect, which encompasses both direct and indirect effects. The smallest ratios are observed in models with significant direct effects: specifically, model 5 second-order (COV on SWL through ACE) and model 6 second-order (COV on SHS through ACE). However, these models are deemed unreliable as their confidence intervals include zero. Among the effect sizes with confidence intervals excluding zero, the average effect size is greater for SHS compared to SWL. ACE, as a mediator, demonstrates smaller effect sizes than the RAS and BRA mediators. Despite criticisms regarding the instability of this effect size measure (Hayes, 2018; MacKinnon, 1995, 2002), it remains a simple and widely utilized metric.

In both scenarios, the calculated effect sizes are not statistically significant. Although the ranges between the lower and upper confidence intervals do not encompass zero, they are relatively large. This measure may be unreliable when the effect size exceeds 0.6. As Hayes(2018)generalized, when the direct effect "approaches zero, even tiny indirect effects will explode in size relative to the direct effect…. It simply can’t be trusted as a description of the size of the indirect effect unless the sample size is at least 2,000 or so (p. 138)."

Effect size measures for individual paths—Partial Correlation: The preceding discussion on effect size concentrated on the total mediation effect, defined as the product of path a from COV to the moderator (RAS, BRS, AAS, or ACE) and path b from the moderator (RAS, BRS, AAS, or ACE) to the dependent construct (SWL or SHS). This moderation effect may arise from various combinations of a and b. MacKinnon(2008)advocated for the use of partial correlations to delineate the contributions of each path. He stated, “The partial correlation effect size measure is the correlation between one predictor and the dependent variable with the relation of the other predictor and the dependent variable removed” (p. 80). MacKinnon(2008)further explained, “Of primary interest for the mediated effect is the correlation between the mediating variable and the dependent variable adjusted for the correlation between the independent variable and the dependent variable” (p. 81). In our study, these partial correlations are the correlation between SWL or SHS and RAS, BRS, AAS, or ACE (b) partialled for COV, and the correlation between SWL or SHS and COV (a) partialled for RAS, BRS, AAS, or ACE. He proposed the following equations (p. 81):

$$YX.M = (c1 - c2*c3)/SQRT((1-c3*c3)*(1-c2*c2)),$$

$$YM.X = ((c3 - c1*c2))/SQRT((1-c1*c1)*(1-c3*c3));$$

where YX.M represents the correlation between X and Y partialled for M, and YM.X denotes the correlation between M and Y partialled for X. For this study, the following equivalences were applied: c1 (rxy) is the correlation between x (COV) and y (SWL or SHS); c2 (rxm) is the correlation between x (COV) and m (any of the four mediators); and c3 (rmy) is the correlation between m (any of the four mediators) and y (SWL or SHS).

Effect sizes were calculated using Mplus and generated p-values and confidence bands (Table 9).

Table 9: Effect Size Measures for Individual Paths of the Mediated Effects

Effect	Estimate	SE	Est/SE	p-value	L2.5%	U2.5%
Correlation between SWL and COV partialled for RAS	0.21	0.04	5.38	<.001	0.13	0.29
Correlation between SWL and RAS partialled for COV	0.2	0.05	3.91	<.001	0.11	0.3
Correlation between SHS and COV partialled for RAS	0.13	0.05	2.77	<.001	0.04	0.21
Correlation between SHS and RAS partialled for COV	0.3	0.06	5.19	<.001	0.04	0.41
Correlation between SWL and COV partialled for BRS	0.22	0.04	5.64	<.001	0.15	0.3
Correlation between SWL and BRS partialled for COV	0.09	0.03	3.31	<.001	0.04	0.14
Correlation between SHS and COV partialled for BRS	0.1	0.03	3.27	.001	0.05	0.17
Correlation between SHS and BRS partialled for COV	0.06	0.02	2.75	.006	0.02	0.1
Correlation between SWL and COV partialled for AAS	0.26	0.04	6.46	<.001	0.19	0.34
Correlation between SWL and AAS partialled for COV	0.07	0.02	3.18	<.001	0.03	0.11
Correlation between SHS and COV partialled for AAS	0.1	0.03	3.27	<.001	0.05	0.17
Correlation between SHS and COV partialled for ACE	0.16	0.04	4.26	<.001	0.09	0.24
Correlation between SHS and ACE partialled for COV	0.06	0.02	2.86	0.004	0.03	0.1

All effect sizes are deemed valid based on the range between the lower and upper confidence intervals for each of these partial correlations and their associated p-values. However, these effect sizes exhibit considerable variation, with those for SWL generally larger than those for SHS. Given that all confidence intervals are positive, it can be concluded that types of effect sizes, denoted as a's and b's, significantly contribute to the overall mediated effect size.

5. Discussion

The findings of the current investigation indicate that all null hypotheses are rejected, apart from the hypothesis concerning the ACE data. Specifically, the model fit was deemed acceptable for the total effects models involving SWL and SHS. The RAS construct was identified as a significant mediator between COV and SWL, as well as between COV and SHS data. As measured by the BRS, COV also influenced resilience in relation to the SWL and SHS results. The ACE results demonstrated that the ACE inventory had no statistically significant effect. However, the direct effect of COV on SWL, while controlling for the effect of ACE, and the effect of ACE on SWL, while controlling for the direct effect, are statistically significant. Based on these results, ACE does not mediate between COV and SWL or between COV and SHS. Finally, the AAS results indicate that mediation is significant between COV, AAS, SHS, and SWL.

The findings related to Adverse Childhood Experiences (ACE) were unexpected.

According to van der Kolk (2014), there is limited capacity for individuals to mitigate the effects of childhood trauma. He posits that individuals with ACE scores exceeding three consistently encounter enduring difficulties in subjective well-being, interpersonal relationships, resilience, and overall happiness. Consequently, van der Kolk's research implies that childhood trauma predicts subjective well-being (SWB). Furthermore, recent studies have demonstrated a correlation between ACE and SWB among college students (Kelifa, Yang, Carly & Wang, 2021). Given that the participants in this study are not college students, it prompts an inquiry into whether age, particularly the distinction between those currently in college and those who have completed their education, is a moderating variable in this relationship.

Additionally, Munoz (2020) has proposed that hope may function as a protective factor against the effects of ACE. His findings suggest that ACE survivors exhibit higher levels of subjective well-being when they report elevated levels of hope. Suppose Munoz's (2020) research is replicable. In that case, the role of hope should be investigated as a mediator in the relationship between SWB and the other factors (AAS, BRS, SHS, SWLS, RAS) examined in this study.

The single mediation model analyzed in this paper encompasses the total effect and the two effects whose products constitute the mediation effect. Effect size measures for both were reported, with ratios and proportions for the former and partial correlations for the latter. As noted earlier, there is no significant mediation effect for ACE models. These conclusions hold for the ratio and proportion effect sizes, as detailed in Table 9.

The title of this paper could have been "The Relative Effects of the Complexity of Mediators in Single Mediator Models." The complexity of the mediator was assessed concerning the mediated effect using the same independent and dependent constructs. A single mediator can be substituted with multiple parallel and serial mediator models. Another extension will employ recently proposed and tested multivariate effect size measures (Gomer et al., 2019; Maydeu-Olivares & Shi, 2017; Raykov & Marcoulides, 2010). Gomer, Jiang, and Yuan (2019) proposed two sets of effect sizes based on the previously discussed discrepancy function, with the other related to Cohen's d. Finally, the dataset utilized in this paper included information on residential location (rural, urban, and suburban). The models employed in this paper can be replicated in future research as a multiple-group Structural Equation Modeling (SEM) model for these three residential types.

6. Conclusion

The study furthered statistical comprehension by calculating various effect size metrics across all mediation models, including indirect-to-direct and indirect-to-total ratios. The most substantial mediated effects were identified for BRS and RAS, whereas ACE effects were negligible and non-significant. Standardized coefficients, R^2 values, and partial correlations were systematically reported, enriching the interpretation of direct and mediated relationships. By integrating rigorous SEM techniques with detailed effect size interpretation, this study exemplifies the application of mediation analysis in complex psychosocial models. It provides a replicable framework for future research on well-being. The study underscores that personal attributes directly and indirectly influence well-being through psychological and relational factors. Relationship satisfaction, resilience, and attachment quality are robust mediators, while adverse childhood experiences, despite their psychological significance, did not demonstrate a mediating role in this model. These findings offer valuable insights for interventions to enhance well-being, particularly by fostering strong relationships and resilience skills.

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