Data Analytic Plan for the Factor Analyses

We conducted exploratory factor analysis (EFA) of the 50 relational spirituality items from eight measures using FACTOR (version 11.05.01; Lorenzo-Seva & Ferrando, 2021). Data were acceptable for EFA (Kaiser-Meyer-Olkin index > .80 considered good; index = 0.87; significant Barlett's test χ^2 = 9768.70(1225), $p < 0.001$). Data were multivariate non-normal (kurtosis statistic = 60.42, $p < 0.001$). We used robust unweighted least squares estimation mean-and-variance adjusted (ULSMV), and the Pearson correlation matrix given response options ≥ 5 on all items (Sellbom & Tellegen, 2019). We used the default oblique Promin rotation and the default 500 bias-corrected (BC) bootstrap samples for robust estimation (Lorenzo-Seva & Ferrando, 2021). We determined model fit using the comparative fit index (CFI > 0.95 = good fit, Schreiber et al., 2006; CFI > 0.90 = acceptable fit, Brown, 2006) and the root mean square error of approximation (RMSEA < 0.06 = good fit, Schreiber et al., 2006; RMSEA < 0.08 = acceptable fit, Brown, 2006). We then estimated the EFA results using a structural equation model (SEM). Together, these analyses comprised our first research aim, to examine the internal structure of a set of items and then extend the findings to the SEM context to test for measurement invariance and examine associations with external variables (Ferrando, 2021).

Results

As an initial step, we explored the dimensionality of 50 items theorized to operationalize RSM constructs. We compared multiple retention methods, which is an advantage of FACTOR. This allowed us to avoid relying on global model fit to determine the number of factors, which tends to result in over-factoring (Schmitt et al., 2018). First, a test of closeness to unidimensionality using the explained common variance was below the threshold of 0.85 and suggested multidimensionality (Lorenzo-Seva & Ferrando, 2021). Second, a plot of eigenvalues from the reduced correlation matrix hinted at between 3-6 factors, given 'elbows' in the plot, however the last 'substantive' drop occurred with the 4th factor, and there was a distinct gradual flattening after the 6th factor (Lorenzo-Seva et al., 2011). The Hull method using the RMSEA as the criterion suggested four factors, as did the minimum average partial test. The RMSEA 90% lower bound criterion of < 0.05 suggested six factors (Preacher et al., 2013) and parallel analysis using minimum rank factor analysis (95% threshold), suggested seven factors (Timmerman & Lorenzo-Seva, 2011). We opted for the 4-factor solution, given our research conditions (e.g., medium sample size, number of variables, ratio of variables to extracted factors), and substantive theoretical interpretability (Lorenzo-Seva et al., 2011; Morin et al., 2016; Schmitt et al., 2018).

The 4-factor first-order solution fit the data (CFI = 0.927, RMSEA = 0.06, 90% confidence interval [CI; 0.058, 0.061]). The solution yielded acceptable estimates of reliability: $\rho = 0.87$ for the seeking factor, comprised of acceptance of doubt and R/S exploration items; $\rho = 0.89$ for the dwelling factor, comprised of perceived closeness to God and low avoidant attachment relating to God items; $\rho = 0.89$ for the struggles factor, comprised of R/S struggles with God and other persons, and anxious God attachment items; $\rho = 0.90$ for the dysregulation factor, comprised of low intra- and interpersonal differentiation, ambiguity *in*tolerance, and experiential avoidance items.

As a sensitivity analysis, we conducted Bayesian structural equation modeling (BSEM), using the items as categorical indicators. BSEM represents EFA and confirmatory factor analysis hybridity or semi-confirmatory modeling, allowing for flexible, theory informed testing of the dimensionality of a set of items and identifying model misfit (Ferrando, 2021; Muthén & Muthén 1998–2017; Schmitt et al., 2018). We used the default equal tail percentages CI, and the default Gibbs sampler. We assessed convergence using the potential scale reduction factor (PSR) < 1.10 and used the rate of convergence to aid in determining the priors (Asparouhov et al., 2015). A posterior predictive *p*-value (*PPP*) > 0.05 indicated acceptable fit. The model fit the data (*PPP* = 0.17; 95% CI for the difference between observed and replicated χ^2 values, -64.68, 224.22; model priors for cross-loadings ~$N(0,0.01)$ and covariances $\sim IW(0,40)$). Table S1 presents the factor loadings from the EFA and BSEM analyses.

Bifactor Solutions

As a second step, we explored the dimensionality of the four first-order EFA factors using FACTOR to conduct exploratory bifactor modeling (Lorenzo-Seva & Ferrando, 2019). For the seeking factor, an oblique bifactor solution (CFI = 0.997; RMSEA = 0.038, 90% CI [0.012, 0.047]) showed a strong general factor, with two specific factors (doubting; exploration) and factor loadings > 0.30 on general *and* specific factors. These results supported the fit of the bifactor solution (Lorenzo-Seva & Ferrando, 2019). Examining the pattern of salient loadings is a recommended criterion for determining the appropriateness of a bifactor solution (Lorenzo-Seva & Ferrando, 2019; Morin et al., 2016; Schmitt et al., 2018). For the dwelling factor, an orthogonal bifactor solution fit the items (CFI = 0.990; RMSEA = 0.05, 90% CI [0.036, 0.061]), and the pattern of salient loadings showed a strong general factor, and two specific factors (perceived closeness to the divine; avoidant God attachment). For the struggles factor, an oblique bifactor solution (CFI = 0.996; RMSEA = 0.042, 90% CI [0.013, 0.054]) showed a strong general factor, with three specific factors (divine struggles; interpersonal struggles; anxious God attachment). Last, an orthogonal bifactor solution fit the items comprising the dysregulation factor (CFI = 0.999; RMSEA = 0.01, 90% CI [0.002, 0.02]), with a strong general factor, and five specific factors (I-positioning; reactivity; experiential avoidance; cutoff; ambiguity intolerance).

Measurement Model

We then fit the four bifactor solutions in a confirmatory SEM using M*plus* (Muthén & Muthén 1998–2017, 2024). Eid et al. (2017) suggested that one way to obtain more interpretable solutions when fitting bifactor models was to use one of the specific factors to define the general factor (S-1 model). We used robust maximum likelihood estimation (MLR). In addition to the CFI and RMSEA, we used the standardized root mean square residual [SRMR] ≤ 0.08 to indicate an approximately well-fitting model (Asparouhov & Muthén, 2018). The model fit the data (CFI = 0.911, RMSEA = 0.042, 90%CI (0.04, 0.044), SRMR = 0.046). The pattern of loadings did not support a bifactor model for the seeking dimension. We proceeded with a first-order model. Table S2 contains the factor loadings from the measurement model.

Invariance Tests

We examined measurement invariance using demographic variables for which we had enough participants to compare age (i.e., ≤ the median age of 27, and > 27), gender (i.e., male and female), and race (i.e., non-White and White). We used a multigroup approach (Brown, 2006) that involved unconstrained versus constrained model comparisons of factor loadings (metric invariance; ∆SRMR ≤ 0.03 supports invariance) and intercepts (scalar invariance; ∆SRMR ≤ 0.015 supports invariance; Putnick & Bornstein, 2016). The SRMR is robust to non-normal data, sample size, and model size and complexity (Maydeu-Olivares et al., 2018; Shi & Maydeu-Olivares, 2020). We also used ∆RMSEA ≤ 0.01 to indicate invariance (Putnick & Bornstein, 2016). The unconstrained (i.e., configural) model for age fit the data (RMSEA = 0.043, 90%CI [0.041, 0.046], SRMR = 0.051). Comparison against the configural model showed metric invariance (∆SMR = 0.002, ∆RMSEA = 0.00) and comparison against the metric model showed scalar invariance (∆SRMR = 0.001, ∆RMSEA = 0.001). The configural model for gender fit the data (RMSEA = 0.045, 90%CI [0.042, 0.047], SRMR = 0.051), and comparisons showed invariance (∆SRMR = 0.002, ∆SRMR = 0.002; ∆RMSEA = 0.001, ∆RMSEA = 0.001; metric and scalar invariance, respectively). The configural model for race fit the data (RMSEA = 0.045, 90%CI [0.043, 0.047], SRMR = 0.052), and comparisons showed invariance (∆SRMR = 0.002, ∆SRMR = 0.001; ∆RMSEA = 0.001, ∆RMSEA = 0.001).

We tested invariance across time using a single sample approach that involved correlating latent factors and loadings across time (i.e., f1λ1 at time1 with f1λ1 at time 2 …; Brown, 2006). The configural model fit the data (RMSEA = 0.028, 90%CI [0.026, 0.029], SRMR = 0.05). Model comparisons supported longitudinal measurement invariance (∆SRMR = 0.001, ∆RMSEA = 0.001 for metric invariance; ∆SRMR = 0.00, ∆RMSEA = 0.001 for scalar invariance).

External Correlates

We extended the measurement model at time 1 to include associations with external correlates (Eid et al., 2018). We used external correlates that indicated flourishing: low anxiety symptoms, high positive emotion (i.e., joy to indicate subjective well-being), and high life purpose (eudaimonic well-being). We used these outcomes as latent variables predicted by the factors comprising the measurement model. The model fit the data (CFI = 0.918, RMSEA = 0.038, 90%CI (0.037, 0.04), SRMR = 0.048; symptoms R^2 = 0.46, positive emotion R^2 = 0.47, life purpose R^2 = 0.36).

The seeking aspect of R/S exploration was positively associated with life purpose (*B* = 0.11, *SE* = 0.04, p = 0.002), whereas the doubting aspect of seeking was negatively associated with life purpose (*B* = -0.04, *SE* = 0.02, p = 0.04) and positively associated with anxiety symptoms (*B* = 0.07, *SE* = 0.02, $p <$ 0.001). The dwelling general factor, with perceived closeness to God as the reference construct, positively predicted life purpose (*B* = 0.26, *SE* = 0.03, $p <$ 0.001) and positive emotion (*B* = 0.34, *SE* = 0.05, $p <$ 0.001). Greater attachment to God avoidance predicted greater symptoms (*B* = 0.10, *SE* = 0.05, p = 0.04). The regulation general factor, with emotional reactivity as the reference construct, was negatively associated with symptoms (*B* = -0.25, *SE* = 0.03, $p <$ 0.001), and positively associated with joy (*B* = 0.21, *SE* = 0.05, $p <$ 0.001) and life purpose (*B* = 0.09, *SE* = 0.03, p = 0.01). Greater I-positioning predicted lower symptoms (*B* = -0.16, *SE* = 0.05, p = 0.002), greater joy (*B* = 0.53, *SE* = 0.09, $p <$ 0.001), and greater life purpose (*B* = 0.15, *SE* = 0.05, p = 0.002). Greater differentiation (i.e., lower cutoff) predicted greater joy (*B* = 0.11, *SE* = 0.03, p = 0.001), whereas greater regulation (I.e., lower experiential avoidance) predicted lower symptoms (*B* = -0.13, *SE* = 0.04, p = 0.001) and greater life purpose (*B* = 0.07, *SE* = 0.04, p = 0.046). The struggles general factor, with divine struggles as the reference construct, was a positive predictor of symptoms (*B* = 0.20, *SE* = 0.04, $p <$ 0.001) and a negative predictor of joy (*B* = -0.14, *SE* = 0.05, p = 0.004).

Sensitivity Analysis for the Latent Transition Analysis

As a robustness check for the results from the 2-step approach to LTA reported in Table S4, we conducted single-step random intercept – latent transition analysis (RI-LTA; Muthén & Asparouhov, 2022), again using the observed score variables as in the 2-step approach. The chief advantage of the RI-LTA is the separation of between-level stable, trait differences, from the within-level transitions among classes (Muthén & Asparouhov, 2022). The sample size for the RI-LTA was *N* = 964, which included *n* = 97 who only had data at time 2. Muthén (2007) noted, “the best approach is to use all available information: those who have data at both occasions + those who have data at only one of the 2 occasions” (para. 1). We used the direct approach to testing for measurement invariance (Cheung & Lau, 2012), which involved using the bias-corrected bootstrap 99% confidence interval to test the significance of the difference between each pair of parameters over time. Two comparisons demonstrated longitudinal non-invariance (i.e., the doubts as positive indicator among subgroup 2 across time, and the doubts as positive indicator among subgroup 4 across time). Results paralleled the pairwise comparison of parameter differences using the Wald test, constraining one pair of parameters at a time. The overall Wald test comparing the full noninvariant model to the full invariant model was significant (Wald χ^2 = 100.68(48), $p < 0.001$). RI-LTA results are presented in Table S4 and largely replicated those obtained from the 2-step approach, in terms of the likelihood of staying in the same class *and* the patterns of movement among classes across time. The main difference that emerged was the greater likelihood of staying among the *regulated seekers* in the RI-LTA results, although both analyses suggested that the likelihood of their movement was greatest to the *contented dwellers*.

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Table S1

Exploratory Factor Analysis and Bayesian Structural Equation Model Results

	EFA				BSEM			
Items	F1	F2	F3	F4	F1	F2	F3	F4
DOS3_1	**-0.41**	0.19	0.10	0.05	**0.34**	0.07	0.07	-0.05
DOS3_2	**-0.42**	0.10	0.12	0.06	0.27	0.02	0.02	-0.06
DOS3_3	**-0.35**	0.09	-0.10	0.11	**0.33**	-0.01	-0.05	0.11
DOS3_4	**0.63**	0.06	-0.06	0.09	**0.49**	0.01	-0.01	0.06
DOS3_5	**0.74**	0.07	-0.07	0.06	**0.57**	-0.01	-0.03	0.06
DOS3_6	**0.72**	-0.004	-0.10	0.12	**0.55**	-0.01	0.03	0.02
DOS3_7	**0.61**	0.08	-0.04	0.13	**0.43**	-0.04	-0.04	0.05
DOS3_8	**0.70**	-0.01	-0.08	0.09	**0.50**	0.01	-0.004	-0.01
DOS3_9	**0.79**	-0.02	-0.11	0.16	**0.58**	-0.004	0.02	0.04
DOS3_10	**0.42**	-0.03	0.15	-0.01	**0.79**	0.01	0.002	0.01
DOS3_11	**0.39**	-0.02	0.12	-0.01	**0.79**	-0.01	0.05	-0.01
DOS3_12	**0.38**	-0.03	0.16	0.01	**0.70**	0.003	-0.01	0.01
AMB3_1	**0.43**	-0.03	0.08	0.02	**0.57**	-0.01	0.03	0.001
AMB3_2	**0.39**	-0.06	0.10	0.06	**0.58**	0.001	0.04	0.04
AMB3_3	**0.45**	-0.08	0.13	0.02	**0.51**	0.02	-0.03	-0.01
DBT3_1	0.12	**0.44**	-0.21	**-0.31**	-0.03	**0.39**	0.03	0.09
DBT3_2	0.13	**0.47**	-0.24	**-0.34**	0.004	**0.39**	0.06	0.09
DBT3_3	0.10	-0.13	**0.41**	0.09	-0.08	-0.08	0.20	0.08
DBT3_4	0.16	**0.38**	-0.27	-0.29	-0.02	0.29	0.04	0.08
SSG3_1	0.20	0.19	0.15	-0.26	0.01	-0.003	**0.54**	0.02
SSG3_2	0.12	0.10	**0.43**	-0.07	-0.01	-0.01	**0.71**	-0.06
SSG3_3	0.14	0.14	**0.33**	-0.20	0.001	0.00	**0.65**	0.03
SSI3_1	0.25	0.27	-0.01	-0.18	-0.01	0.01	**0.40**	-0.04
SSI3_2	0.11	0.23	0.11	-0.17	0.01	0.01	**0.41**	-0.01
SSI3_3	0.21	**0.34**	-0.12	**-0.32**	-0.01	0.07	0.29	0.06
ATGAX3_1	0.01	0.04	**0.71**	-0.10	-0.001	0.03	**0.74**	0.06
ATGAX3_2	-0.01	-0.04	**0.81**	0.01	0.01	-0.02	**0.84**	-0.05
ATGAX3_3	-0.06	0.003	**0.83**	0.03	0.01	0.01	**0.80**	-0.04
ATGAX3_4	0.00	-0.01	**0.70**	-0.10	-0.01	-0.01	**0.72**	0.11
ATGAX3_5	0.14	0.003	**0.55**	0.003	-0.01	-0.01	**0.65**	-0.02
ATGAV3_1	-0.03	0.06	-0.004	**-0.58**	-0.01	-0.01	0.002	**0.64**
ATGAV3_2	-0.04	0.06	0.02	**-0.65**	-0.01	-0.002	0.01	**0.69**
ATGAV3_3	-0.02	0.06	0.11	**-0.55**	0.00	0.01	0.07	**0.56**
ATGAV3_4	-0.10	-0.01	0.24	**-0.41**	-0.03	-0.01	0.09	**0.51**
ATGAV3_5	-0.04	0.07	-0.02	**-0.44**	0.01	0.01	-0.004	**0.45**
DSE3_1	0.13	0.05	-0.14	**0.70**	-0.01	-0.02	0.01	**-0.81**
DSE3_2	0.09	0.08	-0.03	**0.77**	-0.01	0.03	-0.02	**-0.74**
DSE3_3	0.08	0.03	-0.11	**0.74**	0.001	-0.02	0.002	**-0.84**
DSE3_4	0.06	0.003	0.14	**0.73**	-0.03	-0.001	0.12	**-0.72**
DSE3_5	-0.12	0.15	-0.06	0.19	0.05	0.03	-0.02	**-0.30**
DSE3_6	0.05	0.16	-0.12	**0.38**	0.01	0.03	0.001	**-0.52**
QST3_1	-0.07	**0.47**	0.01	0.12	0.01	**0.49**	-0.01	-0.07
QST3_2	-0.16	**0.53**	0.10	0.03	0.004	**0.63**	-0.04	0.11
QST3_3	-0.13	**0.64**	0.10	0.25	0.03	**0.72**	-0.02	-0.07
QST3_4	-0.04	**0.75**	0.03	0.15	-0.01	**0.85**	-0.02	-0.02
QST3_5	-0.08	**0.81**	0.11	0.16	0.002	**0.89**	0.01	-0.01
QST3_6	-0.08	**0.58**	0.22	0.14	-0.01	**0.70**	0.06	0.01
AVD3_1	**0.36**	-0.02	0.23	-0.10	**0.57**	0.02	-0.03	-0.06
AVD3_2	**0.48**	0.02	0.21	-0.04	**0.59**	-0.02	-0.02	-0.05
AVD3_3	**0.54**	0.03	0.20	-0.05	**0.60**	-0.01	-0.07	-0.03
ω	0.81	0.81	0.82	0.85	0.89	0.84	0.86	0.88
H-index	0.90	0.88	0.89	0.89	0.91	0.91	0.90	0.91

Note: F = factor, QST = quest – religious/spiritual exploration; DBT = doubts as positive; SSG = spiritual struggles with God; SSI = spiritual struggles – interpersonal; ATGAX = attachment to God anxiety;

DSE = daily spiritual experiences – perceived closeness to God; ATGAV = attachment to God avoidance; DOS = differentiation of self; AMB = ambiguity tolerance; AVD = experiential avoidance. Bold font = salient factor loadings > 0.30. *H*-index value > 0.80 suggests stability of the latent variable across research contexts. BSEM = Bayesian structural equation model. ω for both models and *H* for the BSEM model calculated using Excel (Dueber, 2017).

Table S2

Confirmatory Structural Equation Measurement Model

	F1	F2	F3			F4		F5				
Items			G	S1	S2	G	S1	G	S1	S2	S3	S4
QST3_1	0.46											
QST3_2	0.61											
QST3_3	0.74											
QST3_4	0.84											
QST3_5	0.91											
QST3_6	0.66											
DBT3_1		0.79										
DBT3_2		0.89										
DBT3_4		0.63										
SSG3_1			0.78									
SSG3_2			0.73									
SSG3_3			0.80									
SSI3_1			0.45	0.65								
SSI3_2			0.37	0.55								
SSI3_3			0.41	0.62								
ATGAX3_1			0.43		0.72							
ATGAX3_2			0.46		0.75							
ATGAX3_3			0.37		0.78							
ATGAX3_4			0.48		0.54							
ATGAX3_5			0.44		0.48							
DSE3_1						0.82						
DSE3_2						0.77						
DSE3_3						0.89						
DSE3_4						0.63						
DSE3_6						0.51						
ATGAV3_1						-0.42	0.57					
ATGAV3_2						-0.47	0.68					
ATGAV3_3						-0.42	0.50					
ATGAV3_4						-0.32	0.42					
ATGAV3_5						-0.29	0.36					
DOS3_4								0.69				
DOS3_5								0.72				
DOS3_6								0.74				
DOS3_7								0.65				
DOS3_8								0.75				
DOS3_9								0.80				
DOS3_1								0.36	0.60			
DOS3_2								0.37	0.61			
DOS3_3								0.40	0.50			
DOS3_10								0.38		0.84		
DOS3_11								0.34		0.84		
DOS3_12								0.34		0.67		
AMB3_1								0.31			0.80	
AMB3_2								0.27			0.87	
AMB3_3								0.40			0.55	
AVD3_1								0.35				0.67
AVD3_2								0.48				0.67
AVD3_3								0.55				0.62

Note: F = factor, G = general factor, S = specific factor; QST = quest – religious/spiritual exploration; DBT = doubts as positive; SSG = spiritual struggles with God; SSI = spiritual struggles – interpersonal; ATGAX = attachment to God anxiety; DSE = daily spiritual experiences – perceived closeness to God; ATGAV = attachment to God avoidance; DOS = differentiation of self; AMB = ambiguity tolerance; AVD = experiential avoidance.

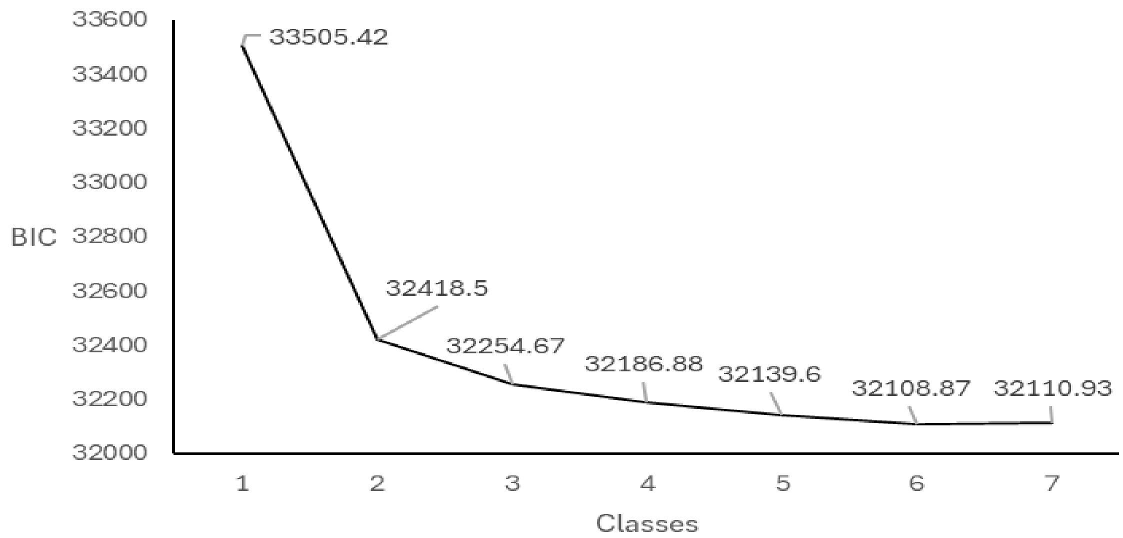

Figure S1. Plot of Bayesian information criteria values to determine number of subgroups at time 1.
Note: BIC = Bayesian information criterion.

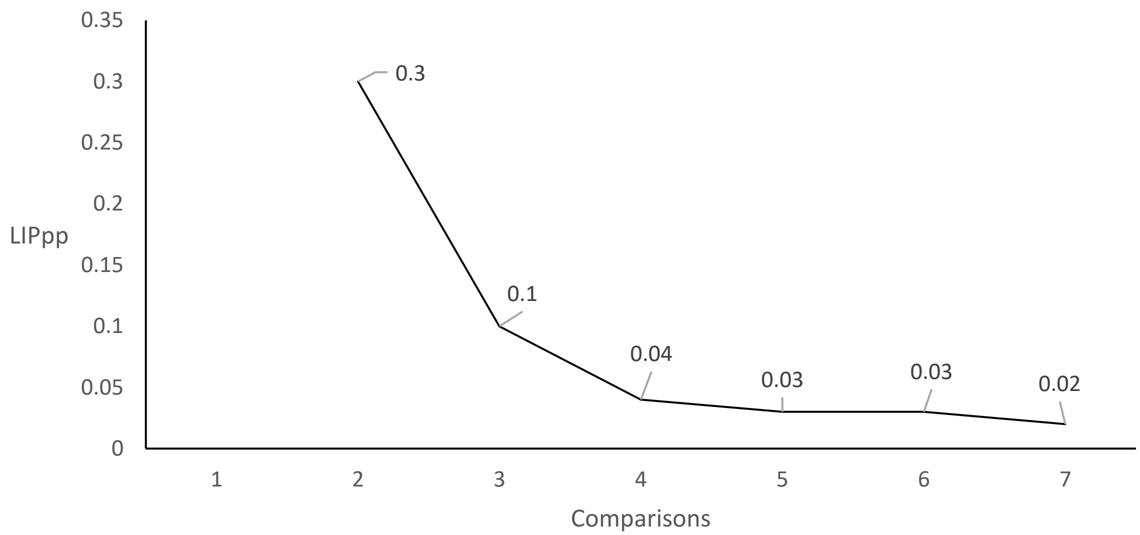

Figure S2. Plot of effect sizes to determine number of subgroups at time 1.
Note: LIPpp = likelihood increment percentage per parameter. Comparison 2 = 2-class solution versus 1-class solution, comparison 3 = 3-class solution versus 2-class solution, ... comparison 7 = 7-class solution versus 6-class solution. LIPpp ≥ 0.3 indicates large effect size/improvement in fit, LIPpp ≥ 0.1 < 0.3 indicates moderate effect size/improvement in fit, LIPpp ≥ 0.02 < 0.1 indicates small effect size/improvement in fit (Grimm et al., 2021).

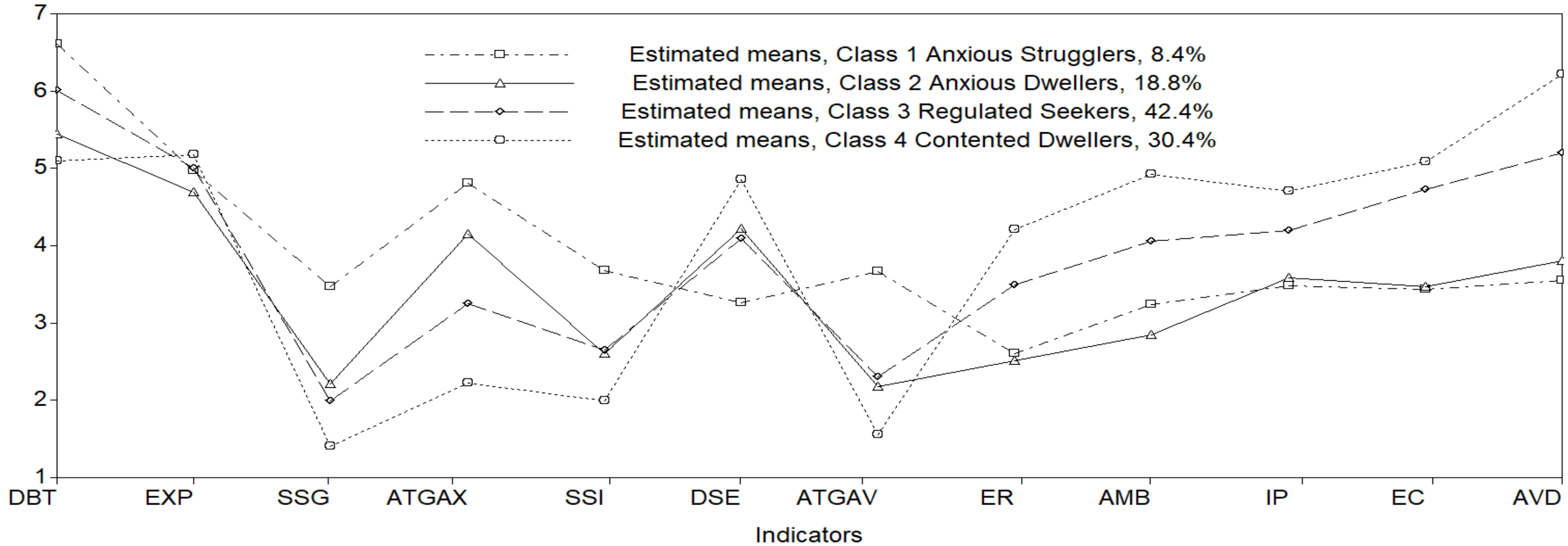

*Figure S*3. Estimated means from the relational spirituality model variables at time 1.

Note: DBT = doubts as positive, EXP = religious/spiritual exploration, SSG = religious/spiritual struggles with the divine/God, ATGAX = attachment to God – anxiety, SSI = spiritual struggles with others/interpersonally, DSE = daily spiritual experiences – perceived closeness to the divine/God, ATGAV = attachment to God – avoidance, ER = emotion regulation – reactivity, AMB = ambiguity tolerance, IP = I-positioning, EC = differentiation – emotional cutoff, AVD = experiential avoidance. ER - AVD indicators coded so that high scores = greater regulation.

Table S3

Estimated Probabilities for the Covariates on Class Membership and Estimated Means for the Distal Outcomes by Class

	Anxious Strugglers	*Anxious Dwellers*	*Regulated Seekers*	*Contented Dwellers*		
Time 1 Covariates		Probabilities			*M* (*SD*) for Entire Sample	Range for Entire Sample
Age	-0.16	-0.08	-0.08	--	31.95 (10.79)	21.00 – 77.00
Ideological Commitment	0.45	NS	0.38	--	3.74 (1.76)	1.00 – 7.00
Gender	NS	0.81	NS	--		
Sexual Identification	NS	NS	NS	--		
Race	NS	-0.69	NS	--		
Outcomes		Means			T1 *M* (*SD*) for Entire Sample	T1 Range for Entire Sample
Humility	4.11[a] (4.12[a])	4.17[a] (4.06[b])	4.14[a] (4.13[b])	4.33[b] (4.25[c])	4.20 (0.48)	1.00 – 5.00
Gratitude	5.20[a] (5.20[a])	6.08[b] (5.91[b])	6.13[b] (6.06[b])	6.58[c] (6.49[c])	6.17 (0.75)	1.00 – 7.00
Forgiveness	2.83[a] (2.89[a])	2.97[a] (2.89[a])	3.56[b] (3.54[b])	4.09[c] (4.02[c])	3.55 (0.90)	1.00 – 5.00
Spiritual Grandiosity	1.81[a]	2.32[b]	1.89[a]	2.21[b]	2.06 (0.90)	1.00 – 5.00
RW-authoritarianism	2.45[a] (2.15[a])	2.90[ab] (2.40[a])	2.28[a] (2.18[a])	2.86[ab] (2.30[a])	2.54 (1.35)	1.00 – 7.00
Social Justice Advocacy	3.82[a] (3.48[a])	3.37[b] (3.23[a])	3.46[b] (3.48[a])	3.51[b] (.3.50[a])	3.49 (0.99)	1.00 – 5.00
Illusory Spiritual Health	2.27[a] (2.21[a])	3.00[b] (2.90[b])	2.66[c] (2.50[a])	3.51[d] (3.44[c])	2.95 (0.85)	1.00 – 5.00
Intrinsic Religiousness	3.03[a]	3.64[b]	3.48[c]	3.65[b]	3.52 (0.54)	1.00 – 4.00
Materialistic Prayer	2.73[a] (2.65[a])	3.13[b] (3.23[b])	2.77[a] (2.75[a])	3.12[b] (3.17[b])	2.98 (1.05)	1.00 – 5.00
Meditative Prayer	3.19[a] (3.22[a])	4.08[b] (3.80[b])	3.91[b] (3.58[ab])	4.50[c] (4.45[c])	4.02 (0.94)	1.00 – 5.00
Anxiety Symptoms	3.13[a] (3.58[a])	2.52[a] (2.18[b])	1.69[b] (1.64[b])	0.41[c] (0.53[c])	1.54 (1.50)	0.00 – 6.00
Joy	3.97[a] (3.37[a])	4.74[b] (4.86[b])	5.04[c] (4.72[b])	6.02[d] (5.99[c])	5.21 (1.24)	1.00 – 7.00
Life Purpose	3.13[a] (2.61[a])	3.57[b] (3.69[b])	3.64[b] (3.77[b])	4.33[c] (4.32[c])	3.83 (0.81)	1.00 – 5.00
Belongingness	3.91[a] (3.39[a])	4.05[a] (3.82[a])	4.64[b] (4.30[b])	5.28[c] (5.18[c])	4.66 (1.17)	1.00 – 6.00

Note: Gender coded 0 = male, 1 = female; sexual orientation coded 0 = non-heterosexual, 1 = heterosexual; race coded 0 = non-White, 1 = White. Probabilities significant at $p < 0.05$. T1 = time 1. *M* = mean, *SD* = standard deviation. NS = nonsignificant. RW = right-wing. Covariate effects on likelihood of class membership determined using the R3STEP method in M*plus*. Different superscripts represent significant mean differences from pairwise comparisons on the outcome variables derived from the BCH command in M*plus*. Time 2 outcome means in parentheses for the variables that were available at time 2, for comparison.

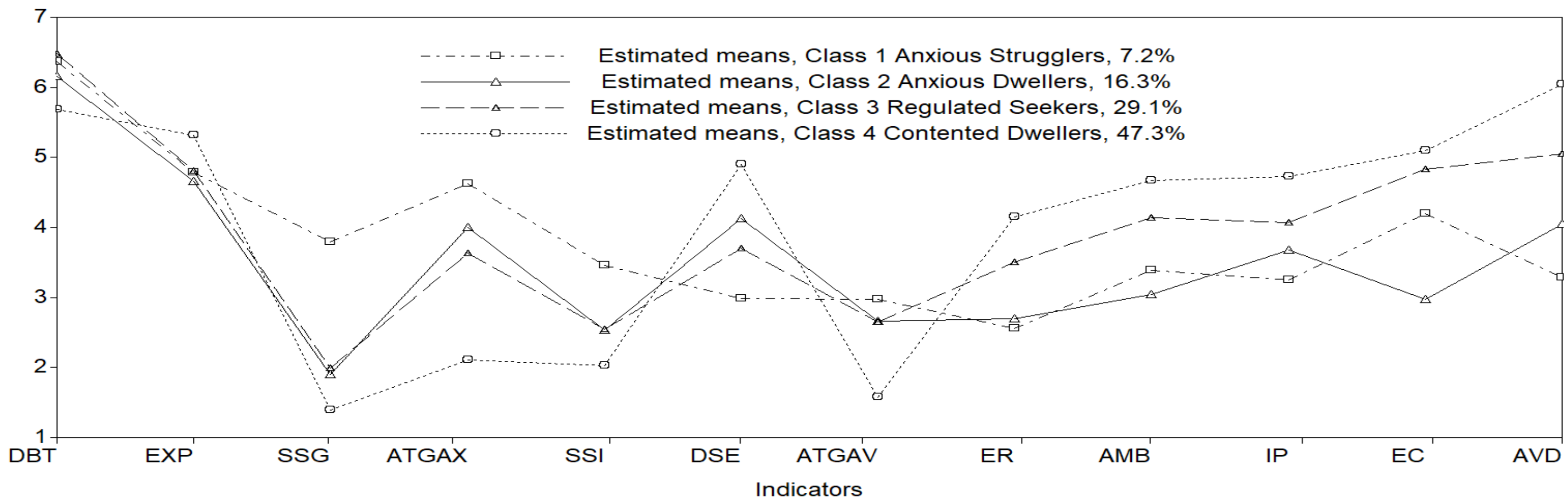

Figure S4. Estimated means from the relational spirituality model variables at time 2.
Note: DBT = doubts as positive, EXP = religious/spiritual exploration, SSG = religious/spiritual struggles with the divine/God, ATGAX = attachment to God – anxiety, SSI = spiritual struggles with others/interpersonally, DSE = daily spiritual experiences – perceived closeness to the divine/God, ATGAV = attachment to God – avoidance, ER = emotion regulation – reactivity, AMB = ambiguity tolerance, IP = I-positioning, EC = differentiation – emotional cutoff, AVD = experiential avoidance. ER - AVD indicators coded so that high scores = greater regulation.

Table S4

Latent Transition Probabilities from Time 1 to Time 2

LTA 2-step	*Anxious Strugglers*	*Anxious Dwellers*	*Regulated Seekers*	*Contented Dwellers*
Anxious Strugglers	**0.45**	0.31	0.24	0.00
Anxious Dwellers	0.08	**0.78**	0.15	0.00
Regulated Seekers	0.06	0.02	**0.59**	0.33
Contented Dwellers	0.00	0.00	0.00	**1.00**
RI-LTA noninvariant	*Anxious Strugglers*	*Anxious Dwellers*	*Regulated Seekers*	*Contented Dwellers*
Anxious Strugglers	**0.53**	0.30	0.17	0.00
Anxious Dwellers	0.03	**0.69**	0.17	0.11
Regulated Seekers	0.11	0.00	**0.74**	0.15
Contented Dwellers	0.00	0.00	0.04	**0.96**

Note: Time 1 classes on the left, in the first column, Time 2 classes along the top row. LTA 2-step = latent transition analysis, longitudinal measurement non-invariance modeled, time 1 and time 2 latent class parameters fixed from the independent latent profile analysis, time 1 class sizes fixed, and time 2 class sizes freely estimated (Bakk & Kuha, 2021). RI-LTA noninvariant = random intercept – latent transition analysis, with a single continuous random intercept, longitudinal measurement non-invariance modeled, and correlated residuals among the same indicator across time (Muthén & Asparouhov, 2022), and indicators of the random intercept set to 1 (Moore et al., 2025). Unconditional models.