

Guide to Latent Profile Analysis

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What is latent profile analysis?

Latent Profile Analysis (LPA) tries to identify clusters of individuals (i.e., latent profiles) based on responses to a series of continuous variables (i.e., indicators). LPA assumes that there are unobserved latent profiles that generate patterns of responses on indicator items. LPA differs from most typical analytic approaches in that it takes a person-centered approach to data instead of a variable-centered approach. Analyses like regression, path analysis, and SEM use variable-centered approaches as they seek to compare variables to each other. LPA, as a mixture modeling approach, seeks to group people together based on similarity in how they respond to indicator items.

Unique Aspects of LPA

I typically call LPA “the most qualitative quantitative analysis.” It is very difficult to make specific a priori (prior to data analysis) predictions regarding an LPA, as its makeup is determined by the data. It is difficult to even predict the number of profiles that will emerge in a specific dataset. As such, you must test multiple models of LPA, moving from a single profile model to a two-profile model to a three-profile model and so on. You can then compare the various models on indices to narrow down your choices of model to present.

Power

It is difficult to assess statistical power for latent analyses, but simulations suggest anywhere from 300 to 1,000 participants (Nylund-Gibson & Choi, 2018) or a minimum of 500 participants (Finch & Bronk, 2011), so we recruited 300-500 participants for new data collected.

Key Indices for LPA

Information Criteria (includes Akaike [AIC], Bayesian [BIC], and adjusted BIC [aBIC]): It is necessary to report at least one of these indices when reporting LPA findings. As you test increasingly complicated profiles, you want to see these indices trend toward smaller numbers.

Entropy: This index ranges from 0 to 1 (much like correlation) and informs you on the distinctiveness of each profile from each other profile. The closer to 1 you are, the more distinct each profile is. Rule of thumb is .70 and up indicates distinctive profiles. As you iterate multiple profile models, you want to see entropy increasing.

Class Counts and Proportions: This breaks down the number/percentage of participants in each profile. Typically, you want at least 5% of the participants in the smallest profile. Profiles that are smaller and have fewer participants (~10) may not generalize to other samples and may represent an odd quirk in the data. If you are examining nationally representative data (more than 1,000 participants), this rule does not necessarily apply as 2% may encompass quite a few participants.

Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (aLRT): The Lo-Mendell-Rubin adjusted likelihood ratio test (aLRT) compares the estimated model to the model with one fewer profile and estimates p -values, which indicate if model fit improves when adding the additional profile (Lo et al., 2001). If the p value exceeds .05, then the estimated model is not a significantly better fit for the data than the model with one fewer profile. As such, you should return to the model with one fewer profile.

Rule of High, Medium, Low: This is not a specific index that Mplus provides, however, as you graph the indicator items in a figure, take a look at the patterns of your different profiles. If they all resemble the same pattern, just with high, medium, and low values, you should probably switch back to a variable-centered approach. Patterns of high, medium, and low are not qualitatively distinct from each other and instead suggest that a variable-centered approach is more suited to the data.

Transferring Data from SPSS to Mplus

Initial Preparation

1. Make sure that your SPSS file does not have any string type (qualitative) data. Mplus cannot read string variables.
2. If your dataset has missing data, you will need to code it as such. Mplus cannot read blanks in your files. I typically set my missing data at 999, but truthfully you can choose whatever value you like as long as it is consistent across variables and the value is not the same as scored variables.
3. Ensure that the variable names are 8 characters or shorter as Mplus will not read beyond the first 8 characters of each variable.

Transfer

1. SPSS → File → Export → Tab-delimited → Uncheck the box that says “Write variable names to file” → Name the data file → Press Save.
2. SPSS → Variable View → Click “Name” to highlight all variable names → Copy the highlighted names → Go to Word and paste the names → Highlight names → Go to Insert → Click Table → Click Convert Text to Table → Change Number of Columns to “6” → Press Ok → Go to Table Layout → Click Convert to Text → Separate Text with Other and Set the Other to a Single Space → Press Ok → Copy the variables → Paste variables into Mplus under the Variable category.

Wald Test of Parameter Constraints

As part of your LPA, you will need to test each profile against each other profile on the indicator items (items included as part of the profile make-up). To do so, you will need to run Wald tests of parameter constraints to determine if profiles significantly differ on the indicator items. This is a crucial component of LPA, as this testing reveals where the profiles significantly differ on their make-up.

Mplus

- ❖ Mplus language requires you to end a clause in ;

TITLE: Name your project

DATA: FILE IS DataFileName.dat;

- ❖ This is your data file, the tab-delimited (.dat) file you created in SPSS. You need to make sure that your Mplus file and your data file are saved in the same folder so Mplus can access it.

VARIABLE: NAMES ARE ...

- ❖ This is where you would paste the variables you copied over from Word
- ❖ Make sure to put a ; after the last variable

usevariables = ...

- ❖ These would be the indicator items for the LPA

auxiliary = ...

- ❖ This is where you would include each of the outcomes that you want to compare the profiles on
- ❖ Categorical outcomes are labeled as (DCAT) and continuous outcomes labeled as (DCON)

missing are all (999);

- ❖ This is how you tell Mplus to not include the missing data in analysis, you'll put whatever number you set in the parentheses.

classes=c(1);

- ❖ This is the command to run an LPA. With each iteration, you will increase the number in the parentheses by 1, until the fit indices indicate otherwise.

ANALYSIS:

type=mixture;

- ❖ This tells Mplus that you are running a mixture-model which LPA is a subtype of. Other mixture-models include latent class analysis, growth modeling, latent transition analysis, and so on.

MODEL:

%OVERALL%

- ❖ Writing syntax for a model under this command indicates that you want the model to run on the overall latent profile model (across all profiles)

%C#1%

- ❖ Writing syntax for a model under this command indicates that you want the model to run on only the first profile. Changing the number will change which profile you are running the model on (e.g., %C#4% would run the model only on the fourth profile).
- ❖ This is where you will write the syntax for the Wald test. It is a little complicated, so see the syntax at the end of this document. You will adjust the parameters listed in your model based on the number of indicator items and profiles you have in your model. In mine, I have 10 items in a 3-profile solution, so t1-t10 are for profile 1, t11-t20 are for profile 2, and t21-t30 are for profile 3. If you had 15 items in a 4-profile solution, you would list out each of those 15 items below all 4 of the profiles, resulting in t1-t60.

Model Test:

0=t1-t11;

- ❖ To compare profiles on indicator items, you will need to run the syntax above, substituting out t1 and t11 for the comparisons you want to make. So, in my example with 10 items in a 3-profile solution, I would need to run the following tests to compare profiles on the first indicator item: t1-t11, t1-t21, t11-t21. In the other example of 15 items in a 4-profile solution, I would need to run these tests: t1-t16, t1-t31, t1-t46, t16-t31, t16-t31, t31-t46. I would iterate tests for each indicator item to make these comparisons.
- ❖ In the output, the Wald test of parameter constraints is below the Information Criteria (AIC, BIC, aBIC).

OUTPUT: tech11 tech14 STDYX;

- ❖ tech11 gives you the aLRT output
- ❖ tech14 gives you the bootstrapped LRT (which can be used instead of aLRT, I just prefer aLRT personally)

- ❖ **STDYX:** If your indicator items are on different scales, this command will standardize them in the output. Typically though, if I am dealing with indicator items on different scales, I standardize them in SPSS before transferring it over to Mplus.

Applied Example of LPA Syntax

TITLE: values lpa

DATA: FILE IS Values LPA just q-sort.dat;

VARIABLE: NAMES ARE ID Sex Age Ethnic College
SES Income PollIssues1 PollIssues2 PollIssues3
PollIssues4 Political Q46 Religion Prayer
RelAttendance RelInterest PVQBEN PVQUNI PVQDIR
PVQSTM PVQHED PVQACH PVQPOW PVQSEC
PVQCON PVQTRD BFIEExtra BFIAgree BFIcon
BFINegEm BFIOpen BFISocial BFIAssert BFIenergy
BFICompass BFIRespect BFITrust BFIorgan BFIProd
BFIRespon BFIAnx BFIDep BFIVol BFICur
BFISense BFIImag EXTERN INTROJECT IDENTIFIED
INTEGRATED RICHLIFE SWLS CPSMean CPSGoal
CPSBeyond SOCDOM RWAAGG RWASUB RWACON
RWATOT CNation DHPAT LHPAT IPAT
ISINorm ERQReapp ERQSupp Tasks USDon
STVDon factor ;
 usevariables = PVQBEN PVQUNI PVQDIR
PVQSTM PVQHED PVQACH PVQPOW PVQSEC PVQCON PVQTRD
 ;
 auxiliary = Sex (DCAT) Age (DCON)
 Ethnic - Prayer (DCAT)
 BFIEExtra - BFIOpen (DCON) EXTERN - ERQSupp (DCON)
 Tasks - factor (DCAT);
 missing are all (999);
classes=c(3);

Analysis:

type=mixture;

Model:

```
%C#1%  
[ PVQBEN](t1);  
[ PVQUNI](t2);  
[ PVQDIR](t3);  
[ PVQSTM](t4);  
[ PVQHED](t5);  
[ PVQACH](t6);  
[ PVQPOW](t7);  
[ PVQSEC](t8);  
[ PVQCON](t9);  
[ PVQTRD](t10);
```

%C#2%

[PVQBEN](t11);
[PVQUNI](t12);
[PVQDIR](t13);
[PVQSTM](t14);
[PVQHED](t15);
[PVQACH](t16);
[PVQPOW](t17);
[PVQSEC](t18);
[PVQCON](t19);
[PVQTRD](t20);

%C#3%

[PVQBEN](t21);
[PVQUNI](t22);
[PVQDIR](t23);
[PVQSTM](t24);
[PVQHED](t25);
[PVQACH](t26);
[PVQPOW](t27);
[PVQSEC](t28);
[PVQCON](t29);
[PVQTRD](t30);

Model Test:

0=t1-t11;

Output: tech11 tech14 stdyx;

Sample LPA Write-Up

Pulled from:

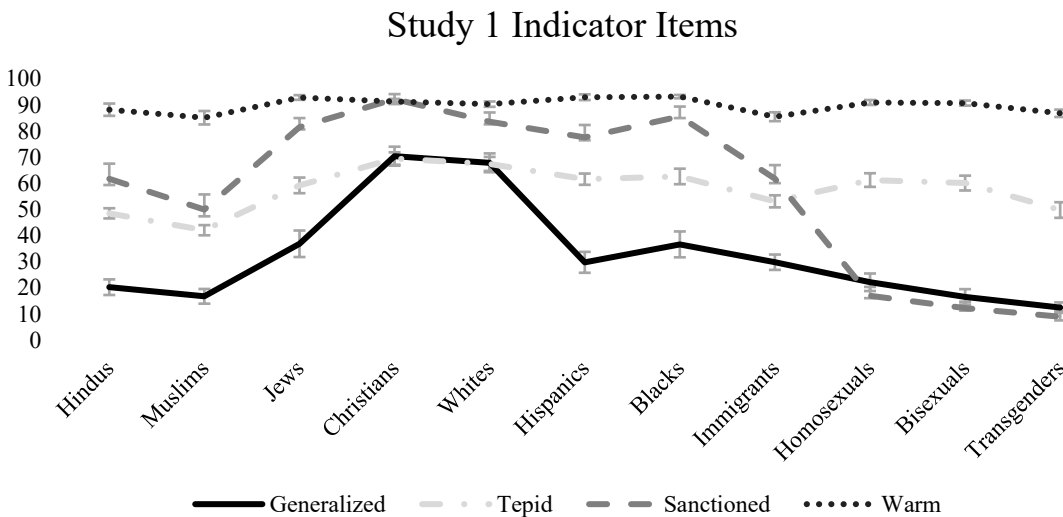
Al-Kire, R. L., Ratchford, J. L., Tsang, J. A., Rowatt, W., & Schnitker, S. A. (under review). *A person-centered approach to religious prejudice among Christians in the United States.*

Study 1 Results and Discussion

We ran models with 1 to 7 profiles to identify the best model fit and parsimony. Fit statistics for the LPAs appear in the online supplement. A four-profile solution fit best. Figure 1 shows thermometer ratings across profiles, and Figure 2 depicts profile distributions on distal outcomes

Figure 1

Thermometer Scores for Study 1



Note. The error bars on each indicator item demonstrate the standard error for the score on the indicator item for that profile.

We labeled the first profile ($n = 72$) *Generalized Prejudice*, as they expressed prejudice toward all minority groups and warmth only toward Christians and Whites. The *Tepid* profile ($n = 154$) consisted of ratings between 40 and 60 relatively indiscriminately across all groups. The *Sanctioned Prejudice* profile ($n = 55$) displayed prejudice mostly toward groups for which Christians endorse hostile attitudes (e.g., Homosexuals, Muslims; Johnson et al., 2012). The final profile ($n = 243$) was labeled *Warm* and showed consistently warm scores across all group ratings (> 80).

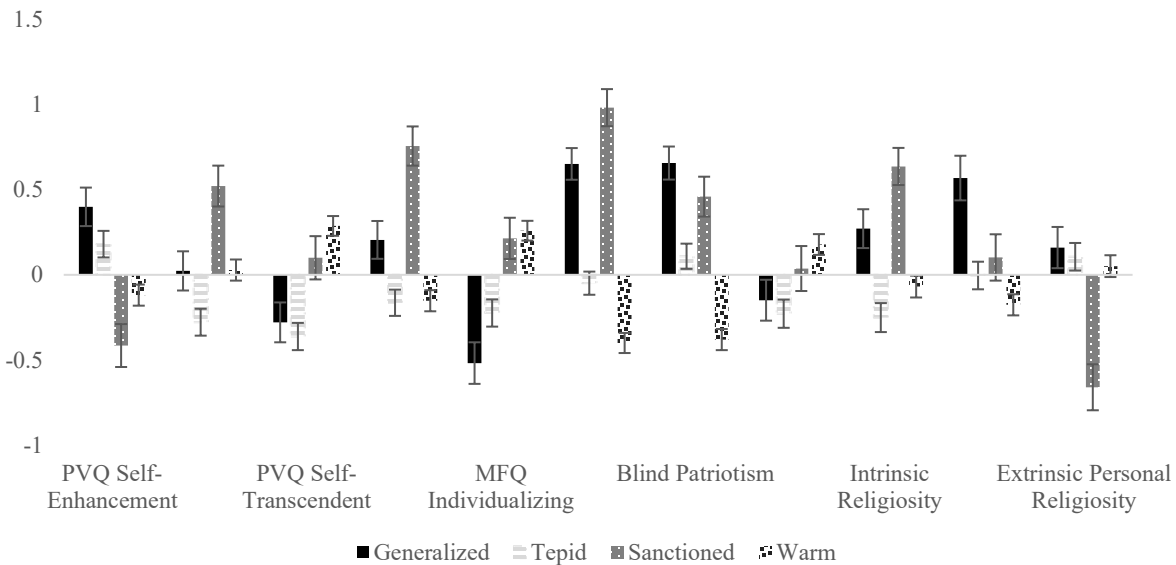
To compare the LPAs on distal outcomes, we used Lanza et al.'s (2013) model-based procedure wherein distal outcomes were included as auxiliary variables for latent profile solutions. This approach is preferable because it does not assume 100% certainty in the profile assignments, which could diminish information around participants' likelihood to be in each profile. Profile differences on outcomes and demographics appear in the online supplement. All tests comparing thermometer items and distal outcomes are available in the online supplement.

Profiles did not differ on gender, race, socioeconomic status (SES), or openness to change. The *Sanctioned* profile differed significantly from the *Warm* profile on behavioral giving, such that the *Warm* profile was more likely to give to *Casa Alianza* and the *Sanctioned* profile was more likely to give to *Covenant House*. The *Sanctioned* profile was significantly older on average than the other three profiles. For values and moral foundations, the *Generalized* and *Tepid* profiles demonstrated higher scores in self-enhancement than the *Sanctioned* and *Warm* profiles. The *Sanctioned* profile scored highest in conservation and binding, above all other profiles. The *Tepid* and *Warm* profiles both demonstrated less binding moral foundations than the *Generalized* and *Sanctioned* profiles. The *Warm* profile was highest in self-transcendent values over all other profiles. The *Generalized* and *Sanctioned* profiles scored highest in RWA, whereas the *Warm* profile scored lowest. The *Warm* profile scored lowest in blind patriotism over all other profiles. The *Sanctioned* profile scored lowest in extrinsic personal religiosity than all other profiles.

Figure 2

Profile Scores Across Standardized Distal Outcomes for Study 1

Study 1 Profiles on Standardized Outcomes



Note. The error bars on each outcome demonstrate the standard error for the score on the outcome for that profile.

Summary

Results from Study 1 suggest four distinct patterns of prejudice among American Christians: *Generalized*, *Tepid*, *Sanctioned*, and *Warm*. Profiles varied across values and moral foundations in theoretically consistent ways: the *Warm* profile scored highest in self-transcendent values (Wolf et al., 2019) and the *Sanctioned* profile scored highest in binding moral foundations (Graham et al., 2011). We were interested in testing the replicability of these profiles while including several new target groups, still focusing on racial, ethnic, and sexual orientation. Moreover, we were interested in testing additional individual difference variables such as personality characteristics, which may help elucidate differences across subgroups of Christians.

Sample LPA-Related Tables

Supplemental Table 1. *LPA Model Fit Statistics for Studies*

Study 1						
Number of classes	AIC	BIC	aBIC	Minimum Class	aLRT	Entropy
1	55123.56	55217.31	55147.48			
2	52450.16	52595.05	52487.13	48.09%	2661.98***	.95
3	51780.75	51976.78	51830.77	16.22%	684.30***	.95
4	51111.20	51358.37	51174.26	10.50%	654.11*	.95
5	50774.66	51072.96	50850.77	10.88%	355.81	.93
6	50538.95	50888.39	50628.10	7.44%	256.30	.94
7	50343.55	50744.13	50445.75	6.11%	216.52	.94
Study 2						
1	58730.37	58850.85	58755.66			
2	56076.71	56261.36	56115.39	42.44%	2658.14***	.95
3	55252.70	55501.71	55304.97	19.76%	847.11*	.95
4	54696.04	55009.30	54761.79	16.10%	582.61**	.95
5	54390.13	54767.65	54469.37	15.61%	334.44	.93
6	54228.51	54670.29	54321.24	5.61%	191.63	.93
7	54081.27	54587.31	54187.49	5.37%	182.89	.94
Study 3						
1	216373.95	216508.71	216432.46			
2	212515.78	212723.53	212605.98	46.94%	3845.33***	.83
3	211269.90	211550.64	211391.79	18.00%	1259.16**	.84
4	210175.88	210529.61	210329.46	16.82%	1108.82*	.85
5	209455.65	209882.37	209640.91	9.50%	739.77	.86
6	208784.78	209284.50	209001.74	7.15%	947.12	.88
7	208441.42	209014.13	208690.07	0.79%	365.66	.89

Note. AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria; aBIC = adjusted Bayesian Information Criterion; aLRT = adjusted Lo-Mendell-Rubin Likelihood Ratio Test. * $p < .05$ ** $p < .01$ *** $p < .001$

Supplemental Table 2. Profiles on Indicator Variables and Distal Outcomes in Study 1

	Generalized (<i>n</i> = 72)	Tepid (<i>n</i> = 154)	Sanctioned (<i>n</i> = 55)	Warm (<i>n</i> = 243)	<i>M</i> s (<i>SD</i> s) for entire sample (<i>N</i> = 524)
<i>Thermometer Items</i>					
Immigrants	29.84(2.94) _a	53.13(2.31) _b	61.79(5.20) _b	85.50(1.70) _c	65.82 (29.32)
Jews	36.90(5.07) _a	59.23(2.99) _a	81.52(3.46) _b	92.85(0.89) _b	74.07 (27.31)
Christians	70.40(3.63) _a	69.50(2.37) _a	92.23(1.91) _b	91.32(0.99) _b	82.11 (21.25)
Muslims	16.81(2.81) _a	42.09(1.95) _b	49.98(5.79) _b	85.11(2.58) _c	59.35 (33.37)
Hindus	20.30(2.99) _a	48.54(1.95) _b	61.72(5.83) _b	88.18(2.35) _c	64.40 (31.34)
Hispanics	29.81(4.00) _a	61.61(2.15) _b	77.58(4.76) _{bc}	92.95(1.10) _c	73.44 (27.65)
Whites	67.86(3.60) _a	67.45(2.68) _{ab}	83.60(3.52) _{bc}	90.30(1.02) _c	79.77 (22.88)
Blacks	36.67(4.95) _a	62.65(2.97) _b	85.62(3.76) _c	93.18(0.65) _c	75.64 (26.95)
Homosexuals	22.18(3.35) _a	61.27(2.61) _b	17.03(3.36) _a	90.94(0.94) _c	64.91 (32.60)
Bisexuals	16.60(2.95) _a	60.12(2.84) _b	12.30(2.45) _a	90.71(0.97) _c	63.14 (33.96)
Transgenderers	12.50(1.98) _a	49.81(2.99) _b	9.00(2.14) _a	86.80(1.41) _c	57.46 (35.44)
<i>Distal Outcomes</i>					
PVQ Self-Enhancement	3.83(0.13) _a	3.58(0.09) _a	2.91(0.14) _b	3.24(0.07) _c	3.38(1.13)
PVQ Conservation	4.47(0.09) _a	4.24(0.09) _b	4.85(0.14) _c	4.47(0.07) _a	4.45(0.77)
PVQ Self-Transcendent	4.38(0.10) _a	4.31(0.07) _a	4.68(0.10) _b	4.84(0.05) _c	4.60(0.82)
MFQ Binding	3.31(0.09) _a	3.02(0.06) _b	3.76(0.09) _c	3.02(0.05) _b	3.15(0.81)
MFQ Individualizing	3.24(0.09) _a	3.46(0.06) _b	3.79(0.09) _c	3.82(0.04) _c	3.63(0.74)
RWA	4.56(0.11) _a	3.71(0.08) _b	5.00(0.13) _a	3.28(0.07) _c	3.77(1.21)
Blind Patriotism	4.32(0.12) _a	3.67(0.09) _b	4.09(0.14) _{ab}	3.09(0.07) _c	3.54(1.19)
Constructive Patriotism	5.25(0.12) _{ab}	5.17(0.08) _a	5.43(0.13) _{ab}	5.57(0.06) _b	5.40(0.98)
Intrinsic Religiosity	3.86(0.09) _{ab}	3.45(0.07) _c	4.14(0.09) _a	3.59(0.05) _{bc}	3.65(0.78)
Extrinsic Social Religiosity	3.02(0.12) _a	2.49(0.08) _b	2.59(0.13) _{ab}	2.33(0.06) _b	2.49(0.92)
Extrinsic Personal Religiosity	3.28(0.10) _a	3.24(0.07) _a	2.61(0.11) _b	3.19(0.05) _a	3.15(0.81)
Age	40.26(1.68) _a	40.89(1.14) _a	51.55(1.98) _b	42.91(0.92) _a	42.95(14.22)
Political	5.22(0.19) _a	4.05(0.14) _b	5.15(0.20) _a	3.68(0.11) _b	4.14(1.73)

Note. Means with different subscripts are significantly different between classes. PVQ = Portrait Values Questionnaire; MFQ = Moral Foundations Questionnaire; RWA = Right Wing Authoritarianism

Supplemental Table 3. Wald Test of Parameter Constraints for Study 1

Indicator	Wald Test
<i>Immigrants</i>	
Generalized vs. Tepid	$W(1) = 35.42, p < .001$
Generalized vs. Sanctioned	$W(1) = 34.21, p < .001$
Generalized vs. Warm	$W(1) = 247.28, p < .001$
Tepid vs. Sanctioned	$W(1) = 2.48, p = .12$
Tepid vs. Warm	$W(1) = 166.58, p < .001$
Sanctioned vs. Warm	$W(1) = 20.43, p < .001$
<i>Jews</i>	
Generalized vs. Tepid	$W(1) = 9.64, p < .01$
Generalized vs. Sanctioned	$W(1) = 43.68, p < .001$
Generalized vs. Warm	$W(1) = 82.32, p < .001$
Tepid vs. Sanctioned	$W(1) = 19.22, p < .001$
Tepid vs. Warm	$W(1) = 133.13, p < .001$
Sanctioned vs. Warm	$W(1) = 10.43, p < .01$
<i>Christians</i>	
Generalized vs. Tepid	$W(1) = 0.47, p = .49$
Generalized vs. Sanctioned	$W(1) = 21.01, p < .001$
Generalized vs. Warm	$W(1) = 22.31, p < .001$
Tepid vs. Sanctioned	$W(1) = 41.26, p < .001$
Tepid vs. Warm	$W(1) = 62.56, p < .001$
Sanctioned vs. Warm	$W(1) = 0.07, p = .79$
<i>Muslims</i>	
Generalized vs. Tepid	$W(1) = 58.24, p < .001$
Generalized vs. Sanctioned	$W(1) = 37.10, p < .001$
Generalized vs. Warm	$W(1) = 310.94, p < .001$
Tepid vs. Sanctioned	$W(1) = 2.33, p = .13$
Tepid vs. Warm	$W(1) = 152.20, p < .001$
Sanctioned vs. Warm	$W(1) = 31.73, p < .001$
<i>Hindus</i>	
Generalized vs. Tepid	$W(1) = 57.57, p < .001$
Generalized vs. Sanctioned	$W(1) = 39.31, p < .001$
Generalized vs. Warm	$W(1) = 259.60, p < .001$
Tepid vs. Sanctioned	$W(1) = 3.45, p = .06$
Tepid vs. Warm	$W(1) = 123.20, p < .001$
Sanctioned vs. Warm	$W(1) = 19.42, p < .001$
<i>Hispanics</i>	
Generalized vs. Tepid	$W(1) = 37.29, p < .001$
Generalized vs. Sanctioned	$W(1) = 52.26, p < .001$
Generalized vs. Warm	$W(1) = 188.06, p < .001$
Tepid vs. Sanctioned	$W(1) = 8.77, p < .01$
Tepid vs. Warm	$W(1) = 224.58, p < .001$
Sanctioned vs. Warm	$W(1) = 10.03, p < .01$
<i>Whites</i>	
Generalized vs. Tepid	$W(1) = 0.56, p = .45$
Generalized vs. Sanctioned	$W(1) = 4.95, p < .05$
Generalized vs. Warm	$W(1) = 24.19, p < .001$
Tepid vs. Sanctioned	$W(1) = 9.24, p < .01$
Tepid vs. Warm	$W(1) = 52.57, p < .001$

Sanctioned vs. Warm	$W(1) = 3.89, p < .05$
<i>Blacks</i>	
Generalized vs. Tepid	$W(1) = 14.11, p < .001$
Generalized vs. Sanctioned	$W(1) = 63.24, p < .001$
Generalized vs. Warm	$W(1) = 82.84, p < .001$
Tepid vs. Sanctioned	$W(1) = 24.60, p < .001$
Tepid vs. Warm	$W(1) = 96.26, p < .001$
Sanctioned vs. Warm	$W(1) = 5.95, p < .05$
<i>Homosexuals</i>	
Generalized vs. Tepid	$W(1) = 77.87, p < .001$
Generalized vs. Sanctioned	$W(1) = 2.38, p = .12$
Generalized vs. Warm	$W(1) = 290.20, p < .001$
Tepid vs. Sanctioned	$W(1) = 167.00, p < .001$
Tepid vs. Warm	$W(1) = 104.99, p < .001$
Sanctioned vs. Warm	$W(1) = 618.05, p < .001$
<i>Bisexuals</i>	
Generalized vs. Tepid	$W(1) = 121.87, p < .001$
Generalized vs. Sanctioned	$W(1) = 0.99, p = .32$
Generalized vs. Warm	$W(1) = 431.24, p < .001$
Tepid vs. Sanctioned	$W(1) = 182.04, p < .001$
Tepid vs. Warm	$W(1) = 101.33, p < .001$
Sanctioned vs. Warm	$W(1) = 824.23, p < .001$
<i>Transgenders</i>	
Generalized vs. Tepid	$W(1) = 119.62, p < .001$
Generalized vs. Sanctioned	$W(1) = 1.03, p = .31$
Generalized vs. Warm	$W(1) = 840.51, p < .001$
Tepid vs. Sanctioned	$W(1) = 127.63, p < .001$
Tepid vs. Warm	$W(1) = 144.13, p < .001$
Sanctioned vs. Warm	$W(1) = 899.71, p < .001$

Supplemental Table 4. *Chi Square Difference Tests on Distal Outcomes in Study 1*

Construct	Chi square
Religious Prime	
$\chi^2(3) = 2.77, p = .43$	
<i>PVQ Benevolence</i>	$\chi^2(3) = 37.92, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 0.73, p = .40$
Generalized vs. Sanctioned	$\chi^2(1) = 5.55, p = .02$
Generalized vs. Warm	$\chi^2(1) = 11.45, p = .001$
Tepid vs. Sanctioned	$\chi^2(1) = 12.53, p < .001$
Tepid vs. Warm	$\chi^2(1) = 31.99, p < .001$
Sanctioned vs. Warm	$\chi^2(1) = 0.10, p = .76$
<i>PVQ Universalism</i>	$\chi^2(3) = 46.56, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 0.02, p = .88$
Generalized vs. Sanctioned	$\chi^2(1) = 2.83, p = .09$
Generalized vs. Warm	$\chi^2(1) = 19.70, p < .001$
Tepid vs. Sanctioned	$\chi^2(1) = 4.34, p = .04$
Tepid vs. Warm	$\chi^2(1) = 37.51, p < .001$
Sanctioned vs. Warm	$\chi^2(1) = 4.23, p = .04$
<i>PVQ Openness to Change</i>	
$\chi^2(3) = 5.03, p = .17$	
<i>PVQ Self-Enhancement</i>	$\chi^2(3) = 32.28, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 2.57, p = .11$
Generalized vs. Sanctioned	$\chi^2(1) = 23.23, p < .001$
Generalized vs. Warm	$\chi^2(1) = 16.20, p < .001$
Tepid vs. Sanctioned	$\chi^2(1) = 16.07, p < .001$
Tepid vs. Warm	$\chi^2(1) = 8.89, p < .01$
Sanctioned vs. Warm	$\chi^2(1) = 4.44, p < .05$
<i>PVQ Conservation</i>	$\chi^2(3) = 31.44, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 4.67, p < .05$
Generalized vs. Sanctioned	$\chi^2(1) = 8.96, p < .01$
Generalized vs. Warm	$\chi^2(1) = 0.00, p = .98$
Tepid vs. Sanctioned	$\chi^2(1) = 30.89, p < .001$
Tepid vs. Warm	$\chi^2(1) = 9.23, p < .01$
Sanctioned vs. Warm	$\chi^2(1) = 13.31, p < .001$
<i>PVQ Self-Transcendent</i>	$\chi^2(3) = 57.34, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 7.45, p < .01$
Generalized vs. Sanctioned	$\chi^2(1) = 11.87, p < .001$
Generalized vs. Warm	$\chi^2(1) = 7.92, p < .01$
Tepid vs. Sanctioned	$\chi^2(1) = 44.21, p < .001$
Tepid vs. Warm	$\chi^2(1) = 0.01, p = .91$
Sanctioned vs. Warm	$\chi^2(1) = 48.62, p < .001$
<i>MFQ Binding</i>	$\chi^2(3) = 57.34, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 7.45, p < .01$
Generalized vs. Sanctioned	$\chi^2(1) = 11.87, p < .001$
Generalized vs. Warm	$\chi^2(1) = 7.92, p < .01$
Tepid vs. Sanctioned	$\chi^2(1) = 44.21, p < .001$
Tepid vs. Warm	$\chi^2(1) = 0.01, p = .91$
Sanctioned vs. Warm	$\chi^2(1) = 48.62, p < .001$
<i>MFQ Individualizing</i>	$\chi^2(3) = 47.95, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 4.05, p < .05$

Generalized vs. Sanctioned	$\chi^2(1) = 18.03, p < .001$
Generalized vs. Warm	$\chi^2(1) = 32.91, p < .001$
Tepid vs. Sanctioned	$\chi^2(1) = 9.05, p < .01$
Tepid vs. Warm	$\chi^2(1) = 23.85, p < .001$
Sanctioned vs. Warm	$\chi^2(1) = 0.11, p = .74$
<i>Right Wing Authoritarianism</i>	$\chi^2(3) = 174.02, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 36.74, p < .001$
Generalized vs. Sanctioned	$\chi^2(1) = 5.29, p < .05$
Generalized vs. Warm	$\chi^2(1) = 90.86, p < .001$
Tepid vs. Sanctioned	$\chi^2(1) = 63.72, p < .001$
Tepid vs. Warm	$\chi^2(1) = 15.11, p < .001$
Sanctioned vs. Warm	$\chi^2(1) = 123.24, p < .001$
<i>Blind Patriotism</i>	$\chi^2(3) = 100.14, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 20.12, p < .001$
Generalized vs. Sanctioned	$\chi^2(1) = 1.67, p = .20$
Generalized vs. Warm	$\chi^2(1) = 81.07, p < .001$
Tepid vs. Sanctioned	$\chi^2(1) = 6.39, p = .01$
Tepid vs. Warm	$\chi^2(1) = 25.78, p < .001$
Sanctioned vs. Warm	$\chi^2(1) = 40.05, p < .001$
<i>Constructive Patriotism</i>	$\chi^2(3) = 17.76, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 0.29, p = .59$
Generalized vs. Sanctioned	$\chi^2(1) = 1.09, p = .30$
Generalized vs. Warm	$\chi^2(1) = 5.96, p = .02$
Tepid vs. Sanctioned	$\chi^2(1) = 2.89, p = .09$
Tepid vs. Warm	$\chi^2(1) = 15.66, p < .001$
Sanctioned vs. Warm	$\chi^2(1) = 0.95, p = .33$
<i>Intrinsic Religiosity</i>	$\chi^2(3) = 48.73, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 13.53, p < .001$
Generalized vs. Sanctioned	$\chi^2(1) = 5.38, p = .02$
Generalized vs. Warm	$\chi^2(1) = 6.81, p = .01$
Tepid vs. Sanctioned	$\chi^2(1) = 41.21, p < .001$
Tepid vs. Warm	$\chi^2(1) = 2.91, p = .09$
Sanctioned vs. Warm	$\chi^2(1) = 31.18, p < .001$
<i>Extrinsic Social Religiosity</i>	$\chi^2(3) = 27.40, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 13.79, p < .001$
Generalized vs. Sanctioned	$\chi^2(1) = 6.12, p = .01$
Generalized vs. Warm	$\chi^2(1) = 26.45, p < .001$
Tepid vs. Sanctioned	$\chi^2(1) = 0.45, p = .50$
Tepid vs. Warm	$\chi^2(1) = 2.85, p = .09$
Sanctioned vs. Warm	$\chi^2(1) = 3.48, p = .06$
<i>Extrinsic Personal Religiosity</i>	$\chi^2(3) = 28.13, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 0.14, p = .71$
Generalized vs. Sanctioned	$\chi^2(1) = 20.45, p < .001$
Generalized vs. Warm	$\chi^2(1) = 0.63, p = .43$
Tepid vs. Sanctioned	$\chi^2(1) = 23.82, p < .001$
Tepid vs. Warm	$\chi^2(1) = 0.29, p = .59$
Sanctioned vs. Warm	$\chi^2(1) = 22.80, p < .001$
<i>Giving</i>	$\chi^2(3) = 27.59, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 0.29, p = .86$
Generalized vs. Sanctioned	$\chi^2(1) = 5.05, p = .08$
Generalized vs. Warm	$\chi^2(1) = 3.88, p = .14$

Tepid vs. Sanctioned	$\chi^2(1) = 10.44, p = .01$
Tepid vs. Warm	$\chi^2(1) = 6.90, p = .03$
Sanctioned vs. Warm	$\chi^2(1) = 23.23, p < .001$
<i>Age</i>	$\chi^2(3) = 24.65, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 0.10, p = .76$
Generalized vs. Sanctioned	$\chi^2(1) = 18.88, p < .001$
Generalized vs. Warm	$\chi^2(1) = 1.92, p = .17$
Tepid vs. Sanctioned	$\chi^2(1) = 21.81, p < .001$
Tepid vs. Warm	$\chi^2(1) = 1.92, p = .17$
Sanctioned vs. Warm	$\chi^2(1) = 15.67, p < .001$
<i>Gender</i>	
$\chi^2(3) = 5.55, p = .14$	
<i>Race</i>	
$\chi^2(15) = 22.64, p = .09$	
<i>SES</i>	
$\chi^2(12) = 14.06, p = .30$	
<i>Political</i>	$\chi^2(3) = 76.42, p < .001$
Generalized vs. Tepid	$\chi^2(1) = 25.45, p < .001$
Generalized vs. Sanctioned	$\chi^2(1) = 0.08, p = .78$
Generalized vs. Warm	$\chi^2(1) = 51.59, p < .001$
Tepid vs. Sanctioned	$\chi^2(1) = 19.83, p < .001$
Tepid vs. Warm	$\chi^2(1) = 4.38, p = .04$
Sanctioned vs. Warm	$\chi^2(1) = 40.77, p < .001$

Supplemental Table 11. Probabilities of Profile Association for Categorical Distal Outcomes in Study 3

Construct	Probabilities by Profile								(N = 1337)
	Generalized (n = 231)		Sanctioned (n = 363)		Tepid (n = 462)		Warm (n = 281)		
	Probability	n	Probability	n	Probability	n	Probability	n	
<i>Political Party</i>	a		a		ab		b		616
Democratic Party	0.20(0.05)	21	0.24(0.04)	43	0.38(0.03)	80	0.52(0.04)	76	220
Republican Party	0.64(0.05)	56	0.60(0.05)	84	0.43(0.03)	98	0.27(0.04)	43	281
Independent/None	0.16(0.04)	15	0.17(0.04)	26	0.18(0.03)	41	0.20(0.03)	28	110
Other	0.01(0.01)	0	0.00(0.00)	0	0.01(0.01)	3	0.01(0.01)	2	5
<i>Religion Importance</i>	ab		a		b		b		1335
Important	0.93(0.02)	212	0.96(0.01)	344	0.80(0.02)	374	0.81(0.03)	229	1159
Not Important	0.07(0.02)	19	0.04(0.01)	19	0.20(0.02)	87	0.19(0.03)	51	176
<i>Religious Attendance</i>	ab		a		c		bc		1057
Every week	0.50(0.05)	92	0.48(0.05)	139	0.26(0.03)	97	0.27(0.03)	59	387
Almost every week	0.22(0.03)	43	0.28(0.03)	81	0.25(0.02)	86	0.22(0.03)	49	259
Once or twice a month	0.13(0.03)	27	0.14(0.02)	43	0.19(0.02)	63	0.22(0.03)	46	179
A few times a year	0.15(0.03)	30	0.10(0.04)	44	0.28(0.02)	91	0.29(0.03)	56	221
Never	0.00(0.00)	1	0.01(0.01)	2	0.02(0.01)	6	0.01(0.01)	2	11
<i>Military</i>	a		a		ab		b		1337
Never served	0.85(0.03)	196	0.86(0.02)	315	0.90(0.20)	413	0.95(0.02)	264	1188
Served	0.15(0.03)	35	0.14(0.02)	48	0.10(0.20)	49	0.05(0.02)	17	149
<i>Race</i>									1331
White, non-Hispanic	0.84(0.03)	180	0.71(0.04)	262	0.81(0.03)	366	0.67(0.03)	190	1008
Black, non-Hispanic	0.08(0.02)	20	0.10(0.02)	35	0.06(0.02)	31	0.17(0.03)	45	131
Asian, non-Hispanic	0.02(0.01)	6	0.02(0.01)	8	0.02(0.01)	11	0.03(0.01)	7	32
Native American, non-Hispanic	0.01(0.01)	2	0.00(0.00)	1	0.01(0.01)	4	0.00(0.00)	1	8
Hispanic	0.03(0.02)	8	0.11(0.02)	37	0.06(0.01)	30	0.10(0.02)	30	105
Other	0.02(0.01)	4	0.05(0.01)	18	0.04(0.01)	17	0.02(0.01)	8	47
<i>Religious Giving</i>	ab		a		b		b		1336
Have not given in past 12 months	0.39(0.05)	94	0.30(0.03)	120	0.52(0.03)	228	0.49(0.03)	134	576
Have given in past 12 months	0.61(0.05)	137	0.70(0.03)	242	0.48(0.03)	234	0.51(0.03)	147	760
<i>Political Giving</i>	a		ab		ab		b		1336
Have not given in past 12 months	0.90(0.02)	206	0.81(0.03)	291	0.83(0.02)	383	0.73(0.03)	210	1090
Have given in past 12 months	0.10(0.02)	25	0.19(0.03)	71	0.17(0.02)	79	0.27(0.03)	71	246

Note. Letters represent differences among profiles; profiles that have the same letter did not differ significantly on that construct. Probability column represents the likelihood of participants in that profile being in that category. The number column represents the actual number of participants in that profile being in that category. Some cells have fewer participant counts as their information was missing.