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Two Classes of Political Activists: Evidence from Surveys of U.S. College Students and U.S. Prisoners

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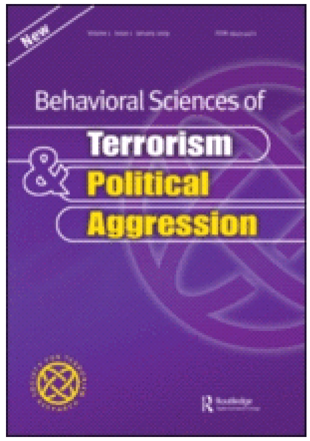

Two Classes of Political Activists: Evidence from Surveys of U.S. College Students and U.S. Prisoners

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Abstract

We applied Latent Class Analysis (LCA) to responses to items from the Activism and Radicalism Intentions Scales (ARIS). In two studies (undergraduates n=530) and prisoners (n=670), item profiles identified four groups--Inert, Moderate Activists, Strong Activists, and Radicals—that confirm and extend the levels of the Action Pyramid of the Two Pyramids Model of Radicalization. Radicals were a higher proportion of prisoner than undergraduate respondents (20% vs. 12%), and, among prisoners, Radicals were more likely than other groups to be gang members. The distinction between Moderate and Strong Activists is unprecedented in studies of political opinion, and we suggest in Discussion that study of Activists, and comparison of Activists and Radicals for the same cause, deserve more attention.

Introduction

Since the attacks of 9/11, security officials and scholars have sought to understand the events that precede and predict a turn to political violence. The term of reference for these events is *radicalization*—a change in beliefs, feelings and behaviors toward increased support for one side of an intergroup conflict (McCauley & Moskalenko, 2017). This definition has been qualified by research showing an important distinction between radicalization of beliefs and feelings *versus* radicalization of action. Ninety nine percent of those with radical beliefs and feelings never move to political violence or terrorism (McCauley & Moskalenko, 2017; Moskalenko & McCauley, 2020).

In radicalization research, empirical methods tend to fall into one of two categories: qualitative (such as interviews or case studies) and quantitative (such as surveys or databases) (Moskalenko, 2021). Qualitative methods offer the richness of material as well as the intuitive appeal of lived human experience that quantitative methods lack. On the other hand, quantitative methods can analyze data from a greater number of individuals or events, and allow for observation of more complex relationships among variables of interest. One shortcoming of quantitative approaches is that means (or factor scores) can hide significant variation of individuals or events.

To bridge the gap between qualitative approaches focused on vivid experience and quantitative approaches focused on sample statistics, the usual strategy is triangulation: exploring findings obtained through quantitative data with qualitative data, and vice versa (Moskalenko & McCauley, 2020). Thus, for example, the Two Pyramids Model of Radicalization (McCauley & Moskalenko, 2017) was developed from (qualitative) case studies, then later confirmed in part through (quantitative) survey research (Fajmonova, et al., 2017). While prudent, triangulation can be difficult in requiring multiple data collections, and multiple research skills (both quantitative and qualitative) from the researchers.

The present paper addresses research questions stemming from this gap in radicalization research between qualitative and quantitative approaches. In particular, we seek to explore the distinction between activism (legal and non-violent political action) and radicalism (illegal and violent political action) by mining quantitative data for two groups of individuals who have responded to the Activism and Radicalism Intentions Scales (ARIS; Moskalenko & McCauley, 2009). Rather than looking at mean scores on the Activism Intentions Scale (AIS) and the Radicalism Intentions Scale (RIS), here we ask whether natural groups of activists and radicals can be identified from profiles of responses to ARIS items. In the next three sections we introduce a statistical methodology that can support this goal.

Variable-centered vs. person-centered approaches

When Moskalenko and McCauley (2009) formed the Activism and Radicalism Intention Scales, they followed a relatively common procedure of questionnaire development: first developing a pool of items that operationalized different political activities, then collecting data using these items with samples from different countries, and then applying factor analysis to these data to determine the latent dimensions reflected in the items. Factor analyses and other dimension reduction techniques can be roughly categorized as variable-centered approaches (Bergman et al., 2003; Collins & Lanza, 2010) –the (roughly defined) goal of these analyses is to show which variables reflect the same construct and can be averaged together to get more reliable scales of individual differences. Although useful, this is not the only valid approach to analysis of such data.

Person-centered approaches begin from the same data as factor analysis, but with a focus on participants: instead of grouping variables with similar patterns of correlation under the presumption they reflect the same (latent) continuous variable, the goal is to group participants with similar response patterns under the presumption they reflect the same (latent) categorical variable (Collins & Lanza, 2010; see also Hagenaars & McCutcheon, 2002; Skrondal & Rabe-Hesketh, 2004).

Latent Class Analysis

One of the more familiar examples of person-centered analysis is Latent Class Analysis (LCA). LCA is a statistical technique based on the presumption that heterogeneity in item scores reflects the existence of multiple unobserved groups (i.e., latent classes; Weller et al., 2020). Therefore, latent classes yielded by LCA represent levels of a nominal unobserved variable (see Hagenaars & McCutcheon, 2002).

This method has been widely used in medical research to divide patients into naturally-occurring classes—groups of individuals with certain characteristics that make them respond differently to different treatments. For example, among all patients who present with Acute Respiratory Distress, certain combinations of characteristics (i.e., diabetes, low socio-economic class, inflammatory biomarkers) predict how patients might react to different treatment protocols, as well as predicting the course of the disease and prognosis for the patients (Zhang, et al., 2018).

LCA forms classes in a way that maximizes the similarity of members of the same class and minimizes the similarity between members of different classes (Lanza & Cooper, 2016). When conducting LCA, a sequence of models is tested, with each model adding another class (Weller et al., 2020). The analytical algorithm is iterative and based on two steps: expectation and likelihood maximization (i.e., EM, see Dempster et al., 1977 for a detailed introduction to EM).

Optimal models are sought by comparing their fit to data. While the outputs of LCA can include multiple statistical indices that can help in choosing the optimal model (with BIC, Bayesian Information Criterion, being the most reliable one, see Nylund et al., 2007), it is also important to consider the interpretability of models with statistically similar fit. Therefore, to ensure that the obtained model will be meaningful to both theorists and practitioners, it is important to validate the obtained LCA model against relevant external criteria (Weller et al., 2020).

According to Weller et al. (2020), there are four important constraints of the LCA procedure. First, the output of LCA is the *probability* for each individual of belonging to a class, indicating that class membership is not certain or all-or-none. The second limitation is related to *class size*: a small class may be hard to separate in a small sample, and multiple models may fit the data similarly well when classes are small. The third limitation is related to the *naming fallacy*: researchers are expected to name the classes established by LCA, which can be complicated if the outputs are based on many and varied items. This limitation echoes the judgment involved in naming factors emerging from factor analysis. Finally, Weller et al. (2020) point out that the quality of class separation depends on the *complexity of the model* (i.e., how many items are included in the analysis and how many levels each item has) and the *natural distinctiveness of the classes* (Nylund-Gibson & Choi, 2018).

Together, these limitations mean that a large sample, preferably with more than 300 participants, responding to multiple and multilevel items, is required for LCA. If one (or some of) the classes researchers are expecting to establish are rare, much larger sample sizes may be required (Nylund-Gibson & Choi, 2018).

LCA as a way forward in studying radicalization

Person-centered approaches, including LCA, can identify homogeneous subgroups of similar individuals (Weller et al., 2020). In the context of radicalization research, multiple relevant subgroups of individuals might exist. Members of these subgroups may share some characteristics, yet may be different with respect to other characteristics. This idea is not new—McCauley and Moskalenko (2008) presented multiple pathways by which individuals may become radicalized. Person-centered approaches might help researchers identify specific subgroups within a political movement and permit testing factors that move some of these groups to peaceful political action and others to violence.

In particular, person-centered approaches, might help differentiate among 1) activists who reject radicalism, 2) activists who accept radicalism, or even 3) radicals who reject activism (presuming all the mentioned groups are substantially present in a population). Studying differences between such groups could be a step forward in distinguishing factors that promote violent versus non-violent collective action.

LCA with ARIS items

To test the potential benefits of using LCA in radicalization research, the present study focuses on a survey measure of radicalization, the Activism and Radicalism Intentions Scales (ARIS; Moskalenko & McCauley, 2009). ARIS is of interest based on its widespread use among radicalization researchers, as well as its psychometric properties (Pavlović, et al., 2021). Translated into multiple languages, ARIS has been used by researchers around the globe: in Ukraine (Moskalenko & McCauley, 2009), Egypt and Morocco (Lemieux et al., 2017) Germany (Jahnke, et al, 2020), Hong Kong (Chui, et al., 2019); France (Morales et al., 2020), Spain (Trujillo et al., 2016), Sweden (Loughery, 2018), Norway (Pedersen et al., 2018), Croatia (Pavlović & Franc, 2021), and Belgium (Frounfelker, et al., 2019).

ARIS has demonstrated versatility not only across geographic locations, but also across diverse demographic groups. Supporting the generalizability of the scale, ARIS has been used in surveys of American Muslims (Fajmonová, et al., 2017), teenagers at risk for violent extremism (Campelo, 2018), Somali refugees (Cardeli et al., 2020), and U.S. prison inmates (Decker & Pyrooz, 2019).

The scale's utility across geographic and cultural divides speaks to its reliability and validity. The two sub-scales, Activism Intention Scale (AIS) and Radical Intentions Scale (RIS), differ in asking about legal versus illegal activities. These two scales reliably produce different patterns of correlation with political and personality measures, supporting the construct validity of the distinction between activism and radicalism (Pavlović et al., 2021).

Of particular interest is whether the outputs of LCA conducted on the items of ARIS map onto the Two Pyramids Model of Radicalization (McCauley & Moskalenko, 2017). Such a mapping has the potential of linking results of case studies (McCauley & Moskalenko, 2008) and results of survey research (Fajmonova et al, 2017). In other words, this study aims to use ARIS data from survey research to look for latent classes that could then be related to the layers of the Two Pyramids Model's Action Pyramid: politically neutral individuals, activists, radicals, and terrorists.

The ARIS scales do not directly measure behavior; both AIS and RIS items ask about intentions in relation to a political cause. Nevertheless, in this study we assume that behavioral intentions are a close enough proxy for behavior that ARIS can be related to the Action Pyramid of the Two Pyramids Model.

In line with best practices described in Weller et al. (2020), we set out to find the latent classes in two data sets of ARIS responses obtained from two different populations:

U.S. college students (Becker, 2020[1]) and U.S. prison inmates (Decker & Pyrooz, 2019[2]). The important difference between these samples is the high prevalence of former and current gang members in the Decker & Pyrooz prisoner sample, which might indicate a higher prevalence of radicalized individuals (Decker & Pyrooz, 2011; Pyrooz, et al., 2017; Becker, et al., 2020), that is, individuals ready to use illegal action for a political cause. In addition to establishing latent classes, we also aimed to validate them with respect to some potentially relevant characteristics (importance of nation, ethnicity and religion in the student sample, gang memberships and importance of nation, ethnicity and religion in the prisoner sample).

To authors' best knowledge, LCA has not previously been applied to ARIS items. Therefore, we conducted exploratory LCA. Based on the triangular form of the scatterplot of ARIS scale scores (individuals low on both Activism and Radicalism to full range of Radicalism scores for those high on Activism; Pavlović et al.,2021), and the Two Pyramids Model (McCauley & Moskalenko, 2017), we hypothesized the existence of four potentially relevant latent classes:

- Passive individuals – individuals scoring low on all the items of ARIS (corresponding to the "Inert" layer of the Action Pyramid)

[1] We are most grateful to the study author, Michael Becker, for generously sharing his data with us.
[2] We are most grateful to the authors of the study, David Pyrooz and Scott Decker, for their generosity in sharing their data, which were part of the Lone Star Project and the foundation of the following publications:

Mitchell, M. M., McCullough, K., Wu, J., Pyrooz, D. C. & Decker, S.H. (2018). "Survey Research with Gang and Non-Gang Members in Prison: Operational Lessons from the LoneStar Project." *Trends in Organized Crime*, March, 1–29.

Pyrooz, D. C., & Decker, S. H. (2019). *Competing for Control: Gangs and the Social Order of Prisons*. Cambridge, UK: Cambridge University Press.

Decker, S. H., & Pyrooz, D. C. (2019). "Activism and Radicalism in Prison: Measurement and Correlates in a Large Sample of Inmates in Texas." *Justice Quarterly* 36 (5): 787–815.

Decker, S. H., & Pyrooz. D. C. (2020). "The Imprisonment-Extremism Nexus: Continuity and Change in Activism and Radicalism Intentions in a Longitudinal Study of Prisoner Reentry." *PLOS ONE* 15 (11).

- Activists – individuals scoring high on activism items, but low on radicalism items (corresponding to the "Activist" layer of the Action Pyramid)
- Radicals – individuals scoring high on radicalism items (corresponding to the "Radicals" layer of the Action Pyramid)
- Uncertains--individuals with scores close to the mid-point of both activism and radicalism items (Not directly mappable on the Action pyramid, these individuals might be avoiding answering honestly or they might be unsure about their political position at the time of answering the questions. In either case, this group might represent a different expression of the Inert level of the Action Pyramid)

The top layer of the Action Pyramid is comprised of Terrorists. They make up an extremely small number relative to the population from which they arise: for example, out of roughly 2.5 million U.S. Muslim adults, fewer than 1 in 10,000 have been indicted for a terrorism-related crime since 9/11 (Moskalenko, 2021). Based on the discussed limitations of LCA with respect to identifying rare classes, we do not expect to observe this class in our study. Therefore, we expected to find at least four latent classes that would substantially match the four classes just described.

Study 1

Methods

Participants

The convenience sample in this study was part of an internet survey by Becker (2020) that reached 617 US college students. Data cleaning (further described in the Analysis section) reduced the sample size to 536 participants. These participants were on average 23 years old (SD = 6.5); most (60%) self-identified as women.

Instruments

A nine-item version of ARIS (Moskalenko & McCauley, 2009) was used in this study to estimate latent classes. Three items (ARIS 1-3) were Activism items as recommended by Moskalenko and McCauley; six items (ARIS 4-9) were Radicalism items, including two items not recommended by Moskalenko and McCauley (2009). The nine items (see Table 1) were rated on a seven-point Likert-type scale ranging from “disagree completely” (1) to “agree completely” (7). Higher agreement indicated a higher willingness to participate in political actions. We treated item ratings as categorical inputs for LCA.

Participants were first asked to think of ‘‘the Group You Feel Closest To…such as religious group, ethnic group, or any other group that is important to you’’ and write the name of that group in the space provided. Participants were instructed that the subsequent questions (ARIS items) were about the group they just named.

Three items measuring importance of specific groups (country, ethnicity, and religion—see Table 1) were available as external criteria for validating LCA-derived classes. These items were measured on a seven-point Likert-type scale ranging from “not important at all” (1) to “extremely important” (7).

Analysis

In order to preserve our sample size, we relied on the option of poLCA to deal with missing values by using available data per participant for classification instead of applying imputations (see Linzer & Lewis, 2011). Data analysis was conducted in R (R Core Team, 2021) using the functions from packages haven (Wickham & Miller, 2021), psych (Revelle, 2018), rstatix (Kassambara, 2021), poLCA (Linzer & Lewis, 2011), careless (Yentes & Wilhelm, 2021), foreach (Microsoft & Weston, 2020), doParallel (Microsoft & Weston, 2020), tidyr (Wickham, 2021), ggplot2 (Wickham, 2016), cowplot (Wilke, 2020), and dplyr (Wickham et al., 2021).

Results

Descriptive data are presented first, followed by outputs of LCA, then test of class differences for importance of country, ethnicity and religion.

Table 1 summarizes means and SDs for group importance ratings and ARIS items.

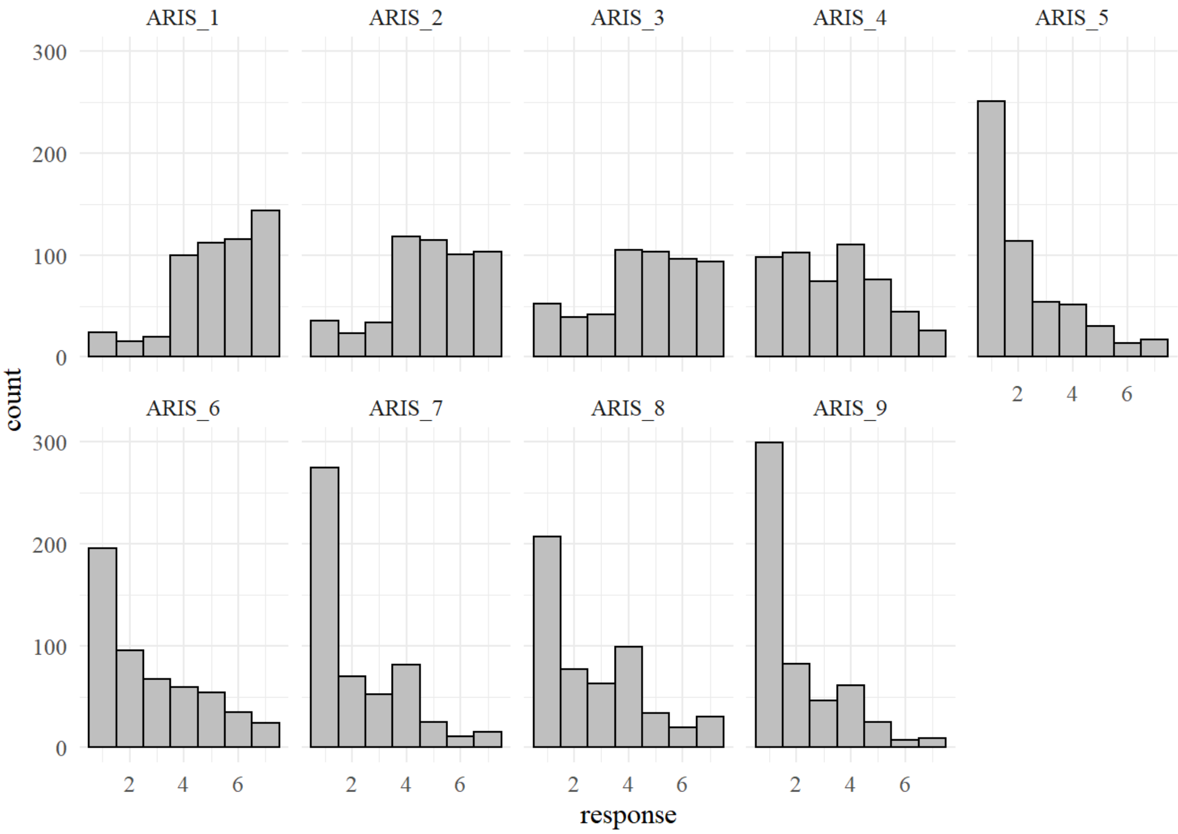
Table 1. *Means and SDs of group importance and ARIS items for US students*

	N	*M*	*SD*
importance of country	535	4.4	1.6
importance of ethnic group	535	3.8	1.9
importance of religion	536	3.3	2.2
… join/belong to an organization that fights for my group's political and legal rights. (ARIS1)	531	5.2	1.6
… donate money to an organization that fights for my group's political and legal rights. (ARIS2)	530	4.8	1.7
… would travel for one hour to join in a public rally, protest, or demonstration in support of my group. (ARIS3)	531	4.6	1.9
… continue to support an organization that fights for my group's political and legal rights even if the organization sometimes breaks the law. (ARIS4)	530	3.4	1.8
… continue to support an organization that fights for my group's political and legal rights even if the organization sometimes resorts to violence. (ARIS5)	531	2.3	1.6
… participate in a public protest against oppression of my group even if I thought the protest might turn violent. (ARIS6)	530	2.8	1.9
… attack police or security forces if I saw them beating members of my group. (ARIS7)	529	2.3	1.6
… go to war to protect the rights of my group. (ARIS8)	530	2.7	1.8
… retaliate against members of a group that had attacked my group, even if I couldn't be sure I was retaliating against the guilty party. (ARIS9)	529	2.0	1.5

Note. All items measured on a 1-7 scale.

Figure 1 presents distributions of college students' responses to each of the ARIS items. Distributions of responses show a positive asymmetry for the three activism items and negative asymmetry for the six radicalism items.

Figure 1. *Distributions of responses to ARIS items for US students*



In the next step, LCA was applied to the data. Outputs[3] of the procedure are presented in Table 2.

Table 2. *LCA Models for US students*

Model	AIC	BIC	Likelihood ratio/deviance	Entropy	% in smallest class
Model 1	15948	16187	9313	-	100
Model 2	14961	15443	8226	0.73	45.47
Model 3	14587	15312	7746	0.75	26.38
Model 4	14329	15299	7379	0.78	16.89
Model 5	14146	15358	7090	0.79	10.10
Model 6	14019	15475	6852	0.80	5.58
Model 7	13985	15684	6710	0.79	5.36
Model 8	13949	15892	6562	0.80	4.83
Model 9	13955	16142	6463	0.81	4.63
Model 10	13968	16397	6361	0.81	4.47

Note. AIC refers to Aikake Information Criterion. BIC refers to Bayesian Information Criterion. Likelihood ratio/deviance refers to likelihood ratio divided by the deviance statistic. Relative entropy refers to clarity of classification on a zero to one scale with higher values indicating greater homogeneity within groups (Zhang et al., 2018).

According to BIC, the optimal number of classes would be three to five, with a minimum BIC at four. We plotted the item choices for each class for models with three to eight classes to check the interpretability of solutions prior to deciding on the optimal number of classes. Figure 1 shows the item choices for the five-class model.

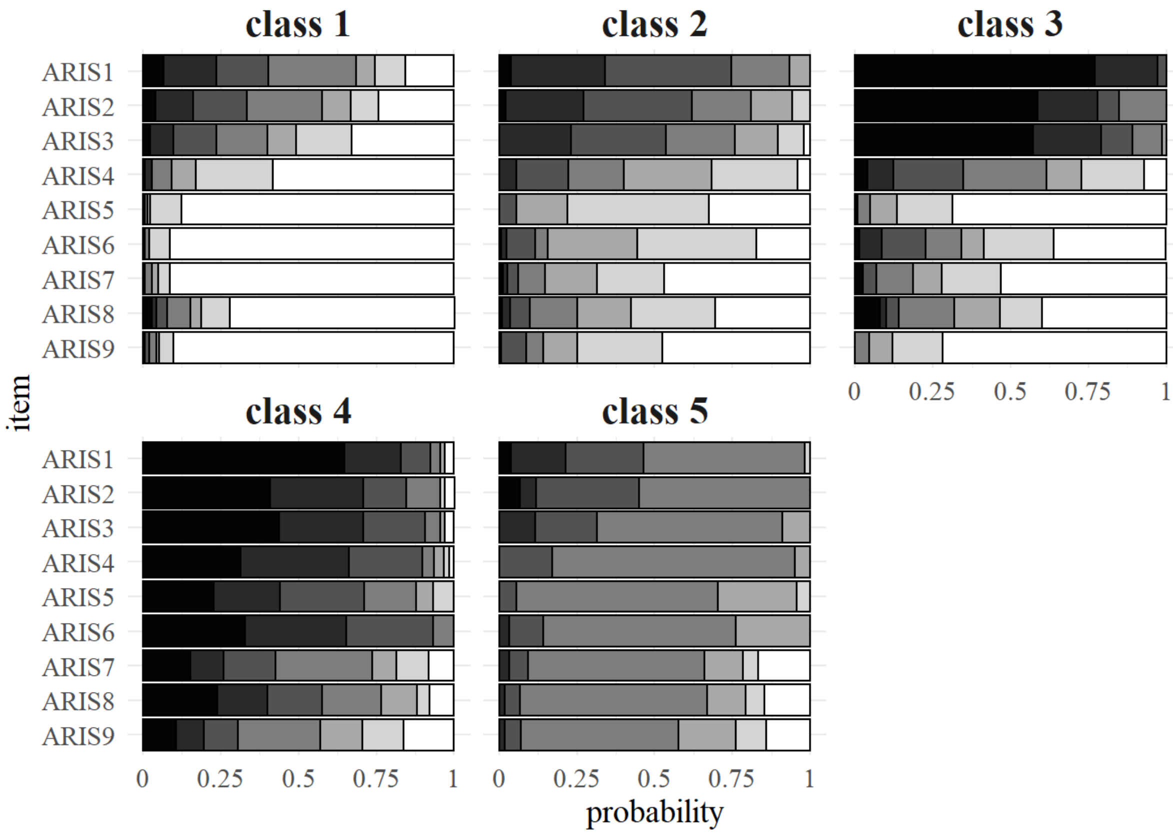
The four-class model (not included in Figure 2), narrowly optimal with respect to BIC, shows first a largely passive class who mostly “strongly disagree” (1) with activist and radical actions. The next class shows strong activist and moderate radical choices. The third class predominantly shows choice of the mid-points of item scales, suggesting uncertainty. The fourth class shows moderate activist but not radical choices.

[3] Visualization of the solutions with two to eight classes are available from the authors.

For the five-class solution (Figure 2), Class 1 consists again of the mostly passive, Class 2 consists of moderate activists, and Class 3 consists of strong activists. Class 4 is defined by relatively high scores on both activism and radicalism items, indicating that this class have radical intentions. Class 5 consists of uncertain individuals who predominantly stick to the scale midpoints.

Examination of models with six, seven, and eight classes indicated that the five-class solution was the best combination of separation and interpretability. Classes 1-5 were named Passive (27%), Moderate Activists (30%), Strong Activists (20%), Radicals (12%), and Uncertain (10%). In Study 1, Passive individuals were 27% of participants, Moderate Activists were 30%, Strong Activists were 20%, Radicals were 12%, and Uncertain were 10%.

Figure 2. *LCA item choices by class for US students*



Note. Darker shades indicate responses reflecting a stronger intention to participate in political actions described in the items.

In the last analysis, we tested whether the importance of country, ethnicity and religion differed significantly across the obtained latent classes. One-way ANOVAs uncovered no significant class differences with respect to the importance of country (F(4, 530) = 1.34, p = 0.255, eta squared = 0.01), ethnicity (F(4, 530) = 2.02, p = 0.090, eta squared = 0.015), or religion (F(4, 531) = 0.508, p = 0.730, eta squared = 0.004).

Study 1 Discussion

In Study 1, we conducted Latent Class Analysis with U.S. college students' responses to nine Activism and Radicalism items. The goal was to identify latent classes within individuals' reported activist and radical intentions that might refine our theoretical understanding of the Two Pyramids Model of radical action. We expected to find four latent classes, three corresponding to the layers of the Action Pyramid (Inert, Activist, and Radical) and one corresponding to non-committal/avoidant responses to the questions on the ARIS scale.

The findings have in part substantiated our predictions. Indeed, among observed latent classes we found three expected classes. Two of these map onto the Action Pyramid of the Two Pyramids Model: Passive individuals (the lowest level of the pyramid, Inert); and Radical individuals (the third level of the pyramid, Radical). And one of these expected and observed classes represented Uncertain or avoidant respondents who were not mappable onto the Two Pyramids Model.

The surprise in our results is that LCA split the Activist level of the pyramid into two parts: a latent class of Moderate Activists and a latent class of Strong Activists. The two classes of activists are not predicted by the Two Pyramids model.

In short, the results of Study 1 in part confirmed theoretical divisions of the Action Pyramid of the Two Pyramids Model, with respect to Inert, Activist, and Radical levels. At the same time, the LCA results suggest a possibility that the Activist layer of the pyramid might have important internal divisions.

To test the generalizability of LCA results in Study 1, Study 2 focused on a sample of respondents different from students in both demographic composition and in life experiences: U.S. prison inmates.

Study 2

Methods

Participants

Data in this study came from a convenience sample of incarcerated men in the US that was developed by Decker and Pyrooz (2019). Researchers interviewed inmates in the weeks prior to their scheduled release from prison. The in-person interviews were conducted in a common area and were not directly observed by any prison staff. Although the total sample consisted of 802 men, data cleaning (described in the Analysis section) left us with 677 participants who were, on average, 39 (SD = 11) years old.

Instruments

ARIS items (Moskalenko & McCauley, 2009) focused on “The Group You Feel Closest To” were again used to estimate latent classes. A ten-item version of the questionnaire (see Table 3) was used and each item was associated with a zero to six scale, ranging from “completely disagree” to “completely agree”. As in Study 1, in this study we treat items as categorical and do not form activism and radicalism scales. As LCA requires positive integers as categories and responses initially ranged from zero to six, we added the value of one to scores of ARIS items.

Two types of items were used to validate classes: gang membership and importance of country, ethnicity/race, and religion. Gang membership was operationalized using three dichotomous variables with a zero indicating that the participant was not a gang member and one indicating that participant was a gang member. One variable reflected the official gang classification of the participant according to Texas Department of Criminal Justice (TDCJ). The remaining two variables reflected self-report measures: one asked if the participant became a gang member prior to incarceration and the other if the participant had ever been a gang member. Importance of the three mentioned groups was assessed on a zero to six scale, ranging from "not important at all" (0) to "extremely important" (6).

Analysis

Multiple steps of data cleaning were conducted prior to LCA. First, participants were excluded who did not respond to the introductory ARIS request for the name of a group the participant "Feels Closest To," or who responded with "none" (n = 125). Responses of the remaining 677 participants were used in the LCA and validation analyses. Again, we used the available data without imputations. Software used to carry out the analyses were the same as in Study 1.

Results

We present means and SDs for ARIS items, gang membership items, and group importance items, followed by the outcomes of LCA used to form classes based on items measuring activism and radicalism, and, finally, tests of class differences in gang membership and group importance ratings.

Table 3. *Means and SDs for items measuring gang membership, group importance and ARIS items for incarcerated men*

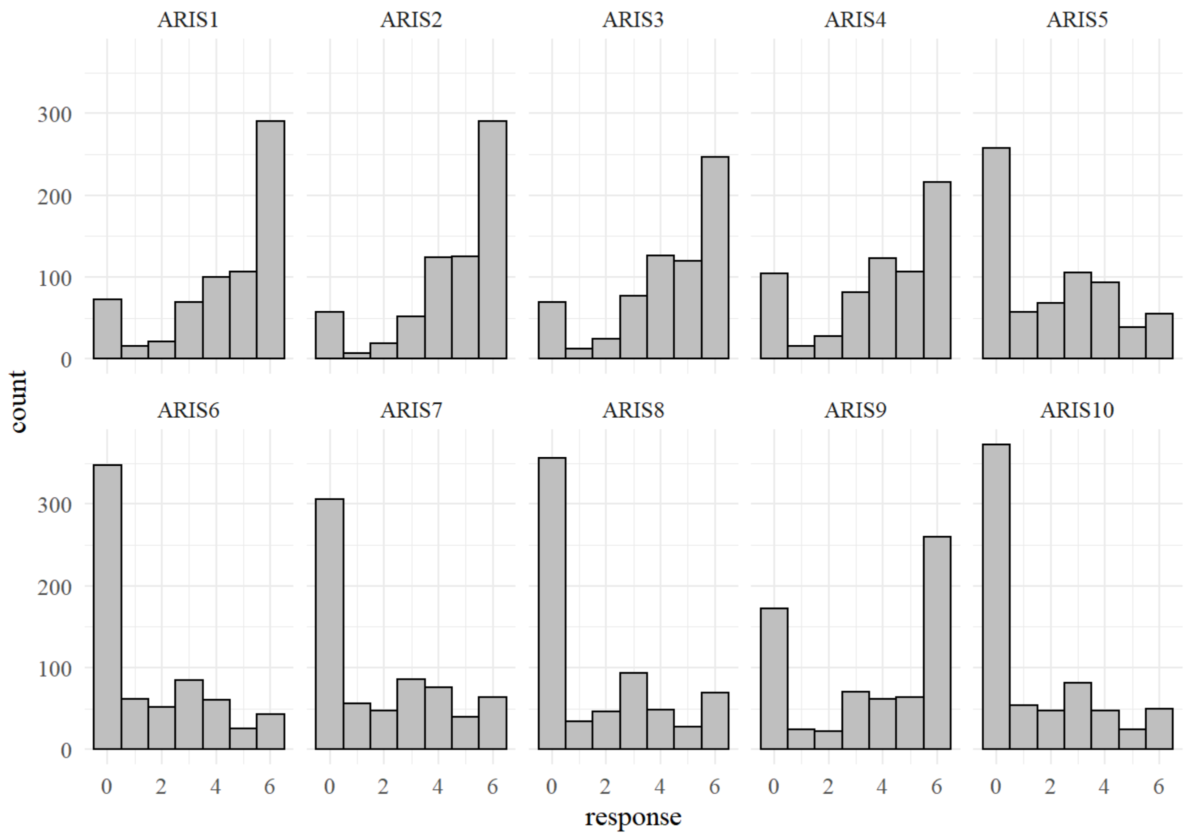
Item	*N*	*M*	*SD*
gang membership – official membership in a gang recognized by TDCJ	677	0.5	0.5
gang membership – respondent was a gang member during his lifetime	675	0.6	0.5
gang membership - respondent was a gang member when incarcerated	677	0.4	0.5
importance – country	677	5.3	1.2
importance – nation	676	4.9	1.4
importance – religion	677	4.8	1.8
…would join a group to fight for ingroup rights (ARIS1)	676	5.3	2.0
…would donate money to group that fights for ingroup rights (ARIS2)	675	5.5	1.8
…would volunteer for an organization that fights for ingroup rights (ARIS3)	676	5.2	1.9
…would travel 1h to protest in support of ingroup (ARIS4)	676	4.9	2.1
…would support an organization that fights for ingroup rights even if law is broken (ARIS5)	676	3.1	2.0
…would support an organization that fights for ingroup rights even if it resorts to violence (ARIS6)	676	2.5	1.9
…would participate in a protest for ingroup, even if violent (ARIS7)	676	2.9	2.1
…would attack police/security if seen beating members of ingroup (ARIS8)	675	2.7	2.1
... would go to war to protect ingroup rights (ARIS9)	676	4.5	2.5
…would retaliate against group that attacked ingroup, even if unsure of guilty (ARIS10)	676	2.5	2.0

Compared to Study 1, group importance among incarcerated men seemed to be about one point higher than group importance among college students. Also, both means and standard deviations of ARIS items tended to be somewhat higher among incarcerated men.

About half of the participants (membership means 0.4 to 0.6) belonged to a gang. In general, participants considered country, race and religion important and were moderately willing to participate in activism to protect their chosen group. While participants expressed low willingness to participate in radicalized actions, one exception was noticed: going to war to protect group rights.

Distributions of participants with respect to responses on ARIS items (Figure 3) suggest grouping may be present. This is especially true for the items of radicalism (ARIS5-10), where three peaks can be noticed: the biggest one for the lowest category that denotes low intentions, another minor peak in the middle of the distribution, and another minor peak on the response denoting the highest willingness to participate in a radicalized political action.

Figure 3. *Distributions of responses to ARIS items for incarcerated men*



After observing the distributions, we conducted latent class analysis on the obtained data, where we again treated responses on the zero to six scale as categorical.

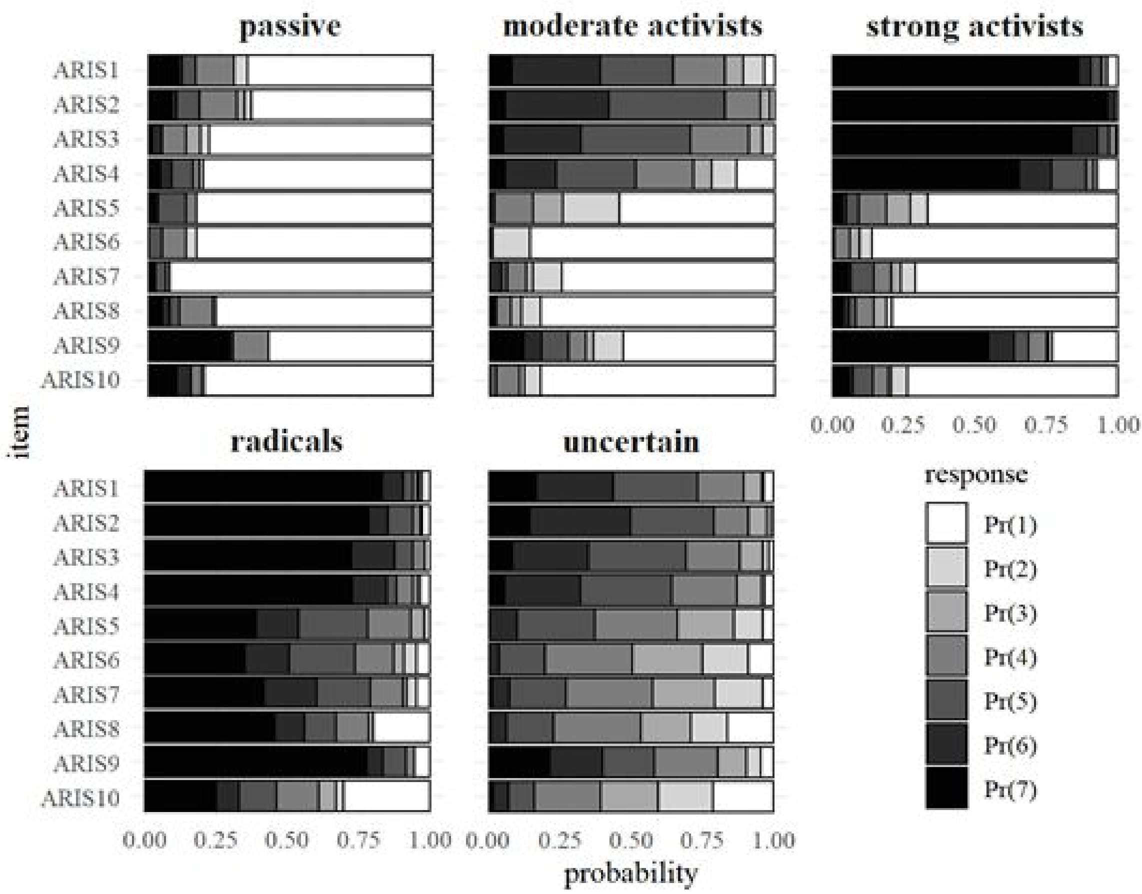
Table 4. *LCA models for incarcerated men*

Model	AIC	BIC	Likelihood ratio	Entropy	% in smallest class
Model 1	21834	22105	13324	-	100
Model 2	20383	20930	11747	0.88	49.69
Model 3	19387	20209	10626	0.91	26.57
Model 4	18928	20026	10052	0.93	20.93
Model 5	18588	19961	9590	0.94	12.02
Model 6	18391	20040	9270	0.94	11.28
Model 7	18267	20191	9027	0.94	9.56
Model 8	18182	20382	8820	0.94	10.09
Model 9	18146	20622	8663	0.95	5.56

The outputs in Table 4 suggest that four to six classes represent an optimal solution for this data set, with BIC achieving a minimum at five latent classes. We visualized all three solutions in order to choose the best fitting one. The four- and five-class solutions yielded similar classes, including moderate activists, strong activists and radicals, but the five-class solution additionally extracted a class of passive individuals. Compared to the four-and five-class solutions, the six-class solution split strong activists into more and less strong, with a small difference in scores on activism items. These results led us to prefer the five-class solution (Figure 4) as most interpretable.

Based on the item scores in Figure 4, these five classes were named Passive (12% of participants), Moderate Activists (20%), Strong Activists (23%), Radicals (20%), and Uncertain (25%).

Figure 4. *LCA item responses with five-class model for incarcerated men*



Note. Darker shades indicate responses reflecting a stronger intention to participate in political actions described in the items.

We tested the discriminant validity of the five-class solution against six criteria: three measures of gang membership and three measures of group importance (country, race and religion).

Owing to the dichotomous nature of the gang membership measures, we applied binary logistic regression with latent classes as categorical predictors to test if the latent classes differ significantly with respect to the proportion of *gang members recognized by TDCJ.* We tested the model with passive individuals as the reference group and bootstrapped it 10000 times to obtain a more robust estimate of outcomes. Results of this model suggested that Passive individuals were as likely to be gang members as Moderate Activists (b = 0.08, 95% BCa CI[-0.48, 0.66], z = 0.291, p = .771), Strong Activists (b = 0.11, 95% BCa CI[-0.42, 0.66], z = 0.406, p = .685) and Mixed class (b = 0.18, 95% BCa CI[-0.36, 0.71], z = 0.650, p = .515). However, Radicals had a higher likelihood of being gang members than individuals from the Passive class (b = 0.67, 95% BCa CI[0.08, 1.24], z = 2.300, p = .021).

We examined two other measures of gang membership in the same manner. Similarly, Passive individuals were as likely to *become gang members during their lifetime* as Moderate Activists (b = 0.08, 95% BCa CI[-0.48, 0.64], z = 0.281, p = .779), Strong Activists (b = -0.01, 95% BCa CI[-0.56, 0.52], z = -0.044, p = .965), and Mixed class (b = 0.35, 95% BCa CI[-0.20, 0.88], z = 1.305, p = .192). Again, Radicals had a higher likelihood of ever being a gang member than Passives (b = 0.94, 95% BCa CI[0.35, 1.53], z = 3.161, p = .002).

Likewise, Passive individuals were as likely to *be gang members while incarcerated* as Moderate Activists (b = 0.02, 95% BCa CI[-0.54, 0.61], z = 0.064, p = .949), Strong Activists (b = 0.09, 95% BCa CI[-0.46, 0.65], z = 0.317, p = .751), and the Mixed class (b = 0.43, 95% BCa CI[-0.14, 0.97], z = 1.562, p = .118). Gang members were more prevalent among Radicals compared to Passives ($b = 1.01$, 95% BCa CI[0.41, 1.59], $z = 3.414$, $p < .001$).

For all three measures of gang membership, then, Radicals were more likely than Passives to be gang members.

In the next step, we tested if the importance of country, race, and religion differ with respect to groups. We used one-way ANOVA with latent classes as predictors and importance variables as criteria, respectively. We found significant differences between classes with respect to importance of country ($F(4, 672) = 6.145$, $p < .001$, eta squared = .035), race ($F(4, 671) = 2.53$, $p = .040$, eta squared = .015), and religion ($F(4, 672) = 9.987$, $p < .001$, eta squared = .056).

In the next step, we used pairwise t-tests with Benjamini-Hochberg false discovery rate (FDR) correction of significance threshold to determine which latent classes significantly differ. For importance of country, Strong Activists achieved significantly higher score ($M = 5.61$) than Passive individuals ($M = 5.00$, corrected $p < .001$), Mixed class ($M = 5.08$, corrected $p < .001$), and Radicals ($M = 5.16$, corrected $p = .004$), but scored similar to Moderate Activists ($M = 5.33$, $p = .080$). No other comparison with importance of country as the criterion yielded a significant outcome.

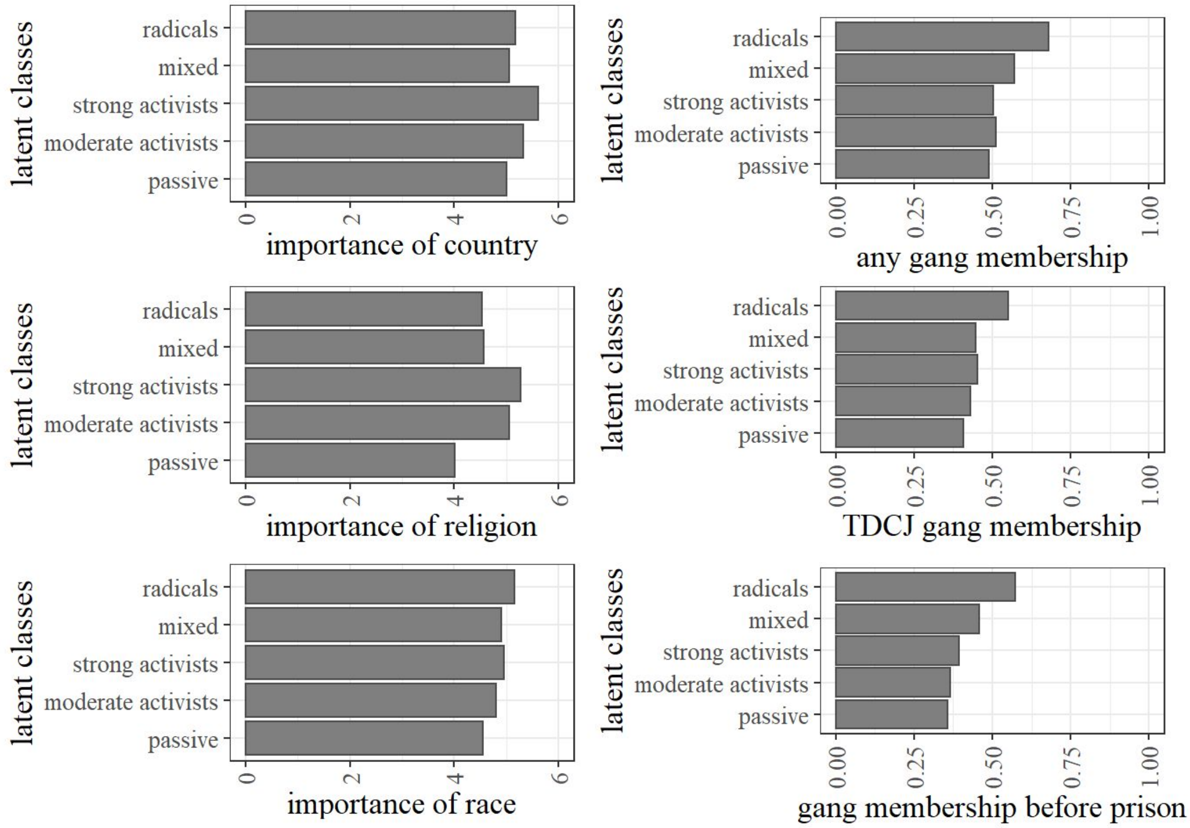
For importance of race, Radicals ($M = 5.15$) scored higher than Passive individuals ($M = 4.54$, corrected $p = .03$), while the corrected p-values of remaining comparisons were not significant.

Finally, for importance of religion, Strong Activists ($M = 5.31$) showed higher scores than the Passives ($M = 4.01$, corrected $p < .001$), Mixed class ($M = 4.60$, corrected $p = .001$) and Radicals ($M = 4.44$, corrected $p < .001$). Furthermore, Moderate Activists ($M = 5.06$) showed higher scores than Radicals ($M = 4.44$, corrected $p = .009$) and Mixed class ($M =$

4.60, corrected p = .031). Individuals from the Mixed class (M = 4.60) also rated importance of religion higher than Passive individuals (M = 4.01, p = .024)

Class differences in gang membership and in importance of country, race, and religion are visualized in Figure 5.

Figure 5. *Gang membership and importance of country, race and religion for latent classes obtained with incarcerated men (N = 670)*



Study 2 Discussion

Study 2 examined a population different in demographics (older, all male), as well as in life experiences (criminal activity and incarceration) and in experiences with violence (known gang membership) than the college students examined in Study 1. These demographic differences provided a useful test of the generalizability of LCA results for ARIS items in Study 1.

As in Study 1, Study 2 found four classes of individuals who can be mapped onto the Action Pyramid of the Two Pyramids Model: Passive (Inert), Moderate Activists, Strong Activists, and Radicals. Study 2 thereby confirmed the surprise of two classes of Activists found in Study 1. The distinction between Moderate and Strong Activists was not predicted by the Two Pyramids Model, which represents Activists as a single class including all those ready to use legal and nonviolent means to advance a political cause. The distinction between Moderate and Strong Activists, consistent across Studies 1 and 2, strongly suggests that the classes uncovered by LCA are capturing real differences among activists that were overlooked in previous studies that relied on factor analysis and mean scale scores to separate activism from radicalism.

A fifth class of Uncertain/Mixed also emerged in both Study1 and Study 2. This class is not linked with the Two Pyramids Model or any existing account of political radicalization, but is nevertheless important as confirmation of the generalizability of LCA results when applied to ARIS item responses from very different respondents.

One of the objectives of Study 2 was to provide discriminant validity for the classes obtained through LCA. Thus, we related these classes to measures of gang membership and to measures of importance of country, race, and religion.

As might be expected, Radicals are consistently higher than Passives on the three measures of gang membership. Radicals are also higher than Passives on importance of race. For importance of religion and importance of country, however, it is the Strong Activists who are highest and Passives lowest.

This pattern of results is a strong validation of the Passives class, who are lowest on every measure of gang membership and every measure of group importance. The pattern also offers moderate validation of the Radicals class, who are highest on every measure of gang membership and on importance of race. The high scores of Strong Activists on importance of country and religion may offer a clue that strong activists are the class most attached to conventional ideals. This is consistent with research that links places of worship and religious social capital with desire to engage in prosocial actions (e.g. Hays, 2015; Kurniadi et al., 2014). Future research might explore a corollary hypothesis: that Strong Activists are less likely than Moderate Activists to escalate to radical and violent action.

Taken together, these results demonstrate significant discriminant validity for the Passive, Moderate Activist, Strong Activist, and Radical classes obtained through LCA in Study 2.

General Discussion

This report provides initial demonstration of the usefulness of Latent Class Analysis (LCA) when studying radicalization. LCA is a statistical tool that can help to bridge the current divide in radicalization research between quantitative approaches that rely on survey data or event data, and qualitative approaches that rely on interview or case study data. By applying LCA to large datasets that include ARIS items, we aimed to connect survey data with the Two Pyramids Model.

The Action Pyramid of the Two Pyramids Model identifies four groups: Politically Inert, Activists, Radicals, and Terrorists. The Activism and Radicalism Intentions Scales (ARIS) offers two scales that distinguish Activism and Radicalism, but the two scales are substantially correlated, often with a correlation above .50 (Pavlović et al., 2021). Bifactor analyses can produce Activism and Radicalism scales that are uncorrelated (Pavlović et al., 2021), but an issue remains: Are groups defined by mean scores on multiple items natural groups? Can these groups be identified as profiles of item responses, without averaging across items?

Two studies with demographically different participants provide a strong affirmative to this question. LCA in both studies identified Inert, Activist, and Radical groups. Indeed, LCA identified two Activist groups, Moderate Activists and Strong Activists—a distinction previously unknown in studies of political mobilization. We conclude that LCA is a useful tool for radicalization research; in particular LCA provides a link between survey studies of radicalization and case-based theorizing about levels of political action.

It is interesting to compare Studies 1 and 2 in the proportion of participants in each of the classes identified. In Study 1, Passive individuals were 27% of participants, Moderate Activists were 30%, Strong Activists were 20%, Radicals were 12%, and Uncertain were 10%. In Study 2, Passive were 12% of participants, Moderate Activists were 20%, Strong Activists were 23%, Radicals were 20%, and Uncertain were 25%. It appears that Radicals were more common in Study 2 (20%) than in Study 1 (12%), and Passive were less common in Study 2 (27% vs. 12%). Given that Study 1 participants were college students and Study 2 participants were prisoners, it is not surprising to find Radicals more prevalent in Study 2. Indeed, the higher prevalence of Radicals among prisoners offers some validation of the class identified as Radicals.

A new technique invites a reasonable question: is it sufficiently useful to warrant the effort required of researchers to understand it? We believe it is. LCA adds to our understanding of the psychology of radicalization beyond what could be achieved with traditional statistical means. In two different samples, LCA consistently produced two classes of activists not predicted by existing theory and not reported by previous studies that used ARIS. In other words, LCA was able to find an important separation among activists, a separation that was validated by differential patterns of correlations with external variables in Study 2.

Another evidence of LCA's utility is its finding of an Uncertain/Mixed class in both Study 1 and Study 2. LCA enables researchers to identify these individuals as a separate group, rather than losing track of them in averaged scores and possibly losing or blurring important predictors of radicalization as a result.

While interpreting our findings, two limitations are worth considering. First, both the student sample and the prisoner sample were convenience samples, not random samples representative of defined populations. Although we found similar latent classes in these qualitatively different samples, which is a strong argument in favor of robustness of our findings, some classes that might exist in a representative sample may have been rare of missing in our samples. However, both students and prisoners were in the age-range in which people become radicalized (Gruenewald & Chermak, 2015; Porter & Kebbel, 2011), which increases the relevance of these samples in studying radicalization. A second limitation is that our approach to validation of classes depended on measures available in our two data sets: group importance ratings and gang membership. More complex solutions for validating classes are recommended (Vermunt, 2010; Bakk & Kuha, 2021).

The surprise of finding two groups of Activists—Moderate and Strong—leads us to wonder if there might be two groups of Radicals. Moderate Radicals might be open to both Activist and Radical action, to both nonviolent and violent action for the cause they care about. This is indeed the profile of Radicals identified by LCA in this report, who were high on both Activist and Radical items. But case histories suggest another kind of Radical, who has given up on non-violent action and Activism, and is committed to violent action as the only effective means of forwarding the cause. This Strong Radical would show a profile of low intentions on Activism items but high intentions on Radicalism items.

We did not find a class or group of these Strong Radicals, but these may be too rare to establish as an LCA class among US college students or even among US incarcerated men. Future research might find Strong Radicals in protracted political conflicts, such as the

Jewish-Palestinian conflicts, in which duration and bitterness of conflict have led some on both sides to give up on peaceful activism and conclude that only violence can help their cause.

The surprise of finding two groups of Activists has another implication. It seems to us (see also Freilich et al., 2014) to highlight a weakness of existing radicalization research, too focused on terrorists and radicals to pay attention to activists as a competing form of political mobilization. Perhaps different classes of activists represent different levels of resistance to violent action, and, as such, present opportunities to reduce extremist violence not only by preventing or deradicalizing violent actors, but also by understanding better how some choose nonviolent over violent action.

Existing research seems to support this direction. For example, Dornschneider and Henderson (2016) interviewed nonviolent activists and terrorists for two 1970s causes—Egyptian Islamists and German leftists. Against the usual story that ideology and grievance explain the turn to terrorism, Dornschneider and Henderson found that the same ideology and grievance led some to activism and others to terrorism. Similarly, Reidy (2019) compared radicalization trajectories of British Muslims who joined Daesh with those who chose instead to engage in sectarian humanitarian aid for civilians in Daesh-controlled territory. Although the two groups (terrorists and activists) shared the same grievances, they differed in the moral frames through which they interpreted those, leading some to engage in violence while others engaged in peaceful activism.

Thus, some activists may emerge from the same pathways that lead to radicalism and terrorism, their commitment to nonviolent and legal action hard won against the current of the attraction (and threat) of terrorist groups around them. It is possible that among the different activist classes reported in this study one represents this kind of hardened activist.

Strong Activists, as identified in this report, may be more resistant to violent action, as they scored higher on importance of country and religion.

Future studies might explore these possibilities by asking about past experiences with both peaceful political action and political violence, as well as about political grievances, attitudes to extremist ideology, and moral frames, to relate these to differences between activists and radicals. Identifying and describing the kind of committed activists observed by Dornschneider & Henderson (2016) and by Reidy (2019) might be a worthwhile goal for those tasked with understanding and reducing extremist violence.

Data availability statement

Restrictions apply to the availability of these data, which were used with the permission of researchers who collected the data. Data used in Study 1 are available from Michael Becker, while data used in Study 2 are available from David Pyrooz and Scott Decker.

Conflict of interest

Authors have no conflicts of interest to declare.

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