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The interplay of trust and justice: Multivariate analysis on post- conflict attitudes toward the Colombian Revised Peace Agreement of 2016

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Abstract

This thesis explores public attitudes toward Colombia's Revised Peace Agreement (RPA) using data from the 2021 MAPS survey. While support for the RPA is known to be fragmented, this study examines whether these attitudes are structured and how they relate to trust, conflict experience, and demographics. Three multivariate methods, Multivariate Correspondence Analysis (MCA), Canonical Correlation Analysis (CCA), and Redundancy Analysis (RDA) are applied to uncover latent patterns. Findings show that trust in reintegrated ex-combatants is the strongest and most consistent predictor of support for contested RPA components, such as political participation of former FARC members. MCA further reveals distinct attitudinal clusters linked to socio-structural profiles and conflict exposure. The study contributes to peacebuilding research by highlighting the role of targeted trust-building in sustaining public support. It also offers a comparative methodological framework for analyzing complex attitudes in post-conflict societies.

Keywords: Public attitudes toward peace agreements, Trust in ex-combatants, Political reintegration, Multivariate analysis (MCA, CCA, RDA), Colombian peace process

Deontological note

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Joke Dirix

A handwritten signature in black ink, appearing to read 'Joke Dirix', with a large, sweeping flourish underneath.

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List of Abbreviations

CCA	Canonical Correlation Analysis.
CFI	Comparative Fit Index.
DDR	Disarmament, Demobilization and Reintegration.
EFA	Exploratory Factor Analysis.
FARC	Fuerzas Armadas Revolucionarias de Colombia: The rebel group FARC-EP has been transformed into a new political party FARC, decided upon in the Revised Peace Agreement with the Colombian government in 2016. In 2021 the political party changed its name to Comunes.
FARC-EP	Fuerzas Armadas Revolucionarias de Colombia – Ejército del Pueblo: Rebel group that has been in conflict with the Colombian government for 50 years, until 2016.
JEP	Special Jurisdiction for Peace.
LAPOP	Latin American Public Opinion Project.
MAPS	Mapping Attitudes, Perceptions and Support.
MCA	Multivariate Correspondence Analysis.
PDET	Programas de Desarrollo con Enfoque Territorial: 16 regions selected based on exposure to violence during the conflict and measures of poverty. These regions are the main focus of the Revised Peace Agreement.
RDA	Redundancy Analysis.
RPA	Revised Peace Agreement: Peace agreement between the rebel group FARC-EP and the Colombian government.
VIFs	Variance Inflation Factors.

1. Introduction

With the 2026 parliamentary elections approaching, the political party Comunes (formerly FARC) is preparing to compete for the first time without the 10 congressional seats that were guaranteed under the 2016 peace accord as part of its transitional political integration efforts (Castaño, 2025; Weintraub et al., 2023). This marks a significant moment in the implementation of the Revised Peace Agreement (RPA), which was signed in 2016 between the Colombian government and the former rebel group FARC-EP, bringing an official end to one of the longest internal armed conflicts in Latin America. The RPA, the result of years of negotiation and international mediation, marked a historic turning point for the country. It introduced mechanisms for the demobilization and reintegration of ex-combatants, as well as substantial commitments to rural development, transitional justice, and the political inclusion of the former guerrilla (García-Sánchez et al., 2023). Despite these ambitious goals, the agreement faced significant societal polarization. A first version of the peace deal was narrowly rejected by the Colombian public in a plebiscite (Téllez, 2019; Wittke, 2018), and even after its revision, public support has remained fragmented and conditional (Phelan, 2019).

In the years following the RPA, scholars have explored both the political and social consequences of the peace process. While early research focused primarily on institutional implementation and the evolution of the FARC into a political actor (Capone, 2018; Phelan, 2019; Cabrera Nossa & Echandía Castilla, 2019), later studies increasingly addressed the importance of public attitudes toward the RPA and/or its individual components (García-Sánchez & Carlin, 2020; Muñoz & Pachón, 2021; García-Sánchez et al., 2023; Weintraub et al., 2023). These attitudes are crucial not only for legitimizing the agreement but also for sustaining peace through democratic participation. In a democratic context such as Colombia's, where former rebels are expected to compete in elections and integrate into political institutions, the opinions and perceptions of ordinary citizens become essential for the agreement's long-term viability (García-Sánchez & Carlin, 2020; García-Sánchez et al., 2023). This is particularly relevant ahead of the 2026 parliamentary elections, in which the political party Comunes will compete without the guaranteed seats previously allocated by the peace accord (Weintraub et al., 2023).

Existing literature has already shown that citizens do not perceive the RPA as a unified whole (García-Sánchez et al., 2023). Support tends to be selective and component-specific: measures related to social development, such as improving education, healthcare, or rural infrastructure, typically receive broader approval than more politically sensitive provisions, such as the reintegration or electoral participation of former FARC combatants, or coca substitution programs (Riomalo Clavijo, 2023; Téllez, 2019). Studies using survey data, including Latin American Public Opinion Project (LAPOP) and Mapping Attitudes, Perceptions and Support (MAPS) datasets, have begun to identify key

determinants that shape this variation in support. For example, ideological orientation, particularly support for left- or right-wing parties, strongly predicts attitudes toward transitional justice and political inclusion (Muñoz & Pachón, 2021; García-Sánchez & Carlin, 2020). Similarly, trust in institutions and ex-combatants, experiences of victimhood, and religiosity play critical roles in determining levels of approval across peace components (Esparza et al., 2020; Weintraub et al., 2023). Women, rural populations, and victims of the armed conflict often express lower support for the reintegration of ex-FARC members, while showing more consistent support for development-related policies (Dirix, 2024).

Yet, much of the existing research tends to examine public attitudes in a fragmented manner. Individual components of the RPA, such as political inclusion, justice mechanisms, or rural development, are often analyzed in isolation, while broader indices of support for the RPA in general, risk oversimplifying public opinion (Carlin et al., 2020; García-Sánchez et al., 2023). As a result, there is still a lack of a deeper understanding of how citizens cognitively organize and relate to the different elements of the peace accord. Specifically, it remains unclear whether certain attitudes coalesce into broader latent dimensions, such as support for peacebuilding or social justice, and how these dimensions relate structurally to sociopolitical variables such as trust, conflict experience, religiosity, or demographics (Dirix, 2024).

This leads to the following research questions:

1. Which structural relationships exist between sets of determinants (e.g., demographics, trust, conflict exposure) and attitudinal subsets of the Revised Peace Agreement?
2. To what extent does support for social development and justice differ from support for peacebuilding and political reintegration?
3. How do different analytical methods (Multivariate Correspondence Analysis, Canonical Correlation Analysis, and Redundancy Analysis) compare in revealing these relationships?

This research seeks to answer these research questions by building upon previous attitudinal research, including my own earlier study on public opinion toward the RPA (Dirix, 2024). Whereas the earlier thesis relied primarily on exploratory factor analysis and linear regression to identify and predict attitudinal dimensions, this study expands the analytical scope by applying a more robust and comparative methodological framework. Specifically, it explores the structural interrelationships between sets of determinants (e.g., demographics, trust, victimhood) and clusters of attitudinal responses (e.g., support for transitional justice, political reintegration, or rural development). In doing so, the study aims not only to deepen the empirical analysis of peace-related attitudes, but also to contribute methodologically by comparing alternative multivariate techniques for modeling attitudinal complexity.

To carry out this analysis, the study uses data from the 2021 Mapping Attitudes, Perceptions, and Support (MAPS) survey (Weintraub et al., 2023), a large-scale, nationally representative dataset designed to capture Colombian citizens' views on various aspects of the peace process. The dataset includes detailed information on individual demographics, conflict exposure, institutional trust, religiosity, and perceptions of former combatants, along with a broad range of attitudinal items related to the RPA. These attitudinal items cover both material and symbolic dimensions, such as support for transitional justice mechanisms, rural development, political reintegration, and coca substitution programs.

To uncover the structural patterns between these sets of variables, the thesis applies and compares three multivariate statistical techniques: Multivariate Correspondence Analysis (MCA), Canonical Correlation Analysis (CCA), and Redundancy Analysis (RDA). These techniques differ in their assumptions and analytical goals, ranging from visual data exploration to theory-driven model testing, but all are suited to analyzing high-dimensional, interdependent survey data. Together, they provide a robust and complementary framework for mapping how different groups of citizens relate to different components of the RPA. This multi-method approach not only enhances the empirical robustness of the findings, but also lays the groundwork for the thesis's broader theoretical, methodological, and societal contributions.

From a theoretical perspective, this research contributes to the growing body of literature that disaggregates public attitudes toward peace processes. Rather than viewing public support for peace as a unidimensional construct, it highlights how citizens differentiate between material, institutional, and symbolic components of an agreement (Branton et al., 2019; Muñoz & Pachón, 2021; García-Sánchez et al., 2023). Understanding these distinctions is essential for analyzing how peace agreements are internalized, legitimized, or resisted by different segments of society. From a methodological standpoint, the thesis introduces a comparative multivariate approach to attitude research in peace and conflict studies. By applying and contrasting MCA, CCA, and RDA, it demonstrates how different techniques can uncover complex interdependencies in high-dimensional survey data. Although widely used in psychology and education (Sherry & Henson, 2005), such techniques remain underutilized in political science and peace research, particularly in Latin American contexts. Finally, the societal and policy relevance of this research lies in its potential to inform the implementation and public communication of the RPA. It offers insights into which social groups support which aspects of the agreement, helping policymakers design more targeted outreach strategies. The findings also provide guidance for political actors like the Comunes party as they navigate electoral competition in 2026, and may offer lessons for other post-conflict contexts engaged in Disarmament, Demobilization, and Reintegration (DDR), where the long-term legitimacy of peace agreements hinges on public support for contested provisions (Rothchild, 2002; Cabrera Nossa & Echandía Castilla, 2019). Taken together, these contributions

position this study at the intersection of public opinion research, peacebuilding theory, and applied multivariate analysis.

The remainder of this thesis is structured as follows. Chapter 2 provides a literature review, starting with the Colombian peace process and the RPA, followed by research on public attitudes toward peace agreements and their determinants, with emphasis on the Colombian context. It also addresses the conceptualization of attitudinal structures and the importance of multidimensional approaches. Chapter 3 outlines the analytical framework and introduces the three multivariate techniques used in this study: MCA, CCA, and RDA, along with their comparative rationale. Chapter 4 details the research design and methodology, including the MAPS dataset, variable operationalization, and statistical procedures. Chapter 5 presents the empirical results and discusses the insights provided by each technique, followed by a comparative triangulation. Chapter 6 concludes with key findings, theoretical and policy implications, methodological contributions, and directions for future research. Thus, the next chapter reviews the existing literature on Colombia's peace process and public opinion toward the RPA.

2. Literature Review

2.1 Colombia's peace process and the Revised Peace Agreement

The peace process between the Colombian government and the guerilla group Fuerzas Armadas Revolucionarias de Colombia – Ejército del Pueblo (FARC-EP) represents a landmark effort to end one of the world's longest internal armed conflicts. The conflict itself dates back to the 1960s and was rooted in deep social and economic inequalities, unequal land distribution, and the marginalization of rural populations from political decision-making. What began as a Marxist-inspired peasant insurgency evolved over time into a complex war involving guerrilla groups, right-wing paramilitaries, drug trafficking cartels, and the Colombian state (Capone, 2018; Téllez, 2019). After decades of violence, forced displacement, and failed peace attempts, a new opportunity arose in 2012 when President Juan Manuel Santos launched formal negotiations with the FARC-EP leadership. These talks, held in Havana and supported by international facilitators including Norway and Cuba, followed a structured six-point agenda that addressed the root causes of the conflict, transitional justice, and long-term institutional reforms. A central innovation of the negotiation framework was its “nothing is agreed until everything is agreed” principle, ensuring an integrated and balanced outcome (Capone, 2018; Wittke, 2018).

In 2016, after four years of dialogue, the parties signed a final peace accord. However, the agreement was narrowly rejected in a national plebiscite, revealing deep societal divisions and concerns about impunity and political concessions. In response, a revised version of the agreement was negotiated within weeks and ratified by Congress later that year. This RPA preserved the structural pillars of the original deal but introduced modifications to address the concerns of opposition groups, including stricter conditions for political participation by ex-combatants, clearer provisions on victim reparations, and adjustments to the transitional justice framework (Téllez, 2019; García-Sánchez et al., 2023).

The RPA is organized around six interdependent pillars. It promotes comprehensive rural reform, aiming to improve land access, agricultural development, and basic infrastructure in historically neglected areas. It guarantees political participation by allowing the former FARC-EP to transition into a legal political party, Fuerzas Armadas Revolucionarias de Colombia (FARC), with temporary congressional representation. The agreement defines a roadmap for disarmament, demobilization, and reintegration (DDR), monitored by international observers. In terms of drug policy, it shifts the focus toward voluntary crop substitution and integrated rural development. The RPA also establishes a robust transitional justice system, including the Special Jurisdiction for Peace (JEP), a Truth Commission, and reparations for victims. Finally, it provides mechanisms for implementation and verification, supported by national institutions and international oversight bodies (Carlin et al., 2020; García-Sánchez & Carlin, 2020).

What distinguishes the RPA from previous peace efforts is its multidimensional scope. It does not merely aim to silence weapons but seeks to transform the structural drivers of conflict through a blend of security guarantees, social policy, and historical recognition. One of its most innovative elements is the creation of the Programas de Desarrollo con Enfoque Territorial (PDET), which direct participatory planning and development funding to the 170 most conflict-affected municipalities. This territorial focus reflects a broader understanding of peace as a process rooted in equity, inclusion, and state presence in marginalized regions (Weintraub et al., 2023).

2.2 Public attitudes toward peace agreements and their determinants

In contemporary peace processes, public opinion is widely recognized as a critical factor in shaping both the legitimacy and the durability of peace agreements. Citizens not only serve as voters in referendums or plebiscites but also as key actors in the implementation phase, where their support or resistance can make or break the success of post-conflict policies. Agreements that lack popular legitimacy are more vulnerable to political reversal, non-compliance, or social unrest (García-Sánchez & Carlin, 2020). A striking example of this was the initial rejection of the Colombian peace agreement in the 2016 plebiscite, which prompted a series of revisions to the accord in an effort to increase its public acceptability and political viability. Especially in democratic contexts, public backing becomes indispensable. Peace agreements are subject to the electoral cycle, and politicians opposing them may gain power if public sentiment turns hostile. Moreover, when former combatants are integrated into the democratic arena, their political viability depends heavily on how they are perceived by the broader population (García-Sánchez et al., 2023).

A growing body of research has sought to identify the key drivers of public attitudes toward peace agreements. One of the most consistent findings is the importance of political orientation and elite cues. Voters tend to follow the positions taken by political leaders, especially in polarized environments or during highly ideological referendums. Rather than relying on issue-specific information, citizens often adopt the stance endorsed by parties or leaders they identify with (Muñoz & Pachón, 2021). This dynamic is further reinforced by elite fragmentation. When political elites are publicly divided on a peace accord, these divisions become easily recognizable cues for voters, who interpret them as signals to support or oppose the agreement (Garbiras-Díaz et al., 2023).

Political identity is not the only factor that shapes attitudes. Several studies have explored whether lived experiences of violence affect support for negotiation and reconciliation. Macro-level analyses of the 2016 Colombian plebiscite suggest that areas most affected by conflict, including zones with high numbers of combatants or displaced populations, were more likely to vote in favor of the RPA

(Muñoz & Pachón, 2021). However, findings at the individual level are less consistent. Some surveys found no significant difference in support for transitional justice mechanisms between victims and non-victims (Nussio et al., 2015; Matanock & Garbiras-Díaz, 2018), while others pointed to a positive association between living in conflict-affected areas and willingness to accept negotiated settlements (Liendo & Braithwaite, 2018).

Yet, exposure to violence does not uniformly increase support for peace. Téllez (2019) argues that alignment with one of the conflict parties, or high levels of perceived threat, can push individuals toward more punitive or rejectionist attitudes. From this perspective, prior experiences with violence may lead not to reconciliation, but to hardened positions. Attitudes are also shaped by psychological expectations about the future. Research shows that more pessimistic individuals, those who perceive continued insecurity or instability, may paradoxically be more open to supporting peace agreements that promise long-term social benefits (Larsen, 1972).

Taken together, these findings suggest that public opinion toward peace agreements is shaped by a complex mix of ideological, political, emotional, and experiential factors.

2.3 Attitudinal Research in the Colombian Context

The public opinion complexity towards peace agreements is particularly evident in the Colombian case, where public responses to the RPA have reflected not only ideological and political divisions, but also lived experiences of violence, levels of institutional trust, and attitudes toward former combatants. As such, analyzing attitudinal patterns in this specific context provides valuable insights into both the challenges and potential of building sustainable peace through democratic consensus (García-Sánchez & Carlin, 2020; Muñoz & Pachón, 2021; Esparza et al., 2020).

One prominent area of research focuses on the role of conflict exposure and victimization. Several studies suggest that proximity to violence increases support for the RPA. Esparza et al. (2020) and Branton et al. (2019), using plebiscite returns and LAPOP survey data respectively, found that individuals residing in more conflict-affected areas tend to hold more favorable views of the RPA. These findings indicate that communities who suffered the most may also be the most receptive to nonviolent solutions. Similarly, Kreiman and Masullo (2020) observed that citizens who had been displaced by the FARC-EP or had suffered violence at their hands were more likely to express support for the peace process. Victimization, in this sense, appears to foster not only a desire for justice, but also a pragmatic acceptance of negotiation.

Nevertheless, the impact of violence on Colombian attitudes is not only positive. Téllez (2019) argues that exposure to violence can also produce hardened stances, especially when individuals identify with one of the conflict parties. In such cases, civilians may view conciliatory measures as unjust or threatening, particularly if they perceive a lack of accountability. These effects are often mediated by the perception of threat, a psychological mechanism that shapes attitudes toward security, reconciliation, and forgiveness.

Another major determinant of attitudes toward the RPA is political alignment. In Colombia's deeply polarized political landscape, support or opposition to the agreement often mirrors party loyalties. Research by Mun et al. (2021) and Branton et al. (2019) shows that those who voted for President Santos in the 2010 and 2014 elections, under whose government the peace process was negotiated, were more likely to support the RPA. Conversely, supporters of former president Uribe, a vocal opponent of the accord, typically opposed it. This reflects broader ideological divides: right-leaning citizens tend to express less support for peacebuilding through negotiation, often favoring more retributive approaches. However, Riomalo Clavijo (2023) found that these ideological effects are less pronounced in conflict-affected areas, where lived experiences may moderate partisan reasoning.

Muñoz and Pachón (2021) offer further nuance by identifying three key voter profiles: government-aligned citizens, right-wing conservatives, and evangelical Christians. The first group was most likely to support the RPA, while the latter two expressed greater ambivalence, particularly regarding provisions related to transitional justice and the political integration of ex-FARC members. These profiles suggest that religion, ideology, and institutional trust jointly shape how citizens interpret the legitimacy and desirability of post-conflict arrangements.

Socio-demographic variables also play a role. Liendo and Braithwaite (2018) report that urban, highly educated Catholics were more likely to oppose the agreement, especially in comparison to their rural or less-educated counterparts. This may reflect a greater detachment from the war's human toll or differing expectations about justice and order. Gender, too, appears to matter: while women tend to support development-related aspects of the RPA, such as education and public health, they are often more skeptical of the political reintegration of former guerrilla fighters, potentially due to concerns about trust or security.

Trust in the key actors of the peace process, both state and non-state actors, emerges as another central factor. Based on LAPOP data, Esparza et al. (2020) found that individuals who trusted the political elite and the FARC-EP negotiators were more inclined to express overall support for the RPA. Paradoxically, however, these same individuals were less likely to have voted in the plebiscite, raising questions about the disconnect between attitudinal support and electoral behavior. Meanwhile, plebiscite voting behavior continues to serve as a long-term indicator of attitudes toward the peace process: those who voted "Yes" tend to support the agreement's implementation, while "No" voters remain more

critical (Muñoz & Pachón, 2021). Carlin et al. (2020) further emphasize that attitudes toward the political integration of ex-combatants are particularly strongly associated with broader support for the RPA, suggesting that public comfort with reintegration is a cornerstone of legitimacy.

Prior research (Dirix, 2024), gives further insights into attitudinal structure and uncovered its determinants through both bivariate and multivariate analyses. As earlier suggested by Liendo and Braithwaite (2018), bivariate correlations revealed that general attitudes toward the RPA did not necessarily align with attitudes toward specific components of the agreement. This discrepancy may point to a lack of detailed public knowledge about the accord, or to symbolic opposition to “peace” as a political project rather than a rejection of the individual policies it contains. Respondents may oppose the agreement in the abstract while supporting concrete initiatives such as land reform or education.

To explore underlying patterns in attitudinal responses, an exploratory factor analysis (EFA) was conducted, which revealed three distinct latent dimensions. The first dimension clustered attitudes related to social development and justice, including views on education, healthcare, women's participation, protection of social leaders, and transitional justice mechanisms. The second dimension reflected peacebuilding-related items, such as coca substitution, the disarmament of the FARC-EP, and the reintegration of former combatants. Interestingly, attitudes toward allowing former guerrillas to participate in elections did not clearly align with either dimension, indicating continued public hesitation on this point (Dirix, 2024).

To identify what drives these three attitudinal dimensions, multiple regression models were employed. The findings showed that trust in reintegrated ex-FARC members, particularly those actively participating in reintegration programs, was the strongest and most consistent predictor of support across the three dimensions. Political trust had a more ambiguous effect: while it enhanced general support for the agreement, it negatively influenced attitudes toward specific measures related to justice and development. Victims of the armed conflict, in turn, expressed notably higher levels of support for both development-oriented and peacebuilding provisions, an indication of their desire for repair, recognition, and forward-looking solutions. Finally, voting behavior in the 2016 plebiscite continued to shape public opinion: those who voted “Yes” were significantly more supportive across the board (Dirix, 2024).

In sum, attitudes toward the Colombian peace process are far from monolithic. They are shaped by a dynamic interplay of political allegiance, personal experience, institutional trust, religious identity, and socio-demographic characteristics. Moreover, support for the RPA is not a singular construct, but rather a constellation of attitudes toward its many components, some of which may be embraced even by those critical of the broader deal (Dirix, 2024).

2.4 Attitude structures and measurement

Public attitudes toward peace agreements are seldom singular or one-dimensional. Instead, they tend to reflect broader belief systems or latent constructs, psychological dimensions that organize and influence a wide array of related evaluations (DeVellis, 2017). These constructs are not directly observable, but can be inferred through consistent response patterns across multiple survey items. In the context of peace processes, this means that support for the RPA is often composed of layered attitudes toward diverse components such as justice, security, political reintegration, and rural development (Fabrigar & Wegener, 2012; Branton et al., 2019). Understanding how these components relate or diverge, within the minds of citizens, requires a methodological focus on underlying attitudinal structures.

Previous research on public support for peace agreements has primarily relied on single-item measures or additive indices, assuming that all aspects of the agreement are perceived similarly by respondents (Liendo & Braithwaite, 2018). However, studies such as García-Sánchez et al. (2023), Muñoz & Pachón (2021), and Dirix (2024) have shown that this assumption does not hold in the Colombian case. Citizens often approve of certain elements of the peace deal, such as investments in education or health, while simultaneously rejecting others, like the political inclusion of former FARC combatants. This indicates that public opinion is fragmented across multiple attitudinal dimensions, which cannot be adequately captured through simple averages or binary indicators. For instance, someone may strongly support transitional justice for victims, but oppose coca substitution programs or FARC participation in elections. These seemingly contradictory positions are not anomalies, but reflections of structurally distinct attitudinal domains (Carlin et al., 2020). Identifying these domains requires analytical tools that go beyond describing individual opinions or estimating single regression coefficients. Rather, they must be able to model how sets of independent variables (e.g., conflict exposure, institutional trust, political ideology) relate to sets of dependent variables (e.g., support for justice, reintegration, or development), in other words, multivariate interdependence.

Despite the conceptual relevance of latent attitude structures, most empirical studies in peace and conflict research, and the Colombian RPA in particular, still rely on univariate methods, such as Ordinary Least Squares regression or bivariate cross-tabulations (García-Sánchez & Carlin, 2020; Esparza et al., 2020). These approaches are effective for isolating the predictors of individual variables, but fall short when the goal is to understand the complex configuration of relationships between entire clusters of variables. For example, how does a specific trust profile (e.g. high institutional trust, low trust in FARC) influence a respondent's combined position on rural development and transitional justice? Or how do political ideology and victim status jointly shape positions across multiple peacebuilding policies?

To address this gap, researchers in psychology and education have long employed multivariate statistical techniques such as MCA, CCA, and RDA (Sherry & Henson, 2005). These methods allow for the simultaneous analysis of interdependencies between two or more sets of variables, capturing how patterns in one domain (e.g., demographic and psychological traits) predict structures in another (e.g., attitudes toward peace components) (Cohen et al., 2003). However, these techniques remain underutilized in political science, and particularly in Latin American peace research. Even when rich survey data are available, most analyses apply descriptive statistics or linear models without investigating the internal coherence or dimensional structure of attitudes (Mun et al., 2021; Weintraub et al., 2023). This methodological gap limits the ability to capture the complexity of public support for peace agreements, which leads to the following research questions:

1. Which structural relationships exist between sets of determinants (e.g., demographics, trust, conflict exposure) and attitudinal subsets of the Revised Peace Agreement?
2. To what extent does support for social development and justice differ from support for peacebuilding and political reintegration?
3. How do different analytical methods (CA, CCA, and RDA) compare in revealing these relationships?

This thesis seeks to answer these questions by applying and comparing four multivariate techniques to investigate how Colombian citizens' socio-political characteristics and experiences relate to their structured responses to different components of the RPA.

3. Analytical framework: Multivariate techniques

In studies of complex attitudes, multivariate statistical methods offer a clear advantage over simpler univariate approaches. Since attitudinal structures rarely follow linear or unidimensional patterns, these methods enable researchers to examine how multiple variables interact, correlate, and give rise to latent structures, offering a more nuanced understanding of the underlying dynamics (Tacq, 1992; Husson et al., 2011). This capacity is particularly important in attitudinal research, where public opinions often span multiple dimensions (Hair et al., 2010). The goal of this chapter is to outline and position four multivariate techniques that are used in this thesis: Multivariate Correspondence Analysis (MCA), Canonical Correlation Analysis (CCA), and Redundancy Analysis (RDA).

Each of these methods provides different insights into the data. MCA is designed to visualize associations between categorical variables, while CCA models the relationship between two sets of continuous variables. Finally, RDA offers a more flexible and assumption-light approach to evaluating the structural coherence between blocks of variables. Selecting between these techniques depends on the nature of the data, the level of theoretical development, and the type of relationships one seeks to examine (Tacq, 1992; Husson et al., 2011; Hair et al., 2010). The table below provides a concise overview of the four multivariate techniques discussed in this chapter, summarizing their main applications, strengths, and limitations.

Table 1. Summary of multivariate analysis techniques used in this study

Method	Primary Application	Advantages	Limitations
Multivariate Correspondence Analysis (MCA)	Exploring associations between categorical variables	Strong for visualizing groupings; low data requirements; useful for cross-tabulated survey data	Exploratory only; no causal testing; interpretation of dimensions may be subjective
Canonical Correlation Analysis (CCA)	Examining relationships between two multivariate sets	Captures shared variance; identifies linear structures between predictors and outcomes	Assumes normality and linearity; complex to interpret; sensitive to outliers and sample size
Redundancy Analysis (RDA)	Measuring overall association between variable blocks	Flexible assumptions; suitable for complex or non-linear survey relationships	Cannot model latent variables or directionality; limited inferential power

Note. Table compiled by the author based on information from Tacq (1992), Husson et al. (2011), and Hair et al. (2010).

3.1 Multivariate Correspondence Analysis

Multivariate Correspondence Analysis (MCA) is a multivariate statistical technique designed to explore relationships within categorical data, particularly useful in the social sciences for analyzing survey responses and contingency tables. Unlike methods tailored for continuous variables, MCA is adept at handling nominal or ordinal data without assuming any specific distribution, making it suitable for exploratory analyses where the goal is to uncover patterns and associations between categories (Greenacre, 2007; Hair et al., 2010). At its core, MCA transforms a contingency table into a graphical representation, allowing researchers to visualize the associations between row and column categories in a low-dimensional space. This visualization helps identify underlying structures and relationships that may not be immediately apparent through traditional tabular analysis. The technique calculates the chi-square distances between categories, positioning them in a way that reflects their associations, categories with similar profiles are plotted closer together (Greenacre, 2007).

One of the strengths of MCA lies in its ability to handle complex datasets with multiple categorical variables, providing a comprehensive overview of the data's structure. This makes it particularly valuable in attitudinal research within political and social sciences, where survey data often involve numerous categorical responses. For instance, MCA has been effectively employed to analyze patterns of violence against women, revealing distinct groupings based on socio-demographic characteristics and types of violence experienced (Mota et al., 2008). However, while MCA offers insightful visualizations and is excellent for exploratory purposes, it does have limitations. This method is descriptive and does not provide inferential statistics, meaning it cannot test hypotheses or establish causality. Additionally, interpreting the dimensions produced by MCA can sometimes be subjective, especially when multiple dimensions account for small proportions of total inertia or when category points overlap in the factor space. This subjectivity especially increases with the inclusion of more than two dimensions, which complicates visual interpretation (Greenacre, 2007; Sourial et al., 2010). Furthermore, MCA is not well-suited for ordinal or continuous variables, as its algorithm is optimized for nominal-level data structured in contingency tables. Therefore, researchers must take care to ensure that the scale of their data aligns with MCA's methodological assumptions (Hair et al., 2010; Sourial et al., 2010).

In summary, MCA is a powerful tool for exploring and visualizing relationships within categorical data. Its application in social and political research has proven valuable for uncovering patterns in complex survey datasets, particularly in the early stages of analysis where the primary goal is to identify potential associations and structures worth further investigation.

3.2 Canonical Correlation Analysis

Canonical Correlation Analysis (CCA) is a multivariate statistical technique developed by Harold Hotelling in 1936 to explore the relationships between two sets of variables. Unlike simple correlation, which examines the relationship between two individual variables, CCA identifies and measures the associations between linear combinations of variables from each set, known as canonical variates. This method is particularly useful in social and political sciences, where researchers often deal with complex, interrelated variables, such as attitudes and demographic factors (Sherry & Henson, 2005). The primary objective of CCA is to find pairs of canonical variates, one from each variable set, that have the highest possible correlation with each other. This is achieved by solving an optimization problem that maximizes the correlation between these linear combinations. The resulting canonical correlations provide insights into the shared variance between the two variable sets, allowing researchers to understand the underlying structure of their data (Uurtio et al., 2017).

However, the application of CCA comes with several assumptions and limitations. One critical assumption is the linearity of relationships between variables. If the true relationships between variable sets are nonlinear, CCA being a linear method, may fail to capture the underlying associations. While CCA does not strictly require multivariate normality or homoscedasticity for computing canonical correlations, these assumptions are necessary for valid significance testing of canonical functions (e.g., via Wilks' Lambda). Violations of these assumptions can lead to biased estimates and incorrect inferences (Thompson, 1984). Another challenge in using CCA is the interpretation of canonical variates. To address this, researchers often examine canonical loadings or structure coefficients, which represent the correlation between each original variable and its corresponding canonical variate. These coefficients help determine which variables most influence each canonical dimension, although interpretation can still be challenging when coefficients are small or cross-load across multiple dimensions. It is also recommended to examine redundancy indices to evaluate how much variance in one set is explained by the canonical functions derived from the other set (Sherry & Henson, 2005). This additional information can assist in identifying whether the identified associations are practically meaningful or merely statistical artifacts. However, this complexity can make it difficult to draw meaningful conclusions about which specific variables drive the observed relationships (Sherry & Henson, 2005). Moreover, CCA is sensitive to multicollinearity within each set of variables. High intercorrelations among variables can inflate the canonical correlations and make them unstable, leading to unreliable results. To mitigate this issue, researchers may need to employ dimensionality reduction techniques or regularization methods before applying CCA (Uurtio et al., 2017). Sample size is another important consideration in CCA. The technique requires a sufficiently large sample to produce stable and reliable estimates. Small sample sizes can lead to overfitting and spurious results, undermining the

validity of the analysis. As a rule of thumb, it is recommended to have at least ten observations for each variable included in the analysis (Thompson, 1984).

In summary, while CCA is a powerful tool for examining the relationships between two sets of variables, its effectiveness depends on meeting certain assumptions and having an adequate sample size. Researchers must be cautious in interpreting the results and consider supplementing CCA with other methods or robustness checks to ensure the validity of their findings.

3.3 Redundancy analysis

Redundancy Analysis (RDA) is a multivariate statistical method designed to quantify the overall association between two blocks of variables, focusing on how well a set of predictors accounts for variation in a set of outcome variables (Lambert et al., 1988). Unlike Canonical Correlation Analysis, which identifies linear combinations from both variable sets that are maximally correlated, RDA adopts an asymmetrical approach: it constructs linear composites of the independent variables that best explain variance in the dependent variable set. The technique is grounded in the concept of the redundancy index, which reflects the average proportion of variance in each dependent variable that can be explained by the predictor set. This index is derived from a set of multiple regressions and provides a straightforward interpretation of overall shared variance between blocks (Lambert et al., 1988). This makes RDA particularly suitable for research questions where the goal is to determine how much explanatory power one block of variables holds over another (Cohen et al., 2003). The strength of this method lies in its flexibility and ability to handle complex, multivariate data structures. RDA does not require strict assumptions about latent variables or directionality, which makes it appealing for the exploration of structural patterns in social science survey data that often involve multidimensional relationships and non-linearities. It is particularly useful when modeling associations between attitudinal variables and demographic, psychological, or experiential predictors, as is common in political and peace research. Moreover, RDA tolerates some violations of multivariate normality, making it a pragmatic choice when classical assumptions cannot be fully met (Cohen et al., 2003; Lambert et al., 1988)

However, this method also has limitations. While RDA is more robust than CCA in some respects, researchers should still check for high multicollinearity among predictors and ensure linear relationships, as violations can compromise interpretability. Furthermore, RDA does not support latent variable modeling, nor can it test mediation, moderation, or indirect effects. As such, it lacks the inferential power of more theory-driven techniques like Structural Equation Modeling. Ultimately, although the method produces interpretable indices, understanding the meaning of specific variable

contributions to each set can be complex, particularly when many variables are included. Researchers should be cautious when interpreting linear composites and may need to complement RDA with other methods to deepen theoretical insights (Van den Wollenberg, 1977). Despite these limitations, RDA remains an accessible and informative approach when the primary interest lies in quantifying shared variance between multivariate constructs, especially in exploratory contexts.

In summary, RDA is a powerful and accessible tool for summarizing the degree to which a set of independent variables explains a multivariate outcome. It is well-suited for exploratory and structural research in contexts, where the aim is to identify strong associations without imposing the stricter assumptions or complexity of latent variable models.

3.4 Triangulation

Triangulation is a methodological strategy used to enhance the credibility, validity, and depth of research findings by combining multiple perspectives, data sources, or analytical techniques. In its most classical form, triangulation refers to the use of more than one method to study a single research question, allowing researchers to cross-verify results and reduce the likelihood that findings are merely artifacts of a single approach (Denzin, 2009). The term originates from land surveying, where measuring from multiple angles improves accuracy, an analogy that has been widely adopted in the social sciences to describe multi-method research (Jick, 1979).

There are several types of triangulation, including data triangulation (using different data sources), investigator triangulation (involving multiple researchers), theoretical triangulation (applying different theoretical perspectives), and methodological triangulation (using different methods or models) (Patton, 1999). More specifically, the latter one, methodological triangulation, is a way to analyze the same dataset using distinct statistical frameworks, each with different assumptions and interpretive angles. According to Flick et al. (2004), methodological triangulation is especially useful in complex social settings where no single method can capture the full richness of the phenomena under investigation.

One of the core rationales behind triangulation is the belief that each method brings its own biases and blind spots. By using multiple methods, researchers can partially offset these limitations, increasing the likelihood that observed patterns are robust and not simply a result of methodological idiosyncrasies (Greene et al., 1989). For instance, where one technique may offer breadth and statistical power, another might provide depth or nuanced interpretability. Triangulation thus contributes not only to validation and credibility, but also to discovery and explanation, enhancing both the reliability and scope of empirical insights (Tashakkori & Teddlie, 2010).

However, triangulation is not without challenges. Integrating results from multiple techniques requires careful methodological planning and a clear rationale for combining approaches. Researchers must remain aware of the differing assumptions behind each method and be transparent about points of convergence and divergence in the results. As Bryman (2006) notes, triangulation should not be seen as a straightforward path to truth, but rather as a tool to generate more complex and well-rounded understandings of empirical relationships.

4. Research design and methodology

To examine the complex attitudinal patterns surrounding Colombia's Revised Peace Agreement (RPA), this study adopts a multivariate methodological design tailored to uncover both latent structures and structural relationships between attitudinal outcomes and their predictors. As outlined in the theoretical framework, public opinion toward peace is rarely unidimensional; rather, it reflects intertwined dimensions shaped by socio-cultural demographics, lived experience, institutional trust, and political predispositions (García-Sánchez et al., 2023; Dirix, 2024). Traditional univariate or bivariate approaches often fall short in capturing this complexity (Hair et al., 2010; Tacq, 1992). Therefore, the current analysis employs three complementary statistical techniques, Multivariate Correspondence Analysis (MCA), Canonical Correlation Analysis (CCA), and Redundancy Analysis (RDA), each offering a distinct analytical lens for understanding how citizen profiles relate to clusters of peace-related attitudes (Greenacre, 2007; Sherry & Henson, 2005; Cohen et al., 2003). These techniques are applied to data from the 2021 Mapping Attitudes, Perceptions, and Support (MAPS) survey, a nationally representative dataset designed to measure Colombian citizens' perceptions of, and support for, different components of the peace agreement (Weintraub et al., 2023). This section thus clarifies the rationale behind each methodological decision, from dataset selection to operationalization and analysis strategy.

4.1 The MAPS dataset

The empirical analysis of this study is based on a cross-sectional dataset collected in 2021, the MAPS survey. At the time of writing, the MAPS dataset represents the most detailed and thematically focused public opinion resource available on Colombian attitudes toward the peace process. While other sources such as the 2021 round of the AmericasBarometer (LAPOP) also capture general public sentiment, MAPS stands out for its extensive coverage of individual provisions of the RPA. Unlike LAPOP, which includes only broad measures of peace support, the MAPS survey disaggregates public opinion across the RPA's multiple thematic dimensions, including rural reform, transitional justice, coca substitution, and political reintegration. In addition to its thematic relevance, MAPS also offers significant methodological advantages. With 11777 respondents, its sample size far exceeds that of LAPOP's 2021 survey, which included only 2993 participants. More importantly, MAPS employs a deliberate sampling strategy that ensures robust representation of communities from conflict-affected regions, an essential feature for a study that seeks to examine variation in attitudes shaped by exposure to violence or regional inequalities. Moreover, the timing and content of the LAPOP 2021 survey pose limitations for the present research. Due to the COVID-19 pandemic, LAPOP significantly reduced the number of

questions related to transitional justice and post-conflict policy, devoting more space to health and crisis management items. As such, MAPS remains the most comprehensive and thematically appropriate source for evaluating citizen perspectives on the substantive components of the RPA. For full details on sampling procedures, questionnaire design, and variable coding, the reader is referred to the technical documentation provided by Weintraub et al. (2023).

Given that the political party formerly known as FARC officially changed its name to Comunes in 2021, it is important to note that the dataset used in this study predates that transition. Consequently, all survey items refer to the party under its original name. For consistency and accuracy in interpreting the data, this thesis also refers to the political actor as FARC throughout the analysis, mirroring the terminology used in the survey instrument.

4.2 Operationalization and variable construction

This study investigates which citizen characteristics are associated with attitudes toward various components of the RPA. The selection of the variables is based on existing empirical literature that identifies them as central determinants in shaping public opinion about peace processes and the availability of variables in the dataset (García-Sánchez & Plata-Caviedes, 2020; Muñoz & Pachón, 2021; Liendo & Braithwaite, 2018). The following section outlines how each variable used in the analysis is operationalized and treated for inclusion in the multivariate techniques. As a general rule, all responses marked as "don't know" or "no answer" are excluded from the analysis and treated as missing data.

General satisfaction with the 2016 RPA is captured through a categorical question offering four options: "not at all satisfied," "somewhat satisfied," "satisfied," and "very satisfied." In line with the coding scheme provided in the MAPS dataset, this variable is treated as quasi-metric, with values ranging from 1 to 4 to reflect increasing levels of agreement. Similarly, attitudes toward specific components of the RPA, such as rural development, transitional justice, and political integration, are measured using a four-point Likert-type scale, ranging from "completely disagree" to "completely agree." These are also treated as quasi-interval data, consistent with previous studies that use attitudinal scales in multivariate frameworks (Carifio & Perla, 2008). To further structure the attitudinal data, this study includes two composite variables based on an earlier EFA (Dirix, 2024). The first captures support for social development and justice (education, healthcare, women's participation, protection of social leaders, transitional justice), and the second reflects support for peacebuilding and reintegration (coca substitution, disarmament, and reintegration of ex-combatants). These dimensions are used in aggregated form where appropriate, depending on the analytical technique applied. Both are constructed as additive indices and treated as continuous variables.

Demographic variables include gender (male, female), age group (six categories from 18 to 65+), highest educational attainment (ranging from no formal education to higher education), religion (Catholic, Evangelical/Christian, other, or spiritual non-affiliated), and ethnic identity (Mestizo, Afro-Colombian, Indigenous, or other). When dummy variables are needed, the reference category for each of these variables was selected based on modal values in the dataset: for example, Catholic, Mestizo, and male respondents aged 18–25 with no formal education are treated as baselines in the analysis, reflecting dominant categories in the Colombian population (Weintraub et al., 2023).

While geographic variables such as municipality or department could provide more granular insight, they contain too many unique categories to be feasible for this study's scope. Instead, a binary variable called "zone" is used to approximate urban versus rural residence. Respondents were asked whether they lived in a municipal seat (urban center) or in a populated rural zone (Weintraub et al., 2023).

Political trust is operationalized as a composite index derived from respondents' evaluations of four political institutions: the president, congress (house and senate), and the mayor. Each item is originally measured on an ordinal four-point scale, from "not at all" to "a lot." For the purpose of this study, a summated trust index is constructed and treated as continuous (Weintraub et al., 2023). Trust in former members of the FARC-EP is measured through two distinct survey questions. One captures agreement with the statement "I trust ex-combatants if they participate in reintegration programs," while the other directly asks how much trust the respondent places in reincorporated ex-FARC members. Though both address reintegration, the nuances between them warrant separate treatment in the analysis. Each is measured on a four-point categorical scale and used as-is (Weintraub et al., 2023). Trust in the political party FARC (now Comunes) is assessed through a single item asking for agreement or disagreement on a four-point scale. This item, too, is treated as a continuous variable ranging from complete rejection to full endorsement (Weintraub et al., 2023).

Experience of armed conflict is incorporated through a binary variable that captures whether the respondent or a family member has experienced victimization through forced displacement, sexual violence, kidnapping, or other forms of conflict-related harm. A "yes" response is coded as 1, and "no" as 0 (Weintraub et al., 2023). Additional indicators of conflict impact include whether the respondent had to relocate due to violence, and whether they voted in the 2016 plebiscite on the Peace Agreement. Both are binary variables with "yes" or "no" responses, and "no" serving as the reference category.

Descriptive statistics for all variables discussed above are available in the annex, see Figures 5 and 6, and Table 5.

4.3 Research design and analytical implementation

To systematically address the three research questions outlined in this thesis, a sequential and multi-method analytical strategy is adopted. The questions are as follows: (1) What structural relationships exist between sets of determinants (e.g., demographics, trust, conflict exposure) and attitudinal subsets of the Peace Agreement? (2) To what extent does support for social development and justice differ from support for peacebuilding and political reintegration? And (3) How do different analytical methods compare in revealing these relationships? Each question is explored through a different phase of the analysis, using three multivariate techniques, MCA, CCA, and RDA. All analyses are performed in R (version 4.4.3), the script is added in the annex.

The first technique, MCA provides an entry point into RQ1 by exploring how categorical predictors (e.g., gender, religion, victim status) are positioned in relation to categorical attitudinal responses. MCA is particularly well-suited to identifying latent association patterns and clusters in high-dimensional categorical data (Greenacre, 2007). In this study, it will be applied to contingency tables linking socio-demographic categories with grouped RPA component items, allowing for a visual assessment of possible attitudinal structures. As a purely descriptive method, MCA does not test causal or latent relationships and does not require strong distributional assumptions. However, it does rely on the assumption of adequate cell frequencies and is sensitive to sparsity, therefore, variables with low marginal counts will be excluded or recoded (Greenacre, 2007). The quality of representation will be evaluated through the proportion of total inertia explained by the first two dimensions. Interpretation will focus on identifying coherent attitudinal spaces and social profiles as a basis for more formal analysis in later stages.

Canonical Correlation Analysis is then employed to formally address RQ1 through the simultaneous modeling of two multivariate variable sets: one consisting of predictors (trust in institutions, trust in FARC, religiosity, conflict exposure, plebiscite voting, etc.), and the other of attitudinal outcomes toward various peace components. CCA identifies pairs of canonical variates, linear composites within each set, that maximize shared variance (Sherry & Henson, 2005). This allows for the detection of overarching profiles of citizens whose attitudes across RPA components are shaped by a particular combination of background characteristics. The following assumptions must be checked prior to estimation. First, the method assumes linearity between the predictor and outcome variables, which will be assessed via scatterplots and partial regression residuals. Second, although inferential CCA procedures assume multivariate normality, particularly for computing structure coefficients and canonical loadings, violations are common in survey data. Mardia's test will be used to test normality. Third, CCA is sensitive to multicollinearity within each variable set. Variance Inflation Factors (VIFs) will be calculated, and where appropriate, highly collinear variables will be combined or dropped. To

interpret results, canonical correlations, loadings, cross-loadings, and redundancy indices will be examined. The latter will inform the degree to which variance in the attitudinal block is explained by the predictor block, providing a direct answer to RQ1.

Redundancy Analysis is then introduced to further develop both RQ1 and RQ2. As an asymmetrical technique, RDA quantifies how much of the variation in a block of dependent variables (attitudes) can be accounted for by an independent block (predictors) using a redundancy-based approach (Lambert et al., 1988; Cohen et al., 2003). Unlike CCA, RDA does not search for symmetric correlations, but rather focuses on the explanatory power of one block over another. This makes it especially useful for examining whether certain types of predictors, such as institutional trust or victim status, explain greater variance in specific attitudinal domains (e.g., justice vs. reintegration). Assumptions include linearity between individual predictor-outcome relationships and independence of residuals across regressions, both of which will be assessed through scatterplots, Durbin-Watson statistics, and residual diagnostics. Multicollinearity will again be assessed using VIFs. While RDA is relatively robust to violations of normality and homoscedasticity, outlier influence will be examined via Mahalanobis distance to guard against leverage bias. Results from RDA will help determine whether structural distinctions exist between attitudinal subsets, thus directly engaging with RQ2.

Finally, the application of these three methods enables the thesis to address RQ3, which asks how different analytical techniques compare in uncovering relationships between predictors and peace-related attitudes. This comparison will occur in two stages. First, Chapter 5 presents each method's results in parallel subsections using a consistent structure, descriptive and visual summaries, statistical outputs, interpretation, and theoretical linkage, so as to ensure comparability across techniques. Second, a dedicated subsection will provide a comparative assessment of all three techniques, focusing on convergence and divergence of findings, stability of key predictors, replicability of latent attitudinal structures, and methodological trade-offs. For example, whether CCA confirms the dimensions revealed in MCA, or whether RDA highlights variance contributions missed by CCA, will be discussed to assess robustness and epistemic complementarity. Attention will also be paid to assumptions, data requirements, and interpretive clarity. In this way, RQ3 is addressed not merely as a methodological footnote, but as a substantive contribution to the comparative analysis of multivariate modeling techniques in peace and conflict research.

4.4 Limitations

As with any research design, this study has several methodological and empirical limitations that should be considered when interpreting its findings. First, the data originate from the 2021 MAPS survey, conducted before Colombia's second legislative period following the 2016 peace agreement. Since public trust in institutions and perceptions of the agreement's progress are likely to evolve, particularly as political coalitions shift and new actors emerge, the findings capture only a snapshot of attitudes at that moment in time (Weintraub et al., 2023). Second, the MAPS dataset is secondary and publicly available, which restricts analysis to the survey's original questions. Key constructs relevant to peace-related attitudes, such as political ideology or nuanced measures of recent voting behavior, are not included. Given that prior studies identify these variables as important predictors of support for peace agreements (Muñoz & Pachón, 2021; García-Sánchez & Carlin, 2020), their absence may limit the explanatory power of this analysis, particularly regarding ideological positioning.

Third, while exploratory methods like MCA are useful for revealing structural patterns in categorical data, they lack inferential strength and cannot test for latent or directional relationships. As such, their findings should be interpreted as preliminary (Greenacre, 2007; Tacq, 1992). Fourth, despite the use of advanced multivariate techniques, the analytical framework remains largely correlational. Techniques such as CCA and RDA identify associations but do not establish causality and are sensitive to assumptions like linearity and measurement quality (Sherry & Henson, 2005; Cohen et al., 2003). The cross-sectional nature of the data further limits causal inference, making it impossible to determine, for instance, whether conflict exposure shapes attitudes or vice versa (Esparza et al., 2020).

Lastly, although this thesis employs a triangulation strategy by comparing four distinct multivariate techniques, this approach also presents challenges. Methodological triangulation can enhance robustness and interpretive depth but introduces complexity when results diverge. These techniques differ in their assumptions, data structure requirements, and interpretive aims, making full convergence unlikely and complicating unified conclusions (Tashakkori & Teddlie, 2010). Moreover, triangulation does not inherently address the weaknesses of individual methods and may produce conflicting findings that require careful theoretical interpretation (Bryman, 2006).

Taken together, these limitations do not detract from the study's value but highlight areas where future research could improve empirical precision and theoretical scope in the study of peace-related attitudes in post-conflict societies.

5. Results and discussion

Chapter 5 presents the results of each method in parallel subsections, following a consistent structure to facilitate comparison across techniques. Each subsection includes a descriptive summary, assumption checks, model fit assessment, visual or statistical output, an interpretation of the findings, and a theoretical linkage. This structured approach ensures both analytical rigor and clarity in the presentation of results.

5.1 Findings from Multivariate Correspondence Analysis

To explore latent patterns in attitudes toward the RPA, a Multivariate Correspondence Analysis (MCA) is performed using twelve categorical variables. Three of these represent attitudinal positions on key RPA components: peacebuilding measures, social development and justice, and the FARC's participation in elections. Each of these attitudinal variables has been recoded into a binary format distinguishing between respondents with high versus low support. These categories are based on meaningful distributional cut-offs in the underlying data and are illustrated in the accompanying bar charts, see Figure 7 in annex. The remaining nine variables represent socio-demographic and experiential predictors: age group, gender, area of residence (urban/rural), education level, religion, ethnicity, victimization due to crime (p52), displacement due to the conflict (p14e), and voting behavior in the plebiscite of 2016 (p22).

The MCA produced four primary dimensions. Figure 1 below, displays biplots of the twenty categories with the highest contributions to the overall solution, along with all six recoded RPA-related categories, to ensure a balance between interpretability and comprehensiveness. Dimension 1, which explains approximately 7.4% of total inertia, is primarily shaped by experiential variables, particularly victimization by crime (p52_0_Yes) and displacement due to the armed conflict (p14e_Yes). These categories are closely associated with others indicating social marginalization, such as ethnic identity. This dimension captures a continuum of exposure to conflict, ranging from individuals unaffected by violence to those with direct, lived experience of it. It reflects how proximity to conflict shapes broader social and political attitudes, and can be interpreted as a “conflict exposure” axis. Dimension 2, accounting for 6.8% of total inertia, reflects a socio-structural profile, dominated by variables such as age, education, gender, geographical zone, and religion. Respondents with basic primary education, older age, rural background, and no religious affiliation cluster at one end, while younger, more educated, urban respondents appear at the other. This axis captures a divide between more traditional and more progressive segments of the population in terms of social position.

From Dimension 3 onward, attitudinal variables become the dominant contributors. This dimension explains 6.2% of the total variance and is overwhelmingly shaped by support for key provisions of the RPA. In particular, low support for peacebuilding measures contributes nearly 30%, low support for social development and justice about 22%, and positions on FARC participation in elections another 17%. This dimension represents the core ideological axis, separating individuals broadly supportive of peace and reintegration efforts from those who are more skeptical or rejecting of these measures. Dimension 4, accounting for 5.3% of inertia, adds further nuance to the attitudinal landscape. While still shaped by some attitudinal variables, especially low support for social development and justice, it also includes personal identity factors such as age, religious disaffiliation, and education. It appears to capture a gradient of social disengagement versus institutional integration, contrasting those who are more socially or politically disembedded (e.g., elderly, no religion) with those showing more coherent, pro-institutional views. However, dimension 4 is of lesser importance, both statistically and substantively. It explains a smaller portion of total variance and reveals less sharply defined contrasts than the other dimensions. As such, while it provides useful insight into internal consistency and alignment in respondent profiles, it plays a secondary role in structuring attitudes toward the peace process.

To deepen the interpretation of the MCA results and uncover underlying respondent configurations, a k-means clustering is performed on the coordinate scores of dimensions 1 and 2. These dimensions capture, respectively, a continuum of conflict exposure, and a socio-structural gradient shaped by differences in age, education, and gender. To determine the optimal number of clusters, the Elbow Method is applied, see Figure 8 in annex, revealing a clear inflection point at four clusters. This solution strikes a balance between parsimony and meaningful differentiation, as it identifies structurally distinct groupings without overfitting, see Figure 9 in annex. The first cluster includes younger, higher-educated, urban respondents with little or no direct experience of conflict. This group represents a progressive, institutionally confident segment of the population, shaped more by modern values than by the legacy of war. The second cluster is located far to the right on the conflict exposure dimension and high on the socio-structural axis. It consists mainly of older, rural, and lower-educated individuals, many of whom have experienced displacement or victimization due to the armed conflict. This group represents structurally and experientially marginalized victims, whose attitudes are shaped by long-standing exposure to violence, exclusion, and insecurity. The third cluster occupies a more central position, slightly left of center. It includes middle-aged respondents with varied educational backgrounds and limited conflict exposure. Neither highly privileged nor deeply disadvantaged, they likely reflect a pragmatic, centrist group with moderate engagement and balanced perspectives. The fourth cluster appears in the lower-left quadrant and consists of younger respondents, possibly women or minority group members, with technical or vocational education and little personal exposure to conflict.

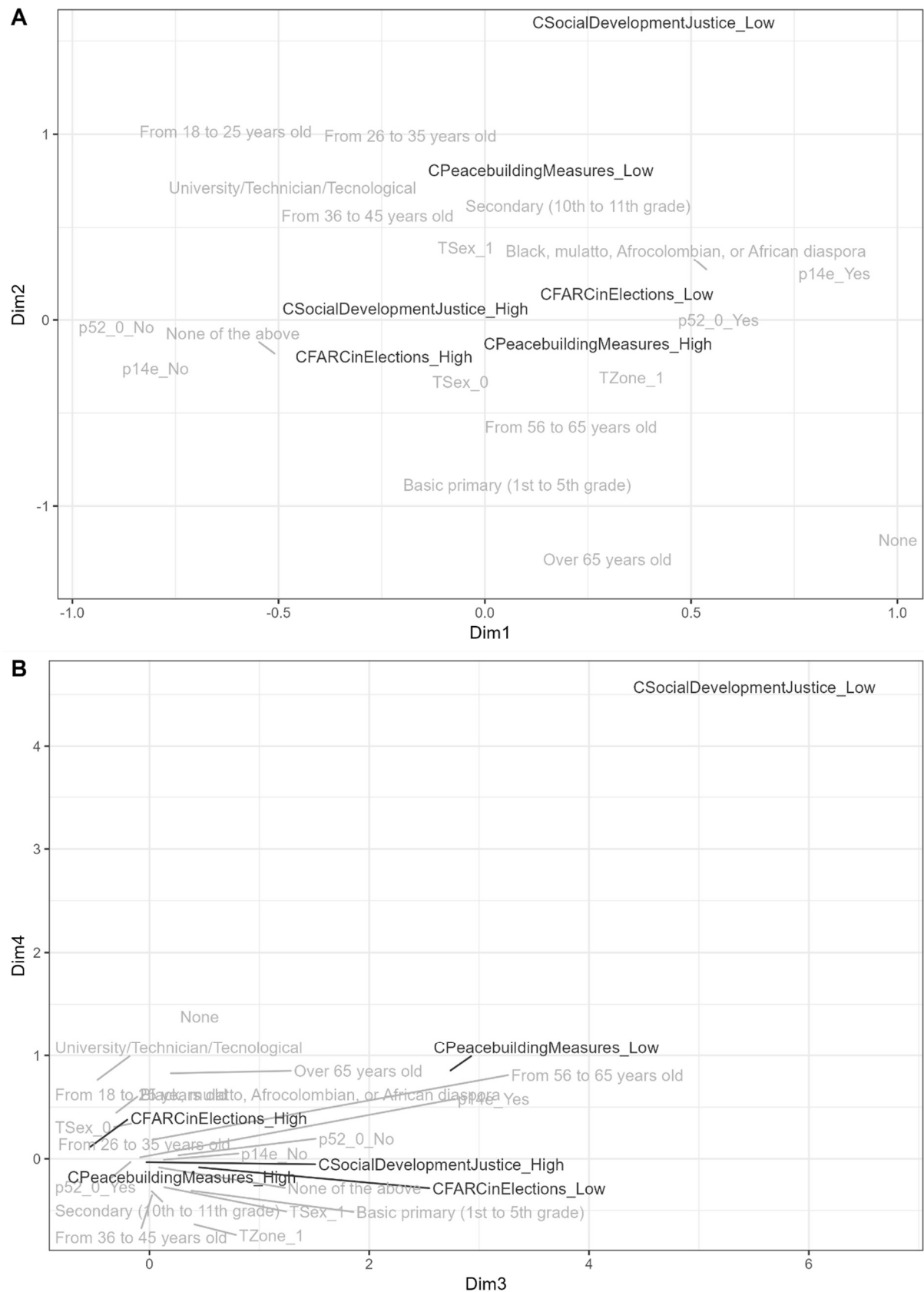


Figure 1. Biplots of dimension 1-2 and 3-4 of the MCA, with the 20 most contributing variables and all support for the RPA component variables

To explore how these structural positions relate to attitudes toward peace, the clusters are projected onto dimensions 3 and 4 of the MCA, see Figure 2 below. These dimensions capture attitudinal variation, with dimension 3 reflecting a clear axis of support versus rejection of the RPA, and dimension 4 indicating the degree of internal consistency or differentiation in those attitudes. The projections reveal distinct patterns. The first cluster expresses moderate support for the RPA, appearing slightly to the right of center on the third dimension. Their lower scores on the fourth dimension suggest that they do not sharply distinguish between peace components. Their support appears broad but uncritical. The second cluster projects strongly to the right on the third dimension, expressing the lowest level of support for the RPA. Despite their proximity to the conflict, this group appears deeply skeptical of the agreement. Their stance likely reflects dissatisfaction with the peace process or a lack of trust in its implementation. The third cluster appears near the center, indicating attitudinal ambivalence or moderate support. This group aligns with a pragmatic, middle-ground perspective, shaped by limited ideological engagement or mixed views on the agreement's effectiveness. Finally, the fourth cluster projects to the left of center on the third dimension, expressing a more favorable view of the RPA. Their low scores on the fourth dimension suggest coherent and structured attitudes. Despite limited direct experience with conflict, this group supports the peace process in a considered and deliberate manner, likely grounded in broader values such as reconciliation, inclusion, and democratic legitimacy.

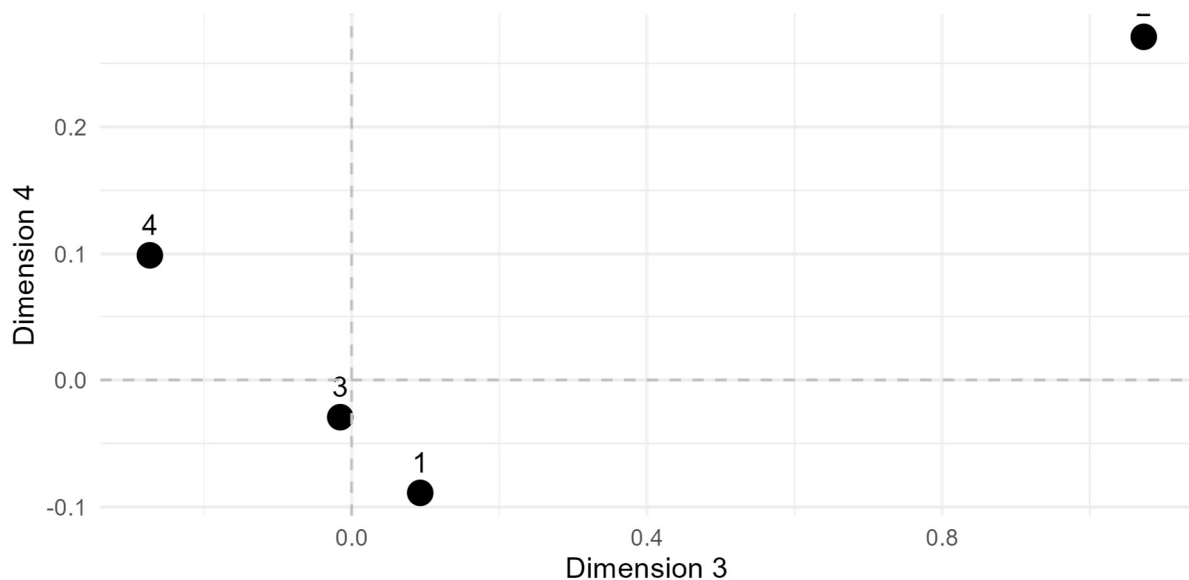


Figure 2. Mean coordinate positions of the four k-means clusters, calculated on MCA dimensions 1 and 2, projected onto dimensions 3 and 4

Together, the four clusters illustrate how attitudes toward the RPA emerge from the interplay between structural position and experiential proximity to conflict. Cluster 1 brings together younger, urban, and higher-educated individuals with little or no direct experience of violence. Their moderate but uncritical support for the RPA appears to be shaped by structural privilege and a general openness to institutional stability. Cluster 2 consists of older, rural, and lower-educated respondents who have been directly affected by the armed conflict through victimization or displacement. Their rejection of the RPA reflects not apathy but deep distrust, grounded in long-standing exclusion and dissatisfaction with the promises of institutional peace. Cluster 3 includes middle-aged respondents with moderate levels of education and limited exposure to violence. Their centrist socio-structural position is mirrored in their ambivalent or pragmatic stance toward the RPA, reflecting neither strong endorsement nor principled opposition. Finally, Cluster 4 brings together younger, often socially engaged individuals, potentially including women or members of minority groups. Despite having little direct experience with conflict, they express relatively consistent and favorable attitudes toward the peace agreement, suggesting that their support is motivated by symbolic or future-oriented commitments rather than personal history.

Although the first MCA dimensions explain only a limited share of total inertia, a common feature in attitudinal survey data, their structure reveals analytically meaningful patterns. As García-Sánchez et al. (2023) and Riomalo Clavijo (2023) note, support for the RPA is not monolithic but fragmented across multiple dimensions. This analysis extends that insight by showing how these attitudinal differences align with distinct socio-structural and experiential profiles. The findings confirm that victimhood does not straightforwardly translate into support for peace. Cluster 2, composed of older, rural, lower-educated victims, illustrates how direct exposure to conflict can lead to distrust rather than reconciliation (Téllez, 2019; García-Sánchez & Carlin, 2020). Meanwhile, clusters 1 and 3 reflect more moderate or ambivalent attitudes, shaped by varying degrees of privilege and limited to moderate conflict experience. These results resonate with earlier findings that public support for peace is shaped by more than just exposure to violence, it is also rooted in political trust, and structural position (Dirix, 2024; Esparza et al., 2020). In contrast, cluster 4, composed of younger, socially engaged respondents with no personal victimization, shows consistent support for the RPA. Their endorsement appears to stem from symbolic or future-oriented commitments, echoing Carlin et al.'s (2020) notion of identity-driven support. While the explanatory power of the MCA remains modest, the patterns it uncovers are theoretically consistent and sociologically grounded.

5.2 Findings from Canonical Correlation Analysis

Because CCA requires continuous variables, this analysis includes a different selection of variables than the previous MCA. Specifically, CCA is being used to examine the multivariate relationship between forms of trust and support for the different components of the RPA, based on variables measured on a continuous 1–4 Likert scale. The independent variable set consists of four trust-related measures: trust in reintegrated ex-FARC members, trust in ex-combatants involved in reintegration programs, trust in the FARC as a political party, and overall political trust in institutions. The dependent variable set includes three indicators of support: support for peacebuilding measures, support for social development and justice, and support for including FARC in elections. Rather than using individual attitude items, this analysis relies on the three combined attitude variables identified through a previous Exploratory Factor Analysis (EFA), which revealed these as distinct and reliable components of the broader attitudes toward the RPA (Dirix, 2024).

Before conducting the CCA, key assumptions are examined. Correlations within and between the variable sets, see Figure 10 in annex, are moderate to low, suggesting no serious issues with multicollinearity. All variables are standardized prior to analysis to ensure comparability across scales. Pairwise scatterplots and density plots, Figure 10 in annex, show clear deviations from multivariate normality and evidence of non-linear patterns, which is typical for Likert-scale data. This visual impression is supported by Mardia's test, which indicates statistically significant departures from multivariate normality in both skewness and kurtosis for both variable sets (X: skewness = 29571.54, kurtosis = 188.68; Y: skewness = 4671.59, kurtosis = 48.13; all $p < .001$). Due to the use of listwise deletion, the sample size decreased from 11,777 to 9,266 complete observations. Nevertheless, the remaining sample is sufficiently large to mitigate concerns regarding assumption violations and justifies the use of canonical correlation analysis in an exploratory context.

Three canonical functions are extracted, corresponding to the number of variables in the smaller set. Statistical significance is assessed using Wilks' Lambda and Rao's F-approximation, see Table 2. All three functions are statistically significant ($p < .001$). However, only the first function explains a meaningful proportion of shared variance between the variable sets (canonical correlation = 0.358). The second and third functions show very small canonical correlations (0.074 and 0.059 respectively), and their significance likely results from the large sample size rather than substantive relationships. Violations of assumptions such as multivariate normality may further inflate Type I error rates. Therefore, interpretation focuses on the first canonical dimension only.

Table 2. Canonical functions and their significance

Canonical Function	Wilks' Λ	F-value	df1	df2	p-value
Function 1	0.864	115.75	12	24,497	< .001
Function 2	0.991	13.84	6	18,520	< .001
Function 3	0.997	16.16	2	9,261	< .001

The structure coefficients, Table 3, show that the first canonical dimension reflects a pattern in which greater trust in reintegrated ex-combatants is strongly associated with greater support for including the FARC as a political party (p36_d). Both variables load above $|0.95|$. Additional contributions come from general trust in ex-combatants (p19_j) and support for peacebuilding measures, though these are weaker. Political trust (SumPolTrust) shows only a very weak association on this dimension.

Table 3. Structure loadings of canonical function 1

Predictor variable	Loading	Outcome variable	Loading
Trust in reintegrated ex-combatants	-0.974	Support for Including FARC in Elections	-0.988
Trust in ex-FARC-EP members	-0.354	Support for Peacebuilding Measures	-0.384
Trust in FARC as party	-0.190	Support for Social Development and Justice	-0.097
Political trust	-0.074		

Visual inspection of the canonical loadings, Figure 3, confirms that the most influential variables in the first dimension relate to trust in ex-combatants and support for their political integration. The second and third canonical dimensions, despite being statistically significant, explain little additional variance and are therefore not further interpreted.

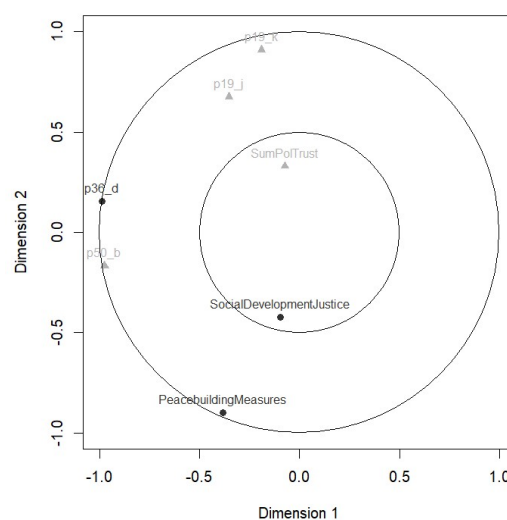


Figure 3. Canonical correlation loadings for X and Y variable sets

Overall, the analysis suggests that trust in reintegrated ex-combatants plays a central role in shaping public support for the political reintegration of the FARC as a political party. This finding aligns with previous research emphasizing that public trust in former combatants and institutions is key to legitimizing contested aspects of peace agreements (Esparza et al., 2020; García-Sánchez & Carlin, 2020). More specifically, the results show that trust in ex-combatants who participate in reintegration programs is most strongly associated with support for the FARC's participation in elections. This implies that perceptions of credible reintegration processes may reduce public resistance to political inclusion. These findings contribute to broader discussions on attitudinal fragmentation and conditional support for peace agreements. As highlighted by García-Sánchez et al. (2023) and Riomalo Clavijo (2023), citizens often distinguish between development-oriented and political provisions. The present analysis supports this distinction and shows that these differences are not arbitrary, but structurally linked to distinct trust profiles. In particular, trust rooted in reintegration efforts appears to bridge the gap between general support for peace and endorsement of more controversial elements, such as the political participation of former combatants.

While the results offer valuable insights into these structural relationships, it is important to note that the analysis is exploratory in nature. The canonical correlation analysis violates several underlying assumptions, including multivariate normality and linearity, and although the sample size is large, some associations may appear statistically stronger than they are substantively. Nevertheless, the overall patterns are robust and consistent. They underscore the importance of designing reintegration processes that are not only effective, but also visible and credible in the eyes of the public. Such visibility may enhance acceptance of ex-combatants' political roles and, in turn, contribute to long-term public support for peace.

5.3 Findings from Redundancy Analysis

This RDA builds on the previous CCA by using the same sets of standardized variables. The dependent variable set includes support for peacebuilding measures of the RPA, support for social development and justice items of the RPA, and support for including FARC as a political party in the elections. The independent variable set consists of political trust, trust in ex-combatants if they followed reintegration programs, trust in ex-FARC-EP members, and trust in FARC as a political party. While the CCA investigates the symmetrical association between the two variable sets, RDA focuses on the extent to which the independent variables are able to explain variance in the dependent set. This approach allows for a more targeted understanding of the predictive power of the independent set.

Before conducting the analysis, all key assumptions for RDA were systematically evaluated. Visual inspection of scatterplots suggests that the relationships between variables are not fully linear, likely due to the use of ordinal Likert-scale items, see Figure 10 in annex. However, as noted in the literature, it is common to apply RDA to ordinal data, especially in large samples. Multivariate outliers were detected using Mahalanobis distance, indicating that several observations deviate substantially from the multivariate center. In addition, residual plots show a non-random, diagonally clustered pattern, which may indicate violations of linearity and homoscedasticity. Nevertheless, multicollinearity does not appear to be a concern: all VIF values are below 1.4, well under the accepted threshold of 5. Although multivariate normality and other assumptions are not fully met, this does not preclude meaningful interpretation. The study is exploratory in nature and does not rely on strict statistical inference. Taken together, the diagnostics suggest that while the assumptions are partially violated, the data remain suitable for robust and interpretable exploratory RDA.

The RDA results indicate that the model explains 5.1% of the total variance in the dependent variables. While this is a modest amount, it is not unusual in social science research involving attitudinal or perceptual constructs. Importantly, the permutation test confirms that this explained variance is statistically significant ($F(4, 9261) = 124.86, p < .001$), suggesting that the set of trust-related predictors reliably contributes to variance in attitudes towards the RPA components. Although permutation testing is generally robust to violations of the multivariate normality assumption, such deviations may still influence the precision of the p -values. Therefore, while the findings are statistically significant, they should be interpreted with appropriate caution. An examination of the canonical axes reveals that the first axis (RDA1) captures 94.7% of the explained variance, indicating that the primary structure in the data is largely unidimensional, consistent with the earlier findings from the canonical correlation analysis. While the second (RDA2) and third (RDA3) axes are also statistically significant ($p = .001$ and $p = .042$ respectively), they contribute only marginally to the explained variance (4.3% and 0.96%).

These findings are further visualized in the RDA biplot, see Figure 4 below, which shows that trust in reintegrated ex-combatants (p50_b) is the dominant predictor, as indicated by the length and direction of its vector along RDA1. This also aligns with earlier CCA results. Trust in ex-FARC-EP members (p19_j) contributes as well, but to a lesser extent. Other predictors, such as trust in the FARC as a political party (p19_k) and the general political trust index (SumPolTrust), show weaker relationships, consistent with their shorter vectors in the biplot and their lower unique explained variances.

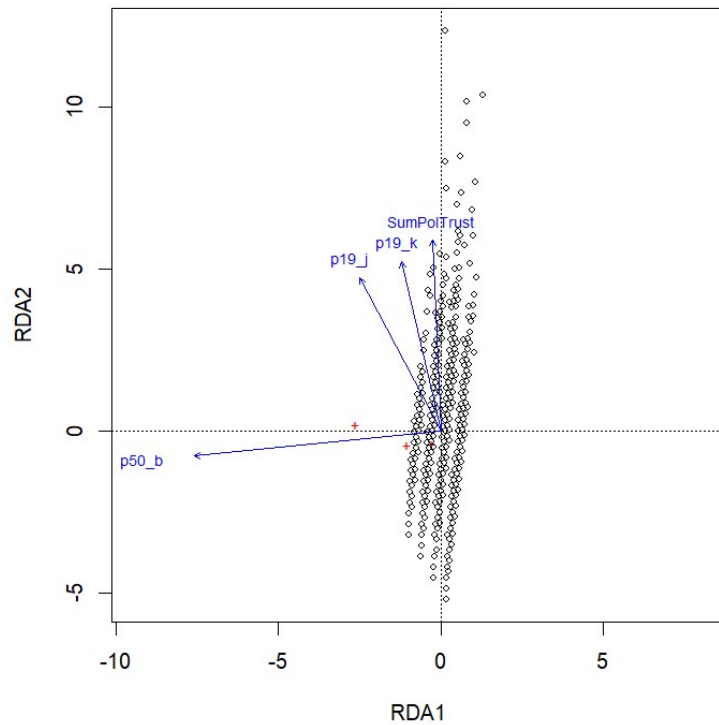


Figure 4. RDA biplot. The plot shows standardized scores for cases (black circles), response variable centroids (red crosses), and predictor variable vectors (blue arrows)

The permutation tests by term, support these visual patterns, see Table 4. Trust in ex-combatants following reintegration programs accounts for the largest share of explained variance ($F = 424.18$, $p < .001$), followed by trust in ex-FARC-EP members ($F = 57.74$, $p < .001$). Trust in FARC as a political party ($F = 5.90$, $p = .005$) and general political trust ($F = 11.65$, $p < .001$) are also statistically significant, though their effects are notably smaller. This suggests that specific, reintegration-based trust is more relevant than generalized or institutional trust in explaining variation in attitudes toward including FARC as a political party. Nevertheless, given the assumption violations, especially regarding multivariate normality and linearity, these findings should be interpreted in an exploratory light.

Table 4. Unique contribution of each predictor to the RDA model

Predictor	F-value	p-value	Variance explained
Trust in ex-FARC-EP members	57.74	< .001	0.0178
Trust in ex-combatants following reintegration programs	424.18	< .001	0.1304
Trust in FARC as a political party	5.90	0.005	0.0018
General political trust (index)	11.65	< .001	0.0036

The RDA shows that trust in ex-combatants who have participated in reintegration programs is the strongest predictor of public support for peace-related measures, followed by trust in ex-FARC-EP members. More abstract forms of trust, such as general political trust and trust in the FARC as a political party, contribute significantly but explain far less variance. These findings suggest that specific, experience-based trust in demobilized individuals is more influential than generalized or institutional trust in shaping attitudes toward peacebuilding. Although the model explains only 5.1% of the total variance, this level of explanatory power is not uncommon in public opinion research on complex and contested topics such as post-conflict reintegration. The results align with previous work emphasizing the conditional nature of public support for peace, where perceptions of credibility and reintegration matter more than institutional labels (Esparza et al., 2020; García-Sánchez & Carlin, 2020). In line with García-Sánchez et al. (2023), the analysis also reflects the multidimensionality of peace attitudes, showing that support for political reintegration is structured differently than support for development or justice-related provisions. Trust in ex-combatants appears to act as a bridging mechanism, linking general support for peace with acceptance of more polarizing components such as the FARC's political participation.

It is important to acknowledge that the assumption of multivariate normality was not fully met. While permutation tests are generally robust, violations of this assumption may still affect the precision of p -values. Therefore, the results, although statistically significant, should be interpreted with some caution. Nevertheless, they underscore the importance of designing visible and credible reintegration processes to foster public acceptance of former combatants' political and civic roles.

5.4 Comparative reflections and triangulation

This study employs triangulation through the integration of three complementary multivariate techniques: MCA, CCA, and RDA. Each method offers a distinct analytical perspective on the relationship between different forms of trust and attitudes toward Colombia's RPA, allowing for a more nuanced and robust understanding of the data. Despite their methodological differences, all three techniques converge on a shared substantive conclusion: trust in ex-combatants, especially those participating in reintegration programs, is the strongest and most consistent predictor of public support for their political inclusion. This consistency strengthens the credibility of the findings, even though key statistical assumptions, such as multivariate normality and linearity, are not fully met. Consequently, the results of CCA and RDA are interpreted as exploratory, and caution is warranted in drawing causal inferences.

MCA is particularly well-suited to this study due to its ability to accommodate categorical and ordinal data, which dominate the dataset. Unlike CCA and RDA, which require continuous or near-continuous input, MCA allows for the inclusion of a broader and more diverse range of survey items. Its primary analytical strength lies in detecting latent structures or clusters within the data by reducing it to a few interpretable dimensions based on shared category profiles. In this study, MCA reveals meaningful groupings of respondents who align differently across components of the peace agreement, based not only on their trust profiles but also on their socio-demographic characteristics and experiences with the armed conflict. However, MCA's exploratory nature comes at a cost: it does not produce inferential statistics or direct measures of variance explained in the conventional sense. Interpretations are largely visual and descriptive, relying heavily on the researcher's judgment, which makes MCA highly flexible but less confirmatory.

CCA introduces a more formal statistical framework by estimating linear associations between two multivariate sets: predictors (types of trust) and outcomes (support for peace-related measures). It extracts canonical functions that quantify how much shared variance exists between the two sets. In this case, the first canonical dimension strongly reflects the same patterns revealed in MCA, namely, that trust in reintegrated ex-combatants is closely associated with political support for the FARC. However, CCA assumes linearity, homoscedasticity, and multivariate normality, assumptions that are only partially satisfied in this dataset. As a result, CCA serves primarily as a confirmatory extension of MCA, offering insight into overall multivariate associations but with limited robustness due to assumption violations.

RDA, a constrained ordination technique, further complements the analysis by combining the dimensional reduction strengths of MCA with the inferential testing capabilities of CCA. Using permutation-based inference, RDA evaluates how much variance in the outcome variables can be attributed to the predictor set. Although the explained variance is modest (5.1%), it is statistically significant and typical for attitudinal research in complex, real-world settings. RDA is more flexible than CCA in that it does not assume multivariate normality, making it a useful compromise between explanatory power and statistical rigor. It confirms the dominance of trust in reintegrated ex-combatants and provides variance partitioning to quantify the unique contribution of each predictor, something MCA and CCA cannot do as explicitly.

In methodological terms, each technique contributes a distinct strength: MCA identifies latent attitudinal clusters, CCA models inter-set correlations, and RDA estimates the explanatory power of predictors under relaxed assumptions. While MCA is most powerful in this study for capturing complex response patterns across a wide array of variables, its insights are interpretive rather than statistical. In contrast, CCA and RDA provide formal structures for inference and prediction, but are constrained by data assumptions and the requirement for continuous variables. Taken together, these methods produce a coherent and mutually reinforcing understanding of how public trust, especially in reintegrated

individuals, shapes support for peacebuilding in Colombia. The triangulated design thus compensates for the limitations of any single approach and provides a methodologically balanced account of the attitudinal underpinnings of peace support.

6. Conclusion

This thesis aimed to explore the structural underpinnings of public attitudes toward Colombia's Revised Peace Agreement (RPA), using the 2021 Mapping Attitudes, Perceptions and Support (MAPS) dataset (Weintraub et al., 2023). With the 2026 elections on the horizon and the political party Comunes (formerly FARC) competing without previously guaranteed seats by the RPA, understanding the attitudinal configurations of Colombian citizens toward peace-related policies remains both timely and crucial. Previous research has shown that public support for the RPA is fragmented and component-specific, yet few studies have systematically examined the latent structure of these attitudes or the multivariate relationships between attitudinal subsets and key predictors such as trust, conflict exposure, and socio-demographics (Téllez, 2019; García-Sánchez & Carlin, 2020; Dirix, 2024).

To address this gap, the study posed three interrelated research questions:

- (1) What structural relationships exist between predictors (e.g., demographics, trust, conflict exposure) and attitudes toward the RPA?
- (2) To what extent does support for social development and justice differ from support for peacebuilding and political reintegration?
- (3) How do different analytical methods (MCA, CCA, RDA) compare in uncovering these relationships?

Each method contributed uniquely to answering these questions. Multivariate Correspondence Analysis (MCA) explored how socio-demographic and experiential variables relate to clustered attitudinal positions. It revealed four distinct citizen profiles, showing that combinations of conflict victimization, residence, education, gender, and religion strongly shape levels of support for different RPA components. Notably, victimized and structurally marginalized citizens expressed the most skepticism, even toward development-oriented measures, challenging assumptions that victimhood leads to reconciliation (Téllez, 2019). Conversely, younger, urban citizens with little conflict exposure showed consistent and principled support. These clusters demonstrated that attitudes toward peace are socially patterned, and thus not random, answering RQ1 and RQ2 from a descriptive and structural perspective.

Canonical Correlation Analysis (CCA) modeled the shared variance between blocks of trust-related predictors and attitudinal subsets. It found that trust in reintegrated ex-combatants, especially those involved in reintegration programs, was the most influential predictor of support for political reintegration, particularly FARC participation in elections. Other trust variables, such as political trust or trust in the FARC as a party, showed much weaker associations. This confirms that specific, credible reintegration experiences carry more explanatory power than general institutional trust (Esparza et al., 2020; García-Sánchez & Carlin, 2020). CCA thus provided a statistical answer to RQ1 and deepened the understanding of RQ2, showing that attitudes towards political reintegration and social development are linked to different trust configurations. Redundancy Analysis (RDA) quantified how much variance in attitudes could be explained by each predictor. It showed that trust in reintegrated ex-combatants alone explained a substantial share of the explained variance, particularly regarding electoral participation of the FARC. RDA confirmed the unbalanced explanatory weight of different trust types, reinforcing the insight that reintegration-focused trust bridges an otherwise fragmented attitude structure. This validated the findings of CCA and answered RQ3, demonstrating how each method, despite different assumptions, revealed overlapping conclusions. It also highlighted the added value of combining methods to gain a fuller view of attitudinal complexity. Even though MCA is mostly used as an exploratory technique, its ability to include categorical variables adds to its importance, while CCA and RDA can provide statistical inference on numerical variables only.

Altogether, the study confirmed that support for development-related provisions is broad and cross-cutting, while support for reintegration-related provisions is more conditional and fragmented. The clear divide between these domains aligns with prior research emphasizing that citizens do not perceive peace agreements as unified wholes (García-Sánchez et al., 2023; Muñoz & Pachón, 2021). Moreover, the convergence of all three methods around the central role of trust in ex-combatants if they followed reintegration programs, strengthens the credibility of this conclusion and supports calls for more visible, transparent reintegration efforts as a foundation for legitimacy.

Nevertheless, this study has several limitations. First, the use of cross-sectional data restricts causal inference: while strong associations were found, particularly between trust in ex-combatants and political reintegration, it remains unclear in which direction these effects operate. Second, the MAPS dataset lacks key variables such as political ideology, recent voting behavior, and media exposure, which are known to influence peace-related attitudes and could have added explanatory depth (García-Sánchez et al., 2023; Muñoz & Pachón, 2021). Third, the statistical assumptions of methods like CCA and RDA, such as linearity and multivariate normality, were only partially met. Although the large sample size provides robustness, these violations limit the models' generalizability. Finally, while attitudinal constructs were grouped based on prior analysis, the absence of validation calls for cautious interpretation.

Therefore, future research could explore longitudinal designs to assess attitude change over time and test causality. Structural Equation Modelling (SEM) could further validate recently found latent dimensions and their predictors, therefore combining categorical and numerical variables. Including variables such as ideology, media framing, and perceptions of implementation progress would also strengthen future attitudinal models.

In sum, this thesis shows that attitudes toward the RPA in Colombia are structured, conditional, and multidimensional. They reflect not only what citizens think about former combatants or social development, but also how they interpret the very idea of peace in a society marked by decades of armed conflict. As the RPA continues to unfold, understanding these attitudes, and the factors that shape them, remains critical for the future of Colombia's democracy and reconciliation trajectory.

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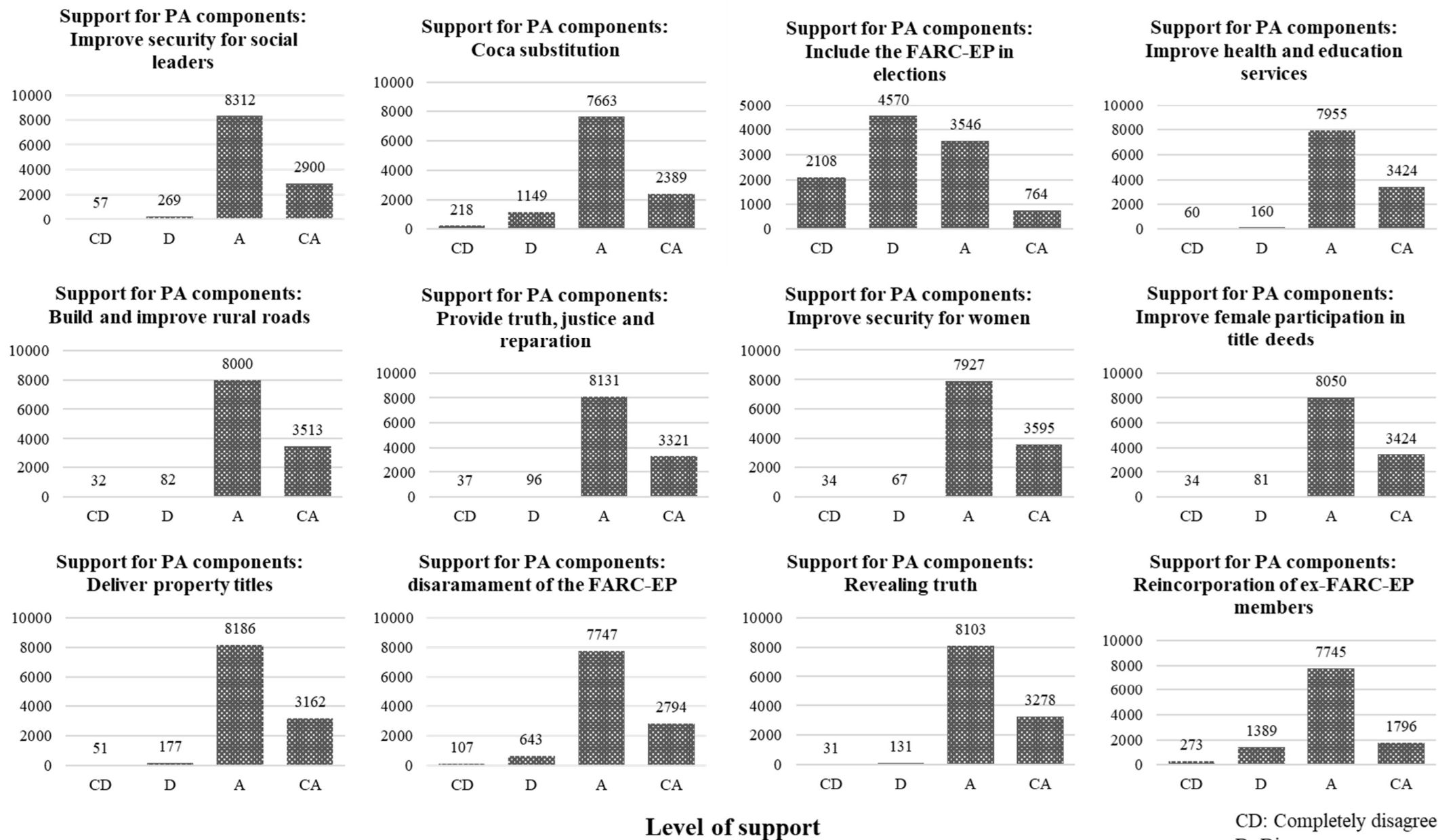
Annex

Descriptive statistics

Table 5. Descriptive statistics of the attitudes toward the Peace Agreement in general and toward its specific components

Variables support for PA components	Statistics					
	N	Missing	Mean	Std. Deviation	Skewness	Kurtosis
General satisfaction with content of 2016 peace agreement	10097	1680	2,00	0,843	0,397	-0,665
Disarmament of the FARC-EP	11291	486	3,17	0,559	-0,294	1,447
Improve security for social leaders	11538	239	3,22	0,497	0,135	1,375
Coca substitution	11419	358	3,07	0,617	-0,531	1,399
Include the FARC-EP in elections	10988	789	2,27	0,848	0,138	-0,653
Improve health and education services	11599	178	3,27	0,506	0,091	0,972
Build and improve rural roads	11627	150	3,29	0,486	0,378	0,168
Deliver property titles	11576	201	3,25	0,494	0,206	1,023
Provide truth, justice and reparation	11585	192	3,27	0,483	0,371	0,499
Improve security for women	11623	154	3,30	0,488	0,353	0,148
Improve female participation in title deeds	11589	188	3,28	0,484	0,386	0,302
Revealing truth	11543	234	3,27	0,484	0,386	0,373
Reincorporation of ex-FARC-EP members	11203	574	2,99	0,618	-0,613	1,579

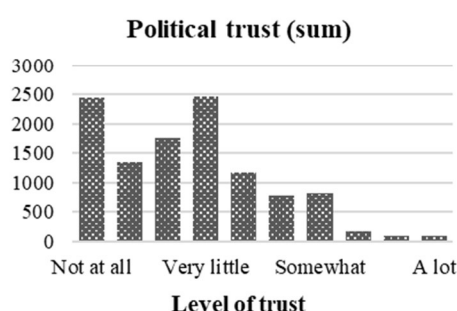
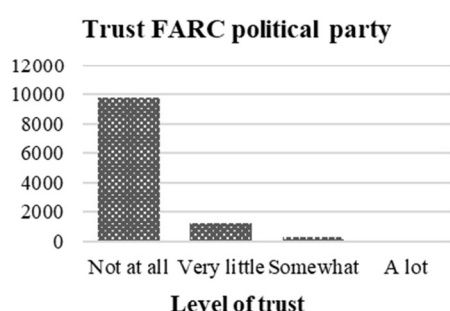
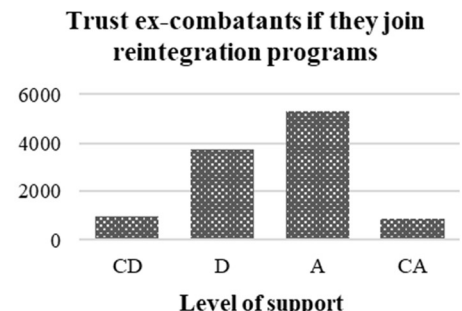
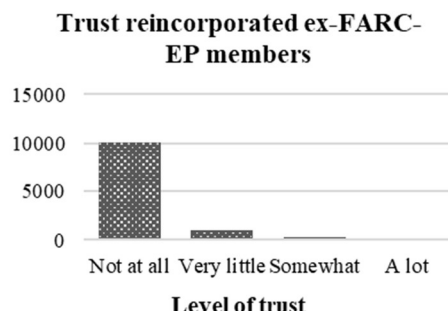
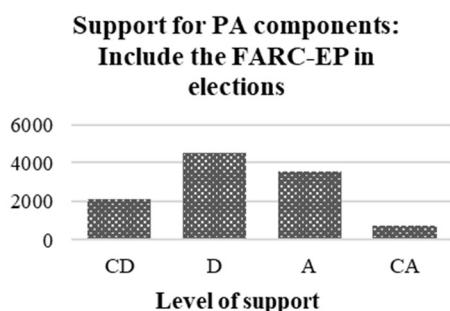
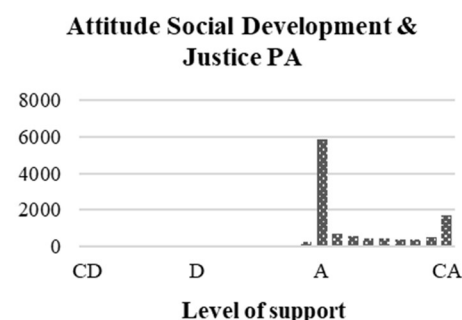
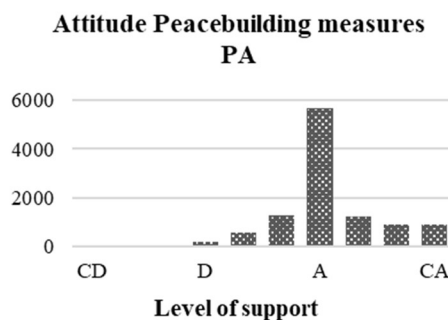
Note 1. Total number of respondents is 11777. Table retrieved from Dirix (2024).



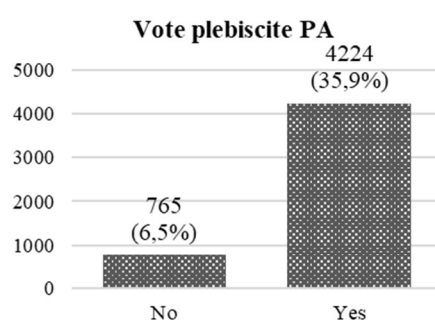
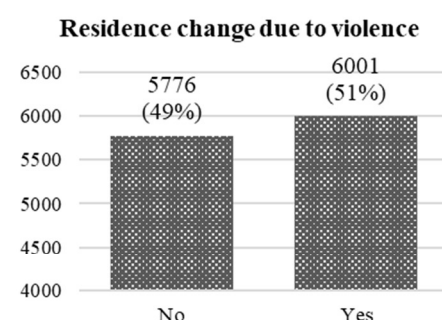
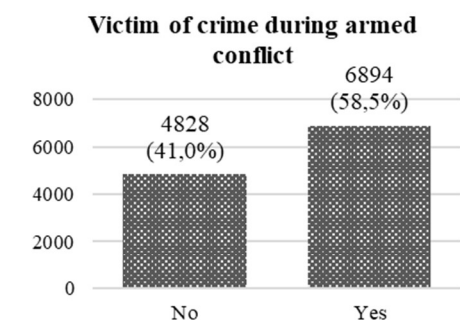
CD: Completely disagree
D: Disagree
A: Agree
CA: Completely agree

Figure 5. Level of support for the different components of the RPA in 2021. Figure retrieved from Dirix (2024).

Number of respondents



CD: Completely disagree
D: Disagree
A: Agree
CA: Completely agree



Number of respondents

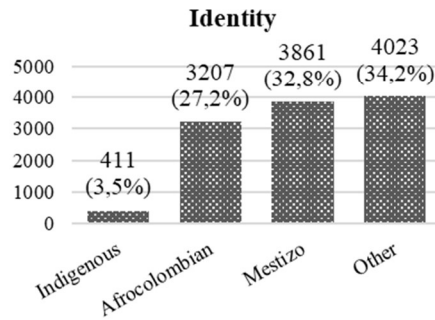
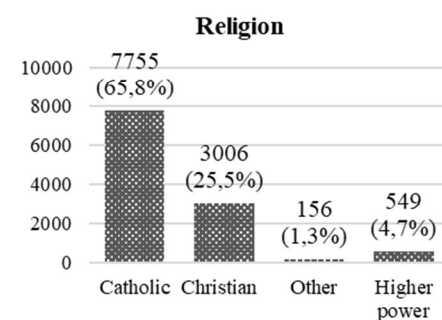
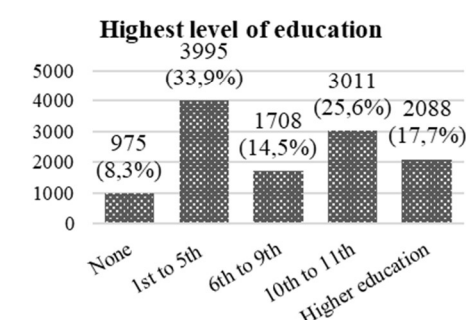
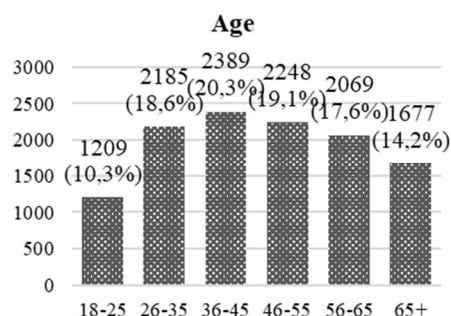
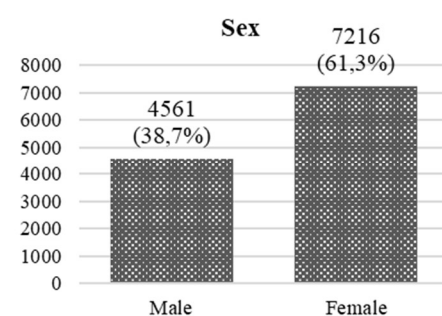
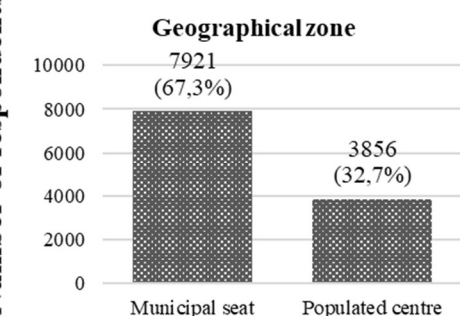


Figure 6. Distributions of the (quasi)-metric and categorical variables. Figure retrieved from Dirix (2024).

Multivariate Correspondence Analysis

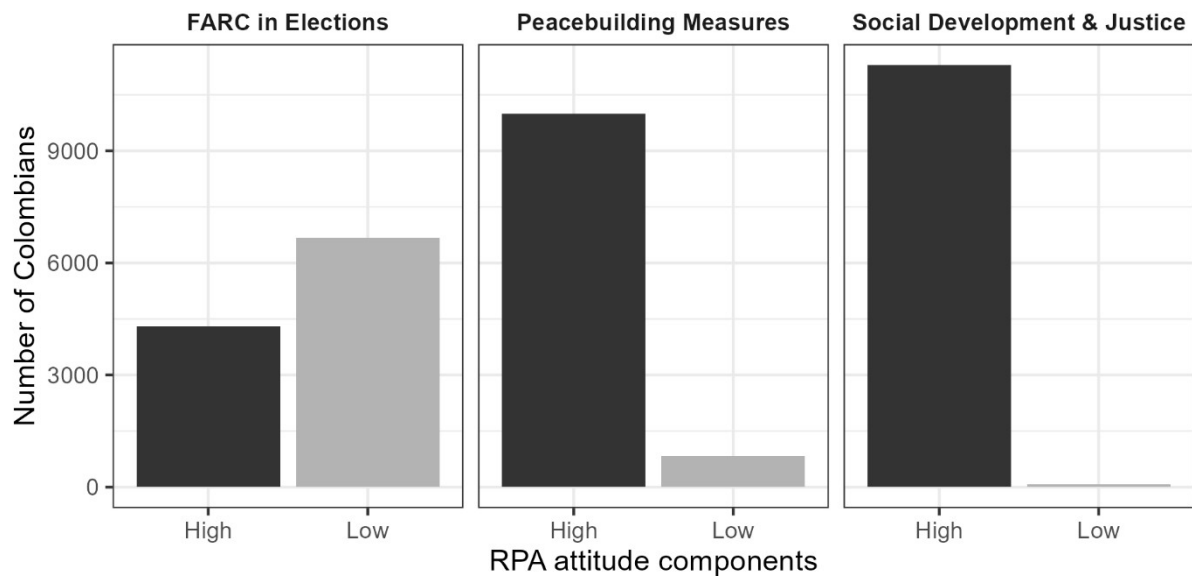


Figure 7. Bar charts of transformed attitude variables

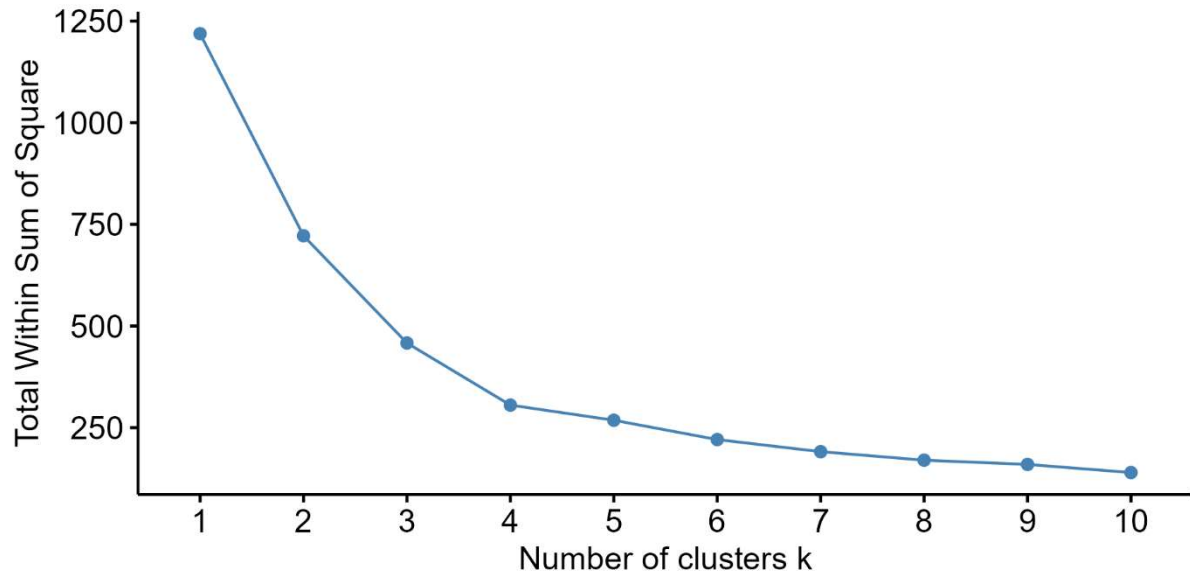


Figure 8. Elbow plot for determining optimal cluster number

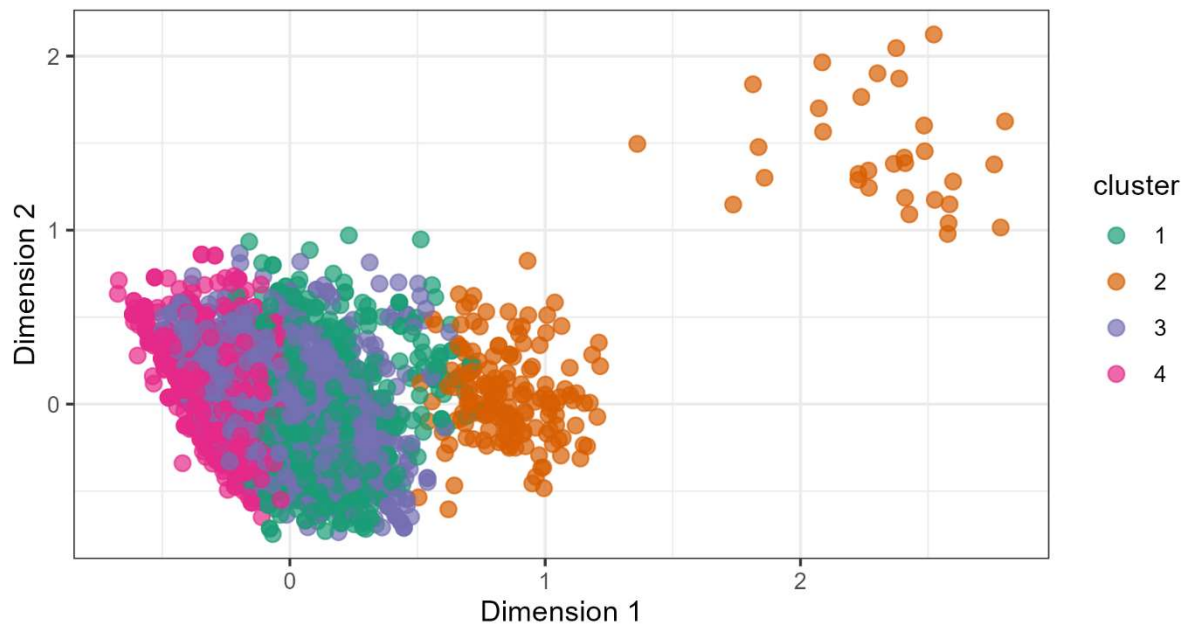


Figure 9. K-means Clusters Based on dimensions 1 and 2 of the MCA

Canonical Correlation Analysis and Redundancy Analysis

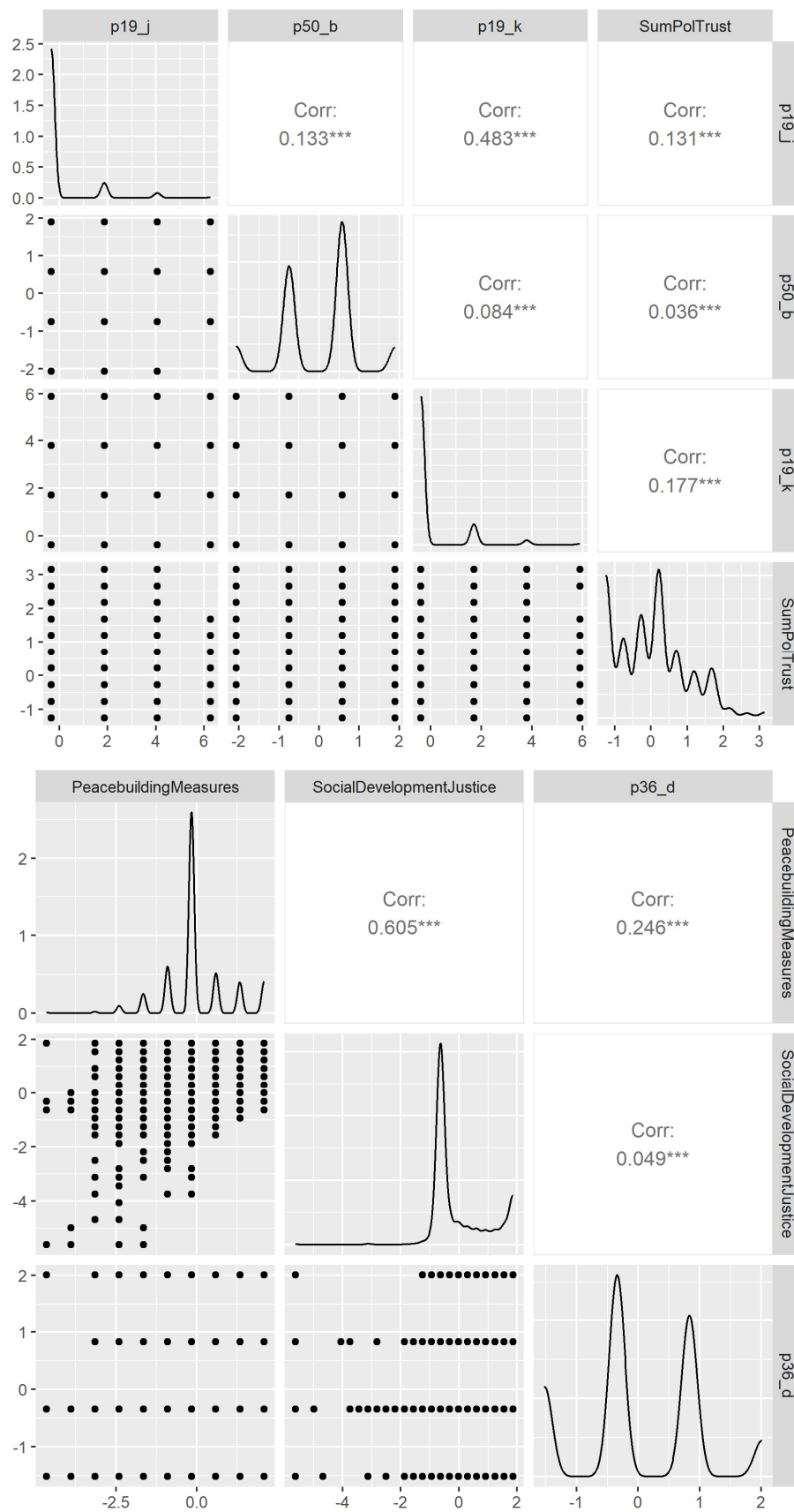


Figure 10. Correlation matrix of standardized predictor and outcome variables

```
##-----Preparation-----##
```

```
library(haven)
data <- subset(Data, wave == 1)

#RPA attitude component
table(data$PeacebuildingMeasures)
summary(data$PeacebuildingMeasures)
summary(data$SocialDevelopmentJustice)
table(data$SocialDevelopmentJustice)
summary(data$p36_d)
table((data$p36_d))

data$CPeacebuildingMeasures <- ifelse(data$PeacebuildingMeasures < 2.5, "Low", "High")
table(data$CPeacebuildingMeasures)
data$CSocialDevelopmentJustice <- ifelse(data$SocialDevelopmentJustice < 2.5, "Low",
"High")
table(data$CSocialDevelopmentJustice)
data$CFARCElections <- ifelse(data$p36_d < 2.5, "Low", "High")
table(data$CFARCElections)

library (tidyverse)
Data_long <- data %>%
  pivot_longer(cols = c(CPeacebuildingMeasures, CSocialDevelopmentJustice,
CFARCElections),
               names_to = "item",
               values_to = "response") %>%
  filter(!is.na(response))
ggplot(Data_long, aes(x = response, fill = response)) +
  geom_bar() +
  facet_wrap(~ item,
            nrow = 1,
            labeller = labeller(item = c(
              CPeacebuildingMeasures = "Peacebuilding Measures",
              CSocialDevelopmentJustice = "Social Development & Justice",
              CFARCElections = "FARC in Elections"
            ))) +
  scale_fill_manual(values = c("gray20", "gray70")) +
  labs(x = "RPA attitude components", y = "Number of Colombians") +
  theme_bw() +
  theme(legend.position = "none",
        strip.background = element_blank(),
        strip.text = element_text(face = "bold"))
ggsave("CAfig1.png", width = 16, height = 8, units = "cm", dpi = 300)
```

```
##-----MCA-----##
```

```
library(tidyverse)
library(FactoMineR)
library(factoextra)
library(ggplot2)
library (ggrepel)
library(cowplot)

#MCA all categories of all variables
cat_predictors <- c("p52_0", "p14e", "p22", "TZone", "TSex", "p7", "p10a", "p9", "p10")
rpa_vars <- c("CPeacebuildingMeasures", "CSocialDevelopmentJustice",
"CFARCElections")

df_mca <- data %>%
  select(all_of(c(cat_predictors, rpa_vars))) %>%
  mutate(across(everything(), haven::as_factor)) %>%
  drop_na()

mca_all <- MCA(df_mca, graph = FALSE)
fviz_mca_biplot(mca_all, repel = TRUE, ggtheme = theme_bw()) +
  ggtitle("MCA - Combined RPA Attitudes")
```

```

#MCA top 20 categories
fviz_mca_var(mca_all, select.var = list(contrib = 20), repel = TRUE, ggtheme =
theme_bw()) +
  ggtitle("Categories Only")

#MCA dim 1 and 2 top 20 categories and RPA attitudes
contrib_all <- mca_all$var$contrib
top_contrib_names <- rownames(contrib_all)[order(-rowSums(contrib_all[, 1:2]))][1:20]
rpa_names <- rownames(contrib_all)[grepl(paste(rpa_vars, collapse = "|"),
rownames(contrib_all))]
selected_categories <- unique(c(top_contrib_names, rpa_names))

fviz_mca_var(mca_all,
  select.var = list(name = selected_categories),
  repel = TRUE,
  ggtheme = theme_bw()) +
  ggtitle("MCA - Top Contributors and RPA Attitudes")

var_type <- ifelse(rownames(contrib_all) %in% rpa_names, "RPA variable",
  ifelse(rownames(contrib_all) %in% selected_categories, "Top
contributor", NA))

coord <- as.data.frame(mca_all$var$coord)
coord$label <- rownames(coord)
coord$type <- var_type
coord <- coord %>% filter(!is.na(type))
colnames(coord)[1:2] <- c("Dim.1", "Dim.2")

plot1 <- ggplot(coord, aes(x = Dim.1, y = Dim.2, label = label, color = type)) +
  geom_text_repel(size = 3.5, max.overlaps = 100) +
  scale_color_manual(values = c("Top contributor" = "gray70", "RPA variable" =
"grey20")) +
  theme_bw() +
  labs(x = "Dim1",
    y = "Dim2",
    color = "Variable type") +
  theme(legend.position="none")
plot1
ggsave("MCAFig2.pdf", plot = p, width = 16, height = 14, units = "cm", dpi = 300)

res.mca <- MCA(df_mca, graph = FALSE)
eig <- get_eigenvalue(res.mca)
eig
colnames(coord)[1:4] <- c("Dim.1", "Dim.2", "Dim.3", "Dim.4")

#MCA dim 3 and 4 top 20 and 6 RPA attitude variables
plot2 <- ggplot(coord, aes(x = Dim.3, y = Dim.4, label = label, color = type)) +
  geom_text_repel(size = 3.5, max.overlaps = 100) +
  scale_color_manual(values = c("Top contributor" = "gray70", "RPA variable" =
"grey20")) +
  theme_bw() +
  labs(x = "Dim3",
    y = "Dim4",
    color = "Variable type")+
  theme(legend.position="none")

combined_plot <- plot_grid(plot1, plot2,
  labels = c("A", "B"), # optioneel, bv. A = Dim 1&2, B = Dim
3&4
  ncol = 1) # onder elkaar
ggsave("combined_mca_plot.png", combined_plot, width = 20, height = 28, units = "cm",
dpi = 300)

#kmeans and clustering
coords <- as.data.frame(mca_all$ind$coord)
set.seed(123)
elbow <- fviz_nbclust(coords[, c("Dim 1", "Dim 2")],
  kmeans,

```

```

        method = "wss") +
  labs(title = "Elbow Method - Optimal Number of Clusters")
ggsave("elbow.png", elbow, width = 16, units = "cm", dpi = 300)
km <- kmeans(coords[, c("Dim 1", "Dim 3")], centers = 4)
coords$cluster <- as.factor(km$cluster)

#Clusters in dim 1 and 2
clusters <- ggplot(coords, aes(x = `Dim 3`, y = `Dim 4`, color = cluster)) +
  geom_point(alpha = 0.7, size = 2.5) +
  theme_bw() +
  labs(x = "Dimension 1",
       y = "Dimension 2"
  ) +
  scale_color_brewer(palette = "Dark2")
ggsave("clusters.png", clusters, width = 16, units = "cm", dpi = 300)

#Clusters of dim1 en 2 projected on dim 3 en 4
cluster_means <- coords %>%
  group_by(cluster) %>%
  summarise(
    Mean_Dim3 = mean(`Dim 3`),
    Mean_Dim4 = mean(`Dim 4`)
  )

clustersopdim <- ggplot(cluster_means, aes(x = Mean_Dim3, y = Mean_Dim4, label =
cluster)) +
  geom_point(size = 4, color = "black") +
  geom_text(vjust = -1) +
  theme_minimal() +
  labs(
    title = "Mean coordinate scores of clusters (based on Dim 1 & 2) on Dimension 3 and
4",
    x = "Dimension 3",
    y = "Dimension 4"
  ) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray") +
  geom_vline(xintercept = 0, linetype = "dashed", color = "gray")
ggsave("clustersopdim.png", clustersopdim, width = 16, units = "cm", dpi = 300)

##-----CCA-----##
#Preparation
library(CCA)
library(CCP)
library(psych)
library(GGally)
library(MVN)
library(patchwork)
library(gridExtra)
library(ggpubr)
library(cowplot)
library(grid)

table(data$p19_j)
table(data$p50_b)
table (data$p19_k)
table(data$SumPolTrust)

X <- data[, c("p19_j", "p50_b", "p19_k", "SumPolTrust")]
Y <- data[, c("PeacebuildingMeasures",
              "SocialDevelopmentJustice",
              "p36_d")]
X_std <- scale(X)
Y_std <- scale(Y)

#Assumptions
cor(X) #Too many missings
cor(Y) #Too many missings

```

```

data_cca <- na.omit(cbind(X, Y))
X_cc <- data_cca[, colnames(X)]
Y_cc <- data_cca[, colnames(Y)]
X_std <- scale(X_cc)
Y_std <- scale(Y_cc)

cor(X_std)
cor(Y_std)

pairs1 <- ggpairs(data.frame(X_std))
pairs2 <- ggpairs(data.frame(Y_std))

g1 <- ggmatrix_gtable(pairs1)
g2 <- ggmatrix_gtable(pairs2)
combined <- arrangeGrob(g1, g2, ncol = 1)
png("combined_pairs.png", width = 16, height = 30, units = "cm", res = 300)
grid.newpage()
grid.draw(combined)
dev.off()

mardia(data.frame(X_std))
mardia(data.frame(Y_std))

#CCA
cca_model <- cc(X_std, Y_std)
cca_model$cor
n <- nrow(X_std)
p.asym(cca_model$cor, n, ncol(X_std), ncol(Y_std))

results <- comput(X_std, Y_std, cca_model)
str(results)
round(results$corr.X.xscores, 3)
round(results$corr.Y.yscores, 3)

CCA <- plt.cc(cca_model)
x_loadings <- results$corr.X.xscores[, 1:2]
y_loadings <- results$corr.Y.yscores[, 1:2]
plot(x_loadings, xlim=c(-1,1), ylim=c(-1,1), asp=1,
     pch=17, col="grey70", xlab="Dimension 1", ylab="Dimension 2",
     main="Canonical Loadings")
points(y_loadings, pch=19, col="grey20")
symbols(0, 0, circles=1, inches=FALSE, add=TRUE, lty=2)
symbols(0, 0, circles=0.5, inches=FALSE, add=TRUE, lty=2)
text(x_loadings[,1], x_loadings[,2],
     labels = rownames(x_loadings), col = "grey70", pos = 3, cex = 0.8)
text(y_loadings[,1], y_loadings[,2],
     labels = rownames(y_loadings), col = "grey20", pos = 3, cex = 0.8)

##-----RDA-----##
library(MVN)
library(vegan)
library(car)

#Assumptions

mahalanobis_dist <- mahalanobis(X_std, colMeans(X_std), cov(X_std))
cutoff <- qchisq(0.975, df = ncol(X_std))
which(mahalanobis_dist > cutoff)

complete_data <- cbind(Y_std, X_std)
complete_data <- na.omit(complete_data)

Y_complete <- complete_data[, colnames(Y_std)]
X_complete <- complete_data[, colnames(X_std)]

rda_result <- rda(Y_complete ~ ., data = as.data.frame(X_complete))
plot(residuals(rda_result), main = "RDA Residuals")

```

```
vif_model <- lm(Y_std[, 1] ~ ., data = as.data.frame(X_std))
vif(vif_model)

#RDA
rda_result <- rda(Y_complete ~ ., data = as.data.frame(X_complete))
summary(rda_result)

anova(rda_result)
anova(rda_result, by = "axis")
anova(rda_result, by = "terms")

explained_total <- summary(rda_result)$constr.chi
total_variance <- summary(rda_result)$tot.chi
redundancy_index <- explained_total / total_variance
cat("Redundancy Index:", round(redundancy_index, 3), "\n")

plot(rda_result, scaling = 2, main = "RDA Biplot (Scaling 2)")
```

