Quarto_Paper_MaC

Democracy and social media: Between the dialogue and the strategy

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Abstract

This study analyzes the role of traditional news media and social media in public deliberation within democratic systems. Using the concepts of Understanding Orientation (consensus-oriented, communicative rationality) and Strategic Orientation (goal-oriented, instrumental rationality), proposed by Jürgen Habermas, this study looks at the public space in a digital context to explore how the news media can either contribute to the existence of rational communication in the public debate or, conversely, promote interventions of a strategic nature. To estimate the influence of traditional news media and social media on the orientation to engage in dialogue with others within a framework of rationality and equality, this study relies on a two-wave online panel survey conducted in Chile before and after the constitutional referendum, held on September 4, 2022, a period of intense political polarization. The first wave (T1) received 2,117 responses, and the second wave (T2) received 903 responses. Results show that Understanding Orientation is a predictor of political situations linked to public deliberation, such as Political Participation and Political Interest. However, news consumption in both traditional news outlets and social media is not associated with the presence of Understanding Orientation, but rather with Strategic Orientation. These results support a more pessimistic view of the contribution of the news media and social media to creating a rational public sphere, where reason should predominate in interactions between citizens to strengthen democracy.

Literature Review

In recent decades, the concept of deliberative democracy has increasingly appeared in theoretical discussions (Dahl, 1989; Delli Carpini and Jacobs, 2004; Habermas, 1996; Rawls, 1971) and empirical studies on the formation of public opinion (Fishkin, 2005). As Page (1996) stated, "public deliberation is essential to democracy."

The expansion of the deliberative democracy concept broadens the idea of political participation, which for decades was restricted to electoral participation. The vote-centric view of politics considers the

political system a mere aggregator of individual preferences, assuming that citizens form opinions in isolation and express them periodically in elections to determine majority positions (Delli Carpini and Jacobs, 2004). In contrast, deliberative democracy processes opinions before voting occurs in democratic systems (Delli Carpini and Jacobs, 2004). Through dialogue and reasoning, citizens can build agreements. However, this facet of citizenship does not compete with electoral democracy; rather, they complement each other.

Fishkin (2005), who has conducted both theoretical reflection and extensive empirical research, argues that deliberative democracy must reconcile deliberation with democratic values, political equity, and avoid majority dictatorship. This requires an attitude of listening to others (Burkhalter et al., 2002). Listening is central, but so is the ability to speak and argue in the public sphere under equal conditions.

Regarding the characteristics of deliberation, Moy and Gastil (2006) assert that for deliberation to occur, certain conditions must be met: openness to political conflict, absence of conventional forms of domination, clear and responsible arguments, and mutual understanding. They argue that not all media stimulate democratic deliberation; for example, written media facilitate it through face-to-face interactions, while television complicates it by making rational arguments harder to present and for recipients to grasp as intended.

Not all conversations, however, constitute democratic deliberation. Many face-to-face conversations are merely social interactions without a clear objective or problem to resolve (Moy and Gastil, 2006; Schudson, 1997). The key difference between democratic deliberation and other forms of conversation lies in its conflictual nature, the use of rational arguments, and the goal of reaching a consensus (Moy and Gastil, 2006).

Since the mid-20th century, research has demonstrated the relationship between democratic deliberation and interpersonal conversations. Interpersonal conversation is a privileged space for dialogue, where several characteristics converge to facilitate reaching agreements, such as: a) participants being in the same spatiotemporal context, b) use of multiple symbolic signals, c) specific orientation toward others, and d) the possibility of feedback (Thompson, 1998). The importance of interpersonal communication in deliberation was first found in research by the Columbia School, which analyzed the role of personal conversations in shaping undecided voters' choices. These findings were later extended by other authors who have continued studying the importance of interpersonal communication (Delli-Carpini, Cook, & Jacobs, 2004; Habermas, 1962; Rawls, 1971; Rojas et al., 2005).

Alongside interpersonal conversation, the relationship between deliberation and the media has also been intensely studied (Habermas, 1962; Moy and Gastil, 2006; Page, 1998). The debate began with Katz and Lazarsfeld (1955), who measured how the media influenced personal conversations and found that the effect varied according to audience characteristics. Later, Habermas gave a central role to the media—particularly the press—in constructing the public sphere, stating that the media fueled rational debate among private individuals, constituting a public sphere for discussing issues of common interest (1962). This debate, now including digital media and social media, continues to evolve. Moy and Gastil (2006) argue that consuming news through the media opens up political conflicts that are part of deliberation, and Mais (XXX) claims that the media can promote deliberation, despite skepticism about their impact.

Digitalization, especially the emergence of social media, has renewed interest in political deliberation studies, raising questions about differences between the effects of traditional media and new digital platforms. Social media have significant potential to boost political participation by reducing organization time, lowering economic costs of participation, helping build collective identities (Dalton, Sickle, and Weldon, 2009), reaching critical masses, forming groups with common interests, accessing vast amounts of information, and increasing social capital (Ellison et al., 2014; Valenzuela, Park, and Kee, 2009). These characteristics make social media a space of constant interaction, though these interactions do not necessarily lead to political deliberation and may also foster other forms of personal interaction. Since 2016, doubts have increased about the beneficial effects of social media on public deliberation. The proliferation of fake news, echo chambers, election campaigns using micro-targeting techniques to understand voters, and opaque algorithms have heightened skepticism about these platforms' contribution to democracy (Chambers, 2023). In this context, Volker (2019) explains that the quality of deliberation on social media depends on various factors and their interaction: a) infrastructure quality, b) political context, c) legal framework, and d) discourse participants.

Public Sphere and Action Orientations

One of the most important authors on the relationship between public opinion, deliberation, and democracy is Jürgen Habermas. In 1962, he published The Structural Transformation of the Public Sphere, a seminal text in the debate on this topic. One of Habermas' central concepts is the "public sphere."

In this work, Habermas describes the public sphere as a space where individuals use reason to discuss public issues in accessible places. His research focuses on three European countries—France, Germany, and England—and highlights a new social structure that emerged in the 18th century in bourgeois gathering places, where debates were fueled mainly by print media publications (Habermas, 1991). The public sphere not only allows individuals to use reason to debate public issues but also acts as a hinge between the public sphere (where state action occurs) and the private sphere (where work, intimate relationships, and family life reside) (Habermas, 1991).

One of the most significant consequences of the public sphere's emergence is the equality it creates between people, transcending origin and economic status. When differences are addressed through reason, only the strength of arguments and persuasion matters. Social differences tend to fade in the public sphere, where the principle of equality is affirmed through the use of reason. In his work, Habermas takes a critical view of the public sphere's evolution since the late 19th century. He argues that public space is no longer driven by reason but has become dominated by manipulation and the public representation of interests, a phenomenon he calls "representative publicity." He also criticizes the media for no longer fostering rational dialogue among citizens, having instead succumbed to commercial logic, interest defense, and cultural consumption (Habermas, 1991; Thompson, 1998).

Despite his pessimistic view of the public sphere's function in the 20th century, Habermas later revised and modified some of his initial positions (Calhoun, 1992; Habermas 2006, 2022, 2023). In these later works, he reexamines various aspects of his proposal, most notably reassessing the idea of the public sphere's decline throughout the 20th century and the media's role in this process. He argues that two key actors are necessary for the public sphere to function: media professionals who generate mediated public opinion and politicians who occupy the center of the public sphere. Additionally, he asserts that

the public sphere can function properly as long as media professionals maintain independence from surrounding actors and feedback occurs between media publications and civil society (Habermas, 2006).

In his most recent writings, Habermas (2022, 2023) further explores the media's role, stating that one of their tasks is to generate "competing public opinions" (p.157) to meet the standards of public deliberation. He argues that the media's space is the only venue where effective opinions can reach a broad audience (Habermas, 2022). He also highlights that political messages' effectiveness varies depending on individuals' interest, education, and economic situation.

Social media's influence on the public sphere is also analyzed. Habermas takes a pessimistic view of these platforms, arguing that they lack the editorial and professional controls that journalists face, leading to an unregulated process with a centrifugal effect that drives citizens apart rather than fostering consensus (Habermas, 2022).

Consistent with his description of the public sphere, Habermas proposed two orientations for social interactions: a) strategic (goal-oriented) and b) communicative (understanding-oriented). The first seeks to manipulate others to achieve predefined objectives, while the second seeks to establish relationships through language and reason, aiming to reach consensus, which all actors in the situation deem legitimate.

Habermas's proposal contrasts with a long-standing tradition that views reason as operating solely instrumentally—or strategically—in social life (Coleman, XXX; Dewey, 1988; Weber, XXX). Habermas offers a counterproposal, suggesting that face-to-face interactions can involve reason and achieve significant levels of understanding. Achieving agreements, according to Habermas, is essential for societies' symbolic and normative interactions. His proposal underscores the importance of rationally established decision-making processes, as adherence to norms shaped by collective participation leads to final decisions being considered legitimate by all affected parties.

Strategic and understanding-oriented interactions play roles in different moments of social life. Strategic orientation is appropriate for decisions emphasizing technical efficiency, while understanding orientation is essential in situations involving normative aspects or when actors seek to harmonize their objectives with others in a shared definition of from the situation in which they find themselves (Habermas, 2003).

As in his proposal of the public sphere, in the description of the orientations of conversation, the use of reason—or its absence—plays a fundamental role. In his work, Habermas seeks to expand the instrumental action or rational action oriented towards ends, as defined by Max Weber, by incorporating a rational action in which language plays a central role, which he calls communicative action (Habermas, 2003). Although both actions have a basis in rationality, their differences are significant. Instrumental action is non-social—it does not involve other actors—and aims to use means as rationally as possible to achieve a desired state of affairs in the world. Finally, Habermas argues that there are social actions that are not instrumental, which occur when actors are not driven by selfish calculations but seek, through language, to reach a consensus with others. In this way, success orientation is typical of strategic actions, and understanding orientation happens in communicative actions (Habermas, 2003).

This proposal by Habermas has undergone few empirical tests. One of them is the work of Rojas (2008), who studied how the orientations of conversations impact relevant variables of the democratic system, such as political interest and political efficacy, in addition to establishing the determining variables of strategic orientation and understanding orientation (Rojas, 2008). In this latter analysis, the influence of news consumption in traditional media—TV, newspapers, and radio—on the two described forms of orientation was studied.

Although it has its differences, Habermas's proposal brings him closer to other authors who have also highlighted the importance of deliberation in democratic life (Dahl, 1989; Delli Carpini and Jacobs, 2004; Fishkin, xxxx; Page, 1996).

Incorporating the effect of traditional media and social media in the current public debate Considering the relationship established by previous research between deliberation and the characteristics of Jürgen Habermas's concept of understanding orientation, our first research hypothesis is:

This point needs to be correctly address H1: Understanding orientation is positively related to interpersonal confidence.

Regarding the relationship between media consumption and the previous findings on the link between traditional media and social media with different forms of democratic deliberation, we propose:

H2a: News consumption in traditional media is positively related to understanding orientation.

H2b: Exposure to news on social media is negatively related to understanding orientation.

Political Variables

In addition to media and social media, there are other variables that the literature shows influence democratic deliberation processes, such as political interest and the perception of political efficacy.

Political interest is considered the basis for holding democratic political beliefs (Rebenstorf, 2004) and one of the central variables for explaining political participation (Sherrod et al., 2010; Torney-Purta, 2001). "Political interest is a necessary precondition for the desired characteristics of a responsible and democratic citizen" (Rebenstorf, 2004). In the same vein, Gil de Zúñiga and Diehl (2018). Unlike the civic obligations imposed by the state—which are normative in nature—high levels of social capital are associated with voluntary political engagement behaviors (Delli Carpini and Keeter, 1996). Moreover, members of audiences with lower social capital tend to avoid news consumption more frequently (Prior, 2007), while high levels of social capital are related to high news consumption (Boulainne and Shehata, 2022). Given the precondition status that political interest holds for the development of civic behaviors, we propose:

H3: Political interest is positively related to understanding orientation.

Political efficacy is another key variable for understanding the level of commitment to the political system and participation. It is understood as the perception of individuals' abilities to understand the political process and the influence they have on authorities' decisions (Prats and Meunier, 2021). Political efficacy creates a self-selection effect, where individuals' perceptions influence their willingness to participate politically (Gamson, 1968; Prats and Meunier, 2021; Schulz, 2005). Efficacy

has two distinct dimensions: external efficacy and internal efficacy. External efficacy refers to individuals' perception of their ability to influence authorities' decisions through various methods, such as elections or public protests. Meanwhile, internal efficacy studies individuals' perception of their competence in understanding the functioning of the political system (Parent, Vandebeek, and Gemino, 2005). Considering the background on the behavior of efficacy and its relationship with participation, we propose the following hypothesis:

H4: Political efficacy (internal and external) is positively related to understanding orientation.

Methodology

Data

The data for this study was obtained from a national survey conducted in Chile under the supervision of the Millennium Nucleus for the Study of Politics, Public Opinion, and Media in Chile (Nucleo MEPOP). The complete survey consisted of three waves, but this study only utilizes data from the first and third waves. Wave 1 was conducted between August 25 and September 8, while Wave 3 was conducted between [insert dates]. The total sample size for this analysis was 950 individuals, specifically those who participated in both Wave 1 and Wave 3.

It is important to note that the survey instrument did not necessarily include the same questions across all three waves. As a result, the analyses presented in this paper are cross-sectional in nature. While the dependent variable was constructed from responses in Wave 3, all independent variables were drawn from Wave 1. The survey design employed quotas based on gender, age, and socioeconomic level, ensuring alignment with national distributions.

Variables

Understanding orientation:

Following the previously mentioned literature, understanding orientation was measured by asking respondents to indicate how much they agree or disagree with the following statements:

Under1: "In political conversations, it is essential to listen carefully to what others have to say."

Under2: "When I talk about politics, learning is more important to me than convincing."

Under3: "Through my conversations, I promote solidarity with others."

Under4: "At its core, politics aims to reach agreements through conversation."

Under5: "When I talk about politics, I feel connected to the people I talk with."

Under6: "Through conversation, political interests can be directed toward the common good."

Under7: "Talking about politics allows me to understand why others see things differently."

Under8: "Political conversations are important for protecting people's rights."

All responses were measured on a 5-point Likert scale, where 1 indicated strong disagreement and 5 indicated strong agreement. A factor was constructed using the eight responses (α = 0.86).

Strategic Orientation

Similarly, to measure strategic orientations, all respondents were asked to indicate how much they agree or disagree with the following statements:

Strate1: "Saying one thing while thinking another is fundamental when talking about politics."

Strate2: "I talk about politics if I gain something from it."

Strate3: "In political conversations, form is more important than content."

Strate4: "When talking about politics, it is sometimes better not to express what you truly think."

Strate5: "People are tired of being asked to talk in order to reach political agreements."

Strate6: "The head of the household decides and does not need to reach an agreement with other family members."

Strate7: "Instead of so much discussion, it's better for someone to just say how things are."

Strate8: "Trying to reach agreements through conversation is a waste of time; it's better if someone decides what to do and gets it done."

All responses were measured on a 5-point Likert scale, where 1 indicated strong disagreement and 5 indicated strong agreement. A factor was constructed using the eight responses (α = 0.75).

Interpersonal Confidence

To measure interpersonal trust, respondents were asked: "Generally speaking, do you think most people can be trusted, or do you think you need to be careful when dealing with others?" Those who answered that most people can be trusted were coded as 1, and all others were coded as 0 (mean = 0.13).

Political Efficacy

In line with the literature, political efficacy was divided into three distinct dimensions. First, external efficacy—i.e., beliefs about system responsiveness—was measured using the following statements:

extef1: "Politicians don't really care about what voters think."

extef2: "Politicians waste a lot of taxpayers' money."

extef3: "People like me have no influence over what is decided in parliament or government."

Similarly, internal efficacy—self-competence beliefs—was measured with the following statements:

intef1: "In general, I don't find it difficult to take a stance on political issues."

intef2: "People like me are qualified to participate in political discussions."

intef3: "People like me have political opinions that are worth listening to."

Finally, following recent literature, an additional set of questions was used to measure online political efficacy—i.e., the belief that, because of the Internet, it is possible to have more influence on politics and public issues:

ope1: "Using the internet, people like me have more political power."

ope2: "Using the internet, I can have more say over what the government does."

ope3: "Using the internet, it is easier for me to understand politics."

ope4: "Using the internet, public officials care more about what I think."

All responses were measured on a 5-point Likert scale, where 1 indicated strong disagreement and 5 indicated strong agreement. A factor was created for each of the dimensions (external efficacy: α = 0.74; internal efficacy: α = 0.74; online political efficacy: α = 0.84).

Political Interest

To measure political efficacy, respondents were asked to indicate their level of interest in the following areas:

polint1: Politics

polint2: The constituent process

polint3: The exit plebiscite

All responses were measured on a 5-point Likert scale, where 1 indicated low interest and 5 indicated high interest (α = 0.88).

Media Exposure

To measure media exposure, respondents were asked to indicate how frequently they informed themselves using different channels. Specifically, we used three sets of questions: one related to traditional media, i.e., broadcast TV, cable TV, print media, and radio (α = 0.74); another focused on digital media, i.e., online versions of traditional media, digital-only outlets, news podcasts, and social media platforms of digital media (α = 0.76); and a third set focused solely on social media, i.e., Facebook, Twitter, Instagram, WhatsApp, YouTube, and TikTok (α = 0.84). All questions were measured on a 5-point Likert scale, where 1 indicated low frequency and 5 indicated high frequency.

Sociodemographic Variables

Additionally, we controlled the models by incorporating various sociodemographic variables. These included education level, sex (mean = 0.45, where 0 = male and 1 = female), socioeconomic status (range: 1 to 5, mean = 3.2), and age (range: 18 to 84, mean = 44.91).

Analysis

To test our hypothesis, the analysis was divided into two parts. First, different factors were created for the variables described in the previous section using Confirmatory Factor Analysis (CFA). We chose this technique because the selection of variables was theoretically grounded and supported by previous literature. Figures 1, 2 and 3 present the measurement models for the nine factors we developed.

Figure 1 Measurement Model for Political Efficacies
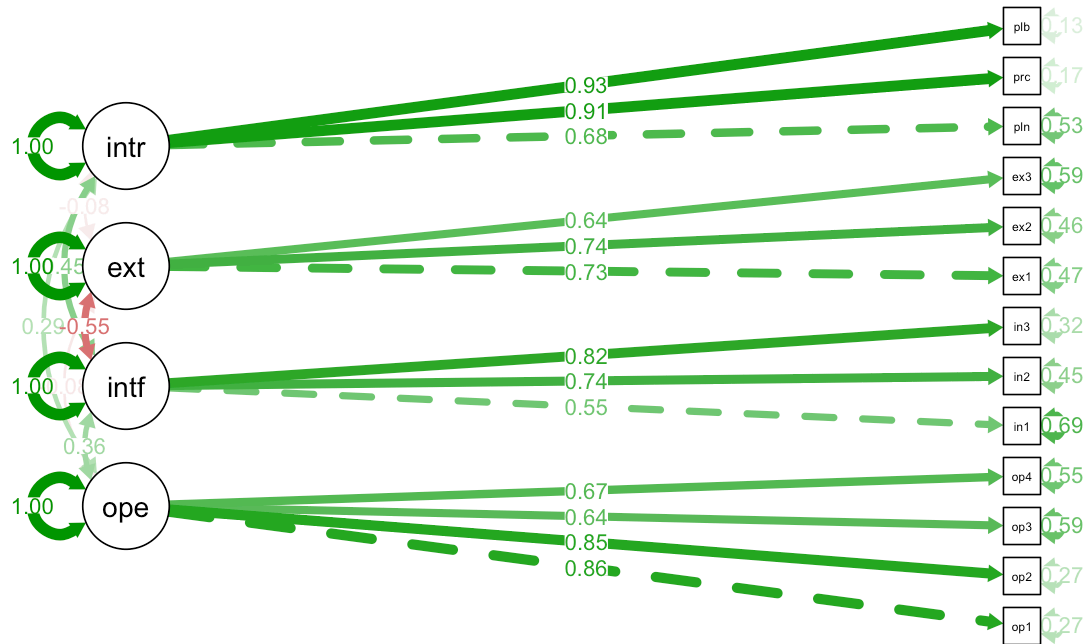
Note: Own elaboration.

Figure 2 Measurment model for Media Exposure
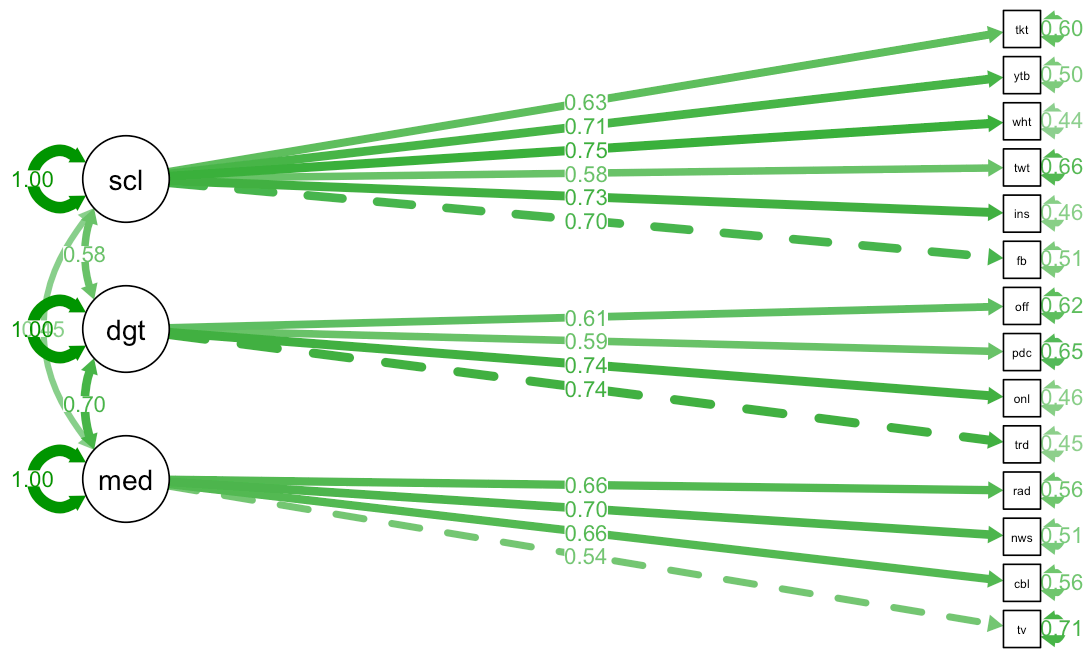
Note: Own elaboration.

Figure 3 Measurment model for understanding and strategic orientations
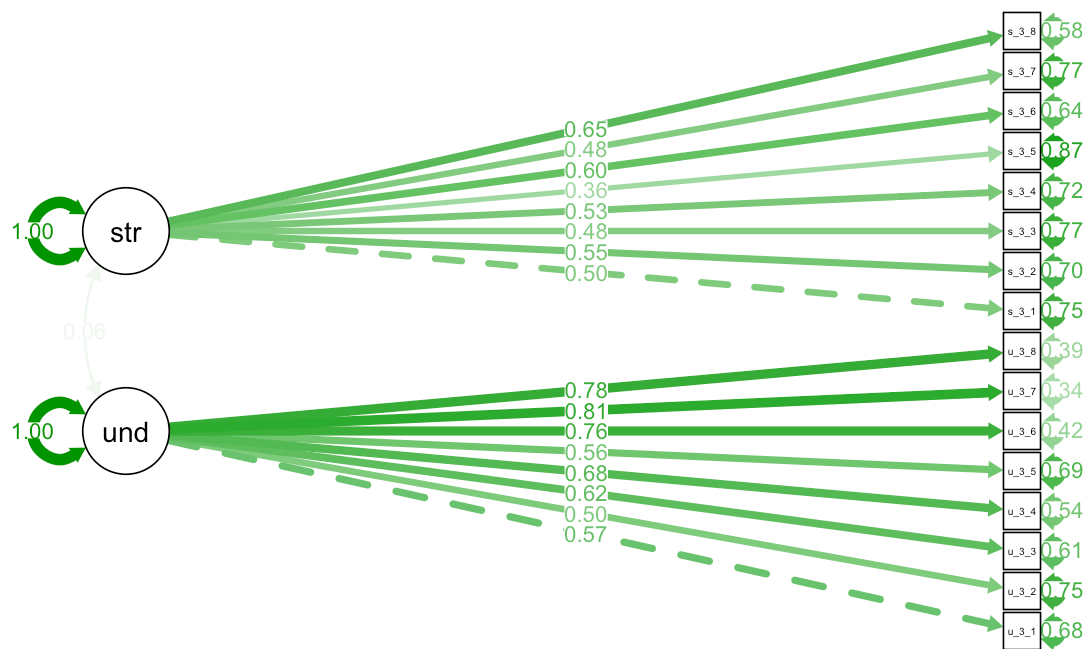
Note: Own elaboration.

The second part of the analysis explored which variables might be related to the propensity for having an understanding or strategic orientation toward political interactions, using traditional OLS regressions. We recognize that, given the nature of our data and the design of the analysis, Structural Equation Modeling (SEM) could be a more appropriate method to test these interactions. The advantage of SEM is that it allows us to create latent factors from observable variables—as we did—and simultaneously test the interactions between variables in the model. Thus, to ensure the robustness of our results, we also applied SEM for the two orientations under studied. These results, which are presented in the appendix, are consistent with the findings described in the following section.

Results

Table 1 presents a parsimonious model that examines the relationship between understanding and political orientations, and interpersonal confidence.

Table 1 Logistic Regression for Interpersonal Confidence

```
Call:
glm(formula = intercon ~ under + ses + sex + age_num, family = binomial,
    data = merged_data)

Deviance Residuals:
```

```
    Min       1Q    Median        3Q       Max
-0.9302  -0.5658  -0.4480  -0.3222    2.6612


Coefficients:
              Estimate Std. Error z value  Pr(>|z|)
(Intercept) -1.2708473  0.6405523  -1.984    0.0473 *
under        1.1124624  0.2806836   3.963 0.0000739 ***
ses         -0.1676500  0.1085913  -1.544    0.1226
sex         -0.5656042  0.2735393  -2.068    0.0387 *
age_num     -0.0008476  0.0094649  -0.090    0.9286
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


(Dispersion parameter for binomial family taken to be 1)


    Null deviance: 436.83  on 571  degrees of freedom
Residual deviance: 410.18  on 567  degrees of freedom
AIC: 420.18


Number of Fisher Scoring iterations: 5


Call:
glm(formula = intercon ~ strate + ses + sex + age_num, family = binomial,
    data = merged_data)


Deviance Residuals:
    Min       1Q    Median        3Q       Max
-0.8008  -0.5626  -0.4777  -0.3828    2.5329


Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.389568   0.641570  -2.166   0.0303 *
strate      -0.520942   0.242999  -2.144   0.0320 *
ses         -0.140746   0.106699  -1.319   0.1871
sex         -0.633852   0.272466  -2.326   0.0200 *
age_num      0.002727   0.009379   0.291   0.7712
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


(Dispersion parameter for binomial family taken to be 1)


    Null deviance: 436.83  on 571  degrees of freedom
Residual deviance: 423.26  on 567  degrees of freedom
AIC: 433.26


Number of Fisher Scoring iterations: 5
```

Figure 5 Coefplot for Interpersonal Confidence
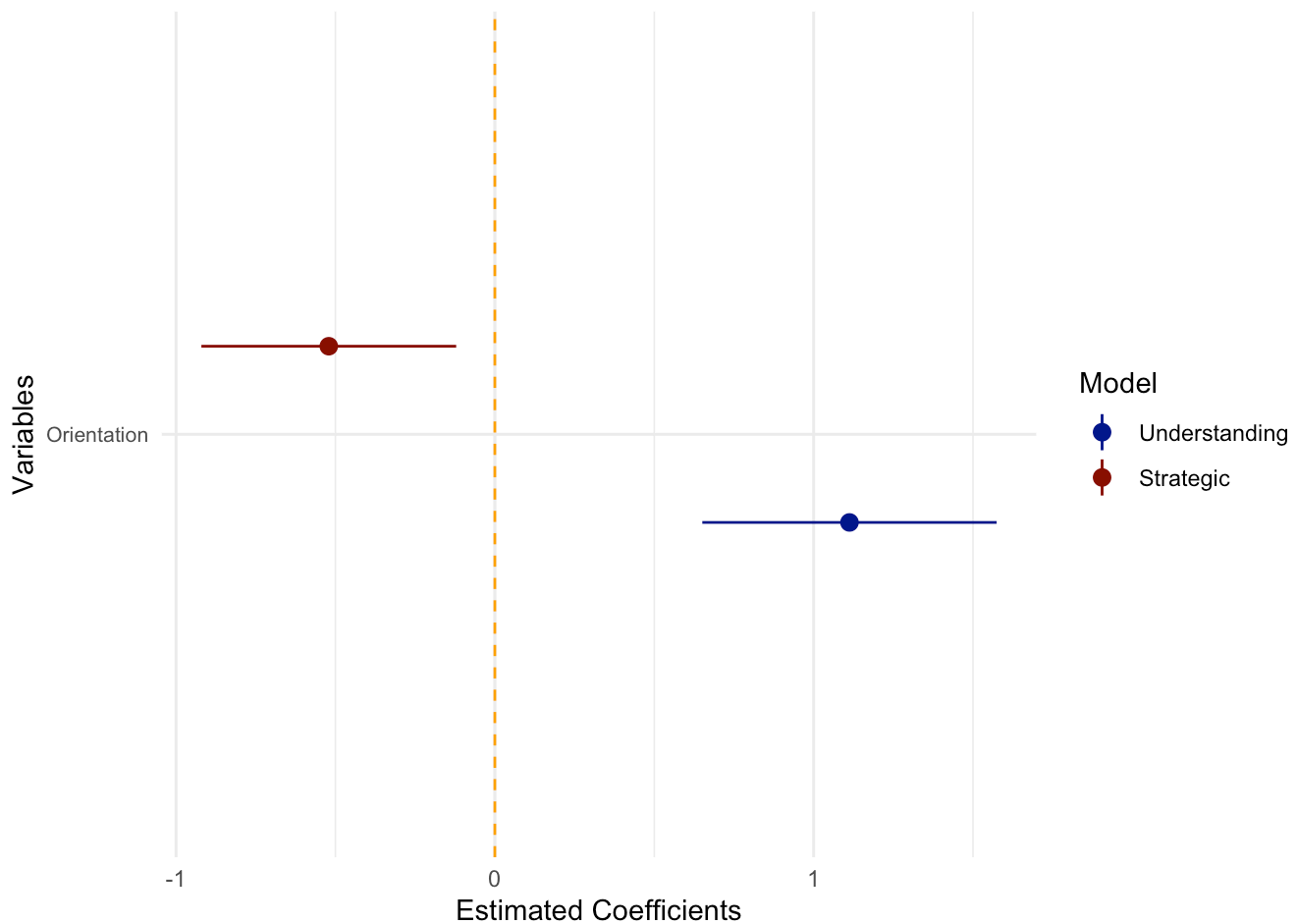
Tables 2, 3 and Figure 6 show the models for understanding and political orientations.

Table 2 OLS Regression for Understanding Orientation.

```
Call:
lm(formula = under ~ ses + sex + age_num + media + digital +
    social + interest + extef + intef + ope, data = merged_data)

Residuals:
    Min      1Q  Median      3Q     Max
-1.7932 -0.3117  0.0253  0.3595  1.2029

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.152832   0.109443  -1.396   0.1631
ses         -0.008877   0.018431  -0.482   0.6302
sex         -0.021132   0.043320  -0.488   0.6259
age_num      0.004248   0.001652   2.571   0.0104 *
media        0.008075   0.053851   0.150   0.8809
digital      0.016813   0.046820   0.359   0.7197
social       0.054122   0.028618   1.891   0.0591 .
interest     0.070605   0.027927   2.528   0.0117 *
extef        0.019843   0.037720   0.526   0.5990
intef        0.152683   0.059612   2.561   0.0107 *
```

```
ope             0.053846    0.023708    2.271    0.0235 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5031 on 561 degrees of freedom
Multiple R-squared:  0.1613,    Adjusted R-squared:  0.1464
F-statistic: 10.79 on 10 and 561 DF,  p-value: < 0.00000000000000022
```

Table 3 OLS Regression for Strategic Orientation.

```
Call:
lm(formula = strate ~ ses + sex + age_num + media + digital +
    social + interest + extef + intef + ope, data = merged_data)

Residuals:
     Min       1Q    Median       3Q       Max
-1.62487  -0.35016   0.02713   0.29937   1.86995

Coefficients:
             Estimate Std. Error t value  Pr(>|t|)
(Intercept)  0.115931   0.115424   1.004   0.31562
ses          0.042154   0.019438   2.169   0.03053 *
sex         -0.099543   0.045687  -2.179   0.02976 *
age_num     -0.004573   0.001743  -2.624   0.00893 **
media        0.225616   0.056794   3.972 0.0000804 ***
digital     -0.104436   0.049379  -2.115   0.03487 *
social       0.072571   0.030182   2.404   0.01652 *
interest    -0.028968   0.029453  -0.984   0.32577
extef       -0.056526   0.039782  -1.421   0.15590
intef       -0.154817   0.062870  -2.462   0.01410 *
ope          0.076627   0.025004   3.065   0.00228 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5306 on 561 degrees of freedom
Multiple R-squared:  0.1147,    Adjusted R-squared:  0.09897
F-statistic: 7.272 on 10 and 561 DF,  p-value: 0.00000000007361
```

Figure 5 Coefplot for understanding orientation and strategic orientation.
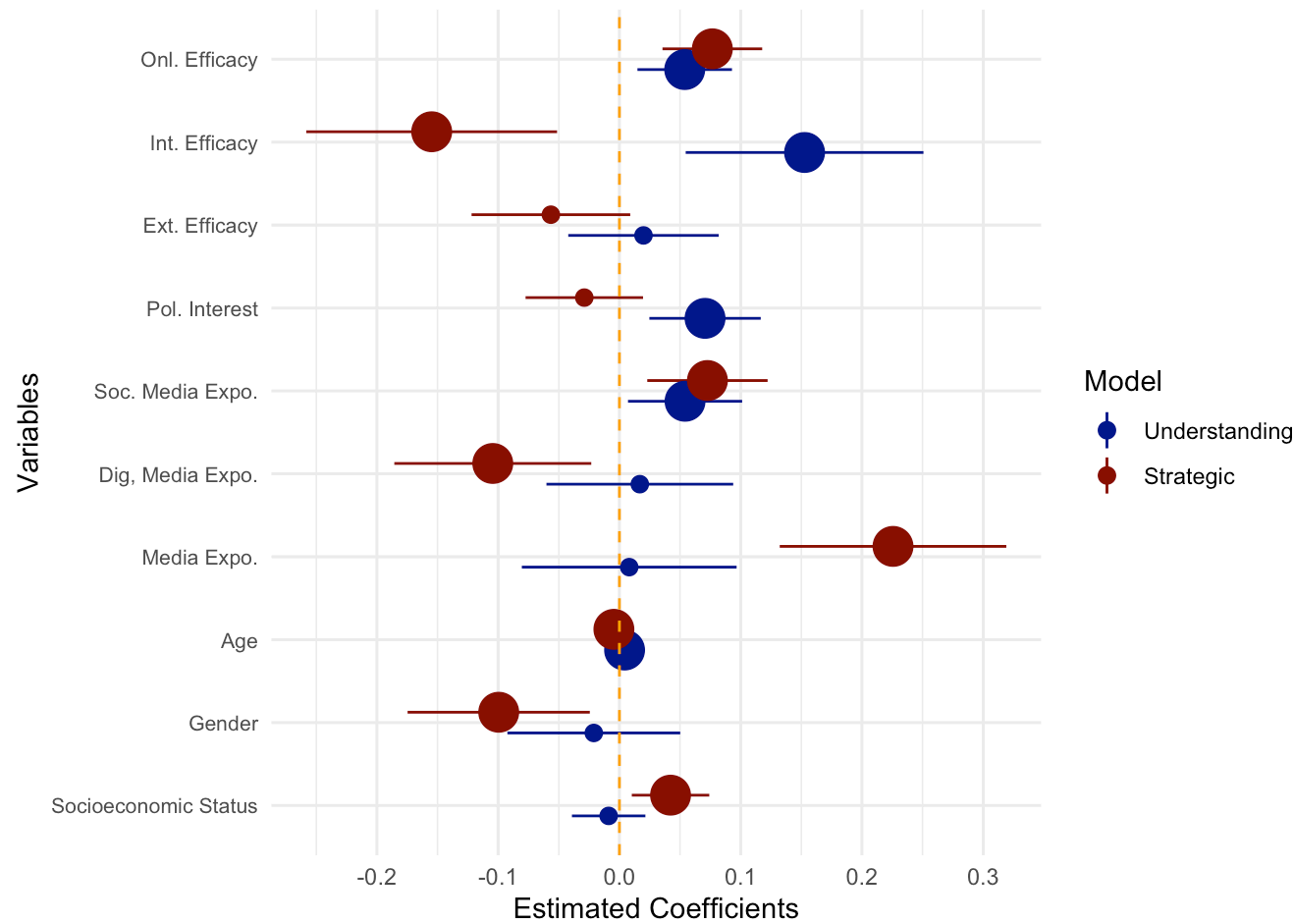
Appendix

Appendix 1 SEM for Understanding Orientation

```
lavaan 0.6.16 ended normally after 69 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                       102

  Number of observations                           572

Model Test User Model:

  Test statistic                              1991.961
  Degrees of freedom                               668
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              9457.615
  Degrees of freedom                               735
  P-value                                        0.000
```

```
User Model versus Baseline Model:

  Comparative Fit Index (CFI)                       0.848
  Tucker-Lewis Index (TLI)                          0.833


Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)          -30419.686
  Loglikelihood unrestricted model (H1)  -29423.706


  Akaike (AIC)                           61043.372
  Bayesian (BIC)                         61486.984
  Sample-size adjusted Bayesian (SABIC)  61163.179


Root Mean Square Error of Approximation:

  RMSEA                                             0.059
  90 Percent confidence interval - lower            0.056
  90 Percent confidence interval - upper            0.062
  P-value H_0: RMSEA <= 0.050                        0.000
  P-value H_0: RMSEA >= 0.080                        0.000


Standardized Root Mean Square Residual:

  SRMR                                              0.063

Parameter Estimates:

  Standard errors                            Standard
  Information                                Expected
  Information saturated (h1) model          Structured


Latent Variables:
                 Estimate  Std.Err  z-value  P(>|z|)   Std.lv   Std.all
  ope_a1 =~
    ope1           1.000                                1.109    0.854
    ope2           1.001    0.045   22.234    0.000     1.110    0.854
    ope3           0.758    0.047   16.143    0.000     0.841    0.645
    ope4           0.774    0.045   17.068    0.000     0.858    0.674
  intef_a1 =~
    intef1         1.000                                0.676    0.548
    intef2         1.391    0.118   11.791    0.000     0.941    0.744
    intef3         1.473    0.122   12.109    0.000     0.996    0.826
  extef_a1 =~
    extef1         1.000                                0.916    0.725
    extef2         0.984    0.076   13.010    0.000     0.901    0.737
    extef3         0.943    0.077   12.214    0.000     0.864    0.639
  interest_a1 =~
    polint         1.000                                1.003    0.686
    procint        1.360    0.070   19.441    0.000     1.364    0.909
```

plebint	1.401	0.072	19.530	0.000	1.405	0.932
media_a1 =~						
tv	1.000				0.805	0.541
cable	1.201	0.114	10.506	0.000	0.966	0.662
newspaper	1.137	0.106	10.778	0.000	0.915	0.699
radio	1.178	0.112	10.511	0.000	0.948	0.662
digital_a1 =~						
tradonline	1.000				1.013	0.734
online	1.026	0.067	15.397	0.000	1.039	0.744
podcast	0.694	0.055	12.625	0.000	0.703	0.593
officialsm	0.888	0.068	13.014	0.000	0.899	0.612
social_a1 =~						
fb	1.000				1.111	0.705
insta	1.035	0.066	15.746	0.000	1.150	0.740
twitter	0.827	0.065	12.676	0.000	0.919	0.585
whatsapp	1.099	0.070	15.777	0.000	1.222	0.741
youtube	0.970	0.064	15.065	0.000	1.077	0.704
tiktok	0.852	0.063	13.614	0.000	0.947	0.631
under_a1 =~						
under_w3_1	1.000				0.571	0.562
under_w3_2	1.046	0.107	9.741	0.000	0.598	0.494
under_w3_3	1.152	0.100	11.480	0.000	0.658	0.620
under_w3_4	1.432	0.119	12.054	0.000	0.818	0.668
under_w3_5	1.154	0.108	10.676	0.000	0.659	0.559
under_w3_6	1.566	0.120	13.047	0.000	0.894	0.761
under_w3_7	1.637	0.122	13.431	0.000	0.935	0.803
under_w3_8	1.586	0.120	13.189	0.000	0.906	0.776

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
under_a1 ~						
ses	-0.008	0.020	-0.420	0.674	-0.015	-0.018
sex	-0.011	0.048	-0.233	0.816	-0.019	-0.010
age_num	0.005	0.002	2.631	0.009	0.008	0.114
media_a1	0.020	0.058	0.342	0.733	0.028	0.028
digital_a1	0.002	0.052	0.038	0.969	0.004	0.004
social_a1	0.067	0.032	2.060	0.039	0.130	0.130
interest_a1	0.074	0.031	2.359	0.018	0.130	0.130
intercon	0.221	0.072	3.064	0.002	0.387	0.129
extef_a1	0.002	0.042	0.042	0.966	0.003	0.003
intef_a1	0.158	0.069	2.291	0.022	0.187	0.187
ope_a1	0.057	0.027	2.089	0.037	0.111	0.111

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
ope_a1 ~~						
intef_a1	0.272	0.044	6.170	0.000	0.363	0.363
extef_a1	-0.083	0.053	-1.565	0.118	-0.081	-0.081
interest_a1	0.325	0.056	5.801	0.000	0.292	0.292
media_a1	0.090	0.047	1.921	0.055	0.101	0.101
digital_a1	0.304	0.060	5.070	0.000	0.270	0.270

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
social_a1	0.349	0.064	5.461	0.000	0.283	0.283
intef_a1 ~~						
extef_a1	−0.339	0.046	−7.419	0.000	−0.547	−0.547
interest_a1	0.309	0.044	7.059	0.000	0.455	0.455
media_a1	0.087	0.031	2.792	0.005	0.159	0.159
digital_a1	0.162	0.039	4.144	0.000	0.237	0.237
social_a1	0.061	0.039	1.578	0.114	0.081	0.081
extef_a1 ~~						
interest_a1	−0.072	0.046	−1.560	0.119	−0.079	−0.079
media_a1	0.036	0.041	0.858	0.391	0.048	0.048
digital_a1	0.004	0.051	0.076	0.939	0.004	0.004
social_a1	0.134	0.054	2.461	0.014	0.131	0.131
interest_a1 ~~						
media_a1	0.144	0.043	3.365	0.001	0.179	0.179
digital_a1	0.298	0.054	5.477	0.000	0.293	0.293
social_a1	0.250	0.056	4.480	0.000	0.224	0.224
media_a1 ~~						
digital_a1	0.570	0.068	8.354	0.000	0.699	0.699
social_a1	0.402	0.060	6.703	0.000	0.449	0.449
digital_a1 ~~						
social_a1	0.658	0.074	8.864	0.000	0.584	0.584

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.ope1	0.458	0.047	9.845	0.000	0.458	0.271
.ope2	0.458	0.047	9.830	0.000	0.458	0.271
.ope3	0.995	0.066	15.187	0.000	0.995	0.584
.ope4	0.884	0.059	14.879	0.000	0.884	0.545
.intef1	1.065	0.070	15.294	0.000	1.065	0.700
.intef2	0.716	0.061	11.808	0.000	0.716	0.447
.intef3	0.462	0.054	8.509	0.000	0.462	0.318
.extef1	0.756	0.070	10.852	0.000	0.756	0.474
.extef2	0.685	0.065	10.466	0.000	0.685	0.458
.extef3	1.083	0.082	13.251	0.000	1.083	0.592
.polint	1.132	0.072	15.664	0.000	1.132	0.529
.procint	0.390	0.050	7.765	0.000	0.390	0.173
.plebint	0.297	0.050	5.893	0.000	0.297	0.131
.tv	1.566	0.105	14.948	0.000	1.566	0.707
.cable	1.198	0.091	13.156	0.000	1.198	0.562
.newspaper	0.877	0.071	12.302	0.000	0.877	0.512
.radio	1.149	0.087	13.143	0.000	1.149	0.561
.tradonline	0.881	0.071	12.480	0.000	0.881	0.462
.online	0.869	0.071	12.185	0.000	0.869	0.446
.podcast	0.911	0.061	14.889	0.000	0.911	0.648
.officialsm	1.347	0.092	14.668	0.000	1.347	0.625
.fb	1.246	0.088	14.116	0.000	1.246	0.502
.insta	1.095	0.081	13.494	0.000	1.095	0.453
.twitter	1.626	0.105	15.456	0.000	1.626	0.658
.whatsapp	1.222	0.091	13.459	0.000	1.222	0.450
.youtube	1.183	0.084	14.142	0.000	1.183	0.505
.tiktok	1.358	0.090	15.058	0.000	1.358	0.602

.under_w3_1	0.706	0.044	15.875	0.000	0.706	0.684
.under_w3_2	1.106	0.068	16.189	0.000	1.106	0.756
.under_w3_3	0.694	0.045	15.509	0.000	0.694	0.616
.under_w3_4	0.832	0.055	15.099	0.000	0.832	0.554
.under_w3_5	0.957	0.060	15.894	0.000	0.957	0.688
.under_w3_6	0.580	0.042	13.782	0.000	0.580	0.420
.under_w3_7	0.481	0.038	12.778	0.000	0.481	0.355
.under_w3_8	0.542	0.040	13.467	0.000	0.542	0.397
ope_a1	1.231	0.103	11.916	0.000	1.000	1.000
intef_a1	0.457	0.071	6.455	0.000	1.000	1.000
extef_a1	0.839	0.099	8.498	0.000	1.000	1.000
interest_a1	1.006	0.111	9.092	0.000	1.000	1.000
media_a1	0.648	0.105	6.185	0.000	1.000	1.000
digital_a1	1.027	0.111	9.267	0.000	1.000	1.000
social_a1	1.235	0.136	9.089	0.000	1.000	1.000
.under_a1	0.265	0.039	6.863	0.000	0.812	0.812

Appendix 2 SEM for Strategic Orientation

```
lavaan 0.6.16 ended normally after 65 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                       102


  Number of observations                           572


Model Test User Model:

  Test statistic                              1977.587
  Degrees of freedom                               668
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              8440.118
  Degrees of freedom                               735
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.830
  Tucker-Lewis Index (TLI)                       0.813

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -31514.243
  Loglikelihood unrestricted model (H1)     -30525.449

  Akaike (AIC)                               63232.485
  Bayesian (BIC)                             63676.098
```

```
    Sample-size adjusted Bayesian (SABIC)       63352.292


Root Mean Square Error of Approximation:

    RMSEA                                           0.059
    90 Percent confidence interval - lower          0.056
    90 Percent confidence interval - upper          0.062
    P-value H_0: RMSEA <= 0.050                     0.000
    P-value H_0: RMSEA >= 0.080                     0.000


Standardized Root Mean Square Residual:

    SRMR                                            0.065


Parameter Estimates:

    Standard errors                              Standard
    Information                                  Expected
    Information saturated (h1) model           Structured


Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
    ope_a2 =~
      ope1           1.000                               1.110    0.854
      ope2           0.999    0.045   22.209    0.000    1.108    0.853
      ope3           0.758    0.047   16.131    0.000    0.841    0.644
      ope4           0.776    0.045   17.141    0.000    0.861    0.677
    intef_a2 =~
      intef1         1.000                               0.680    0.551
      intef2         1.388    0.117   11.843    0.000    0.944    0.746
      intef3         1.458    0.120   12.142    0.000    0.991    0.822
    extef_a2 =~
      extef1         1.000                               0.918    0.727
      extef2         0.978    0.075   13.008    0.000    0.898    0.734
      extef3         0.944    0.077   12.239    0.000    0.866    0.640
    interest_a2 =~
      polint         1.000                               1.002    0.685
      procint        1.361    0.070   19.402    0.000    1.363    0.909
      plebint        1.403    0.072   19.486    0.000    1.406    0.933
    media_a2 =~
      tv             1.000                               0.809    0.543
      cable          1.205    0.113   10.642    0.000    0.974    0.667
      newspaper      1.131    0.104   10.878    0.000    0.914    0.698
      radio          1.163    0.110   10.559    0.000    0.940    0.657
    digital_a2 =~
      tradonline     1.000                               1.013    0.733
      online         1.024    0.067   15.361    0.000    1.037    0.743
      podcast        0.694    0.055   12.606    0.000    0.702    0.592
      officialsm     0.892    0.068   13.055    0.000    0.903    0.615
    social_a2 =~
      fb             1.000                               1.114    0.707
```

insta	1.030	0.065	15.741	0.000	1.147	0.737
twitter	0.823	0.065	12.663	0.000	0.917	0.583
whatsapp	1.098	0.069	15.833	0.000	1.223	0.742
youtube	0.968	0.064	15.108	0.000	1.078	0.704
tiktok	0.851	0.062	13.651	0.000	0.948	0.631
strate_a2 =~						
strate_w3_1	1.000				0.647	0.510
strate_w3_2	1.082	0.119	9.073	0.000	0.700	0.564
strate_w3_3	0.987	0.121	8.128	0.000	0.639	0.472
strate_w3_4	1.042	0.123	8.452	0.000	0.674	0.501
strate_w3_5	0.646	0.103	6.291	0.000	0.418	0.334
strate_w3_6	1.234	0.132	9.343	0.000	0.799	0.594
strate_w3_7	1.020	0.123	8.270	0.000	0.660	0.484
strate_w3_8	1.363	0.139	9.810	0.000	0.882	0.656

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
strate_a2 ~						
ses	0.054	0.025	2.157	0.031	0.084	0.102
sex	-0.148	0.061	-2.440	0.015	-0.229	-0.114
age_num	-0.006	0.002	-2.840	0.005	-0.010	-0.137
media_a2	0.301	0.081	3.737	0.000	0.376	0.376
digital_a2	-0.135	0.068	-1.983	0.047	-0.211	-0.211
social_a2	0.087	0.041	2.110	0.035	0.150	0.150
interest_a2	-0.034	0.039	-0.861	0.389	-0.052	-0.052
intercon	-0.167	0.089	-1.875	0.061	-0.258	-0.086
extef_a2	-0.069	0.054	-1.285	0.199	-0.098	-0.098
intef_a2	-0.205	0.088	-2.330	0.020	-0.215	-0.215
ope_a2	0.115	0.036	3.207	0.001	0.197	0.197

Covariances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
ope_a2 ~~						
intef_a2	0.274	0.044	6.173	0.000	0.363	0.363
extef_a2	-0.083	0.053	-1.564	0.118	-0.081	-0.081
interest_a2	0.325	0.056	5.799	0.000	0.292	0.292
media_a2	0.091	0.047	1.928	0.054	0.101	0.101
digital_a2	0.304	0.060	5.070	0.000	0.270	0.270
social_a2	0.350	0.064	5.462	0.000	0.283	0.283
intef_a2 ~~						
extef_a2	-0.342	0.046	-7.443	0.000	-0.549	-0.549
interest_a2	0.310	0.044	7.076	0.000	0.456	0.456
media_a2	0.088	0.031	2.809	0.005	0.160	0.160
digital_a2	0.163	0.039	4.146	0.000	0.237	0.237
social_a2	0.061	0.039	1.566	0.117	0.081	0.081
extef_a2 ~~						
interest_a2	-0.073	0.047	-1.564	0.118	-0.079	-0.079
media_a2	0.036	0.042	0.864	0.388	0.048	0.048
digital_a2	0.004	0.051	0.078	0.937	0.004	0.004
social_a2	0.134	0.055	2.458	0.014	0.131	0.131
interest_a2 ~~						

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
media_a2	0.145	0.043	3.374	0.001	0.179	0.179
digital_a2	0.298	0.054	5.475	0.000	0.293	0.293
social_a2	0.250	0.056	4.476	0.000	0.224	0.224
media_a2 ~~						
digital_a2	0.571	0.068	8.377	0.000	0.697	0.697
social_a2	0.406	0.060	6.734	0.000	0.450	0.450
digital_a2 ~~						
social_a2	0.659	0.074	8.873	0.000	0.585	0.585

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.ope1	0.457	0.046	9.833	0.000	0.457	0.271
.ope2	0.462	0.047	9.911	0.000	0.462	0.273
.ope3	0.996	0.066	15.187	0.000	0.996	0.585
.ope4	0.879	0.059	14.848	0.000	0.879	0.542
.intef1	1.060	0.070	15.254	0.000	1.060	0.696
.intef2	0.711	0.061	11.711	0.000	0.711	0.444
.intef3	0.471	0.054	8.668	0.000	0.471	0.324
.extef1	0.752	0.070	10.806	0.000	0.752	0.472
.extef2	0.691	0.065	10.571	0.000	0.691	0.462
.extef3	1.079	0.082	13.217	0.000	1.079	0.590
.polint	1.134	0.072	15.670	0.000	1.134	0.531
.procint	0.392	0.051	7.753	0.000	0.392	0.174
.plebint	0.294	0.051	5.790	0.000	0.294	0.129
.tv	1.560	0.104	14.969	0.000	1.560	0.705
.cable	1.183	0.090	13.142	0.000	1.183	0.555
.newspaper	0.879	0.071	12.429	0.000	0.879	0.513
.radio	1.163	0.087	13.345	0.000	1.163	0.568
.tradonline	0.882	0.071	12.487	0.000	0.882	0.462
.online	0.873	0.071	12.220	0.000	0.873	0.448
.podcast	0.912	0.061	14.892	0.000	0.912	0.649
.officialsm	1.341	0.092	14.635	0.000	1.341	0.622
.fb	1.241	0.088	14.092	0.000	1.241	0.500
.insta	1.103	0.081	13.543	0.000	1.103	0.456
.twitter	1.630	0.105	15.470	0.000	1.630	0.660
.whatsapp	1.218	0.091	13.440	0.000	1.218	0.449
.youtube	1.181	0.084	14.136	0.000	1.181	0.504
.tiktok	1.356	0.090	15.053	0.000	1.356	0.601
.strate_w3_1	1.191	0.079	15.124	0.000	1.191	0.740
.strate_w3_2	1.054	0.073	14.539	0.000	1.054	0.682
.strate_w3_3	1.424	0.092	15.457	0.000	1.424	0.777
.strate_w3_4	1.356	0.089	15.207	0.000	1.356	0.749
.strate_w3_5	1.395	0.086	16.278	0.000	1.395	0.889
.strate_w3_6	1.169	0.083	14.123	0.000	1.169	0.647
.strate_w3_7	1.421	0.093	15.354	0.000	1.421	0.765
.strate_w3_8	1.029	0.079	13.048	0.000	1.029	0.570
ope_a2	1.232	0.103	11.923	0.000	1.000	1.000
intef_a2	0.462	0.071	6.488	0.000	1.000	1.000
extef_a2	0.842	0.099	8.518	0.000	1.000	1.000
interest_a2	1.004	0.111	9.078	0.000	1.000	1.000
media_a2	0.654	0.105	6.240	0.000	1.000	1.000

```
    digital_a2        1.025     0.111     9.257     0.000     1.000     1.000
    social_a2         1.241     0.136     9.117     0.000     1.000     1.000
   .strate_a2         0.334     0.060     5.562     0.000     0.798     0.798
```

Working with W1

Appendix 3. OLS for Understanding Orientation just using W1.

```
Call:
lm(formula = under_1 ~ ses + sex + age_num + media_1 + digital_1 +
    social_1 + interest_1 + intercon + extef_1 + intef_1 + ope_1,
    data = data_justw1_na)

Residuals:
     Min       1Q   Median       3Q      Max
-2.49417 -0.36644  0.04804  0.40449  1.86981

Coefficients:
             Estimate Std. Error t value              Pr(>|t|)
(Intercept) -0.112761   0.078035  -1.445               0.14869
ses         -0.007048   0.013548  -0.520               0.60299
sex          0.010200   0.030837   0.331               0.74086
age_num      0.002752   0.001143   2.408               0.01617 *
media_1      0.034251   0.038221   0.896               0.37034
digital_1    0.056332   0.035766   1.575               0.11549
social_1    -0.004627   0.023972  -0.193               0.84699
interest_1   0.197071   0.020292   9.712 < 0.0000000000000002 ***
intercon     0.084182   0.047030   1.790               0.07368 .
extef_1     -0.074802   0.025581  -2.924               0.00351 **
intef_1      0.081919   0.042773   1.915               0.05567 .
ope_1        0.099274   0.018039   5.503          0.0000000445 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5604 on 1365 degrees of freedom
Multiple R-squared:  0.2616,    Adjusted R-squared:  0.2556
F-statistic: 43.96 on 11 and 1365 DF,  p-value: < 0.00000000000000022
```

Appendix 4. OLS for Strategic Orientation just using W1.

```
Call:
lm(formula = strate_1 ~ ses + sex + age_num + media_1 + digital_1 +
    social_1 + interest_1 + intercon + extef_1 + intef_1 + ope_1,
    data = data_justw1_na)

Residuals:
     Min       1Q   Median       3Q      Max
-1.13516 -0.30497  0.02747  0.27601  1.54873
```

```
Coefficients:
              Estimate Std. Error t value     Pr(>|t|)
(Intercept) -0.0752466  0.0588454  -1.279     0.201214
ses          0.0299412  0.0102160   2.931     0.003437 **
sex          0.0064777  0.0232537   0.279     0.780620
age_num     -0.0002269  0.0008618  -0.263     0.792387
media_1      0.0723703  0.0288224   2.511     0.012157 *
digital_1   -0.0015713  0.0269711  -0.058     0.953551
social_1     0.0218022  0.0180770   1.206     0.227999
interest_1  -0.0198537  0.0153017  -1.297     0.194684
intercon    -0.1190581  0.0354647  -3.357     0.000809 ***
extef_1     -0.0489088  0.0192902  -2.535     0.011342 *
intef_1     -0.0623574  0.0322543  -1.933     0.053405 .
ope_1        0.0752496  0.0136028   5.532 0.0000000379 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.4226 on 1365 degrees of freedom
Multiple R-squared:  0.06843,   Adjusted R-squared:  0.06092
F-statistic: 9.115 on 11 and 1365 DF,  p-value: 0.0000000000000006786
```

Appendix 5. OLS for Strategic Orientation just using W1, no factor.

```
Call:
lm(formula = strate1 ~ ses + sex + age_num + media_1 + digital_1 +
    social_1 + interest_1 + intercon + extef_1 + intef_1 + ope_1,
    data = data_justw1_na)

Residuals:
    Min      1Q  Median      3Q     Max
-1.7723 -0.8411 -0.4247  0.7983  3.6886

Coefficients:
            Estimate Std. Error t value           Pr(>|t|)
(Intercept)  2.021428   0.159284  12.691 < 0.0000000000000002 ***
ses          0.073236   0.027653   2.648            0.00818 **
sex         -0.182289   0.062943  -2.896            0.00384 **
age_num     -0.006388   0.002333  -2.738            0.00626 **
media_1      0.207450   0.078017   2.659            0.00793 **
digital_1   -0.075383   0.073006  -1.033            0.30199
social_1     0.052556   0.048931   1.074            0.28298
interest_1  -0.106521   0.041419  -2.572            0.01022 *
intercon    -0.038388   0.095996  -0.400            0.68930
extef_1      0.129939   0.052215   2.489            0.01295 *
intef_1     -0.110383   0.087306  -1.264            0.20633
ope_1        0.193417   0.036820   5.253        0.000000173 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 1.144 on 1365 degrees of freedom
```

```
Multiple R-squared: 0.07612,   Adjusted R-squared: 0.06867
F-statistic: 10.22 on 11 and 1365 DF,  p-value: < 0.0000000000000022


Call:
lm(formula = strate2 ~ ses + sex + age_num + media_1 + digital_1 +
    social_1 + interest_1 + intercon + extef_1 + intef_1 + ope_1,
    data = data_justw1_na)


Residuals:
    Min     1Q  Median     3Q     Max
-2.6277 -1.1027  0.1110  0.7694  3.2126


Coefficients:
             Estimate Std. Error t value        Pr(>|t|)
(Intercept)  2.729928   0.177930  15.343 < 0.0000000000000002 ***
ses          0.035149   0.030890   1.138         0.25537
sex          0.073360   0.070312   1.043         0.29697
age_num     -0.003071   0.002606  -1.178         0.23884
media_1      0.138490   0.087150   1.589         0.11227
digital_1   -0.005785   0.081552  -0.071         0.94346
social_1     0.069923   0.054659   1.279         0.20103
interest_1  -0.002738   0.046268  -0.059         0.95282
intercon    -0.227711   0.107234  -2.123         0.03389 *
extef_1     -0.176242   0.058327  -3.022         0.00256 **
intef_1     -0.100461   0.097527  -1.030         0.30315
ope_1        0.197286   0.041131   4.797      0.00000179 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 1.278 on 1365 degrees of freedom
Multiple R-squared: 0.05068,   Adjusted R-squared: 0.04303
F-statistic: 6.625 on 11 and 1365 DF,  p-value: 0.00000000007123


Call:
lm(formula = strate3 ~ ses + sex + age_num + media_1 + digital_1 +
    social_1 + interest_1 + intercon + extef_1 + intef_1 + ope_1,
    data = data_justw1_na)


Residuals:
    Min     1Q  Median     3Q     Max
-2.52100 -1.22181  0.06647  1.07819  2.87355


Coefficients:
             Estimate Std. Error t value        Pr(>|t|)
(Intercept)  2.483483   0.191686  12.956 < 0.0000000000000002 ***
ses          0.079257   0.033278   2.382         0.017372 *
sex          0.094929   0.075748   1.253         0.210338
age_num      0.002498   0.002807   0.890         0.373719
media_1      0.084965   0.093887   0.905         0.365640
```

```
digital_1    0.053219    0.087857    0.606              0.544784
social_1    -0.002932    0.058885    -0.050             0.960302
interest_1  -0.036705    0.049845    -0.736             0.461623
intercon    -0.457867    0.115524    -3.963             0.0000777 ***
extef_1     -0.224895    0.062837    -3.579             0.000357 ***
intef_1     -0.225144    0.105067    -2.143             0.032300 *
ope_1        0.067779    0.044311    1.530              0.126338
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.377 on 1365 degrees of freedom
Multiple R-squared:  0.03809,   Adjusted R-squared:  0.03034
F-statistic: 4.914 on 11 and 1365 DF,  p-value: 0.0000001663

Call:
lm(formula = strate4 ~ ses + sex + age_num + media_1 + digital_1 +
    social_1 + interest_1 + intercon + extef_1 + intef_1 + ope_1,
    data = data_justw1_na)

Residuals:
    Min      1Q  Median      3Q     Max
-2.1544 -1.2661  0.1892  0.6979  3.1543

Coefficients:
            Estimate Std. Error t value        Pr(>|t|)
(Intercept)  2.035952   0.182648  11.147 < 0.0000000000000002 ***
ses          0.074693   0.031709   2.356             0.01864 *
sex          0.035224   0.072176   0.488             0.62561
age_num      0.004519   0.002675   1.689             0.09138 .
media_1      0.159179   0.089461   1.779             0.07541 .
digital_1   -0.010405   0.083715  -0.124             0.90110
social_1     0.053166   0.056109   0.948             0.34352
interest_1  -0.121590   0.047495  -2.560             0.01057 *
intercon    -0.305882   0.110078  -2.779             0.00553 **
extef_1     -0.069278   0.059874  -1.157             0.24745
intef_1     -0.131184   0.100113  -1.310             0.19029
ope_1        0.107057   0.042221   2.536             0.01134 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.312 on 1365 degrees of freedom
Multiple R-squared:  0.03572,   Adjusted R-squared:  0.02795
F-statistic: 4.597 on 11 and 1365 DF,  p-value: 0.0000006762
```
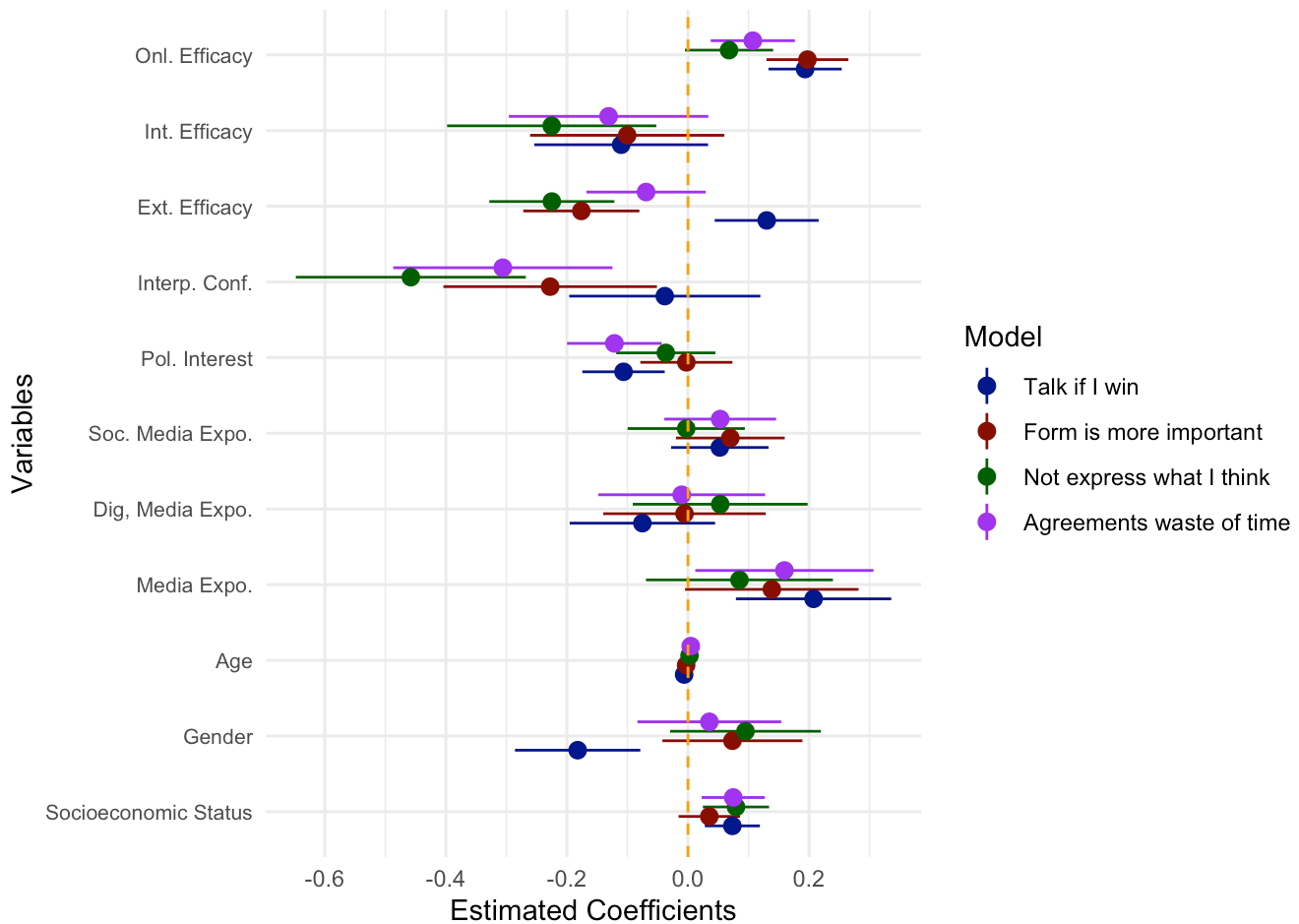
Alternative models, by adding observable variables.

Appendix 6. OLS for Understanding Orientation and Strategic Orientation just using W1 and by adding observable variebles (not CFA).

```
Call:
lm(formula = undersum ~ ses + sex + age_num + mediasum + digitalsum +
    socialsum + polint + intercon + extefsum + intefsum + opesum,
    data = data_justw1_na)

Residuals:
    Min      1Q  Median      3Q     Max
-3.7224 -0.5300  0.0645  0.6093  2.5387

Coefficients:
             Estimate Std. Error t value          Pr(>|t|)
(Intercept)  2.031871   0.173197  11.732 < 0.0000000000000002 ***
ses         -0.032482   0.019858  -1.636           0.102139
sex          0.021778   0.045585   0.478           0.632907
age_num      0.005033   0.001706   2.950           0.003237 **
mediasum     0.051037   0.024502   2.083           0.037437 *
digitalsum   0.071047   0.029310   2.424           0.015479 *
socialsum   -0.001829   0.025080  -0.073           0.941880
```

```
polint      0.165386    0.018309    9.033 < 0.0000000000000002 ***
intercon    0.151221    0.069699    2.170              0.030208 *
extefsum   -0.088821    0.024367   -3.645              0.000277 ***
intefsum    0.104214    0.028288    3.684              0.000239 ***
opesum      0.160797    0.023436    6.861     0.0000000000103 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.8301 on 1365 degrees of freedom
Multiple R-squared:  0.25, Adjusted R-squared:  0.244
F-statistic: 41.37 on 11 and 1365 DF,  p-value: < 0.00000000000000022


Call:
lm(formula = stratesum ~ ses + sex + age_num + mediasum + digitalsum +
    socialsum + polint + intercon + extefsum + intefsum + opesum,
    data = data_justw1_na)


Residuals:
     Min      1Q  Median      3Q     Max
-2.06854 -0.63264  0.04264  0.56253  3.05127


Coefficients:
             Estimate Std. Error t value      Pr(>|t|)
(Intercept)  2.023230   0.179134  11.294 < 0.0000000000000002 ***
ses          0.070436   0.020539   3.429              0.000623 ***
sex          0.003422   0.047148   0.073              0.942158
age_num     -0.001025   0.001765  -0.581              0.561427
mediasum     0.089545   0.025342   3.534              0.000424 ***
digitalsum   0.014408   0.030314   0.475              0.634656
socialsum    0.025342   0.025940   0.977              0.328763
polint      -0.039613   0.018936  -2.092              0.036632 *
intercon    -0.267352   0.072089  -3.709              0.000217 ***
extefsum    -0.048023   0.025202  -1.905              0.056926 .
intefsum    -0.050356   0.029258  -1.721              0.085456 .
opesum       0.129347   0.024239   5.336            0.000000111 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.8585 on 1365 degrees of freedom
Multiple R-squared:  0.06881,  Adjusted R-squared:  0.06131
F-statistic:  9.17 on 11 and 1365 DF,  p-value: 0.0000000000000005238
```