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A longitudinal study of the bidirectional causal relationships between online political participation and offline collective action

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ABSTRACT

The longitudinal causal relationships between individuals' online and offline forms of civic participation requires further understanding. We provide a robust test of four competing theoretical perspectives to establish the direction of causality between online political participation and offline collective action as well as the persistence of their longitudinal effects. Two longitudinal panel studies were conducted in the socio-political context of Chile. Study 1 involved university students (a 2-year, 5-wave longitudinal study, $N_{\text{wave 1}} = 1221$, $N_{\text{wave 2}} = 954$, $N_{\text{wave 3}} = 943$, $N_{\text{wave 4}} = 905$, and $N_{\text{wave 5}} = 786$) and Study 2 used a nationally representative sample of adults (a 3-year, 3-wave longitudinal study, $N_{\text{wave 1}} = 2927$, $N_{\text{wave 2}} = 2473$ and $N_{\text{wave 3}} = 2229$). Results from both studies supported the spillover perspective compellingly showing that offline participation fostered subsequent online collective action over time, whereas the reverse causal path from online political participation and offline collective action was consistently non-significant. In Study 2, previous offline collective action predicted increased online participation after controlling for the effects of age, gender, and educational level. The need for further fine-grained longitudinal research on the causal relations between offline and online collective action is discussed.

1. Introduction

The rapid expansion of the Internet and social media has enabled people to engage in social and political activism in ways that were previously unfeasible (e.g., Greijdanus et al., 2021; Jost et al., 2018). During the past two decades, the world's largest social change movements such as Occupy Wall Street, #BlackLivesMatter, #MeToo as well as anti-authority uprisings in the Middle East, Latin America, and East Asia, have allegedly started in the online sphere with national conversations about social injustices and economic inequalities before they occupied public spaces (Ayanian et al., 2020; Castells, 2012; Jost et al., 2018; Thomas et al., 2018). Because the success of these real-world social movements has been attributed in large part to Internet-mediated activism (e.g., Serhan, 2019), it is crucial for scholars to investigate the causal dynamics that shape contemporary civic activism in both virtual (e.g., e-petitioning, participating in political forums, and posting political thoughts on social media) and physical (e.g. demonstrations, rallies, marches, sit-ins) domains.

The causal relationship between online and offline collective action has been a subject of controversial debate in the literature (for recent meta-analyses, see Boulianne & Theocharis, 2018; Chae, Lee, & Kim, 2018)—with some suggesting that digital activism is mere "clictivism" that does not transcend the virtual space (e.g., Emmer, Wolling, & Vowe, 2012; Schumann & Klein, 2015) and others arguing that online participation can propel individuals toward real-world collective action for social change (e.g., Kende, van Zomeren, Ujhelyi, & Lantos, 2016; Odağ, Uluğ, & Solak, 2016; Wilkins, Livingstone, & Levine, 2019). It has been further suggested that the prevalence of political engagement in either online or offline spheres may vary across socio-demographic groups based on age, educational level, family circumstances, occupation status, rural-urban differences, income (e.g., Erhardt & Freitag, 2019; Greijdanus et al., 2021; Hirzalla, Van Zoonen, & De Ridder, 2011). Despite a vast amount of empirical research on digitally-enabled political activism, a causal bidirectional association between online and offline collective action is yet not well understood. Determining the direction of causality between online political participation and offline collective action at the individual level may have pivotal theoretical and practical implications for scholars and decision-makers concerned with facilitating active citizenship and civic political behavior. The current research was designed to systematically address this issue.

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A review of existing research in the field suggests that there are at least four theory-based and empirically-tested propositions about the causal associations between online political participation and offline collective action – the *independence,* the *facilitation*, the *spillover*, and the *reciprocity* hypotheses, respectively (see Kim, Russo, & Amna, 2017). Evidence supporting each of these competing propositions has been derived from studies that used a confirmatory approach (i.e., set to investigate a single preferred hypothesis). However, this kind of approach is essentially limited to drawing any persuasive conclusion concerning the supremacy of one hypothesis over a set of equally plausible hypotheses. It has been therefore suggested that to reconcile the existing approaches and to obtain compelling evidence for causal associations between the two constructs (i.e., online and offline political engagement), it is necessary to examine *a set of all possible hypotheses* in a comparative and systematic manner (Kim et al., 2017).

An initial exploration of the bidirectional associations between online political participation and offline collective action has been carried out by Kim and colleagues (2017) yet the adopted two-time points design has not allowed these authors to adequately examine the intra-individual stability, the direction, the dynamics, and the persistence of the effects over time that can only be estimated using the data collected at three or more time points (for methodological recommendations, see Curran & Bauer, 2011; Singer & Willett, 2003). The current paper was, therefore, designed to empirically determine the phenomenon of the causality in the relationship between online political participation and offline collective action by employing an autoregressive longitudinal cross-lagged panel design. This analytic strategy enabled us to test and compare the *four causal* hypotheses identified by Kim and associates (2017). In addition, we controlled for the effects of individual socio-demographic factors (e.g., age, gender, educational level) that have been previously shown to correlate with higher civic engagement (e.g., Emmer et al., 2012; Finlay, Wray-Lake, & Flanagan, 2010; Kim et al., 2017).

To scrutinize the bidirectional causal relationships between online political participation and offline collective action, we used the data from two ecological longitudinal panel studies spanning five (Study 1, university student movement) and three (Study 2, nationally representative adult population) measurement points, respectively. We situated our research in the socio-political context of Chile, a Latin American country that continues to experience political transformation through demonstrations and social protests[1] (HuHuman Development Report, 2019), attracting high rates of support and validation among the general public (e.g., González et al., 2020; Jiménez-Moya, Miranda, Drury, González, & Saavedra-Morales, 2019; Saavedra & Drury, 2019; Somma & Medel, 2017). Reportedly, Chile is a country with relatively large Internet penetration: by the beginning of 2020, 15.67 million Chilean citizens were using the Internet, making up 82.3 percent of the total population (Global Digital Insights Center, 2020). Some scholars have argued that in the highly segregated Chilean society, online sites and digital social networks provide an accessible platform for individuals' sustainable collective action and rights-claiming that has a potential of translating into durable mobilization (e.g., Valenzuela, Arriagada, & Scherman, 2015).

To sum up, informed by the inconclusiveness of extant literature on digital activism, our article set the goal to systematically examine a causal longitudinal dynamics shaping online political participation and offline collective action. Our research was thus designed to contribute to previous research in two distinctive ways. The first contribution is to offer empirical insights into the longitudinal link between online and offline participation. We use an autoregressive cross-lagged panel design to determine the direction of causality empirically by comparing all possible theoretical models and controlling for the effects of socio-demographic variables. Besides the theoretical contribution, our research sought to furnish new insights for researchers and decision-makers concerned with facilitating active citizenship and civic political behavior.

1.1. The longitudinal association between online political participation and offline collective action: the overview of competing theoretical perspectives

Recent scholarship on digitally-enabled political activism have offered a number of convergent and divergent studies designed to disentangle the way in which online political participation and offline collective action are causally related (e.g., Gil de Zúñiga, Jung, & Valenzuela, 2012; Greijdanus et al., 2020; Jost et al., 2018; Kim et al., 2017). Specifically, four competing causal perspectives have been identified known in the literature as the independence, the facilitation, the spillover, and the reciprocity hypotheses, respectively (for a graphical representation, see Fig. 1).

1.1.1. The independence hypothesis

The independence hypothesis builds on the argument that participation in online and offline spheres of collective action develops independently of each other, thus empirically presenting two correlated but causally disjoint linear paths (see Fig. 1). This hypothesis has been examined using cross-sectional (e.g., Baumgartner & Morris, 2010), experimental (e.g., Schumann & Klein, 2015; Vissers, Hooghe, Stolle, & Mahéo, 2012), and longitudinal (e.g., Emmer et al., 2012) data. For instance, the study of Baumgartner and Morris (2010) has shown that in spite of the promise of social network websites in mobilizing offline political participation, people engaged in online civic activities were not likely to participate in politics by traditional means. These findings resonated with the experimental study of Schumann and Klein (2015) who conceptualized lower-cost and lower-risk online collective actions as slacktivism showing that it is suited for individualistic and hedonistic motives and is likely to foreclose subsequent offline collective actions. Another experimental study with young people found that web-based mobilization had a significant effect only on online participation, whereas face-to-face mobilization had a significant impact only on offline behavior, which led the authors of the study to conclude that mobilization online and offline constitute two independent processes (Vissers et al., 2012). The longitudinal evidence for the independence hypothesis stems from the eight-wave annual panel-survey study of Emmer and associates (2012) showing that individuals' prior participation in civic activities was the strongest predictors of their subsequent engagement in the same domain (either online or offline). In a series of regression analysis, the longitudinal effects of offline civic activities were, however, found to be stronger in magnitude than those of online political participation. In addition, education and gender were found to play a negligible role in participation in both online and offline domains, whereas participants' age had a significant effect suggesting that on the aggregate level younger people were more inclined towards online political participation over time. The question arises as to whether these *independent* effects, derived from regression analysis, will hold when using a cross-lagged model technique which is believed to be better suited to examine causal influences in longitudinal panel data (e.g., Curran & Bauer, 2011). So far the studies that sustain the independence hypothesis have not systematically examined the possibility of spuriousness.

1.1.2. The facilitation hypothesis

The facilitation (also known as the gateway) hypothesis builds on the assumption that online political participation precedes and nurtures subsequent offline participation (see Fig. 1). Proponents of this hypothesis have argued that online political participation can precede

[1] We note that the country's major social unrest, known as the 2019–2020 *Chile Despertó* social movement (Spanish: Chile woke up) started on October 18, 2019 after the data collection for both studies of the current project was completed.

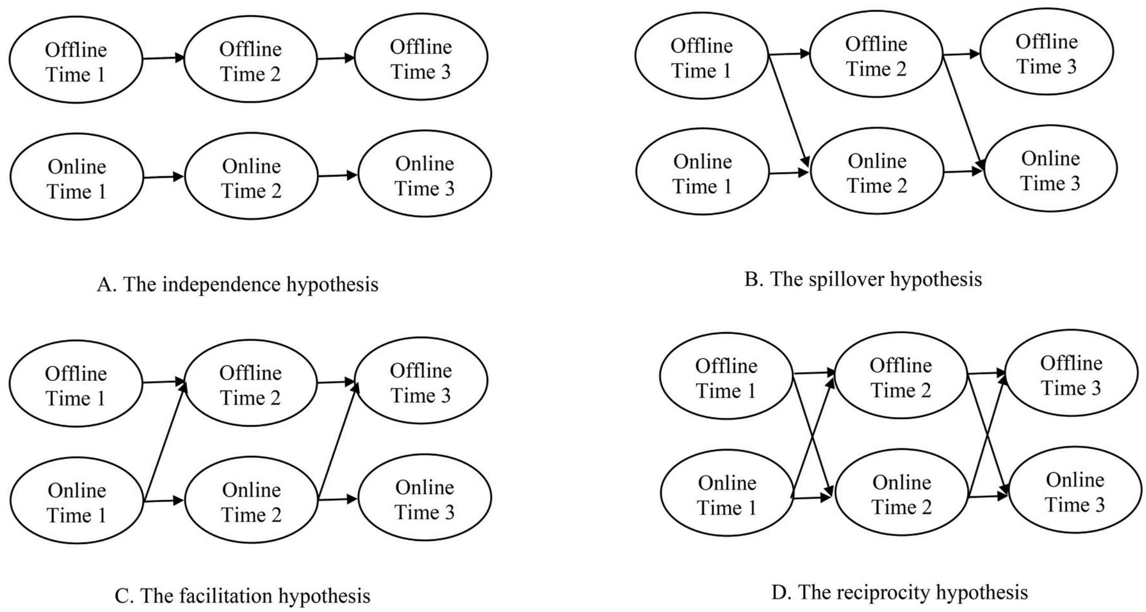

Fig. 1. Causal graphs for causal assumptions about the longitudinal bidirectional relations between online political participation and offline collective action. A: graph shows the basic autoregressive longitudinal model (the independence hypothesis); B: graph accounts for the unidirectional forward longitudinal relations between offline collective action and online political participation (the spillover hypothesis); C: graph represents the unidirectional reverse longitudinal relations between online political participation and offline collective action (the facilitation hypothesis); D: graph shows the bidirectional longitudinal relations between the two constructs (the reciprocity hypothesis).

further enduring engagement in higher-threshold offline activities because digital media is seen to have a potential to foster communities of like-minded people, increase bonding of social capital, and connect heterogeneous groups of societal members in their quest for a common cause (Bennett & Segerberg, 2012; Ellison, Steinfield, & Lampe, 2007; Gil deZúñiga, Jung, & Valenzuela, 2012; Jost et al., 2018; Kende et al., 2016; McGarty, Thomas, Lala, Smith, & Bliuc, 2014; Tufekci & Wilson, 2012). It has been suggested that the interactivity feature of digital media is likely to facilitate the connection between like-minded but previously unengaged individuals thus pointing to the role of sense of group identity in fostering the link between online political participation and subsequent offline collective action (Conroy, Feeze, & Guerrero, 2012; Ellison et al., 2007; Kende et al., 2016; Wilkins et al., 2019). So far, the proponents of the facilitation perspective have provided cross-sectional (e.g., Conroy, Feezell, & Guerrero, 2012; Ellison et al., 2007; Odağ et al., 2016), experimental (e.g., Kende et al., 2016; Wilkins et al., 2019) and short-term longitudinal (e.g., Gil de Zúñiga et al., 2012) empirical evidence to this viewpoint whereas the long-term follow-up studies sustaining this stance have been lacking.

1.1.3. *The spillover hypothesis*

According to proponents of the spillover hypothesis, people who have been previously engaged in offline collective action are expected to adopt and carry out additional online activities aimed at amplifying the public awareness of a cause by involving third-group parties and society at large (e.g., Uluğ, Odağ, & Solak, 2020; Van Laer, 2010; Xenos & Moy, 2007; see Fig. 1). This notion has been examined in correlational (e.g., Uluğ et al., 2020) and short-term longitudinal studies (e.g., Kim et al., 2017), leading, however, to somewhat inconclusive understanding of the causal processes. For instance, Kim and colleagues (2017) have taken an exploratory approach to the study of bidirectional longitudinal associations between online political participation and offline collective action among a nationally representative sample of young adults, controlling for the effects of age. These authors have provided some longitudinal support to the spillover hypothesis in the cohort of young adults while discomfiting it for adolescents, thus showing that the pattern of longitudinal bidirectional associations between online and offline forms of civic activism among the general population may vary depending on respondents' age. Some scholars have suggested that the spillover effects can be observed behind the emergence of an entirely new form of connective bottom-up collective action that occurs when activists' local calls to combat the incidents of social injustice, a message that can be transformed into transnational social movements spread through interconnected social networks (Greijdanus et al., 2021; Mendes, Ringrose, & Keller, 2018; Nekmat, Gower, Zhou, & Metzger, 2019; Thomas et al., 2018).

1.1.4. *The reciprocity hypothesis*

The reciprocity hypothesis builds on the assumption that in individuals' online political participation and offline collective action can be inextricable elements of their broader behavioral repertoire (see Fig. 1). The notion has been supported in the studies using cross-sectional data (e.g., Harlow & Harp, 2012; Milosevic-Dordevic & Zezelj, 2017) and longitudinal (e.g., Vissers & Stolle, 2014) data. For instance, Harlow and Harp (2012) conducted quantitative and qualitative research with activists in Colombia, Guatemala, and the United States to explore the relationship between online and offline participation. These authors found that activists believed in the utility of both forms of political participation and were likely to engage in them interchangeably. However, the observed effects might be limited to so-called devoted activists (i.e., intensely involved in social movement) and thus might not be sustained in more heterogeneous subsamples of the population (we will address this issue in Study 2). Finally, Vissers and Stolle (2014) examined the relation between online and offline participation among college students using a two-wave panel design. After controlling for the effects of background and attitudinal factors, they found that online political participation at Time 1 predicted offline participation at Time 2 and, *vice versa*. However, the employed design spanning two time points does not allow to adequately determine the direction of causality. Therefore, this issue of spuriousness in the reciprocity hypothesis has yet to be scrutinized.

Summing up, a systematic literature review identified four competing theoretical perspectives that could be understood as scholarly attempt to resolve the causal inference problem in the relationships between people's engagement in online and offline forms of civic activism. Because the conclusions derived from previous cross-sectional, experimental, and a few longitudinal studies have been inconsistent, the current research was designed to provide a robust and simultaneous exploration of the aforementioned causal hypotheses using a longitudinal cross-lagged panel modelling. Further, it is crucial to examine these hypotheses when controlling for socio-demographic variables (e.g., Emmer et al., 2012; Kim et al., 2017). Determining the direction of causality between both forms of civic engagement is important to advance the literature on digital mobilization, participatory cultures, and formation of social capital. Our research provides the test of *all possible causal hypotheses* first with a large sample of university students (Study 1) and then with the nationally-representative sample of adult population (Study 2) in Chile.

2. Study 1: the university students' sample

2.1. Overview

We tested the competing causal hypotheses about the longitudinal relationships between online political participation and offline collective action using the panel data from a convenience sample of Chilean university students. According to many scholars (e.g., González et al., 2020; Somma & Medel, 2017; Valenzuela et al., 2015), since the "Penguin Revolution" in 2006, the student social movement has been an impactful driving force for social change in this Latin American country. Although the initial demands of the activists centered around inequalities in the education system, the movement has gradually evolved into a large-scale political mobilization of students demanding radical economic and political democratization, including gender equality, the higher-quality pension system, reforms in the country's environmental and indigenous policies among others (e.g., Saavedra & Drury, 2019; Somma & Medel, 2017). Study 1 was conducted in 2017–2019. The first two waves of the data collection took place in 2017 (May and November, respectively), the year when Chile held general election, including presidential, parliamentary and regional elections. Conservative former president, Sebastián Piñera, was elected as Chilean president, defeating his centre-left opponent Alejandro Guillier, in a wider margin than expected (The Guardian, 2017). Before and after 2017 Chilean general election, there had been a number of social movements echoing the concerns of left-leaning voters such as inequality, educational reform, indigenous rights, and gender emancipation (e.g., Reuters, 2017). Therefore, Study 1 was situated in this socio-political context.

3. Method

3.1. Participants

This 2-year, 5-wave longitudinal panel study is part of a larger project on collective action, that was approved by the Ethics Committee of *anonymous* University. Based on the recommendations regarding the appropriate sample size in panel studies (e.g., Cohen, 1988; Lenth, 2001) and considering the issue of attrition (i.e., loss of participants) in longitudinal research (e.g., Satherley et al., 2015; Schoeni, Stafford, Mcgonagle, & Andreski, 2013), the sample size was set up to at least 1000 participants for Time 1 with the expected attrition rate up to 20% between the succeeding measurement points (i.e., Times 2, 3, 4 and 5). This sample size has been considered to be appropriately powered and effective for a different series of analyses such as autoregressive cross-lagged longitudinal panel analyses, latent class analyses, trajectory analyses, and latent transitional analyses (e.g., Cumming, 2014; Maxwell, 2004).

A sample of 1227 university students (370 males, 719 females, 137 did not report their gender), aged between 24 and 40 years old at Time (T) 1 ($M_{age} = 18.89$, $SD = 1.63$; 87.4% Chilean), completed the survey at T1, 954 at T2, 943 at T3, 905 at T4, and 786 at T5, respectively. They participated in the study in exchange for a fee of $10 at T1, $12 at T2, $15 at T3, $15 at T4, and $18 at T5. The attrition rates were generally good, meaning that only 21.42% of participants dropped out at T2, 1.15% at T3, 4.03% at T4, and 13.15% at T5. The final sample that have information for at least one variable was 1090 cases.

The sample in Study 1 was homogeneous in terms of participants' age and educational level (i.e., the target sample comprised students studying at different universities of Santiago de Chile), therefore we provide a statistical control for the effects of participants' identified gender only.

3.2. Procedure

Participants were recruited by research assistants at five universities in Santiago, Chile or via social media networks (e.g., Facebook). They received a link to complete the survey on a personal computer, tablet, or cell phone. After giving informed consent, participants filled out an extensive questionnaire that included measures of offline and online collective action participation. At the end of the survey, participants were thanked, debriefed, and paid for their participation. The first wave was administrated in May 2017 and the last wave in May 2019. The time lag between waves was of 6 months (Wave 1 in May 2017, Wave 2 in November 2017, Wave 3 in May 2018, Wave 4 in November 2018, and Wave 5 in May 2019). We used full information maximum likelihood method available in the software MPlus 7.4 (Muthén & Muthén, 2015) to handle missing data, which allows to include any case that have information for any variable (Schafer & Graham, 2002).

3.3. Measures

During each panel wave the respondents replied to the same set of questions about the frequency with which they engaged in online participation and offline collective action. The measures used in the present research have been extensively validated in longitudinal studies on civic activism (e.g., Correa, Willard Hinsley, & Gil de Zúñiga, 2010; Erhardt & Freitag, 2019; González et al., 2020).

Online political participation. Participants were asked to report in a single item how often they used social networks to express their opinion on public issues during the last year (from 1 = *never*, to 5 = *very frequently*).

Offline collective action. Participants were asked to report how often they took part in three forms of offline collective action over the past 12 months: "signed a letter or petition, supporting a cause"; "attended a march or political manifestation"; "participated in meetings or assemblies (from 1 = *never*, to 5 = *very frequently*). The internal reliability of the scale was relatively adequate at each time point: 0.65, 0.64, 0.71, 0.72 and 0.70, respectively.

4. Results

4.1. Analytical strategy

In order to test our hypotheses, we compared four autoregressive cross-lagged panel longitudinal models[2] (autoregressive, unidirectional forward, unidirectional reverse, and bidirectional), and in each case we compared the unconstrained with the constrained version of the models. The baseline model consisted of the autoregressive relationships between constructs estimated over time. To test the stability of the effects

[2] These models assume that each latent construct is a function of its former value at the previous time point, but with a random error. Thus, the autoregressive components of the models are described by stability coefficients that reflect the amount of change between the two points over time (e.g., Schlüter et al., 2006). The cross-lagged coefficients indicate the directional influence of each variable at T_1 on the other over time.

between constructs over time, the paths between T_1 and T_2, T_2 and T_3, T_3 and T_4, and T_4 and T_5, were first freely estimated, and these models were then systematically compared with models in which these paths were constrained to be equal (Cole & Maxwell, 2003). If the latter models did not change substantially the CFI and RMSEA indicators, we retained and interpreted the results of the more parsimonious constrained model in which the stability effects of the variables' scores across different time points were set to be equal. This decision is made using the criteria introduced by Rutkowski and Svetina (2014) and suggestions provided by Chen (2007). When determining invariance between different models with samples bigger than 300 cases, they recommend focusing on the change in CFI and RMSEA of the models in such a way that the CFI's decrease should not be greater than 0.02 when compared to the previous model, and the RMSEA should not change by more than 0.03. It is worth noting that Chen (2007) and Rutkowski and Svetina (2014) argued that the traditional scaled chi-square difference test (Satorra & Bentler, 2001) is less recommended when comparing models with large samples because it turns out to be a very sensitive technique that declares significant changes even if the variations in the fit of the models are very small. Unstandardized parameters are reported (Cole & Maxwell, 2003).

The data and syntaxes reported in the current manuscript are publicly available in Open Society Framework at https://osf.io/thns6/?view_only=0807776270554e25b0a8f84684fa1567.

4.2. *Descriptive statistics*

Means, standard deviations and correlations of constructs over time are presented in Table 1. The analyses of descriptive statistics revealed that all associations between the study variables were positive, significant and in the expected direction (see Table 1).

4.3. *Autoregressive longitudinal models: the independence hypothesis*

Model a1 (see Table 2) estimated the autoregressive paths for the two variables (online political participation and offline collective action). After this model was tested, a second model (see Table 2, Model a2) assessed if the autoregressive effects between T_1 and T_2 were equivalent to those between T_2 and T_3; T_3 and T_4 and between T_4 and T_5, that is, if the stability in the variables was itself consistent across time (Cole & Maxwell, 2003). The invariance between the models was confirmed (ΔCFI = 0.004; ΔRMSEA = 0.002), therefore, the second, more parsimonious model (Model a2) was retained. All estimated paths were significant in this model ($p < .05$), confirming that individuals' prior participation in civic activities was the strongest predictors of their subsequent engagement in the same domain (either online or offline), according to the independence hypothesis.

4.4. *Unidirectional forward longitudinal models: the spillover hypothesis*

The next model was built on the autoregressive model (Model a2) by estimating the hypothesized paths between the predictor (offline collective action) and the outcome variable (online political participation), respectively, as per the spillover hypothesis (see Fig. 1). This model showed a good fit (see Table 2, Model b1). The next step was to constrain the hypothesized paths to be equivalent between T_1 and T_2, between T_2 and T_3, between T_3 and T_4, b and between T_4 and T_5. This more constrained model also showed good fit (see Table 2, Model b2), and did not significantly differ from the former model (ΔCFI = −0.001; ΔRMSEA = 0.001). Hence, the more constrained b2 model was retained. All estimated paths for this model were significant ($p < .05$).

Consistent with the spillover hypothesis, the results indicated that respondents' participation in offline collective action significantly predicted their subsequent participation in online civic activities over time. The higher was the observed level of involvement in offline collective action at Time $_1$, the more participants tended to participate in online activities six months later in T_2. This pattern of results was systematic

Table 1
Descriptive statistics and correlations between the variables (N = 1090, Study 1).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	*M*	*SD*
1. Offline Meetings T1	–																				2.82	1.26
2. Offline Meetings T2	.61	–																			2.60	1.20
3. Offline Meetings T3	.55	.60	–																		2.93	1.33
4. Offline Meetings T4	.46	.50	.62	–																	2.49	1.21
5. Offline Meetings T5	.45	.49	.58	.61	–																2.51	1.26
6. Offline Marching T1	.54	.48	.44	.38	.39	–															2.37	1.33
7. Offline Marching T2	.50	.56	.51	.43	.42	.73	–														2.20	1.19
8. Offline Marching T3	.48	.49	.60	.53	.46	.68	.74	–													2.51	1.36
9. Offline Marching T4	.42	.46	.50	.57	.51	.56	.64	.73	–												2.27	1.20
10. Offline Marching T5	.37	.41	.49	.48	.55	.50	.56	.66	.69	–											2.38	1.20
11. Offline Signing T1	.30	.25	.23	.27	.25	.25	.25	.26	.25	.25	–										2.42	1.07
12. Offline Signing T2	.23	.29	.29	.28	.26	.19	.28	.27	.29	.30	.50	–									2.43	1.04
13. Offline Signing T3	.25	.31	.39	.33	.30	.24	.29	.36	.30	.30	.41	.50	–								2.42	1.10
14. Offline Signing T4	.24	.29	.32	.42	.33	.18	.22	.26	.38	.33	.34	.43	.51	–							2.24	1.05
15. Offline Signing T5	.21	.20	.30	.30	.38	.18	.19	.27	.28	.40	.35	.46	.46	.51	–						2.25	1.06
16. Online Participation T1	.37	.37	.35	.33	.32	.39	.38	.37	.36	.34	.34	.33	.29	.28	.24	–					2.83	1.29
17. Online Participation T2	.33	.39	.34	.32	.29	.34	.44	.37	.37	.36	.30	.39	.30	.27	.24	.69	–				2.70	1.31
18. Online Participation T3	.32	.34	.38	.35	.35	.32	.36	.42	.40	.37	.31	.34	.38	.32	.26	.64	.70	–			2.81	1.33
19. Online Participation T4	.29	.28	.31	.41	.35	.29	.34	.37	.44	.39	.29	.33	.33	.39	.27	.63	.65	.72	–		2.72	1.34
20. Online Participation T5	.27	.29	.33	.35	.41	.28	.31	.35	.36	.49	.31	.28	.30	.31	.34	.56	.59	.64	.70	–	2.76	1.35

Notes: M = mean; SD = standard deviation; All correlations are significant at $p < .001$. All the reported variables ranged from 1 to 5.

Table 2
Fit indices of longitudinal cross-lagged Offline-Online collective action participation model (Study 1).

Model	Model Fit	Model Comparison	Model Invariance Testing
a1	χ^2 (136) = 370.673. $p < .001$; CFI = .979; TLI = .967; RMSEA = .040; SRMR = .061		
a2	χ^2 (142) = 413.030$p < .001$; CFI = .975; TLI = .963; RMSEA = .042; SRMR = .071	a2 vs. a1	ΔCFI = .004; ΔRMSEA = .002
b1	χ^2 (138) = 345.459. $p < .001$; CFI = .981; TLI = .971; RMSEA = .037; SRMR = .040		
b2	χ^2 (141) = 361.004. $p < .001$; CFI = .980; TLI = .970; RMSEA = .038; SRMR = .044	b2 vs. b1	ΔCFI = −.001; ΔRMSEA = .001
		b2 vs. a2	ΔCFI = .001; ΔRMSEA = −.004
c1	χ^2 (138) = 403.325. $p < .001$; CFI = .976; TLI = .963; RMSEA = .042; SRMR = .066		
c2	χ^2 (141) = 404.037. $p < .001$; CFI = .976; TLI = .964; RMSEA = .041; SRMR = .066	c2 vs. c1	ΔCFI = .000; ΔRMSEA = −.001
		c2 vs. a2	ΔCFI = −.003; ΔRMSEA = −.001
		c2 vs. b2	ΔCFI = −.004; ΔRMSEA = −.003
d1	χ^2 (134) = 343.028. $p < .001$; CFI = .981; TLI = .970; RMSEA = .038; SRMR = .039		
d2	χ^2 (140) = 359.037. $p < .001$; CFI = .980; TLI = .970; RMSEA = .036; SRMR = .043	d2 vs. d1	ΔCFI = −.001; ΔRMSEA = .000
		d2 vs. a2	ΔCFI = .001; ΔRMSEA = −.004
		d2 vs. b2	ΔCFI = .000; ΔRMSEA = .000
		d2 vs. c2	ΔCFI = .004; ΔRMSEA = −.003

Note. CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root-mean-square error of approximation; SRMR = standardized root-mean-square residual; a1 = autoregressive model (freely estimated parameters); a2 = autoregressive model (within construct path equivalence); b1 = unidirectional forward model: predictor and outcome (freely estimated parameters); b2 = unidirectional forward model (within construct path equivalence); c1 = unidirectional backward model: outcome and predictor (freely estimated parameters); c2 = unidirectional backward model (within construct path equivalence); d1 bidirectional model (paths freely estimated); d2 bidirectional model (within construct path equivalence). The model included a statistical control of participants' gender.

and significant over time (between T_2 - T_3, T_3 -T_4, and between T_4 and T_5, constrained unstandardized $\beta = 0.302$, $p = .011$).

4.5. Unidirectional reverse longitudinal models: the facilitation hypothesis

To test the reverse causal specification, the predictor and the outcome variables were then switched; i.e., T_1 online political participation in civic activities was considered as a predictor of T_2 offline collective action participation and so on, which allowed us to simultaneously test predictions of the facilitation hypothesis. This reverse model also showed good fit, as can be seen in Table 2 (Model c1). As in the forward unidirectional model, equivalent paths were constrained to be equal in magnitude between the time points. This inverse model with equivalent paths exhibited good fit indexes (see Table 2, Model c2), and demonstrated no significant decrease in fit when compared to an unconstrained Model c1 (ΔCFI = 0.000; ΔRMSEA = −0.001). All estimated paths were significant. The reverse path from online political participation in collective action at T_1 to offline collective action six months later at T_2 was also significant, supporting the facilitation hypothesis. This pattern of result was systematic and significant over time (between T_2 - T_3, T_3 -T_4, and between T_4 and T_5, unstandardized $\beta = 0.018$, $p = .003$).

A model comparison between b2 (forward) and c2 (reverse) indicate that neither was preferable in statistical terms (see Table 2; ΔCFI = −0.004; ΔRMSEA = −0.003). We then proceeded to test a bidirectional longitudinal model that estimated both the 'forward' and the 'reverse' paths simultaneously, a proper procedure to test the reciprocity hypothesis.

4.6. Bidirectional longitudinal models: the reciprocity hypothesis

The first bidirectional model was freely estimated, except for the autoregressive paths that were already constrained to be equal in magnitude between T_1 and T_2, from T_2 to T_3, and so on, as in the previous models. This model had a good fit (see Table 2, Model d1), and was then compared with a model in which equivalent cross-lagged paths were constrained to be equal in magnitude between different time points (see Table 2, Model d2). The two models did not vary in terms of their fit (ΔCFI = −0.001; ΔRMSEA = 0.000), so the more parsimonious bidirectional model was treated as the definitive one for parameter estimation.

As can be seen in Fig. 2, our results reveal that when estimated altogether, only the forward model testing the spillover hypothesis was significant (i.e., from offline collective action to online political participation). The longitudinal cross-lagged paths from offline collective action at T_1 to online collective action at T_2 and from offline collective action at T_2 to online activities at T_3 and so on, were all significant (unstandardized $\beta = 0.288$, $p < .001$), indicating that respondents' stability in online political participation directly depended on their previous engagement in offline collective action and not the other way around.

5. Discussion

Study 1 analyzed the longitudinal bidirectional relation between online political participation and offline collective action among a large convenience sample of university students in Chile. Because previous research has mostly taken a confirmatory approach testing a single preferred causal hypothesis with cross-sectional or short-term longitudinal data, to the current study was set to explore how the relations between online political participation and offline collective action evolve over time. By using a longitudinal cross-lagged panel approach, we provided a rigorous test of four competing causal hypotheses (i.e., independence, spillover, facilitation, and reciprocity) and examined the longitudinal relation between the two forms of political behavior measured at five time points spanning two years. The results provided support for the spillover hypothesis suggesting that respondents' engagement in offline collective action was likely to affect their increased online political participation over time. This causal longitudinal effect remained significant after controlling for participants' gender. The reverse causal hypothesis (i.e., facilitation) and the other two discussing the independent and reciprocal relations between the constructs were therefore disconfirmed. As such, Study 1 with a sufficiently large sample size of university students observed at five time points provides support to the findings of Kim et al. (2017). We note, however, that the sample in Study 1 was homogenous in terms of participants' age and educational level. Therefore, to provide a robustness check and to test the relative importance of individual socio-demographic variables we conducted Study 2 among the nationally representative population of Chilean adults. In particular, we controlled for age, gender, and educational level such that prior work has shown that younger and highly educated people are more likely to engage in civic and political activities as compared to those from other subsamples of the population (e.g., Finlay et al., 2010; Kim et al., 2017). In Study 2, we measured participants' educational level such as this socio-demographic variable has been commonly referred in the literature as a crucial proxy of socio-economic status (e.g., Brady, Verba, & Schlozman, 1995; Schlozman, Verba, & Brady, 2010; Smets & van Ham,

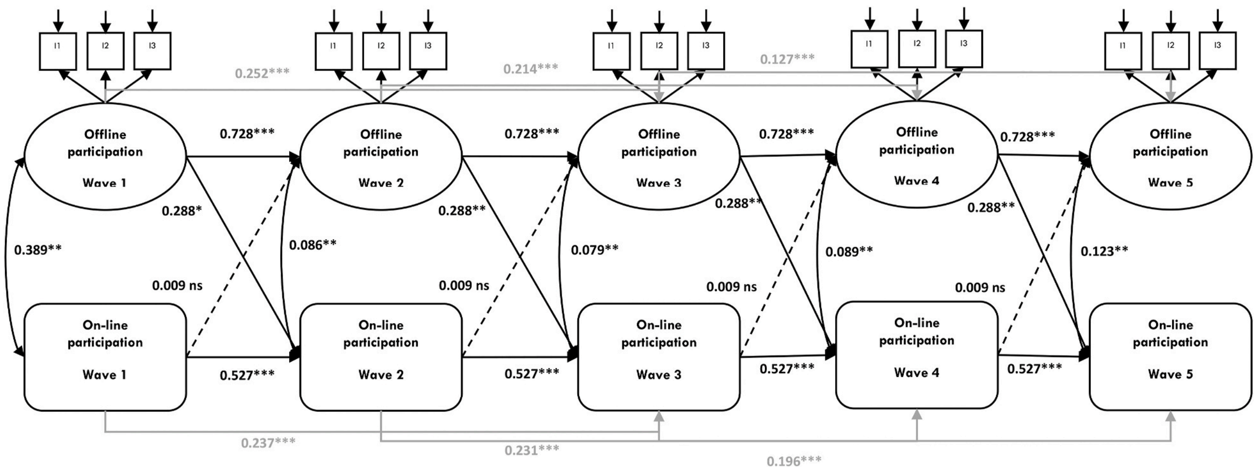

Fig. 2. Full longitudinal bidirectional model for online and offline participation in collective action, Study 1. *Note.* Explanation of the abbreviations: $*p < .05$; $***p < .001$. Full longitudinal bidirectional model showing the cross-lagged relationship between offline and online participation in collective action over time (Model d2 in Table 3). ($N = 1090$): χ^2 (140) = 359.037. $p < .001$; CFI = 0.980; TLI = 0.970; RMSEA = 0.036; SRMR = 0.043. Unstandardized coefficients were reported; the dotted lines show non-significant paths. For clarity, covariates within time points and non-significant paths values were not depicted.

2013).

5.1. Study 2: nationally representative sample of Chilean adults

Study 2 was conducted in Chile, a Latin American country that continues to experience political transformation through demonstrations and social protests. During the time of the data collection (2016–2018) there were a few social movements echoing the concerns of left-leaning voters such as inequality, educational reform, indigenous rights, and gender emancipation (e.g., Reuters, 2017). These social movements took place, in particular, before and after 2017 Chilean general election (e.g., Reuters, 2017). In 2017, conservative candidate (and former president) Sebastián Piñera was elected as Chilean president, defeating his socialist opponent Alejandro Guillier and succeeding the centre-left government of Michelle Bachelet (The Guardian, 2017). Therefore, we situated Study 2 in this social-political context.

6. Method

6.1. Participants

A nationally representative sample of 2924 adults aged 18–75 (60.27% females; M_{age} = 46.10, SD = 15.28) was recruited from 40 Chilean cities as part of the first three waves of the Longitudinal Social Study of Chile (ELSOC), conducted by the Centre for Social Conflict and Cohesion Studies (COES). The study was approved by the Research Ethics Committee of *anonymous* University. From this omnibus dataset, the relevant variables of study were chosen. Participants were surveyed annually in 2016 (Time $_1$), 2017 (Time $_2$), and 2018 (Time $_3$). The baseline sample (T1) included 2927 participants (39.7% male, 60.3% female). At T2, 2473 participated (38.5% male, 61.5% female), and T3 included 2229 individuals (38.6% male, 61.4% female). The attrition rate from Time 1 to Time 2 (15.5%) and from Time 2 to Time 3 (9.9%), was conveniently low. We used full information maximum likelihood method available in the software MPlus 7.4 (Muthén & Muthén, 2015) to handle missing data, which allows to include any case that have information for any variable (Schafer & Graham, 2002).

6.2. Procedure

Using a four-stage probabilistic stratified sampling framework, 40 cities from urban areas were randomly selected from different regions of Chile (92 Municipalities distributed in 13 regions). Within these cities, 1067 blocks were chosen at random. Households within these blocks were then randomly selected, and an individual over the age of eighteen was chosen randomly from each household. All participation was voluntary, with participants providing written consent. In each wave, participants completed a face to face 55-min survey in their own homes, facilitated by a trained interviewer who was outsourced from an external organization. At the end of the survey, respondents were debriefed and thanked for their participation. Respondents received a monetary incentive equivalent to 9 USD at all points of data collection.

6.3. Measures

As in Study 1, we used the same measures over the three waves of the study.

Online political participation. Participants were asked to report in a single item how often they used social networks to express their opinion on public topics over the past 12 months (from 1 = *never*, to 5 = *very frequently*).

Offline collective action. Participants were asked to report how often they took part in three forms of offline collective action over the past 12 months: “signed a letter or petition supporting a cause”, “attended a march or political manifestation”; “participated in a strike”, (from 1 = *never*, to 5 = *very frequently*). The internal reliability of the scale was adequate at each time point: 0.92, 0.63, and 0.91, respectively.

7. Results

7.1. Descriptive statistics

Means, standard deviations and correlations of constructs over time are presented in Table 3. In addition, all associations between the study variables were positive, significant and in the expected direction. Three socio-demographic variables (i.e., gender, age, and educational level) were included to the models as control variables.

7.2. Autoregressive longitudinal models: the independence hypothesis

In order to test the hypothesized cross-lagged panel models, the same analytic strategy used in Study 1 was subsequently replicated in Study 2. Model a1 (see Table 4) estimated the autoregressive paths for each of the variables (offline and online forms of collective action). After this model was tested, a second model (see Table 4, Model a2) assessed if the autoregressive effects between T_1 and T_2 were equivalent to those

Table 3
Descriptive statistics and correlations between the variables ($N = 2924$, Study 2).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	*M*	*SD*
1. Offline Strike Participation T1	–															1.24	0.69
2. Offline Strike Participation T2	.28	–														1.14	0.54
3. Offline Strike Participation T 3	.25	.30	–													1.12	0.48
4. Offline March Participation T1	.46	.25	.21	–												1.31	0.78
5. Offline March Participation T2	.22	.50	.23	.42	–											1.21	0.64
6. Offline March Participation T3	.20	.19	.42	.39	.45	–										1.18	0.59
7. Offline Signing Participation T1	.29	.11	.08	.37	.19	.16	–									1.62	0.98
8. Offline Signing Participation T2	.10	.31	.15	.21	.40	.23	.28	–								1.55	0.93
9. Offline Signing Participation T3	.14	.14	.26	.21	.25	.42	.26	.35	–							1.43	0.83
10. Online Participation T1	.31	.11	.12	.41	.26	.26	.36	.23	.24	–						1.71	1.18
11. Online Participation T 2	.14	.28	.13	.25	.42	.27	.18	.40	.25	.43	–					1.60	1.09
12. Online Participation T3	.13	.15	.24	.28	.32	.38	.19	.28	.40	.44	.52	–				1.59	1.06
13. Age of participants	-.10	-.13	-.15	-.18	-.18	-.18	-.16	-.20	-.20	-.29	-.30	-.30	–			46.10	15.28
14. Educational level	.15	.13	.12	.27	.23	.23	.23	.23	.27	.32	.27	.30	-.35	–		5.26	2.20
15. Gender	-.06	-.04	-.06	-.05	-.04	-.00	-.00	-.02	.01	-.02	-.04	-.02	.06	-.08		0.60	0.49

Notes: M = mean; SD = standard deviation. All correlations between the study variables were significant at $p < .001$ except for gender. All the reported variables ranged from 1 to 5. Participants' age ranged from 18 to 88 ($Mdn = 46$).

Table 4
Fit indices of longitudinal cross-lagged Offline-Online collective action participation model (Study 2).

Model	Model Fit	Model Comparison	Model Invariance Testing
a1	χ^2 (57) = 255.307, $p < .001$; CFI = .963; TLI = .934; RMSEA = .034; SRMR = .034		
a2	χ^2 (59) = 252.945, $p < .001$; CFI = .964; TLI = .938; RMSEA = .034; SRMR = .034	a2 vs. a1	ΔCFI = .001; ΔRMSEA = .000
b1	χ^2 (57) = 236.596, $p < .001$; CFI = .967; TLI = .940; RMSEA = .033; SRMR = .032		
b2	χ^2 (58) = 241.300, $p < .001$; CFI = .966; TLI = .940; RMSEA = .033; SRMR = .032	b2 vs. b1	ΔCFI = −.001; ΔRMSEA = .000
		b2 vs. a2	ΔCFI = .002; ΔRMSEA = −.001
c1	χ^2 (57) = 249.152, $p < .001$; CFI = .964; TLI = .936; RMSEA = .034; SRMR = .033		
c2	χ^2 (58) = 248.981, $p < .001$; CFI = .964; TLI = .938; RMSEA = .034; SRMR = .033	c2 vs. c1	ΔCFI = .000; ΔRMSEA = .000
		c2 vs. a2	ΔCFI = .000; ΔRMSEA = .000
		c2 vs. b2	ΔCFI = −.002; ΔRMSEA = .001
d1	χ^2 (55) = 235.085, $p < .001$; CFI = .967; TLI = .938; RMSEA = .033; SRMR = .031		
d2	χ^2 (57) = 239.702, $p < .001$; CFI = .966; TLI = .939; RMSEA = .033; SRMR = .032	d2 vs. d1	ΔCFI = −.001; ΔRMSEA = .000
		d2 vs. a2	ΔCFI = .002; ΔRMSEA = −.001
		d2 vs. b2	ΔCFI = .000; ΔRMSEA = .000
		d2 vs. c2	ΔCFI = .003; ΔRMSEA = −.001

Note. a1 = autoregressive model (freely estimated parameters); a2 = autoregressive model (within construct path equivalence); b1 = unidirectional forward model: predictor and outcome (freely estimated parameters); b2 = unidirectional forward model (within construct path equivalence); c1 = unidirectional backward model: outcome and predictor (freely estimated parameters); c2 = unidirectional backward model (within construct path equivalence); d1 bidirectional model (paths freely estimated); d2 bidirectional model (within construct path equivalence). The model included a statistical control for gender, age and educational level.

between T_2 and T_3; that is, if the stability in a variable was itself consistent over time (Cole & Maxwell, 2003). Mirroring Study 1, invariance between the models was confirmed (ΔCFI = 0.001; ΔRMSEA = 0.001), therefore the second, more parsimonious model (see Table 4, Model a2) was retained. All estimated paths were significant in this model ($p < .05$).

7.3. Unidirectional forward longitudinal models: the spillover hypothesis

The next model was built on the autoregressive model (see Table 4, Model a2) by estimating the hypothesized paths between the predictor (offline collective action participation) and outcome variable (online collective action participation), respectively. The model showed a good fit (see Table 4, Model b1). The next step was to constrain the hypothesized paths to be equivalent between T_1 and T_2 and between T_2 and T_3. This more constrained model also showed good fit (see Table 4, Model b2), and did not significantly differ from the former model (ΔCFI = −0.001; ΔRMSEA = 0.000). Hence, the more constrained b2 model was retained. All estimated paths for this model were significant ($p < .05$).

Mirroring Study 1 and consistent with the spillover hypothesis, the results revealed that participation in offline collective action significantly predicted change in people's participation in online collective action over time. Thus, the higher was respondents' involvement in offline actions at Time 1 (e.g., supporting a cause, attending a march or participating in a strike), the more they tended to use social networks to express their opinion on public topics in T_2 and from T_2 to T_3 (unstandardized $\beta = 0.248$, $p = .003$).

7.4. Unidirectional reverse longitudinal models: the facilitation hypothesis

To test the reverse causal specification, the predictor and outcome variables were then switched; i.e., T_1 online political participation in collective action was considered as a predictor of T_2 offline collective actions participation and so on. This reverse model also showed good fit, as can be seen in Table 4 (Model c1). As in the forward unidirectional model, equivalent paths were constrained to be equal in magnitude between time points. This inverse model with equivalent paths exhibited good fit indexes (see Table 4, Model c2), and demonstrated no significant decrease in fit when compared to the unconstrained Model c1 (ΔCFI = 0.000; ΔRMSEA = 0.000). All estimated paths were significant. Consistent with the facilitation hypothesis, the reverse path from online activities at T_1 to offline collective action at T_2 and from online activities at T_2 to offline collective action at T_3 was significant (unstandardized $\beta = 0.012$, $p = .042$), though the effect size was smaller.

A model comparison between b2 (forward) and c2 (reverse) indicate that neither was preferable in statistical terms (see Table 4; ΔCFI = −0.002; ΔRMSEA = 0.001). We then proceeded to test a bidirectional longitudinal model that estimated both the 'forward' and the 'reverse' paths simultaneously. This strategy allowed us to simultaneously test the independence, spillover, facilitation, and reciprocity hypotheses altogether and see whether both forms of participation can nurture each other in a dynamic process over time.

7.5. Bidirectional longitudinal models: the reciprocity hypothesis

The first bidirectional model was freely estimated, except for the autoregressive paths that were already constrained to be equal in magnitude between T_1 and T_2, and from T_2 to T_3, as in previous models. This model had good fit (see Table 4, Model d1), and was then compared with a model in which equivalent cross-lagged paths were constrained to be equal in magnitude between different time points (see Table 4, Model d2). The two models did not vary in terms of their fit (ΔCFI = −0.001; ΔRMSEA = 0.000), so the more parsimonious bidirectional model was treated as the definitive one for parameter estimation (see Fig. 3).

As depicted in Fig. 3, when estimating altogether, only the hypothesized unidirectional forward model (the spillover effect) was significant (from offline to online political participation). The longitudinal cross-lagged paths from offline collective actions at T_1 to online activities at T_2 and from offline collective action at T_2 to online activities at T_3 (unstandardized $\beta = 0.229$, $p = .001$), was significant even after controlling for the covariate effect of age, gender, and educational level indicating that online involvement one year later was dependent from participation in offline collective actions in the previous year.

8. Discussion

The main objective of Study 2 was to replicate Study 1 using the panel data collected from the nationally representative sample of Chilean adults. By employing the same autoregressive cross-lagged panel design as in Study 1, we examined the longitudinal relation between online political participation and offline collective action. Remarkably, the results provided additional support for the spillover hypothesis suggesting that respondents' engagement in offline collective action predicted their increased online political participation over time. This causal longitudinal effect remained significant after controlling for participants' gender, age, and educational level. Thus, after using this cross-lagged panel analytic strategy we tested step-by-step all predictions simultaneously. The other three theoretical hypotheses (i.e., independence, facilitation, and reciprocity) were also consistently disconfirmed. Our research also showed that the autoregressive paths (i.e., stability estimates) between the two forms of political engagement were significant thus revealing that previous activity in one domain was likely to spur the same activity in the future, consistent with the independence hypothesis. Taken together, the results of Study 2 provided robust empirical support to the spillover hypothesis consistently showing that at the average level citizens' previous engagement in offline collective action was a robust predictor of their further political participation in the online sphere over time.

9. General discussion

In this article, we strived to reassess the longitudinal causal relation between online political participation and offline collective action. Previous research on digital activism and its causal association to real-world protests has been mostly confirmatory in nature and statistical analyses showed mixed results. Our goal in this article was to compare the four causal longitudinal hypotheses debated in the literature and identify the model that most accurately depicts the causal dynamics between online political participation and offline collective action in students and general population over time. Results from both ecological panel studies conducted in the context of Chile compellingly showed that individuals' offline collective action can be a cause for their further online political participation. Noteworthy, the effects in both panel studies remained significant after controlling for socio-demographic variables (gender in Study 1; gender, age, and educational level in Study 2). The pattern of the revealed results is intriguing because for the first time it provided compelling longitudinal evidence to the assumption that pursued and implemented past civic activism in the offline sphere can serve the ground for further durable online political participation. All other alternative causal hypotheses were consistently disconfirmed.

Our research advanced the literature in two important ways. First, drawing on the recent methodological developments in the causal inference literature, our research provides empirical insight into the ongoing debate on the longitudinal relationship between online and offline collective action (e.g., Boulianne & Theocharis, 2018; Schumann & Klein, 2015; Wilkins et al., 2019). Our methodical innovation consisted in applying an autoregressive cross-lagged panel design to determine the direction of causality empirically by systematically testing and comparing all possible causal hypotheses. In our analysis, we made use of two panel studies spanned three and five time points which

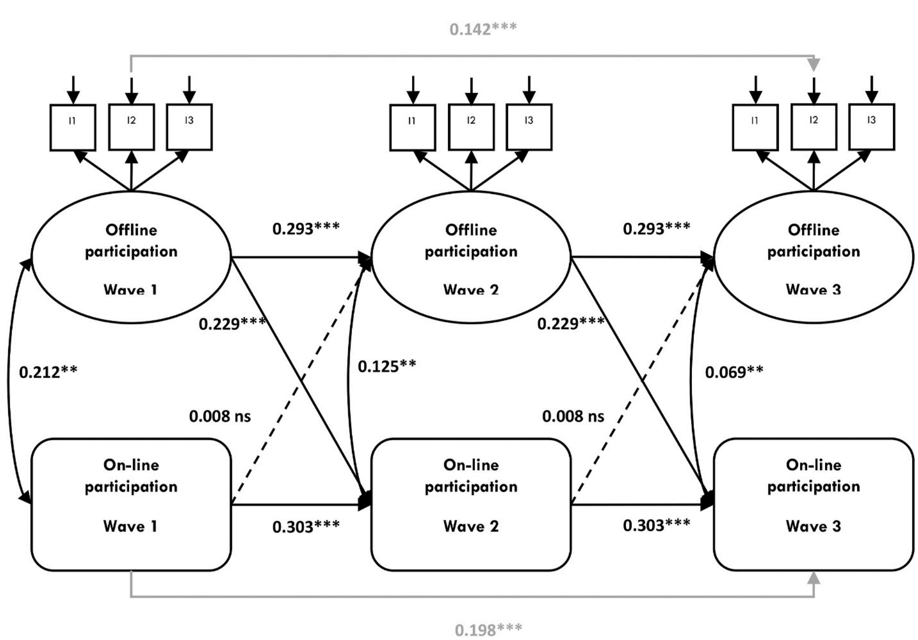

Fig. 3. Full longitudinal bidirectional model for online and offline participation in collective action, Study 2. Note. Explanation of the abbreviations: *$p <$ .05; ***$p < .001$. Full longitudinal bidirectional model showing the cross-lagged relationship between offline and online participation in collective action over time (Model d2 in Table 3). ($N = 2924$): $\chi2$ (57) = 239.702, p < .001; CFI = 0.966; TLI = 0.939; RMSEA = 0.033; SRMR = 0.032. Unstandardized coefficients were reported; the dotted lines show non-significant paths. For clarity, covariates within time points and non-significant paths values were not depicted.

allowed us to adequately examine the intra-individual stability, the direction, the dynamics, and the persistence of the effects over time. Importantly, the inclusion of both lagged-dependent and lagged-independent variables in our statistical models enabled us to diminish the issue of endogeneity which prevails in many cross-sectional studies (e.g., Erhardt & Freitag, 2019). Additionally, by diversifying our samples, we were able to explore the causal dynamics behind civic activism among university students and the nationally-representative sample of adult population in the context of Chile, thus providing robustness test of our results. Therefore, the strength of this research is that it resonates with the articulated importance of matching the theory of change with the appropriate methodology capable of testing the dynamic causal processes. The use of rigorous methodology allowed us to provide empirical insights into the causal dynamics that shape contemporary civic activism in both virtual and physical domains.

Secondly, an a more practical level, the results from this research shed important light on seemingly spurious effects of online political participation and offline activism. The internet is arguably one of the most efficient tools of mass mobilization, communication and the formation of social capital (Greijdanus et al., 2021; (Jost et al., 2018); Kende et al., 2017; Uluğ et al., 2021). However, as our research revealed, online political participation, operationalized here as the engagement in rather informal and expressive social-media activities, did not lead to lasting collective action in the offline sphere. It is therefore possible that more resource-intensive types of online activities such as e-petitioning, e-donating, e-campaigning (e.g., Gibson & Cantijoch, 2013) or information seeking activities (e.g., Adam-Troian, Bonetto, & Arciszewski, 2020) can better predict lasting offline political participation over time. Further, as we have noted on the onset of this paper, social media-driven activism has fostered many real-world issues over the past two decades (Arab Spring, #MeToo, Black Lives Matter) and seemingly opened space for marginalized political voices that otherwise might have faced limits to free expressions (e.g., Schmitz, Coley, Thomas, & Ramirez, 2020). However, it is also true that in parallel to the evolution of the digital activism there have been a shift to machine-driven monitoring and surveillance of the public (i.e., nowadays digital data are collected, generated, and elaborated by law enforcement and intelligence agencies). As such, online social protest may be subjected to both horizontal (other users) and vertical (government) surveillance which under certain circumstances (e.g., fear, self-censorship) can constrain individual-level online participation (e.g., Ayanian et al., 2020; Ruijgrok, 2017; Rød & Weidmann, 2015).

Together, our findings suggest valuable avenues for future research. For instance, research could cover more completely the role of the perceived mass surveillance behind the causal dynamics of civic political engagement in both virtual and physical spaces. Future research may also consider extending this line of inquiry by scrutinizing the role of dynamic macro-level contextual variables pertaining to democratic responsiveness and permeability of regime on offline and online political engagement over time. Additionally, more research is needed to detangle underlying psychological mechanisms (e.g., digital social relationships, political ideology, perceived political efficacy, shared participatory norms) that were beyond the scope of the current investigation. Indeed, interpersonal effects occur when individuals share information online, coordinate, recruit, participate in digital social groups and develop shared social identities (e.g., Greijdanus et al., 2021). In many cases, participation in online discussions and expression of political opinion online takes place with the purpose of expressing one's group identity and building social capital (Kende et al., 2016). The shared group identity with a well-articulated normative core (e.g., Black Lives Matter, #MeToo) can reasonably explain why some social movements remain vibrant and instigate social transformation transcending geographic and temporal borders. Finally, longitudinal research could also benefit from examining whether resource-intensive types of online activities such as e-petitioning, e-donating, e-campaigning (e.g., Gibson & Cantijoch, 2013) can provide a significant stimulus to a lasting political participation over time compared to expressive online political participation (i.e., engagement in online political debates) measured in the current research.

The present studies do have limitations. Although we managed to successfully replicate the pattern of these results across two separate panel studies, we acknowledge that our findings are limited to the use of the single-item measure for the construct of online political participation. Given that our study was embedded in a large research survey, unfortunately, we could not expand on the issue of the multidimensionality of this construct and gauge several facets that it is assumed to comprise (Emmer et al., 2012; Wilkins et al., 2019). Therefore, future studies should expand the scope of the present study and advance the understanding of citizens' participation as a multidimensional concept in both online and offline spheres (Theocharis, 2015; Theocharis & Van Deth, 2016). Besides, although our results from two panel studies exhibited coherent patterns, the generalization needs to be interpreted with caution because these effects may be further explained by other variables that were not measured in the current research studies. Despite of these limitations, our research should be seen as an important initial step in detangling the causal longitudinal processes by employing rigorous methodology.

In conclusion, extant literature on digital activism is inconclusive about longitudinal causal relations between online political participation and offline collective. The present research offered empirical insights into a causal longitudinal dynamics shaping online political participation and offline collective action. We used an autoregressive cross-lagged panel design to determine the direction of causality empirically by comparing all possible theoretical models and controlling for the effects of socio-demographic variables. Overall, the findings from two medium-term ecological panel studies support the thesis that offline collective action involving marching, sit-ins, peaceful rally was likely to pave ground for lasting political participation in both online and offline spheres over time, whereas the cross-lagged associations between online political participation and further offline collective action were found to be consistently non-significant. These findings have implications for scholars and decision-makers concerns with facilitating active citizenship and civic political behavior.

Author contribution

Maria Chayinska (Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Writing – original draft; Writing – review & editing), Daniel Miranda (Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Visualization; Writing – review & editing), Roberto Gonzalez (Conceptualization; Funding acquisition; Supervision; Writing – review & editing).

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