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Article

Scroll. Like. Divide. The filter bubble effect on electoral perceptions

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Scroll. Like. Divide. The filter bubble effect on electoral perceptions

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Keywords: Algorithmic personalisation, Filter bubble, Electoral communication, Ideological polarisation, Confirmation bias

Abstract: This study presents a validated psychometric instrument for assessing filter bubble effects and underscores the need for targeted, system-level interventions that extend beyond individual user-focused solutions. By situating filter bubbles within electoral dynamics, this study contributes to a more nuanced and policy-relevant understanding of how social media platforms shape democratic discourse. This study examines the impact of algorithmic personalisation on electoral perceptions through the lens of the filter bubble phenomenon. Drawing on a multidimensional instrument, the Bubblemetrix Index, we assess four core components: algorithmic curation awareness, perceived source diversity, ideological homogeneity and confirmation bias, and repeated interaction and engagement. Data were collected through an online survey of 451 Romanian Facebook users during the pre-electoral period and analysed using latent profile and latent class modelling. The findings identify three distinct user profiles, with the largest group consisting of younger individuals who demonstrate high algorithmic awareness but also exhibit strong confirmation bias and repeated engagement, which suggest that awareness alone is insufficient to counteract ideological encapsulation. Older users, by contrast, exhibited lower susceptibility to ideological homogeneity and engagement-driven reinforcement. The results challenge the assumption that media literacy and perceived diversity constitute adequate safeguards against polarisation and suggest that algorithmic systems may create an illusion of diversity while structurally amplifying partisan exposure.

ETHICS STATEMENT

This study's protocol was designed in accordance with the ethical requirements specific to the Faculty of Law and Administrative Sciences, “Ovidius” University, Constanța, Romania, prior to the commencement of the study. All participants participated voluntarily in the study and provided written informed consent in accordance with the Declaration of Helsinki and Romanian national legislation governing ethical conduct in scientific research, technological development, and innovation.

DATA AVAILABILITY STATEMENT

The data sets generated and analysed during the current study are available from the corresponding author on reasonable request.

Introduction

Social media platforms such as Facebook, Twitter, YouTube, and Instagram have emerged as dominant arenas for public discourse, fundamentally reshaping how individuals access news, deliberate on political issues, and engage with electoral campaigns. During electoral periods, these platforms also function as critical infrastructure for political advertising, mobilisation, and agenda-setting, raising concerns about systemic risks to democratic processes. A central concept within this evolving digital landscape is the “filter bubble,” a term popularised by Pariser (2012), which suggests that algorithmic personalisation can isolate users within ideologically homogeneous content streams. Scholars in communication, political science, and media studies have investigated whether filter bubbles contribute to political polarisation, perpetuate misinformation, or weaken democratic deliberation (Bruns, 2019; Dubois & Blank, 2018; Kaiser & Rauchfleisch, 2020). Recent integrative reviews emphasise that filter bubbles should be understood as context-dependent phenomena emerging from the interaction between algorithmic personalisation, user behaviour, and platform design, rather than as uniformly deterministic effects of technology (Tasențe, 2025). These debates centre on the extent to which data-driven personalisation – rooted in the tracking of user clicks, likes, and viewing behaviours, limits exposure to diverse perspectives.

Existing research underscores both the possibilities and constraints of personalised feeds. Some argue that people’s information diets remain broader than initially feared because users can seek out new sources or encounter dissenting opin-

ions through their social networks (Bruns, 2019; Dubois & Blank, 2018). Others emphasise that algorithmic curation may push users toward increasingly similar or extreme material, subtly narrowing what they perceive as mainstream (Kaiser & Rauchfleisch, 2020; Whittaker et al., 2021). Although this body of research has expanded considerably, significant gaps remain in our understanding of how filter bubbles manifest within political and electoral communication contexts. Many studies focus on general news consumption or user behaviour without examining the specific interplay between personalisation algorithms and electoral messaging. Furthermore, while some contributions address political polarisation, they often do not distinguish between the distinct mechanisms through which campaign messages, partisan outlets, or microtargeted advertising might accentuate filter bubble effects.

From a policy perspective, the question is no longer whether filter bubbles exist in the abstract, but how platforms and regulators can detect, assess, and mitigate their relevance in electoral contexts. Under the EU Digital Services Act (DSA), Under the EU Digital Services Act (DSA), Very Large Online Platforms are required to assess and mitigate systemic risks, including those affecting civic discourse and electoral processes (European Parliament & Council of the European Union, 2022, Arts. 34–35). However, empirical research rarely translates filter bubble dynamics into measurable indicators capable of supporting regulatory risk assessment, platform audits or targeted mitigation, particularly for identifying vulnerable user profiles during election cycles. This creates a gap between regulatory obligations and the available empirical tools, which this study seeks to address by translating filter bubble dynamics into profile-sensitive indicators relevant for DSA-aligned audits and mitigation strategies.

Recent evidence indicates that social media platforms function as central arenas for political mobilisation and voter persuasion. However, the specific mechanisms through which algorithmic personalisation shapes citizens' perceptions of electoral candidates, policy proposals, and campaign rhetoric remain insufficiently examined (Ackland et al., 2019; Lin et al., 2023). There is also limited empirical evidence on how users' awareness of algorithmic curation processes influences their receptivity to political content. Scholars have highlighted an urgent need to investigate whether and how users' ideological leanings become reinforced in these digital spaces, and to what extent users might break out of these echoic loops during heated election cycles. Accordingly, this study develops and tests a concise, multidimensional indicator (Bubblemetrix) designed to capture key self-reported mechanisms through which personalised social media feeds may shape electoral

perceptions. Using pre-electoral survey data from Romanian Facebook users, the study identifies distinct user profiles that differ in algorithmic awareness, perceived source diversity, ideological homogeneity, and engagement-based reinforcement. These profiles are subsequently interpreted in terms of their relevance for platform governance and electoral risk mitigation.

Literature review

The filter bubble debate

The filter bubble concept is closely related to that of echo chambers, although the two phenomena have distinct emphases. Echo chambers generally concern voluntary self-segmentation, as users consciously follow like-minded communities and avoid contradictory sources (Bruns, 2019; Ferro-Santos et al., 2024). Filter bubbles, in contrast, highlight platform-driven curation mechanisms that elevate certain posts based on engagement metrics, gradually shaping user feeds around content reflective of prior interests (Jacobson et al., 2016; Mueller & Saeltzer, 2022). Research on these topics has produced inconclusive results: while some studies report minimal ideological clustering, others report significant fragmentation (Bruns, 2019; Kaiser & Rauchfleisch, 2020). This inconsistency reflects the complex interaction between technological infrastructures, user decisions, and contextual factors such as political campaigns and electoral cycles.

Key facets of personalisation dynamics

Although terminology varies, scholars generally agree on several key elements that contribute to filter bubble formation. Exposure to divergent opinions may occur but is often fleeting, as users tend to scroll past opposing views or interact primarily with ideologically aligned content (Rhodes, 2022; Valdez, 2020). Perceived source diversity can influence how individuals assess the breadth of their news feed; those who encounter only a limited number of recurring outlets may overestimate the uniformity of public opinion (Ackland et al., 2019; Bruns, 2019). Confirmation bias, reinforced by algorithms that prioritise highly engaging content, can intensify belief systems over time (Jacobson et al., 2016; Mueller & Saeltzer, 2022). Equally important is the extent to which users are aware of and react to algorithmic curation. If they remain unaware of how platform algorithms selectively prioritise certain posts, they may implicitly assume that their feed reflects all relevant information (Bechmann & Nielbo, 2018; Burbach et al., 2019). Over time, repeated interaction with a limited range of sources reinforces these patterns, thereby intensifying the filter bubble effect (Lopes et al., 2023; Puschmann, 2019). While

these mechanisms are well documented at a conceptual level, they are rarely operationalised in ways that allow regulators or platforms to identify varying degrees of exposure or vulnerability across user groups.

Political and Electoral Communication

A growing body of research indicates that these dynamics may have particularly far-reaching implications in political and electoral contexts. Campaigns increasingly depend on digital platforms for micro-targeting potential voters, while partisans and advocacy groups frequently employ emotive or provocative messaging to attract clicks and shares (Knobloch-Westerwick & Westerwick, 2023; Valdez, 2020). Despite its relevance, much of the existing filter bubble literature does not explicitly examine the extent to which algorithms intensify or mitigate exposure to political advertisements, candidate communication, or partisan framing during election cycles. Even fewer studies systematically examine whether users in filter bubbles are more likely to harden their political stances or whether incidental exposure to alternative viewpoints can moderate such tendencies (Lin et al., 2023). Questions remain about the extent to which awareness of curation empowers voters to seek out balanced information or, conversely, to remain within insular communities that reinforce pre-existing beliefs.

Furthermore, although some scholarship points to increased polarisation driven by algorithmic recommendations (Whittaker et al., 2021), a comprehensive understanding of how personalisation influences voter decision-making remains underdeveloped. Some scholars argue that the influence of any single platform should be understood within a broader media and social ecosystem. In fragmented communication environments, political attitudes are shaped through interactions between multiple media channels, social networks, and existing political predispositions (Bennett & Iyengar, 2008; Chadwick, 2013). Others contend that during high-stakes elections, filter bubbles may function as significant echoic silos for partisan communication, potentially reinforcing ideological extremism or producing a distorted perception of consensus (Terren & Borge, 2021; Zuiderveen Borgesius et al., 2016). From a policy perspective, this lack of empirical clarity hampers efforts to assess systemic electoral risks and to design proportionate mitigation measures under emerging regulatory frameworks.

Polarisation, misinformation, and electoral outcomes

Polarisation and misinformation remain central concerns in discussions of political filter bubbles. Scholars caution that once algorithmic systems detect strong en-

gagement with hyper-partisan or misleading content, they tend to reinforce such material within ideologically aligned networks, further marginalising fact-based perspectives (Rhodes, 2022; Valdez, 2020). There is a risk that groups embedded in these feedback loops may develop collective beliefs that resist correction, thereby distorting public discourse and potentially affecting electoral outcomes. Misinformation is not solely a consequence of filter bubbles; coordinated disinformation campaigns, sensationalist news coverage, and limited digital literacy also play a role in the spread of false narratives (Knobloch-Westerwick & Westerwick, 2023). Nevertheless, the iterative nature of personalisation can intensify the impact of partisan framing, conspiratorial messages, or other misleading content, particularly when algorithms prioritise virality during the heightened intensity of electoral campaigns. For policymakers, these dynamics raise concerns not only about content moderation, but also about cumulative exposure patterns that may remain invisible at the level of individual posts.

Mitigation strategies and research gaps

Proposed strategies to mitigate filter bubbles include algorithmic transparency, media literacy programmes, and diversity-by-design interventions aimed at exposing users to content beyond their typical preference spectrum (Dahlgren, 2021; Kaiser & Rauchfleisch, 2020; Whittaker et al., 2021). Although these approaches appear promising, existing research rarely assesses their effectiveness specifically within the context of political campaigns. The question remains whether platform-level reforms or user-level competencies can effectively disrupt siloed exposure during electoral periods, or whether well-resourced targeting efforts by political actors override such protective interventions (Burbach et al., 2019; Plettenberg et al., 2020). Existing studies frequently fall short of analysing the extent to which individuals' decisions to follow specific candidates or political news sources are shaped, or even determined, by algorithmically curated feeds.

Taken together, existing research highlights a persistent gap between theoretical accounts of filter bubbles and the needs of policy-oriented assessment. While studies document mechanisms such as confirmation bias, engagement-driven amplification, and perceived diversity, they rarely translate these insights into indicators that could support regulatory oversight, platform audits, or differentiated mitigation strategies during elections. As a result, current policy debates risk relying on abstract concepts or platform-level transparency measures that may overlook how filter bubble exposure varies across user groups.

Toward a broader perspective

Recent scholarship has increasingly adopted a more nuanced view of filter bubbles, emphasising the dynamic interaction between user agency, platform architecture, and socio-political context. This perspective aligns with recent syntheses showing that filter bubbles coexist with incidental exposure, user agency, and platform-specific affordances, producing heterogeneous patterns of informational narrowing rather than a single dominant effect (Tasențe, 2025). While filter bubbles pose clear risks, particularly when low awareness of algorithmic curation coincides with confirmation bias and engagement – driven reinforcement, they do not affect all users uniformly. Some individuals actively seek out diverse information sources and may partially counter algorithmic narrowing, whereas others remain more susceptible, especially in politically charged environments characterised by microtargeting and emotive campaigning (Dubois & Blank, 2018; Lopes et al., 2023). This heterogeneity underscores the need for empirical approaches capable of distinguishing structurally different forms of filter bubble exposure in electoral contexts, a task the present study seeks to address.

The present study

From a policy-oriented perspective, this study examines how key mechanisms associated with filter bubble exposure operate in electoral contexts and how they differentiate levels of user vulnerability to algorithmic personalisation. Rather than treating filter bubbles as a uniform phenomenon, the study focuses on identifying structurally distinct patterns of exposure with direct relevance for electoral risk assessment and platform governance.

To this end, we employ a concise, multidimensional indicator, Bubblemetrix, capturing users' self-reported awareness of algorithmic curation, perceived source diversity, ideological homogeneity, and engagement-based reinforcement. Using pre-electoral survey data from Romanian Facebook users, we identify distinct user profiles that differ systematically across these dimensions as well as across relevant socio-demographic characteristics.

The study addresses two guiding research questions: **(RQ1)** *How do different configurations of perceived algorithmic exposure cluster within the voting population during the electoral period?* and **(RQ2)** *What types of user profiles emerge that can be regarded as more or less vulnerable to engagement-driven ideological reinforcement?* By answering these questions, the study aims to contribute empirically grounded insights that can inform platform-level mitigation strategies and regulatory discus-

sions concerning electoral integrity.

Method

The study followed established best-practice guidelines for web-based surveys such as CHERRIES (Eysenbach, 2004) to ensure transparency and methodological rigour.

Design. Data were collected between 15 March and 21 April 2025 via an online survey distributed among the target population. A convenience sampling strategy was employed, and the study adopted a cross-sectional design, which does not allow causal inference. The analysis focuses on identifying patterns of association and user profiles relevant to electoral contexts.

Informed consent process. Participation was voluntary and based on informed consent. Respondents were informed that they could withdraw at any time and that all responses were anonymous and confidential. The study complied with the ethical standards of the authors' institution and the principles of the Declaration of Helsinki. No personally identifiable information was collected.

Development and pre-testing. The questionnaire was pre-tested with a pilot group of 54 participants to assess clarity and relevance. Based on feedback, several items were refined before the final data collection phase.

Recruitment process. Participants were recruited through online dissemination using a combination of targeted outreach and snowball sampling. The survey link was shared via social media platforms and direct online communication channels. Participation was voluntary, anonymous, and uncompensated.

Survey administration. The survey consisted of 40 items and required approximately five to seven minutes to complete. No incentives were provided for participation.

Response rates. The survey was accessed by 6,625 individuals, of whom 451 completed the questionnaire in full, resulting in a completion rate of 6.80%. While this rate reflects typical engagement patterns for online political surveys, it also indicates potential self-selection effects, which should be considered when interpreting the findings.

Preventing multiple entries. To prevent duplicate responses, the survey platform restricted submissions to one entry per IP address. No multiple entries were de-

tected in the final data set.

Participants and procedure

Data were collected online from 451 Romanian participants aged between 18 and 71 years ($M = 32.70$, $SD = 13.60$), of whom 67.63% were women. In terms of educational attainment, most participants had a bachelor's degree (38.80%), a high school diploma (33.48%), or a master's degree (20.844%), while in occupational terms, the sample included students (2.22%), civil servants (20.62%), or other professionals (12.86%). Most respondents were from metropolitan areas (56.76%) and rural areas (25.28%), followed by smaller cities (17.96%). Regarding Facebook account duration, most had been active for more than 10 years (54.32%) or between 6 and 9 years (29.71%). In terms of daily online activity, 32.37% spent between 1 and 2 hours online, and 29.71% between 3 and 4 hours. A further 17.29% spent less than an hour online each day, whereas 11.755% reported spending more than 6 hours online. Concerning political orientation, 30.60% of participants identified as sovereigntist, while 55.21% identified as pro-Western

Measures

To evaluate the **Bubblemetrix Index**, a multidimensional instrument was constructed and pre-tested, with the initial version including five factors: "Echo Chamber Exposure", "Algorithmic Curation Awareness", "Source Diversity Perception", "Ideological Homogeneity & Confirmation Bias", and "Repetitive Interaction & Engagement". As preliminary data indicated a lack of consistency in the "Echo Chamber Exposure" factor, and the removal of certain items did not yield acceptable reliability, this factor was excluded from the instrument. The final instrument demonstrated good pre-test metric properties. The final version comprises the following scales:

Algorithmic Curation Awareness consists of eight items, such as "My choice to give 'Like' influences what I see next" and "Facebook shows me content from the same sources because that's what the algorithm prefers." Participants rated their responses on a 5-point Likert-type scale, where 1 indicated "Not true at all" and 5 indicated "Completely true." The scale demonstrated good internal consistency in our data ($\alpha=0.77$, 95% CI [0.73, 0.8]).

Source Diversity Perception. Participants responded to a total of eight items on a 5-point Likert-type scale (1 = "Not true at all", 5 = "Completely true"), including statements such as "I also get my information from outside Facebook (radio, print,

podcasts)” and “The content I receive on Facebook is dominated by 2–3 sources.”

The scale demonstrated good measurement reliability in our data ($\alpha=0.75$, 95% CI [0.71, 0.78]).

Ideological Homogeneity & Confirmation Bias. This scale comprised eight items, such as “I feel that opinions in the feed reinforce my existing beliefs” or “I prefer to interact with posts that don’t make me uncomfortable” were used to assess this factor. Participants rated their responses on a 5-point Likert-type scale ranging from 1 = “Not true at all” to 5 = “Completely true.” The data showed good reliability ($\alpha=0.8$, 95% CI [0.77, 0.82]).

Repetitive Interaction & Engagement comprised eight items, such as “I rarely interact with content that doesn’t get many reactions (likes, shares)” or “If a post gets no reactions, I delete or hide it.” Participants responded using a 5-point Likert-type scale ranging from 1 (Not true at all) to 5 (Completely true). The data demonstrated excellent measurement reliability ($\alpha=0.83$, 95% CI [0.81, 0.86]).

Overview of statistical analysis

Internal consistency for all factors was assessed using Cronbach’s α index (Cronbach, 1951), a widely accepted measure of reliability. Since a multifactorial instrument was used, a total score may be computed if a general latent factor is present and influences the other factors. This general factor serves to account for the common variance among the different components. To further assess the internal consistency of the total score, omega was estimated by means of conducting a factor analysis on the original data set. The factors were rotated obliquely to allow for correlations between them, and a Schmid–Leiman transformation was applied, as recommended by McDonald Revelle & Condon (2019). This transformation allowed the separation of the general and group factors, offering a more detailed understanding of the instrument’s internal structure. The total omega coefficient was used to assess the internal consistency of the total score, reflecting the proportion of variance explained by both general and group factors. This coefficient provides a comprehensive measure of the total score’s reliability, accounting for the inter-correlation among factors.

In addition to the total omega coefficient, the proportion of variance in the group explained solely by the general factor was evaluated using the omega coefficient general (hierarchical). This coefficient offers insight into the extent to which the general factor contributes to the variance in the group factors, allowing for a more

nuanced understanding of the relationships between the factors. To further validate the instrument's internal structure, a confirmatory factor analysis (CFA) was performed using the diagonally weighted least squares (DWLS) estimation method, assuming correlated factors (DiStefano & Morgan, 2014). This approach made it possible to test the feasibility of modelling a latent trait within a multidimensional instrument, offering a more accurate representation of its underlying structure. The results of the CFA supported the use of a latent trait for the multifactorial instrument, indicating that the general factor contributed significantly to the variance within the group factors. These findings suggest that the instrument possesses a robust internal structure, with a general factor accounting for a substantial proportion of the variance in the group factors.

We first examined the data for outliers and missing values and conducted univariate descriptive analyses. This involved evaluating compliance with the univariate normality assumption for continuous data using the Shapiro-Wilk statistical test (J. P. Royston, 1982; P. Royston, 1995) and examining skewness and kurtosis indicators. Outliers were re-coded as missing values if they exceeded three standard deviations from the mean. To assess multivariate normality, we used Mardia's test (Mardia, 1970) under the null hypothesis that the variables follow a multivariate normal distribution. Additionally, a correlation matrix was computed and described for the dependent, independent, and mediator variables.

We also estimated a latent profile based on a finite-mixture model with free variances and covariances (class-varying unrestricted parameterisation) that incorporated the four components of the Bubblemetrix Index, taking age into account as a relevant factor (Fraley & Raftery, 2002; Fraley & Raftery, 2007; J. Rosenberg et al., 2018). A latent class analysis was also conducted to examine the categorical variables of biological gender, education level, place of residence, time spent online, and duration of Facebook account ownership. This analysis employed an independent mixture model that used the multinomial distribution family and was initialised with equal prior probabilities for each class (McCutcheon, 2002). The latent profile analysis involved running a number of four profiles (from 2 class profiles to 5 class profiles) and evaluating the most appropriate profile based on two indicators: BIC (Bayesian information criterion, based on -2 log-likelihood, and penalised by number of parameters adjusted by sample size) and AWE (Approximate weight of evidence that combines information on model fit and on classification errors). The latent class analysis performed three distinct models, one corresponding to the number of classes identified in the latent profile analysis and two additional marginal classes. The selection of the optimal number of classes was in-

formed by the Bayesian information criterion (BIC) and the Akaike information criterion (AIC), both of which are based on the -2 log-likelihood value and penalized by the number of parameters adjusted for sample size. The most efficient model will be chosen based on the criteria outlined by Akogul and Erisoglu (2017).

Results

Preliminary descriptive analysis

An outlier analysis was conducted, and no univariate extreme scores were identified. Low scores of 8 and 12 were noted for “algorithmic curation awareness”, scores of 8, 11, 15, and 16 were observed for “source diversity perception”, and scores of 8, 11, 14, 15, and 16 were found for “ideological homogeneity & confirmation bias”.

TABLE 1: Descriptive statistics and univariate normality assessment

Variables	N	Mean	SD	Median	Min	Max	Skew (SE)	Kurt (SE)	Shapiro (p)
Algorithmic Curation Awareness	451	30.92	5.66	31	8	40	-0.33 (0.12)	-0.04 (0.23)	0.97 (<.001)
Source Diversity Perception	451	30.6	5.48	31	8	40	-0.42 (0.12)	0.36 (0.23)	0.98 (<.001)
Ideological Homogeneity	451	28.68	6.13	28	8	40	-0.23 (0.12)	0.31 (0.23)	0.98 (<.001)
Repetitive Interaction & Engagement	451	23	7.54	23	8	40	0.36 (0.12)	-0.26 (0.23)	0.98 (<.001)

Our analysis indicated that the assumption of univariate normality was violated in our data. The scores for “algorithmic curation awareness” and “source diversity perception” were negatively skewed, whereas “repetitive interaction and engagement” showed a positive skew. All variables exhibited mesokurtic characteristics (see Tab. 1). The assumption of multivariate normality was not met due to the Mahalanobis distances ranging between 0.24 and 4.88, and this was also suggested by the Mardia coefficient (Mardia, 1970). Significant positive multivariate skewness (Mardia=2.07, Skewness=155.39, $p<.001$) and multivariate mesokurtosis (Mardia=25.12, Skewness=1.72, $p=.085$) were also observed.

Correlation analysis

The Spearman's ρ correlations were found to be positive and statistically significant, with coefficients ranging from .17 to .50, as shown in Table 2, and the correlation matrix displayed positive definiteness.

TABLE 2: Spearman correlation matrix (Cronbach's alpha on main diagonal)

	1	2	3	4
(1) Algorithmic Curation Awareness	.77			
(2) Source Diversity Perception	.50***	.75		
(3) Ideological Homogeneity & Confirmation Bias	.38***	.29***	.80	
(4) Repetitive Interaction & Engagement	.19***	.17***	.47***	.83
Means	30.92	30.6	28.68	23
Standard deviations	5.66	5.48	6.13	7.54
*** p<.001; ** p<.01; * p<.05; ^ p<.10				

Algorithmic curation awareness was *positively* associated with source diversity perception ($\rho=.50$, $p<.001$), ideological homogeneity & confirmation bias ($\rho=.38$, $p<.001$), and repetitive interaction & engagement ($\rho=.19$, $p<.001$). **Source diversity perception** was *positively* associated with ideological homogeneity & confirmation bias ($\rho=.29$, $p<.001$), and repetitive interaction & engagement ($\rho=.17$, $p<.001$), and **Ideological homogeneity & confirmation bias** was *positively* associated with repetitive interaction & engagement ($\rho=.47$, $p<.001$).

Model analysis

Latent profile analysis. Four models were assessed, ranging from a 2- to 5-class classification model. Comparative analysis revealed that a 3-class classification model was deemed most efficient according to the Bayesian Information Criterion (BIC), whereas a 2-class classification model was preferred based on the Akaike Weighted Evidence (AWE). The latent profile model was selected for retention based on Akogul's criteria (Akogul & Erisoglu, 2017), resulting in the classification of three distinct classes.

The three-class model yielded the most favourable fit indicators (LogLik=-2,606.03, AIC=5,336.07, AWE=6,154.06, BIC=5,590.98, CAIC=5,652.98, CLC=5,213.90,

KIC=5,401.07, SABIC=5,394.21, and ICL=-5,621.49), as well as an entropy index (Entropy=0.92), suggesting an adequate classification within the three classes. The proposed model achieved an accuracy of approximately 91.60% and a probability ranging from 95.80% to 100%. The smallest class is estimated to comprise approximately 7.30% of participants, while the largest class is expected to include approximately 51.90% of participants. In addition, the bootstrapped likelihood test revealed a statistically significant difference between the three classes (likelihood test=203.30, $p<.001$; see Tab. 3 and Fig. 1).

Classes	LogLik	AIC	AWE	BIC	CAIC	CLC	KIC	SABIC	ICL	Entropy	Prob Min	Prob Max	N% min	N% max	Likelihood test	p
3	-2606.03	5336.07	6154.06	5590.98	5652.98	5213.9	5401.07	5394.21	-5621.49	0.92	0.96	1	0.07	0.52	203.29	<.001

TABLE 3: Latent profile with 3 latent classes based on age and bubblemetrix factors - Fit indices

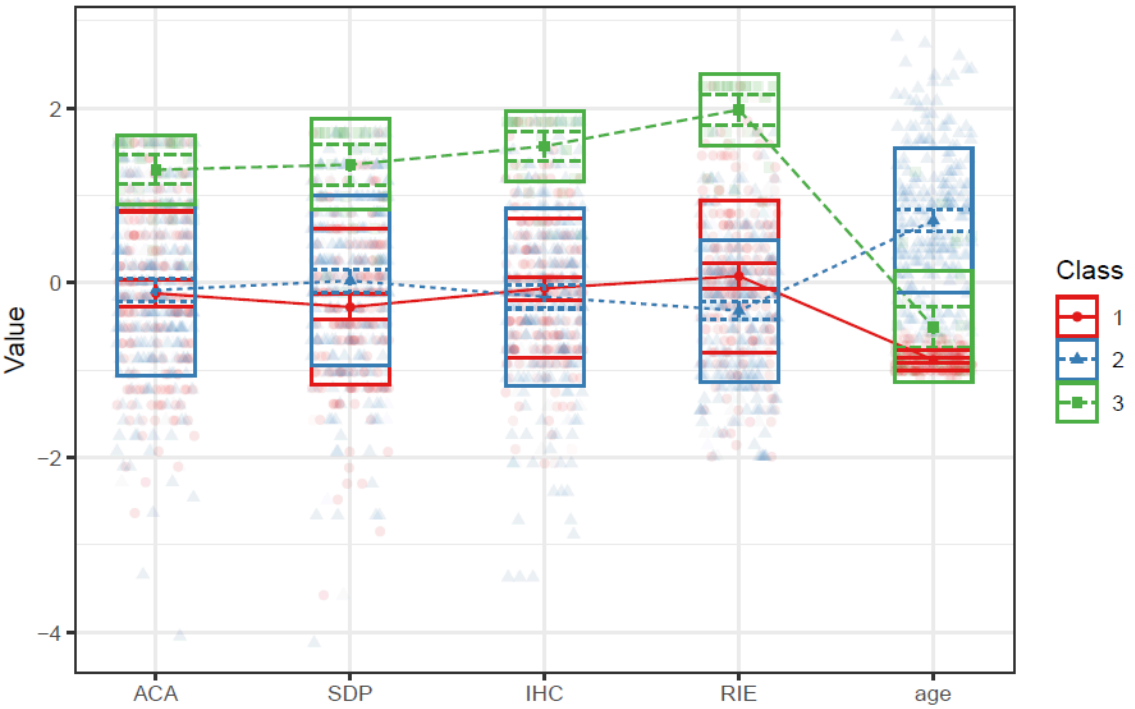


FIGURE 1: Latent profile with 3 latent classes based on age and bubblemetrix factors

The first latent class, as presented in table 4, was distinguished by the fact that the means of the scores for the four Bubblemetrix factors did not differ statistically significantly from zero. However, this class comprises younger individuals ($z=-0.88$, $SE=0.01$, $p<.001$), whose variability in scores was statistically significantly different from zero. Our analysis of the first class revealed that awareness of algorithmic curation was significantly correlated with perceptions of source diversity ($z=0.45$, $SE=0.09$, $p<.001$), and with ideological homogeneity and confirmation bias

($z=0.34$, $SE=0.08$, $p<.001$). Conversely, it was not correlated with repetitive interaction, engagement ($z=0.06$, $SE=0.08$, $p=.39$), or age ($z=0.45$, $SE=0.09$, $p<.001$). Furthermore, perceptions of source diversity were statistically significantly related to ideological homogeneity and confirmation bias ($z=0.34$, $SE=0.07$, $p<.001$), but not to repetitive interaction and engagement ($z=0.12$, $SE=0.08$, $p=.159$) or age ($z=0$, $SE=0.01$, $p=.966$). Additionally, ideological homogeneity and confirmation bias were significantly correlated with repetitive interaction and engagement ($z=0.26$, $SE=0.06$, $p<.001$), but not age ($z=-0.02$, $SE=0.01$, $p=.006$). Finally, repetitive interaction and engagement were not associated with age ($z=0.00$, $SE=0.01$, $p=.522$).

TABLE 4: Latent profile parameter estimation for the first class

Category	Parameter	Estimates (z)	SE	p	Class
Covariances	ACA ~~ SDP	0.45	0.09	<.001	1
Covariances	ACA ~~ IHC	0.34	0.08	<.001	1
Covariances	ACA ~~ RIE	0.06	0.07	=.390	1
Covariances	ACA ~~ age	0.01	0.01	=.490	1
Covariances	SDP ~~ IHC	0.34	0.07	<.001	1
Covariances	SDP ~~ RIE	0.12	0.09	=.159	1
Covariances	SDP ~~ age	0.00	0.01	=.966	1
Covariances	IHC ~~ RIE	0.26	0.06	<.001	1
Covariances	IHC ~~ age	-0.02	0.01	=.006	1
Covariances	RIE ~~ age	0.00	0.01	=.522	1
Means	ACA	-0.12	0.08	=.117	1
Means	SDP	-0.28	0.07	<.001	1
Means	IHC	-0.06	0.07	=.353	1
Means	RIE	0.08	0.07	=.299	1
Means	age	-0.88	0.01	<.001	1
Variances	ACA	0.88	0.08	<.001	1
Variances	SDP	0.80	0.10	<.001	1
Variances	IHC	0.64	0.07	<.001	1
Variances	RIE	0.76	0.08	<.001	1
Variances	age	0.01	0.00	< 0.001	1

The second latent class was characterised by older individuals ($z=0.71$, $SE=0.06$, $p<.001$) who exhibited statistically significantly low mean scores for ideological homogeneity and confirmation bias ($z=-0.16$, $SE=0.07$, $p=.019$) as well as repetitive interaction and engagement ($z=-0.32$, $SE=0.05$, $p<.001$). The mean scores of the remaining two Bubblemetrix factors did not differ significantly from zero (See Tab. 5). The variability of scores was statistically significantly different from zero for all features. The analysis of covariances revealed that algorithmic curation awareness was statistically significantly associated with source diversity perception ($z=0.43$, $SE=0.10$, $p<.001$) and ideological homogeneity and confirmation bias ($z=0.23$, $SE=0.09$, $p=.012$), but not with repetitive interaction and engagement ($z=0.10$, $SE=0.06$, $p=.135$), or age ($z=-0.06$, $SE=0.06$, $p=.278$). Furthermore, source diversity perception was not associated with any of the variables examined. Ideological homogeneity and confirmation bias were associated with repetitive interaction and engagement ($z=0.37$, $SE=0.07$, $p<.001$), but not with age ($z=0.10$, $SE=0.06$, $p=.105$). Additionally, age did not show significant covariance with repetitive interaction and engagement ($z=0.04$, $SE=0.05$, $p=.493$).

TABLE 5: Latent profile parameter estimation for the second class

Category	Parameter	Estimates (z)	SE	p	Class
Covariances	ACA ~ SDP	0.43	0.10	<.001	2
Covariances	ACA ~ IHC	0.23	0.09	=.012	2
Covariances	ACA ~ RIE	0.10	0.06	=.135	2
Covariances	ACA ~ age	-0.06	0.06	=.278	2
Covariances	SDP ~ IHC	0.06	0.09	=.449	2
Covariances	SDP ~ RIE	0.03	0.06	=.565	2
Covariances	SDP ~ age	-0.02	0.05	=.713	2
Covariances	IHC ~ RIE	0.37	0.07	<.001	2
Covariances	IHC ~ age	0.10	0.06	=.105	2
Covariances	RIE ~ age	0.04	0.05	=.493	2
Means	ACA	-0.08	0.07	=.214	2
Means	SDP	0.03	0.07	=.704	2
Means	IHC	-0.16	0.07	=.019	2
Means	RIE	-0.32	0.05	<.001	2
Means	age	0.71	0.06	<.001	2

Variances	ACA	0.96	0.10	<.001	2
Variances	SDP	0.94	0.11	<.001	2
Variances	IHC	1.02	0.11	<.001	2
Variances	RIE	0.66	0.05	<.001	2
Variances	age	0.68	0.06	<.001	2

The final latent class was characterised by participants who were relatively young, with significantly higher mean scores across all Bubblemetrix factors (See Tab. 6). The data revealed reduced variability, with source diversity perception scores exhibiting relatively low variance ($z=0.27$, $SE=0.11$, $p=.014$). Significant covariances were observed between algorithmic curation awareness and source diversity perception ($z=0.17$, $SE=0.08$, $p=.033$) and between algorithmic curation awareness and ideological homogeneity and confirmation bias ($z=0.17$, $SE=0.08$, $p=.033$).

TABLE 6: Latent profile parameter estimation for the third class

Category	Parameter	Estimates (z)	SE	p	Class
Covariances	ACA ~~ SDP	0.17	0.08	=.033	3
Covariances	ACA ~~ IHC	0.13	0.06	=.024	3
Covariances	ACA ~~ RIE	0.10	0.06	=.069	3
Covariances	ACA ~~ age	0.03	0.04	=.402	3
Covariances	SDP ~~ IHC	0.20	0.08	=.011	3
Covariances	SDP ~~ RIE	0.18	0.08	=.020	3
Covariances	SDP ~~ age	0.04	0.04	=.266	3
Covariances	IHC ~~ RIE	0.14	0.06	=.018	3
Covariances	IHC ~~ age	0.04	0.03	=.265	3
Covariances	RIE ~~ age	-0.03	0.03	=.398	3
Means	ACA	1.29	0.09	<.001	3
Means	SDP	1.35	0.12	<.001	3
Means	IHC	1.56	0.09	<.001	3
Means	RIE	1.98	0.09	<.001	3
Means	age	-0.50	0.12	<.001	3
Variances	ACA	0.16	0.06	=.005	3

Variances	SDP	0.27	0.11	=.014	3
Variances	IHC	0.16	0.06	=.006	3
Variances	RIE	0.17	0.06	=.006	3
Variances	age	0.41	0.12	=.001	3

Latent class analysis. Three latent class models were initially examined, following the latent profile analysis. The performance of a 2 latent class model yielded an Akaike information criterion (AIC) of 4025.092 and a Bayesian information criterion (BIC) of 4169.083, while a 3 latent class model yielded an AIC of 4035.729 and a BIC of 4253.661. Furthermore, a 4 latent class model obtained an AIC of 4054.257 and BIC of 4346.13. The analysis suggested that the 2 latent class model was the most suitable classification model, and the two latent class model converged after 160 iterations (logLik=-1972.008, df=37, AIC=4018.015, BIC=4162.006; see Tab. 7).

TABLE 7: Latent class probability estimation for the two-class model

	Class 2	Class 1
Female	.93	.53
Male	.07	.47
Others	.00	.04
Primary	.00	.01
Gymnasium	.00	.01
High school or craft school	.64	.16
Bachelor	.36	.41
Master	.00	.33
PhD	.00	.05
Rural	.30	.22
Small city	.18	.18
Metropolis	.52	.60
Least than 1 hour	.09	.22
Between 1 and 2 hours	.22	.38
Between 3 and 4 hours	.37	.25
Between 5 and 5 hours	.12	.07

Over 6 hours	.19	.07
Not using Facebook	.06	.02
Least than 1 year	.01	.02
Between 1 and 2 years	.05	.01
Between 3 and 5 years	.16	.04
Between 6 and 9 years	.46	.20
10 years or more	.26	.71

By *gender*, the **first latent class** was characterised by a higher probability of containing females (52.80%), and the **second latent class** had a relatively equal probability of including females and males (female=92.90%, male=7.10%; see Fig. 2).

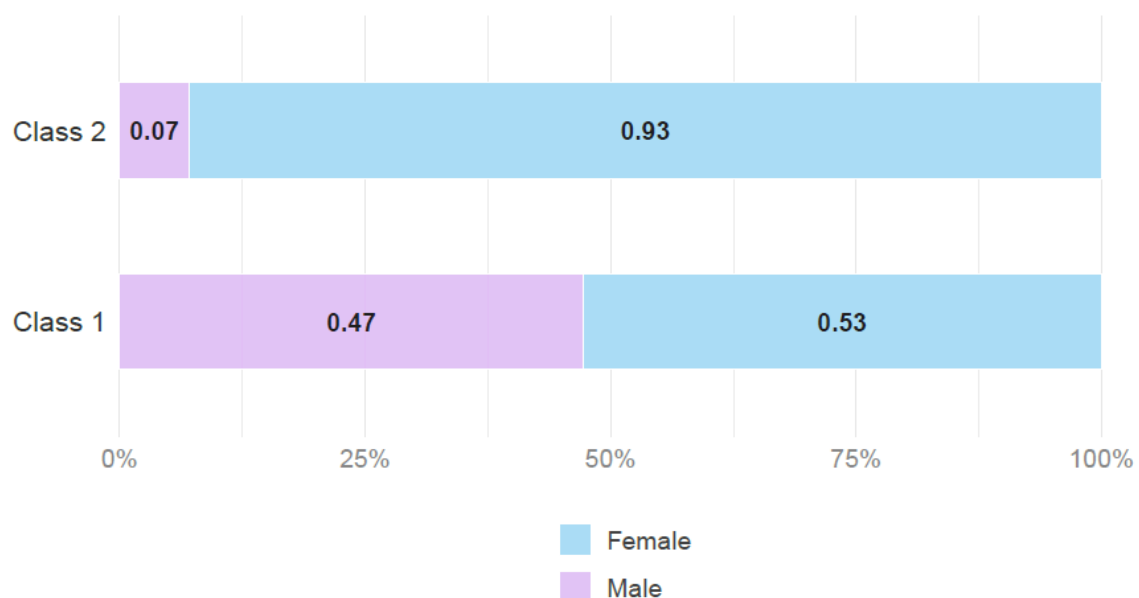


FIGURE 2: Latent probability classification in 2 classes based on gender

The **first latent class** predominantly comprised individuals with high school or craft school qualifications (15.50%) and bachelor's degrees (40.70%), based on *educational attainment*. In contrast, the **second latent class** primarily consisted of individuals with bachelor's degrees (35.50%) and no participants holding a master's degree (0%), alongside a smaller probability of high school or craft school qualifications. (64.30%; see Fig. 3).

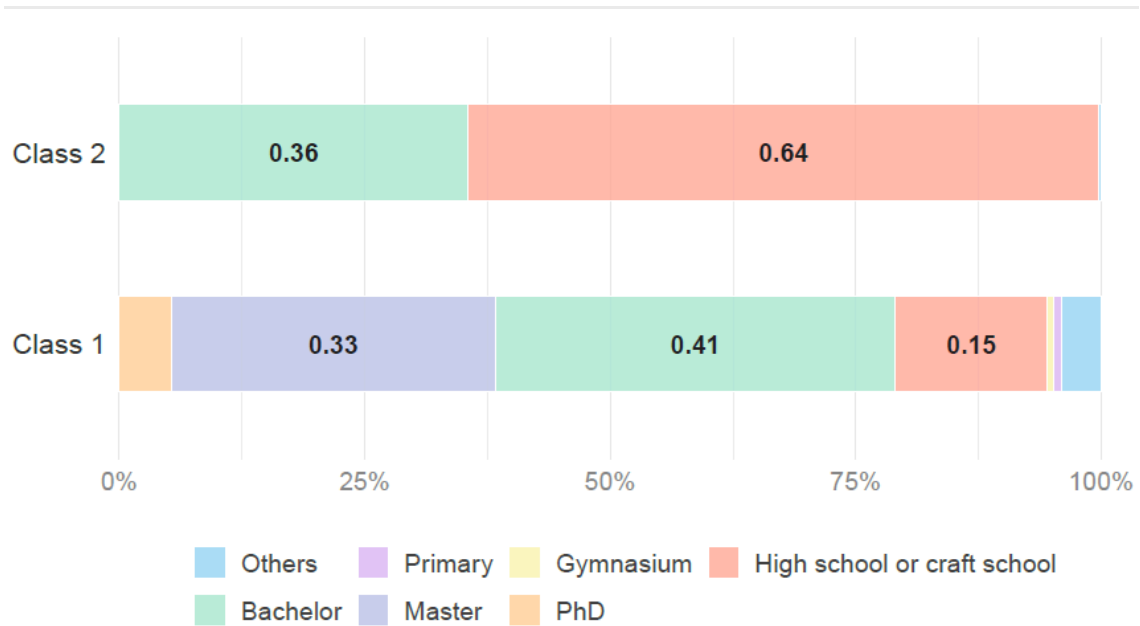


FIGURE 3: Latent probability classification in 2 classes based on education

Place of residence differentiated the two classes in terms of the dominant probability of inclusion of metropolitan participants, which was lower in the **first latent class** (59.90%) than in the **second latent class** (51.50%). The analysis also revealed that the **first latent class** exhibited a significantly higher probability of representation among rural populations (22.40%).

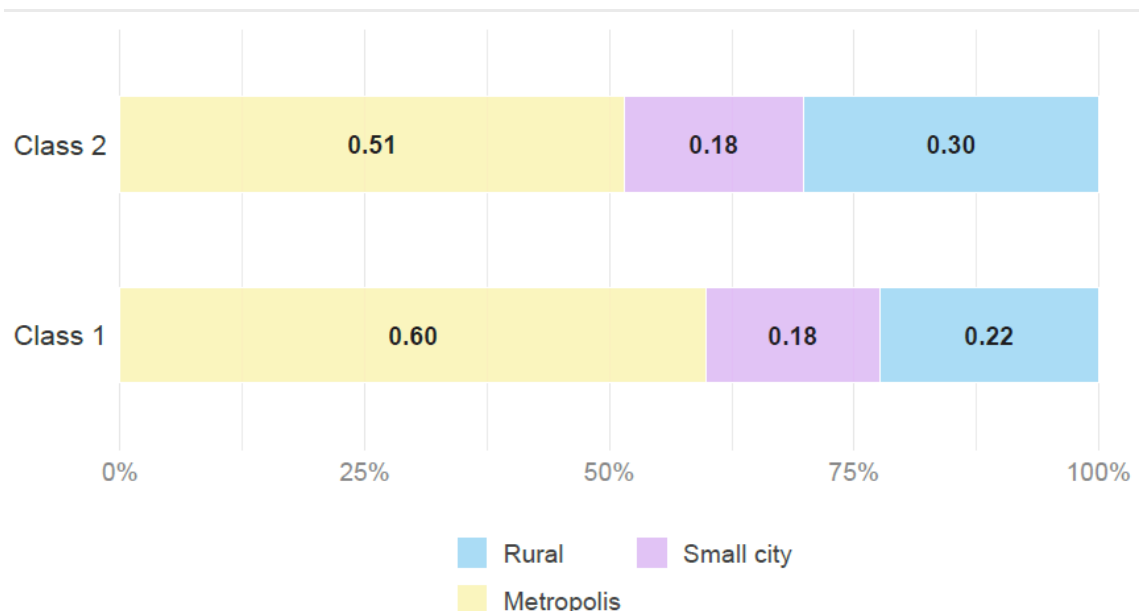


FIGURE 4: Latent probability classification in 2 classes based on residence

The **first latent class** is likely composed of individuals who spent between three and four hours online (25.30%), whereas the **second latent class** is likely composed

of individuals who spent between one and two hours online (22.40%). Notably (see Fig. 5), individuals who spent extensive periods online were predominantly classified in the **first latent class**, with 7.40% exceeding six hours and 7.20% spending between five and six hours, in contrast to the **second latent class**, where only 19.10% and 11.80% fell into these categories.

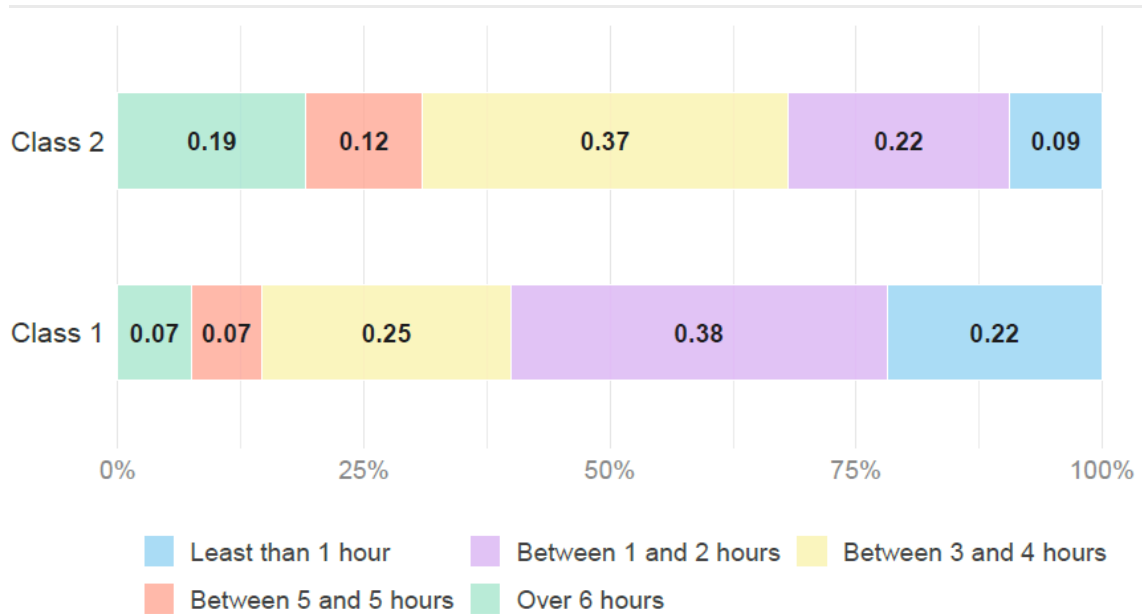


FIGURE 5: Latent probability classification in 2 classes based on time spent online

Finally, people who have had a Facebook account for more than 10 years were more likely to be included in the **second latent class** (26.20%), while the **second latent class** was characterised by a higher probability of inclusion of people who have a Facebook account between six and nine years (19.90%).

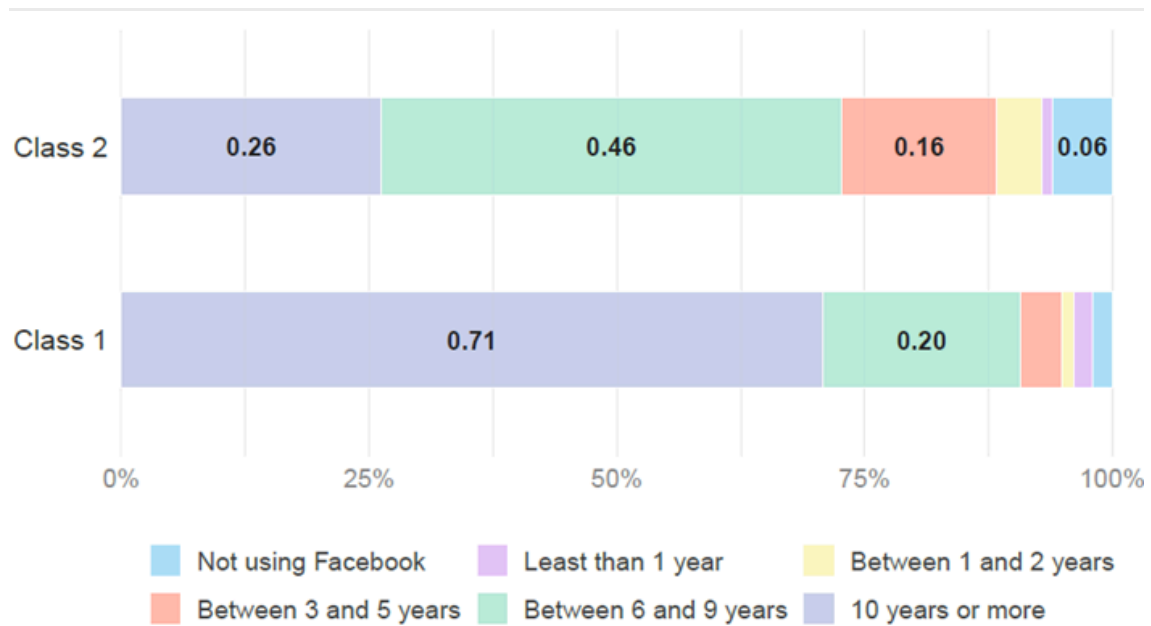


FIGURE 6: Latent probability classification in 2 classes based on the age of the Facebook account

Discussion

This study contributes to ongoing debates on algorithmic personalisation and democratic governance by demonstrating that filter bubble effects are neither uniformly distributed nor primarily attributable to users' lack of awareness. Instead, the findings indicate that filter bubbles are structured phenomena that emerge from the interaction between platform architectures, engagement-oriented algorithms, and differentiated user profiles. By identifying distinct configurations of algorithmic curation awareness, perceived source diversity, ideological homogeneity, and interaction intensity, the study moves beyond binary discussions about the existence of filter bubbles and offers a more nuanced account of how they operate in electoral contexts (Bruns, 2019; Dubois & Blank, 2018; Kaiser & Rauchfleisch, 2020).

A central theoretical implication of the results is that user agency alone cannot account for the observed patterns of ideological reinforcement on social media platforms. While prior research has variously emphasised users' capacity to seek diverse information or the constraining role of algorithmic curation, the present findings suggest that these dimensions are closely intertwined. Users with high levels of algorithmic awareness, that is, those who explicitly recognise personalisation mechanisms, are not necessarily less vulnerable to ideological encapsulation. On the contrary, one of the most prominent user profiles identified in this study combines strong algorithmic awareness with elevated confirmation bias and repetitive

engagement. This counterintuitive pattern challenges optimistic assumptions underlying media literacy-based approaches to mitigating polarisation and calls into question policy strategies that prioritize user education as a standalone solution (Bechmann & Nielbo, 2018; Dubois & Blank, 2018).

The identification of multiple user profiles further highlights the heterogeneity of algorithmic experiences. The results indicate that younger users with higher engagement levels are more likely to exhibit reinforced ideological exposure, whereas older users tend to show lower levels of engagement-driven amplification and confirmation bias. These findings support earlier claims that age and platform experience may moderate filter bubble effects (Lopes et al., 2023; Puschmann, 2019), while extending this literature by demonstrating that such moderation operates through specific psychological and behavioural configurations. Importantly, this heterogeneity suggests that generalised mitigation strategies are unlikely to be effective. Instead, policy interventions should account for differentiated patterns of vulnerability rather than assuming a uniform impact of algorithmic personalisation across user populations.

Another key finding concerns the role of perceived source diversity. Exposure to multiple information sources is frequently assumed to function as an antidote to filter bubbles; however, the present results challenge this assumption. Although users reported encountering content from a range of sources, this perceived diversity did not attenuate ideological homogeneity or repetitive engagement. This finding aligns with arguments that platforms can create an illusion of diversity while continuing to privilege ideologically consistent and highly engaging content (Bruns, 2019; Kaiser & Rauchfleisch, 2020). From a governance perspective, this insight is critical: regulatory approaches that focus on increasing nominal source diversity without addressing algorithmic ranking and amplification mechanisms may have limited impact on democratic deliberation.

Taken together, the findings suggest that filter bubbles should be conceptualised as systemic rather than individual-level phenomena. The persistence of ideological reinforcement among users who are both aware of algorithmic personalisation and exposed to diverse sources indicates that structural features of platform design play a decisive role. Engagement-based ranking systems, feedback loops driven by likes and shares, and the prioritisation of emotionally resonant content collectively contribute to the stabilisation of ideological patterns. These mechanisms operate largely independently of users' reflective intentions and cannot be effectively countered through transparency measures alone (Burbach et al., 2019).

From a policy perspective, these results have direct implications for contemporary platform governance frameworks, particularly within the European Union. Current regulatory approaches within the European Union emphasise transparency and user information as primary mechanisms for addressing online harms. For example, the Digital Services Act (DSA) requires online platforms to disclose the main parameters of their recommender systems and to provide users with at least one option that is not based on profiling (European Parliament & Council of the European Union, 2022, Art. 27). It also mandates transparency in online advertising, including clear identification of the advertiser and the principal targeting criteria used (Art. 26). Moreover, Very Large Online Platforms are required to assess and mitigate systemic risks stemming from the design and functioning of their services, including risks affecting civic discourse and electoral processes (Arts. 34–35; see also Recital 84). These regulatory interventions are premised on the assumption that greater transparency and user awareness enable individuals to make more diversified informational choices. However, the present findings suggest that this assumption may be overly optimistic. If users who understand algorithmic curation remain embedded in self-reinforcing informational environments, transparency-focused measures alone may not suffice to mitigate systemic risks related to political polarisation.

The findings therefore point to a structural gap in existing governance strategies, which tend to privilege disclosure and individual responsibility over architectural intervention. Risk mitigation efforts must move beyond documenting how algorithms function and address how they shape political discourse, especially during electoral periods. As prior research has warned, algorithmic amplification of emotionally charged or partisan content can distort perceptions of public consensus, intensify affective polarisation, and marginalise deliberative forms of engagement (Terren & Borge, 2021; Zuiderveen Borgeius et al., 2016).

Policy implications for DSA governance and VLOP mitigation. Our findings speak directly to the DSA's systemic-risk logic by indicating that electoral risks linked to recommender systems are not evenly distributed but are instead concentrated in identifiable user configurations combining high engagement with perceived ideological reinforcement. For regulators, this implies that platform risk assessments should move beyond content-level prevalence metrics and incorporate exposure-pattern indicators capable of capturing reinforcement loops and concentration dynamics during election periods. Bubblemetrix can function as a scalable, survey-based “risk-sensing” layer that helps segment populations into profiles and identify where mitigation is most needed (e.g., highly engaged younger users reporting

high homogeneity and confirmation bias despite high awareness).

For platforms, these profiles suggest that mitigation cannot rely solely on transparency or media literacy, and that content-based interventions (e.g., downranking borderline content) should be complemented by structural measures targeting engagement-driven amplification. In practice, this could mean implementing friction and diversification mechanisms for political content recommendation during electoral periods (e.g., reducing repetitive source concentration, limiting rapid amplification for highly emotive political posts, and deploying cross-cutting exposure prompts that are not contingent on prior engagement). Importantly, mitigation should be evaluated using profile-sensitive metrics: if the most reinforcement-prone group remains unchanged after downranking, the intervention is likely insufficient at the systemic level. We therefore recommend that DSA-aligned audits assess not only whether borderline content is demoted, but also whether recommendation and ranking changes measurably reduce reinforcement loops and perceived ideological encapsulation in high-risk user segments.

Design-based interventions represent a key implication of this study. Rather than assuming that informed users will self-correct their exposure patterns, platforms could deploy mechanisms that actively disrupt repetitive engagement dynamics. Such measures may include friction-based design choices, diversification mechanisms that operate independently of prior engagement, or limits on the amplification of highly emotive political content during election cycles. These approaches do not require traditional content moderation but instead target the structural conditions that sustain filter bubbles (Whittaker et al., 2021).

The results also suggest that platform responsibility should be calibrated to user profiles. Highly engaged users exhibiting strong ideological reinforcement may require more robust structural safeguards than low-engagement users who already display comparatively higher resilience to algorithmic narrowing. This observation raises broader questions about proportionality and personalisation in platform governance: if platforms personalise content delivery, governance mechanisms may likewise need to adopt differentiated risk mitigation strategies.

Methodologically, the study demonstrates the value of integrating psychometric measurement with person-centred analytical approaches in policy-relevant research. The Bubblemetrix framework offers a structured means of operationalising abstract dimensions such as algorithmic awareness and ideological homogeneity, while latent profiling reveals how these dimensions interact within real user populations. This approach provides a replicable model for future research seeking to

bridge the gap between computational analyses of platform dynamics and normative debates on democratic governance.

Several limitations should be acknowledged. The reliance on self-reported data introduces potential discrepancies between perceived and actual exposure, and the focus on a single national context limits generalisability. Nevertheless, these limitations do not undermine the core policy implications of the findings. Even if self-reports only imperfectly capture behavioural realities, the persistence of ideological reinforcement among highly aware users remains a critical signal for regulators concerned with systemic risks.

In sum, discussions of filter bubbles must move beyond questions of existence toward questions of governance. The findings suggest that algorithmic personalisation can reinforce ideological segmentation in ways that are resilient to individual awareness and perceived diversity. Addressing these dynamics requires a shift from user-centred solutions toward systemic, design-oriented interventions aligned with democratic objectives.

Limitations. This study relies on self-reported perceptions, which may differ from logged exposure; future work should triangulate Bubblemetrix with behavioural tracking. The term “algorithm” is used in a social-scientific sense (perceived behaviour-based curation), yet it may be interpreted differently by IT-trained respondents; we therefore note potential wording and interpretation bias and recommend testing measurement invariance and refining item phrasing. Finally, the cross-sectional convenience sample from a single national pre-electoral context limits causal inference and generalisability; replication across elections, countries, and platforms is needed.

Conclusions

This study set out to examine how algorithmic personalisation shapes electoral perceptions by focusing on users’ experiences within filter bubbles. Through the development and application of the Bubblemetrix framework, the research provides empirical evidence that filter bubbles are structured, differentiated, and politically consequential phenomena. Rather than affecting users uniformly, algorithmic reinforcement emerges through specific configurations of awareness, engagement, and ideological alignment.

One of the most significant conclusions is that algorithmic awareness does not function as a protective factor against ideological encapsulation. Users who recog-

nise personalisation mechanisms may nonetheless remain deeply embedded in self-reinforcing informational environments. This finding directly challenges policy approaches that prioritise media literacy and transparency as sufficient tools for mitigating polarisation (Bechmann & Nielbo, 2018; Dubois & Blank, 2018). While such measures are important, they are insufficient to counter structurally embedded dynamics of amplification.

The study further demonstrates that perceived source diversity does not necessarily weaken filter bubble effects. Exposure to multiple outlets can coexist with pronounced ideological homogeneity when algorithmic systems consistently prioritise engagement-congruent content. This insight has direct implications for regulatory strategies that equate diversity with pluralism without addressing how content is algorithmically selected and amplified (Bruns, 2019; Kaiser & Rauchfleisch, 2020).

From a governance standpoint, the findings underscore the need to reconceptualise filter bubbles as systemic risks rather than individual shortcomings. Approaches centred exclusively on user responsibility overlook the structural role of platform architectures in shaping political discourse. Effective mitigation therefore requires interventions that address engagement-driven ranking systems and feedback loops that entrench ideological segmentation.

The identification of distinct user profiles further suggests that regulatory approaches should account for heterogeneity in vulnerability and engagement patterns. Highly engaged users exhibiting strong ideological reinforcement may require more robust safeguards than users who interact selectively with political content. This observation raises broader questions about proportionality, responsibility, and personalisation in platform governance.

Beyond its substantive findings, the study offers a methodological contribution by demonstrating how psychometric instruments and person-centred analyses can inform policy debates. The Bubblemetrix framework provides a means of assessing algorithmic risks in a manner that is empirically grounded and normatively relevant, supporting the development of evidence-based governance strategies.

Future research should extend this framework across platforms, electoral systems, and cultural contexts, ideally combining self-reported measures with behavioural data. Such efforts would further refine our understanding of how algorithmic personalisation intersects with democratic processes and would inform the design of more effective governance mechanisms.

In conclusion, filter bubbles are neither accidental nor marginal features of contemporary digital communication. They are structured outcomes of engagement-oriented systems operating within politically charged environments. Addressing their democratic implications requires a shift from transparency-focused and user-centred policies toward systemic, design-oriented governance mechanisms capable of disrupting self-reinforcing patterns and promoting genuinely pluralistic exposure.

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