Understanding social media echo chamber, socialbots and trust: Theory of Planned Behavior perspectives

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Abstract

Socialbots that utilize fake accounts on social media and mimic human behaviors rapidly disseminate disinformation that endangers elections, democracy, and public health. Echo chamber effects exacerbated by social media algorithm send distinct perspectives to targeted social groups, resulting in socio-political polarization. In recent years Taiwan has faced increasing challenges of bot-driven disinformation campaigns during elections and COVID-19 outbreaks. The web survey examines 750 Taiwanese socialbot users' perceived echo chamber and its relationships with Theory of Planned Behavior variables, which further affect socialbot trust and interaction intention. Structural Equation Modelling results show that social media echo chamber is significantly positive associated with perceived bot control and moderately related to privacy concern; yet, it has no effect on socialbot attitude. Additionally, socialbot attitude and privacy concern negatively predict socialbot trust, but perceived bot control shows the opposite. Moreover, socialbot trust significantly predicts interaction intent. Implications to theory and practices are discussed.

Keywords: Socialbot, Echo chamber, Theory of Planned Behavior, perceived bot control, privacy concern, trust, socialbot interaction

1. Introduction

Social media's echo chamber effects deteriorate when users are confined to alternative perspectives but selectively exposed to like-minded viewpoints to reinforce common beliefs (Cinelli et al., 2021; Dubois & Blank, 2018). Social media algorithms enhance filter bubble and form stratospheres, resulting in socio-political polarization by sending targeted messages to selected social groups (Cota et al., 2019). Partisan echo chamber on social media increases users' political fragmentation and polarization, demonstrating the vulnerability of social media to the propaganda agenda of radical ideology and extremism (Bright, 2018; Lee et al., 2014; Torres-Lugo et al., 2022). Increasing studies on malicious socialbots that utilize fake accounts on social media and mimic human online behaviors rapidly disseminate misleading information to undermine elections, democracy, and public health (Ferrara et al., 2016; Shi et al., 2020). It is significant to investigate impacts of echo chamber on perceptions of socialbots, trust and interaction intention.

When people interact with disguised socialbots with ill agendas, their perceptions of the emerging technology are associated with their attitude, privacy concerns and perceived ability to control it (Lin, 2022). Perceived bot control consists of perceived controllability and perceived self-efficacy in bot identification (Lin, 2022). In the context of socialbots, privacy concern is viewed as a specific kind of subjective norm, when users usually worry about misuse of private data and information. Attitude toward socialbots and perceptions (control and privacy) are likely to influence user trust in socialbots. As individuals' media trust tend to affect their media attention (Williams, 2012), trust in socialbots is likely to shape users' interaction intention. To fill the research gap, this web survey research adapts variables of Theory of Planned Behavior (TPB) model (i.e., socialbot attitude, bot control and privacy concern) to investigate their complex associations with social media's echo chamber effect and social media trust, as well as their impacts on social media users' interaction intent with socialbots.

News and research reports show that Taiwan in recent years has faced challenges of bot-driven disinformation campaigns during elections and COVID-19 outbreaks (Lin, 2018; Lin, 2021). This study aims to investigate the interplay of echo chamber, TPB variables and trust. The web survey examines 750 Taiwanese socialbot users' perceptions of echo chamber and its relationship with TPB variables (attitude towards socialbots, perceived bot control and privacy norm) and their associations with socialbot trust and interaction intent. Theoretically, this study contributes to extend the TPB theory to the context of socialbots; it also identifies social media echo chamber as a predictor for TPB variables (i.e., socialbot attitude, bot control and privacy concern). Practically, it highlights the significance of promoting digital literacy about disguised socialbots to increase social media users' bot control and privacy concern in order to increase socialbot trust and the interaction intent.

2. Literature Review

Theory of planned behavior (TPB) has been extensively applied to various disciplines such as health research (Zhang et al., 2020) and new media technology studies (Mou & Lin, 2015; Wang & McClung, 2011). TPB focuses on understanding human behaviors led by behavioral beliefs about projected outcomes, which includes normative beliefs about social norms of others and control beliefs about preventing barriers from performing certain behaviors (Ajzen, 2002). It is crucial to examine how users' perceptions towards malicious socialbots and their projected negative outcomes will affect their behaviour intention with the emerging technological risks. Extending TPB to the context of disguised socialbots, Lin (2022) found the associations among disinformation interaction, TPB variables and disinformation threat. Additionally, past studies find that social media algorithms create filter bubbles and intensify echo chamber effects, resulting in socio-political polarization (Cinelli et al., 2021; Cota et al., 2019). Widespread health misinformation on social media amplified by socialbots increase infodemics, trust crisis and conflicting vaccine perspectives (Faris et al., 2020). It is crucial to investigate the complex relationships among social media echo chamber, socialbots' beliefs, trust and behavioural intention. Built upon the TPB theory, this study develops a model to investigate how social media's echo chamber effect is associated with socialbot user attitude, perceived bot control and privacy concerns (replacing subjective norms), which affects their trust in socialbot and interaction intent.

2.1 Echo chamber

Echo chamber, defined as a "bounded, enclosed media space," forms a frame of ideology and feedback loops for people "listen to, read, and watch media outlets" (Jamieson & Cappella, 2008, p.76). According to Buder et al. (2021), echo chambers result from people's tendency to prefer congenial information and disregard uncongenial information. Echo chambers occur when people selectively exposed themselves to homogenous perspectives and interacted primarily with content similar to personal cognitive predispositions and preferences (Garimella et al., 2018). With goal-oriented search engines, Internet use facilitates selective exposure and likely enhances online echo chamber. Scholars raised concerns that social media algorithms could form filtering bubbles to refrain users from reaching alternative perspectives (Hong & Kim, 2016). When group members mutually validate their worldviews and isolate themselves from threatening out-groups could lead to ideological polarization (Buder et al., 2021). Due to algorithmic personalization, online social networks promote collegial contents and encourage users sharing like-minded perspectives, which magnifies echo chamber impacts on divided communities and fragmented society (Dubois & Blank, 2018).

A growing body of interdisciplinary research has investigated to what extent social media echo chamber effects contribute to political polarization (Baumgaertner, 2014; Dubois & Blank, 2018). Regarded as a potential contribution to ideology polarization, echo chambers on social media are found to reinforce and solidify political beliefs, especially influential for political swingers with weak partisan preferences (Rudolph, 2011). In terms of political participation, people are inclined to seek and share political information conforming to their norms and reinforce existing beliefs (Sunstein, 2009). Echo chambers in politics studies suggested that social media users with similar political views tended to form social clusters to share similar political beliefs (Justwan et al, 2018). When examining echo chamber phenomenon during 2016 U.S. presidential election, Guo, et al. (2020) further identified opinion leadership on social media were responsible for developing homogeneous communities.

As social media algorithms filter contents and intervene information accessible or inaccessible to specific user groups, many studies support that social media echo chambers accelerate polarization (Botte et al., 2022). Yet, Dubois and Blank's research (2018) find that those who are interested in politics and those with diverse media diets tend to avoid echo chambers, challenging fears of political segregation and polarization caused by partisan echo chambers. Additionally, Geiß et al. (2021) argue that social media echo chambers are customized to send targeted messages to echo users' similar beliefs, resulting in extreme viewpoints and distorted opinion expressions. They also find that users with high social media dependency hold attitude extremity with radical ideas are more vulnerable to echo chamber effects. When Buder et al. (2021) investigated social media users' sentiments and their echo chamber social networks, the results reveal that negativity of online conversations affects social media users' attitude and increases polarization.

During unusual times such as elections and pandemics, people are prone to enter echo chambers only exposed to agreeable contents, which strengthen their confirmation bias (Jiang et al., 2021). Social media users' vulnerability to online misinformation manipulation is affected by a complex interplay of cognitive, social, and algorithmic biases. Social media algorithms facilitate viral dissemination of misleading information which target at those inclined to believe and share it willingly among like-minded online networks. Regarded as emerging risks, socialbots that disguise as human users are utilized to propagate political disinformation and health misinformation, which brings threats to compromise election results, endanger democracy (Lin, 2021; Lin, et al., 2022; Shao et al., 2017) and sabotage public health (Faris et al., 2020). Bail et al.'s experiment on socialbots and partisan preferences (2018) reveal when people exposing to twitter bots' messages with opposite perspectives, their pre-existing perspectives got strengthened and reduced polarization. To be noted, social media users are vulnerable as visible targets for socialbots' computational propaganda, which can be worsen by filtering bubbles and echo chambers because they reinforce online falsehood and manipulate user attitudes, opinions and behaviors (Mihr, 2017, p.21).

Past research has not examined the complex relationships between the social media users' susceptibility to echo chambers with their planned behaviors towards disguised socialbots (TPB variables in this study). It is crucial to test hypotheses in order to discover the associations between echo chamber with attitude towards socialbot, perceived bot control and privacy concern.

2.2 Socialbot & TPB variables

2.2.1 Attitude towards Socialbot

In TPB theory, user attitude towards technologies (e.g., socialbot in this study) influences their intention to use and actual use. Disguised socialbots were commonly used in political domains as strategic communication to promote and propagate misleading information to manipulate the public (Howard et al., 2018; Ferrara, 2016). Socialbots disseminate unverified contents and share false or misleading information easily, creating serious threats to information credibility and trustworthiness (Shu et al., 2020). Due to the widespread use of socialbots, social media users sometimes unconsciously concur with the non-human actors and share untrustworthy and misleading information, which unfortunately undermine public trust in online debates, and cause socio-political turmoil (Lin, 2022). Yan et al. (2021) argued that malicious political bots engage with human users to manipulate public opinions and even exacerbate political polarization. Based on Wiesenberg and Tench (2020), this study investigates social media user attitudes towards socialbots as a challenge to communities and public debates, a risk to organizations and their images, and ethical concerns for scholars and practitioners. It is worth investigating the relationships of TPB variables with trust; hence, this study adds trust in socialbot before interact intention with this emerging technology.

2.2.2 Perceived Bot Control

Socialbots are a latest innovation in the existing media industry, which is commonly used in media content production, distribution, and audience interaction (Hong & Oh, 2020). This study employs perceived bot control, also known as perceived behavioral control, a TPB variable that influences human intents and behaviors. TPB's perceived control is related to people's views of the ease of performing the desired behavior (Ajzen, 1991). Perceived behavioral control is built on the notion of self-efficacy, which is described as people's views about their ability to create and influence what happens in their lives (Bandura, 1982). Besides perceived self-efficacy (i.e., belief in one's ability to perform a behavior), perceived bot control consists of perceived controllability (i.e., the belief that a performance is entirely up to the individual) (Terry & O'Leary, 1995). When people feel less control of socialbots, they are more inclined to avoid them and feel threatened (Lin, 2022). According to Schmuck and von Sikorski (2020), perceived bot control significantly influenced perceived socialbot threat. They stressed that socialbot-related media stories without explaining how they function or how to identify them tended to erode people's sense of control and trust in socialbots.

Widespread socialbots intended to influence public opinion and potentially alter political behaviors with harm (Yan et al., 2021). Regarding socialbot identification as a critical asset for understanding social media bias, Luceri et al. (2019) exposed malevolent accounts and raised public awareness of the prevalent socialbots and their serious threat to public opinion. They also demonstrated that many political bots that were adept at influencing people earned a higher level of engagement and trust from human users. In addition, Yan et al. (2021) discovered that social media users' capability to spot political socialbots was hampered by cognitive biases. They emphasized that socialbots with specific political personalities stimulated social media users' prejudice, fostering skepticism to misidentify fake and real accounts.

2.2.3 Privacy Concern

This study replaces subjective norm (a TPB variable influencing human intentions and behaviors) with privacy concern. Adapted from Wei et al. (2010), privacy concern refers to individuals' awareness about their private data and their ability to limit sharing of personal information. Individual sensitive data may be obtained without their awareness or prior consent. Privacy concerns also involve the ability to restrict information sharing during online interactions or activities with distant others (Goodwin, 1991). People could lack knowledge about data collecting and ways to use personal information (Nowak & Phelps, 1992). Xiao (2021) raised individual privacy concerns over bot-driven data mining. As privacy issues grow, people were less inclined to give personal information (Sheehan & Hoy, 2000) and felt skeptical about platform's trustworthiness (Wei et al., 2010).

Kerr and Bornfreund (2005) discovered that bots could steal important confidential information and private correspondences without legal consent. Privacy on social media is still being questioned nowadays, as users are not entirely concerned about unintended disclosure of personal data to others such as spammers or data miners (Voloch et al., 2021). According to Graeff (2013), the deployment of socialbots aimed to engage with individuals to develop genuine relationships, which has raised awareness of both private and public social media spaces to expect a higher degree of confidentiality or discretion from socialbots they interact with.

Social media platforms have paid more attention to users' confidentiality, particularly after socialbots have prevalently used (Wald et al., 2013). Li et al. (2020) further noticed that socialbots might be involved in a variety of cyberattacks aimed at automatically collecting users' personal information. The misuse of socialbots puts a risk in privacy policies and violated privacy rights; in response to growing privacy concerns, social media companies ought to disclose reasonable explanations before data collection (Kerr & Bornfreund, 2005). However, Ng et al. (2020) argued that the usage of socialbots in financial service industry helped banking easily assisted their clients to make financial decisions. In this case, socialbots did not compromise trustworthiness or lessen privacy concerns, but increase impression of social presence. Employing socialbots was associated with trust in this emerging technology. Based on the aforementioned literature, this study proposes the hypotheses as follows:

H1a : Echo chamber is positively associated with attitude towards socialbot.

H1b : Echo chamber is positively associated with perceived bot control.

H1c : Echo chamber is positively associated with privacy concern.

2.3 Trust in Socialbot

After Facebook's Cambridge Analytica scandal and Russian trolls interfering US Presidential Election, trust in social media keep decreasing and concerns over partisan echo chambers and political disinformation upsurge. The Insight Intelligence/eMarketer survey shows that US users' trust in social media platforms has declined substantially in 2022 in areas of privacy and safety (Williamson, 2022). According to William (2012), user trust encompasses multi-dimensional components: trust in the information they got (content), trust in who delivered that information (messenger/source), and trust in media outlets or social media companies (content creator). It is crucial to think about how trust relates to individuals' media attention and consumption so as to better understand why users, with freedom of choices, are willing to pay attention to contents on selected media outlets or platforms. As a result of waning social media trust, users ought to find ways to access and evaluate credible, trustworthy and high-quality information on these platforms (Dubois et al., 2020).

Anthropomorphic socialbots are algorithmically designed to act like human, so that they can acquire user trust (Graeff, 2013). Once personified socialbots promote specific viewpoints, users who concur with them gain support and share these like-minded messages, whereas rivals remain silent with worries of being excluded (Hajli et al., 2021). Disguised socialbots use fraudulent accounts and mimic human online behaviors to befriend with social media users for malevolence purposes (Lin, 2021; Lin et al., 2022). During crises, socialbots are identified as the key means to distribute rumor and propaganda (Rabello, et al., 2020). When socialbot activities are intentionally planned to cause harm, they result in falsehoods, spamming, deception, likely reducing trust (Shi, et al., 2020). Social media discussions about online falsehood are frequently amplified by socialbots, which undermines users' efficacy in identifying legitimate news and their trust in legitimacy of news content creators (Al-Rawi et al., 2018). Learning about malicious socialbots from news coverage increases fear, which may erode public trust; however, when news reports include information to support socialbot literacy, negative sentiments and perceived threat are mitigated by increasing perceived behavioral control (Schmuck & von Sikorski, 2020).

Based on the aforementioned literature, this study proposes the hypotheses as follows:

H2a : Attitude towards socialbot is negatively associated with trust in socialbot.

H2b : Perceived bot control is positively associated with trust in socialbot.

H2c : Privacy concern is negatively associated with trust in socialbot.

2.4 Intent to Interact with Socialbot

When examining chatbots used for enterprise social networks, if socialbots are competent at facilitating communication and providing credible information, users' intention to interact increases (Meske & Amojo, 2018). When socialbots' performing social interactions lead to users' feelings of social presence, it is also influential to attract massive effective interactions with other social media users (Grimme et al., 2017). According to Wald et al. (2013), those who are highly active in using social media and more open to experiencing new things tend to interact with socialbots to a greater degree. Although majority of social machines are designed with prosocial intention, such as community development, collaborative knowledge, supportive work assistance, or crime prevention, the beneficial purposes can be undermined as a result of ill agendas of the owners (Shadbolt et al., 2019). Social media platforms have to bear ethical ramifications with declining trust, when their contents involve falsehood or risks in privacy and security (Nadeem et al., 2021; Wang et al., 2020). To establish trust, Shadbolt et al. (2019) highlight ethical issues on social machines (e.g, socialbots), especially user attitudes towards privacy and data sharing. Thus, this study proposes:

H3 : Trust in socialbot is positively associated with intent to interact with socialbot.

Based on the aforementioned literature, this study proposes the following research model:

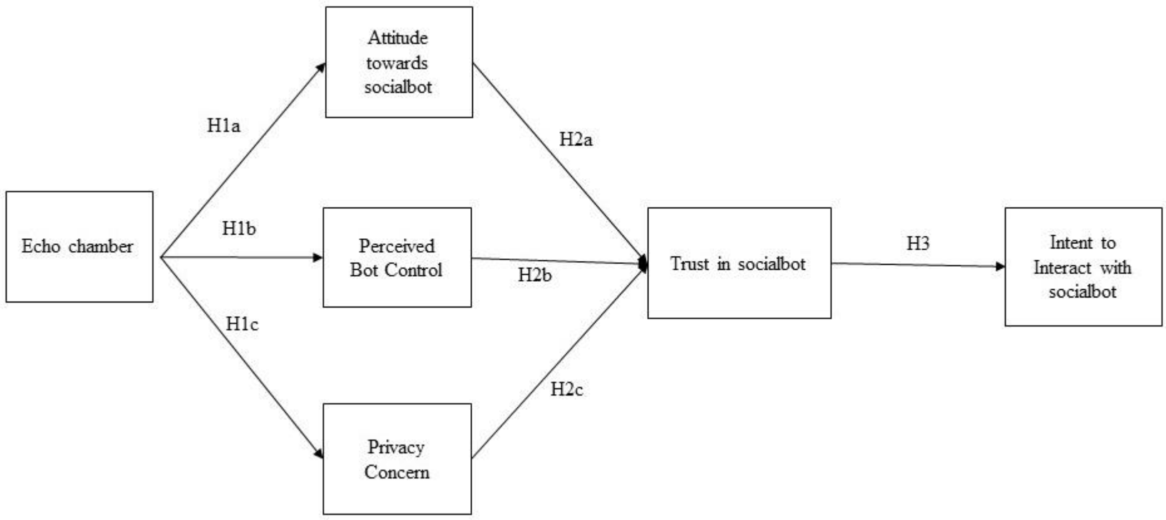

Figure 1 shows the research model consisting of above hypotheses

3 Methods

With a two-party political system and the cross-strait tension with China, Taiwan has suffered from disinformation risks, according to 2019 V-Dem Annual Democracy Report (Lin, 2018). International media reports showed political disinformation and cyberattacks launched by foreign governments occurred frequently during Taiwanese elections (CNA, 2019). When COVID-19 first occurred in Taiwan, media reported that foreign Internet armies and socialbots disseminated coronavirus misinformation to stir public panic in early 2020 (Yuan, 2020). After the coronavirus third-level alert in May 2021, international media revealed that China spread COVID-19 vaccine misinformation among Taiwanese, and distrust of the government's effective epidemic control increased (CNA, 2021). Even if Taiwan is facing challenges of disinformation, polarized politics and information warfare, the crucial line of research on health misinformation, digital literacy and trust is nascent and scare, which requires scholarly investigations.

3.1. Data Collection

The web survey was conducted to examine Taiwanese user perceptions and attitudes towards disguised socialbots in August 2021. The filtering criteria of the respondents from the cyberpanel of IXsurvey are Taiwanese social media above 20 years old with prior experiences of socialbot use. The sample fit 2021 Taiwanese social media user profile in demographic quotas (i.e., gender, age and education attainments) based on InsightXplorer and Comscore data (IXresearch, 2020). Before data collection, the draft questionnaire has been pretested in July 2021 to improve questions' clarity and readability. The web survey has obtained the approval from the Institute Review Board in the host university. Disguised socialbots in this study are defined as human-like fake social media accounts used for malicious activities to amplify selected agendas, manipulate online public opinions, and spread disinformation. As socialbots are an emerging novel technology, respondents were asked to watch a video about disguised socialbot before filling in the questionnaire, in order to ensure their common understanding.

After data cleaning, the survey has the valid sample of 750 respondents that fit the demographic profile of Taiwanese social media users. G*power analysis supports that the sample size exceeds the minimum (N = 287) for SEM model testing, with a power level of 80% (Westland, 2010). Table 1 summarizes the respondents' demographic profile.

Table 1. Respondents' demographic profile

Sample characteristics (N =750).		Frequency	Percentage(%)
Gender	Male	372	49.6
	Female	378	50.4
Age	20-29	169	22.5
	30-39	192	25.6
	40-49	196	26.1
	50-59	154	20.5
	60 and older	39	5.3
Education	Elementary school	8	1.07
	Junior high school	16	2.13
	Senior high school/vocational high school	128	17.07
	Associate degree	107	14.27
	Bachelor's Degree	406	54.13
	Master's degree and above above	85	11.33
Individual Monthly income	Dependent/No income	36	4.8
	Unstable income	34	4.5
	NTD20000 and below	53	7.1
	NTD20001-40000	248	33.1
	NTD40001-60000	174	23.2
	NTD60001-80001	88	11.7
	NTD80001-100000	50	6.7
	NTD100001-150000	42	5.6
	NTD150001-200000	11	1.5
	NTD200,001 and above	14	1.9

Note: One Taiwan Dollar (NTD) is about US$0.036 as of September 1, 2021.

3.2. Measurement

Majority of measurements in this study adapted items from past studies and modified to fit the context of disguised socialbots. Appendix 1 shows the list of items. Some were dropped when their factor loading value was above the benchmark value of 0.70.

Echo chamber. Echo Chamber (α = 0.84, M = 3.16, SD =0.82) is adapted from Dubois & Blank (2018)'s measurement of echo chamber. A 5-point Likert scale was used to indicate responses (1 = strongly disagree, 5= strongly agree). The five items ask different aspects of an echo chamber: disagree, different, confirm, offline, and change. Each measures the extent to which people are exposed to different opinions; that is, the extent to which respondents find themselves in an echo chamber. This measure using five items reflecting media diversity is able to have comprehensive views of possible echo chambers. After adding all coded items, lower values mean respondents are more likely to be in echo chambers.

Attitude towards socialbot. Attitude towards socialbots (α = 0.63, M = 2.99, SD =0.80) is adapted from Wiesenberg & Tench (2020)'s five-item measurement of attitude towards about socialbots. But two items were dropped due to unsatisfied factor loading. A 5-point Likert scale was used to indicate responses (1 = strongly disagree, 5= strongly agree).

Perceived Bot Control. Perceived Bot Control (α = 0.73, M = 4.52, SD =1.21) involved two dimensions: perceived controllability and perceived efficacy for bot detection. Perceived controllability is a four-item measurement adapted from Schmuck & von Sikorski (2020). Perceived efficacy for bot detection has three items adapted from Yan et al. (2020). Above of all a 7-point Likert scale was used to indicate responses (1 = strongly disagree, 7= strongly agree).

Privacy Concern. Privacy Concern (α = 0.94, M = 5.10, SD =1.25) is adapted from Wei et al. (2010)'s four-item measurement of about personal information. A 7-point Likert scale was used to indicate responses (1 = strongly disagree, 7= strongly agree).

Trust in socialbot. Trust in Socialbots (α = 0.94, M = 5.88, SD =1.71) is a six-item measurement of media trust adapted from Williams (2012). Due to unsatisfactory factor loading, an item was dropped. To indicate responses, a 10-point Likert scale was employed (1 = lowest, 10= highest).

Intent to interact with socialbot. Interaction intent with socialbot (α = 0.61, M = 3.23, SD =0.92) is adapted from Edward et al. (2014)'s three-item measurement. A 5-point Likert scale was used to indicate responses (1 = very unwillingly, 5= very willingly).

4 Results

4.1. Model fit

As for data analysis, this study first utilized SPSS 25 for descriptive results. Structural Equation Modeling (SEM) is increasingly used in scientific investigations to test models that explain relationships between measured variables and latent variables. This study used Amos 26 to perform SEM analyses. The results suggest that the proposed model has adequate fit: X2/df = 3.99, CFI = 0.932, TLI = 0. 924, RMSEA =0.063 (90% CI= .060 .067), SRMR =0.085 (Bentler, 1990; Hu & Bentler, 1999).

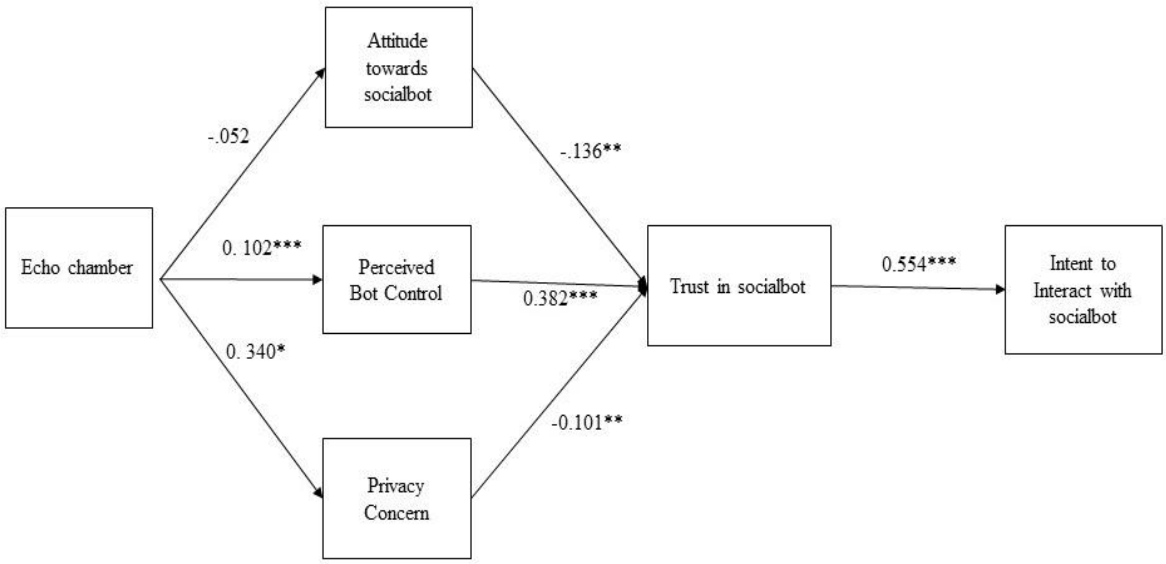

Figure 2. Results of SEM analysis

X2/df = 3.99, CFI = 0.932, TLI = 0. 924, RMSEA =0.063 (90% CI= .060 .067), SRMR =0.085
**p <.05, ** p <.01, *** p <.001; n.s. = non-significant*

4.2. SEM results and hypothesis testing

Although echo chamber on social media has no influence on attitude towards socialbots (*b* = .052, n.s), it is significantly associated with perceived bot control (*b* = .102, *p* <.001) and moderately related to privacy concern (*b* = .340, *p* <.05). Perceived bot control (*b* = .382, *p*

<.001) has a positive association with socialbot trust, when attitude with socialbot (*b* = .136, *p* <.01) and privacy concern (*b* = -.101, *p* <.01) are negatively related to it. Moreover, trust in socialbots predicts interaction intent (*b* =.554, *p* <.001). Table 2 shows the summary of the hypothesis testing. (*b*=standardized coefficients, *p* = p-value).

Table 2. Summary of hypothesis testing

	Hypothesis	Path value	Decision
H1a	Echo Chamber → Attitude towards socialbots	n.s.	Rejected
H1b	Echo Chamber → Perceived Bot Control	0.102***	Supported
H1c	Echo Chamber → Privacy concern	0.340*	Supported
H2a	Attitude towards socialbots → Trust in socialbots	-0.136*	Supported
H2b	Perceived Bot Control → Trust in socialbots	0.382***	Supported
H2c	Privacy Concern → Trust in socialbots	-0.101**	Supported
H3	Trust in socialbots → Intent to interact	0.554***	Supported

Notes: *p <.05, ** p <.01, *** p <.001, n.s. = non-significant. Results were controlled for age, gender, ethnicity, education and income

5 Discussions & Conclusions

When social media algorithms selectively expose like-minded users to similar and collegial perspectives but prevent them from reaching unfamiliar or opposing viewpoints, echo chamber effects are exacerbated by echoing thoughts in stratosphere and widening the gaps among outgroups (Cinelli et al., 2021; Dubois & Blank, 2018), resulting political polarization and social antagonism. The increasing deployment of socialbots in computational campaigns for socio-political purposes accelerate and worsen social media's echo chamber effects. As far as we know, past studies have not yet examined how social media users' susceptibility to echo chambers affect their perceived planned behaviors towards disguised socialbots. To fill the research gap, this present study is one of the first quantitative research to investigate echo chamber effects on users' perceptions of socialbots, which further look into the relationships of TPB variables (i.e., attitude towards socialbots, perceived bot control and privacy norm) with socialbot trust and interaction intention.

A rich body of literature has examined media's echo chamber effects on politics (Jamieson & Cappella, 2008). Recent studies find that social media algorithms amplify echo chambers and accelerate socio-political polarization (Botte et al., 2022; Buder et al., 2021). Adapted from Dubois and Blank (2018), this study examines the extent to which socialbot users find themselves in an echo chamber by checking various ways of seeking news or political information on social media: 1) reading contents that social media users disagree with, 2) different from their perspectives, 3) confirming individual political beliefs, 4) verifying information with offline media, and 5) change personal viewpoints after thinking research searches. Nowadays malicious disguised socialbots are getting more and more difficult to be identified or discovered as a result of their anthropomorphic characteristics and deceiving gimmicks. It is crucial to explore the effects of social media echo chamber on socialbots' TPB perceptions. The SEM results show social media echo chamber has no effect on attitudes towards socialbot which was tested by individual ethical challenges (micro), threat for organizations (meso) and societies and public debates (macro). The non-significant statistical analysis of self-report results reflected that respondents' echo chambers did not have a direct relationship with their attitudes towards the personalized, hardly detected emerging technology.

Most importantly, this study finds social media echo chamber's strong positive association with perceived bot control and a weak relation to privacy concern. Perceived bot control in this study encompasses self-controllability to avoid disguised socialbots' manipulation (Schmuck & von Sikorski, 2020) and self-efficacy to bot detection (Yan et al., 2020). When social media users are highly capable of breaking through the predicament of echo chambers by utilizing diverse media to seek, appraise and verify political news and information, they tend to have very good control over protecting themselves from socialbot harm and detecting bots. Thus, social media echo chamber has strong predicting power over perceived bot control. Adapted from Wei et al. (2010), sociabot users' privacy concerns regarded as TPB's subjective norm are related to information misuse or no prior consent, data stolen or information leaking and personal information used for political propaganda in this study. The results show that people who can mitigate social media echo chamber effects are likely to feel concerned about socialbots' negative impacts.

Based on TPB theory, attitude toward socialbot, perceived bot control, and privacy concern were used to investigate social media users' stance in interacting with disguised socialbots and verifying their threat (Lin, 2022). In this study, the three variables were treated as factors affecting trust in socialbots which predict interaction intent with the emerging sinister technology. Adapted from Williams (2012), trust in socialbot contains users' benign beliefs in social media contents and in individual designing and companies developing or utilizing them. Owing to skepticism embedded in socialbot attitude and privacy concern variables, the results show their negative associations with socialbot trust; on the contrary, the more users perceived individual abilities to control socialbots, the higher degree they trust in socialbots. In comparison, attitude towards socialbot and privacy concern only have moderate influences on socialbot trust. Among the TPB variables, perceived bot control not only has a strong association with echo chamber but also is a strong predictor for trust in socialbots. Finally, socialbot trust positively predict users' interaction intention significantly. That is, socialbot users are more likely to interact with the new media if they have higher levels of trust in bots' contents, developers and ways of using personal information obtained by bots.

Malicious disguised socialbots that mimic human behaviors by posting contents and interacting with others cause the contemporary threat to political disinformation, election intervention, and opinion manipulation in democratic societies. The present study is the pioneering work to investigate echo chamber, TPB variables and trust in the context of disguised socialbots. In theory, it contributes to extend the TPB theory to the context of socialbot and echo chamber. It identifies social media echo chamber as a predictor for TPB variables (i.e., perceived bot control and privacy concern). In practice, it highlights the significance of promoting digital literacy about disguised socialbots. The findings emphasize the significance of improving social media users' bot control and raising their privacy concerns so as to mitigating social media echo chamber and reducing trust in malevolent socialbots. Therefore, digital literacy campaigns can be developed to raise awareness of malignant socialbots, train social media users to detect and differentiate malignant bots as well as to prevent themselves from opinion manipulation and personal data leakage.

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Appendix 1. List of items

Item	Factor Loading
Echo chamber	
When looking for news or political information on social media, how often, if ever, do you read something you DISAGREE with？	0.815
When looking for news or political information on social media, how often, if ever, do you check a news source that is different from what you normally read？	0.802
When looking for news or political information on social media, how often, if ever, do you try to confirm political	0.745

information you found by searching online for another source?	
When looking for news or political information on social media, how often, if ever, do you try to confirm political information by checking a major offline news medium?	0.782
When looking for news or political information on social media, how often, if ever, do you thinking about recent searches you have done online using a search engine, how often have you discovered something that changed your opinion on a political issue?	0.757
Attitude with socialbot	
I have followed the debates about socialbots.	Dropped
Socialbots offer opportunities for strategic communication.	Dropped
Socialbots present ethical challenges for communication professionals.	0.752
Socialbots are a threat for organisations and their reputation.	0.770
Socialbotsare a threat for societies and public debates.	0.875
Privacy concern	
I am concerned that the information I submit to socialbots can be misused	0.856
I am concerned about submitting personal information to socialbots because it can be used in a way I do not foresee	0.821
I am concerned about submitting personal information to socialbots because others might use it for political or propaganda purposes	0.855
If I used socialbots, I would be concerned that my personal data and information can be stolen during interactions	0.800
Perceived bot control	
Whether or not I am influenced by disguised socialbots on social media platforms is up to me	0.721
I have a high level of personal control over whether or not disguised socialbots' false messages affect me;	0.702
Personally, I cannot control whether disguised socialbots on social media platforms affect my opinion	0.782
I am confident that I myself can prevent disguised socialbots from manipulating my opinion;	0.723
I will recognize most disguised socialbots if I encounter them in the future;	0.844
I can succeed at telling disguised socialbots apart;	0.845

When facing disguised socialbots that highly resemble regular users, I can still find clues to weed them out.	0.744
Trust in socialbot	
I trust the information that I get from socialbots.	0.844
I trust the information that I find by socialbots.	0.785
Individual designing socialbots for information purposes is helpful to others.	Dropped
Individual designing socialbots for information purposes can be trusted.	0.884
Companies developing or utilizing socialbots can be trusted.	0.775
Companies developing or utilizing socialbots help solve social problems.	0.853
Intent to interact with socialbot	
To what extend would you like to use socialbots?	0.832
To what extend would you like to interact or follow socialbots?	0.852
To what extend would you like to obtain information from socialbots?	0.878