University of Tehran Press

Interdisciplinary Journal of Management Studies (IJMS) Online ISSN: 2981-0795

Home Page: https://ijms.ut.ac.ir

Human-Made Catastrophe and the Role of AI-Driven Media Exposure in Product Rejection Using the Theory of Planned Behaviour (TPB)

La Ode Nazaruddin[1*] | Qisthina Aulia[2] | Triara Juniarsih[3] | Mária Fekete-Farkas[4] | Kinga Szabó[5]

1. Corresponding Author, Department of Economic and Regional Sciences, Hungarian University of Agriculture and Life Sciences (MATE) - Szent István Campus, Pater Karoly Utca, Hungary. Email: nazaruddin.la.ode@phd.uni-mate.hu
2. Departmentof Law of the Republic of Indonesia, Jl. Raya Gandul, Depok, West Java, Indonesia. Email: qisthina.aulia@gmail.com
3. Department of Agricultural and Food Economics, Hungarian University of Agriculture and Life Sciences - Szent István Campus, Pater Karoly Utca, Hungary. Email: juniarsih.triara@phd.uni-mate.hu
4. Department of Rural Development and Sustainable Economy, Hungarian University of Agriculture and Life Sciences, Pater Karoly Utca, Hungary. Email: farkasne.fekete.maria@uni-mate.hu
5. Department of Rural Development and Sustainable Economy, Hungarian University of Agriculture and Life Sciences, Pater Karoly Utca, Hungary. Email: farkasne.fekete.maria@uni-mate.hu

ARTICLE INFO

Article type:
Research Article

Article History:
Received: 10 October 2025
Revised: 17 November 2025
Accepted: 26 April 2026
Published Online: 01 November 2026

Keywords:
Product boycott,
Unethical business practices,
Social cognitive theory,
Artificial intelligence,
Viral and recommended content.

ABSTRACT

The present study aims to investigate the role of artificial intelligence (AI)-driven media exposure in shaping boycott intention and boycott behaviour during the Israel-Gaza crisis since the end of 2023. A questionnaire survey was adopted. Social media distributed an online questionnaire to respondents in some Indonesian provinces. A total of 504 observations were used in statistical analysis using a higher-order construct under Covariance-Based Structural Equation Modelling (CB-SEM) with smartPLS 4. The result demonstrated the following facts. Boycott intention was directly affected by media exposure (measured through social media use and viral-recommended content) and indirectly by media exposure through perceived behavioural control. In addition, boycott behaviour was directly affected by media exposure and, indirectly, by media exposure through boycott intention. The boycott behaviour was successful because of the development of AI technology, which supports content recommendations for social media users through content-based filtering, collaborative filtering, and hybrid recommendation systems. The present study confirmed the extended model of social cognitive theory of media exposure, in which the role of the social system in affecting behavioural change was not well established. The present study has some academic and scientific implications. For example, the contribution is the use of a higher-order construct, an advanced Structural Equation Modelling (SEM). Moreover, the present study successfully combined the TPB model with cultivation theory and social cognitive theory.

Cite this article: Nazaruddin, L.; Aulia,Q.; Juniarsih, T.; Fekete-Farkas, M. & Szabó, K. (2027). Human-Made Catastrophe and the Role of AI-Driven Media Exposure in Product Rejection Using the Theory of Planned Behaviour (TPB). *Interdisciplinary Journal of Management Studies* (*IJMS*), 20 (1), 77-111. http//doi.org/10.22059/ijms.2026.388564.677311

© Authors retain the copyright and full publishing rights.
Publisher: University of Tehran Press.
DOI: http//doi.org/10.22059/ijms.2026.388564.677311

1. Introduction

Boycott action is the world's oldest form of political consumerism outside the political system (Friedman, 1999; Micheletti, 2003; Schwalb et al., 2023). Nowadays, political consumerism is generally associated not only with political and ethical problems but also with crises. Even the boycott is linked to the interplay between political, crisis, ethical, and religious issues. Boycott action was here used to deal with the situation, as found in some countries such as Greece (Delistavrou, 2022; Delistavrou et al., 2020), Morocco (Zejjari & Benhayoun, 2025), Malaysia (Ghazali et al., 2019; Hamzah & Mustafa, 2019), Indonesia (Asnawi et al., 2019; Roswinanto & Suwanda, 2023; Salma & Aji, 2023; Sari et al., 2017; Suhud et al., 2017), Tunisia (Dekhil et al., 2017), Saudi Arabia (Abosag & Farah, 2014), Spain (Palacios-Florencio et al., 2021), and Egypt (Mady et al., 2025).

In consumer movements, the study of boycott action is necessary to consider the theory of consumer behaviour. In this case, the theory of planned behaviour (TPB), as Ajzen (1991) suggested, is necessary to investigate the effectiveness of boycott behaviour. A simple review of articles was conducted, including those retrieved from the Scopus database (Scopus, 2022) using the keywords "boycott AND planned AND behaviour" and "boycott AND TPB AND social media." The review results demonstrated that the studies on humanitarian- and catastrophic-related boycotts were limited (Aish et al., 2013; Farah & Newman, 2010; Hamzah & Mustafa, 2019; Mady et al., 2025; Zejjari & Benhayoun, 2025). In addition, studies on boycotts related to humanitarian catastrophes and the influence of social media were also limited (Mady et al., 2025; Zejjari & Benhayoun, 2025). Nowadays, studying boycott behaviour on social media is essential, as social media use can accelerate boycott activity. The acceleration is enabled by the use of artificial intelligence (AI) in social media, facilitating massive virality and content recommendations to social media users (Balaji et al., 2021; Narayanan, 2023; Saheb et al., 2024). The use of AI-powered social media in boycott studies was rarely investigated by the previous studies above. Thus, the present study would fill a gap in AI-driven social media use in boycott studies by using the TPB model.

Due to limited studies on boycotts related to the humanitarian catastrophe and the prevalence of boycott action in Muslim-majority countries above, the present study would investigate boycott action regarding the Gaza crisis since the end of 2023. The crisis began with the attack led by the Harakat al-Muqawwamatul Islamiyah (abbreviated as Hamas, the militia in the Gaza Strip) against Israel on October 7, 2023, as a result of the accumulation of long oppression. The 2023 war between Hamas and Israel exploded with Israel's retaliation against the Hamas attack. The war was the greatest since the Yom Kippur War (between Arab countries and Israel, also known as the October War) on October 6, 1973 (The Editors of E.B., 2023b, 2023c). The Israel-Gaza Crisis since the end of 2023 became the new *Nakba* (catastrophe in the Palestinian Language) when the war caused thousands of deaths and casualties from both sides (AJLabs, 2024). The use of *Nakba* and catastrophe terms would be interchangeable in the later coverage of this study. As a result, some people revived the boycott of international brands they alleged were pro-Israel (Allam & Chamaa, 2023). Previous studies indeed found that some multinational companies supported Israel's oppression, and therefore, many people boycotted their products (Dekhil et al., 2017; Ghazali et al., 2019; Hamzah & Mustafa, 2019; Kaikati, 1978; Losman, 1972; Zejjari & Benhayoun, 2025).

During the Israel-Gaza crisis since the end of 2023, pro-humanitarian groups used social media to create awareness and mobilise support from global stakeholders. For example, some digital content (e.g., footages and videos) about the Israeli attacks against the Gaza Strip went viral on Facebook, X social media (formerly Twitter), and TikTok. Then, the Gaza calls became the trending topic on the social media since October 2023 (Darcy, 2023; Harwell & Lorenz, 2023; Oremus & Nix, 2023; Scott et al., 2024). Social media uses AI-powered algorithms to recommend relevant content to users, boost content virality, and propagate crisis-related information (Balaji et al., 2021; Narayanan, 2023; Saheb et al., 2024; Scott et al., 2024).

The study was conducted in Indonesia. As a sizable Muslim society in the world (PEW Research Center, 2015), Indonesian society mainly supports the struggle of Palestinians. The support for Palestine (Gaza) in Indonesia since October 2023 was expressed through a boycott of some allegedly pro-Israel brands due to unethical practices by companies (Bedi et al., 2023; RachmawatiI, 2024). The boycott action was also supported by the *fatwa* of the Indonesian Council of Ulama (Majelis Ulama Indonesia or MUI) about the ban on the purchase and use of products affiliated with Israel and

supporting the oppression of Israel against Palestine (MUI, 2023). The *fatwa* implies the meaning of boycott, as argued by Friedman (1999), in response to the 2023 *Nakba* in Gaza. Mass media (Rachmahyanti, 2021; Rahmawati & Marboen, 2014) also reported that boycott actions against alleged pro-Israel brands occurred in Indonesia in the past.

Based on the research gap and situation above, the present study used the comprehensive TPB model to investigate the role of AI-driven media exposure in shaping boycott intention and boycott behaviour during the Israel-Gaza crisis since the end of 2023. The proposed research questions are: What are the direct and indirect effects of AI-driven media exposure on boycott intention? What is boycott behaviour directly and indirectly affected by AI-driven media exposure? The study on boycott behaviour under the TPB model using media exposure is relevant in Indonesia because half of the country's population is social media users, and the media play an important role in changing behaviour. The fact demonstrates that the number of social media users in Indonesia was 139 million or 48.65% of the total population in 2024 (143 million or 50.2 % of the total population in 2025), increasing from 72 million users (28% of the total population) in 2015 and placing Indonesia as the fifth largest social media users in the world in 2024 (Kemp, 2015, 2025; WPR, 2025). The present study is relevant, as the anti-Israel boycott in Indonesia is a recurrent movement in response to the occupation and humanitarian crisis in Palestine (Rachmahyanti, 2021; Rahmawati & Marboen, 2014; Suhud et al., 2017). In addition, Indonesia and Palestine have a historical relationship, in which Palestine supported the birth of the republic in 1944 (Detikcom Team, 2021). Thus, examining the media's effect on boycott behaviour is important for the Indonesian case.

The results of this study are expected to advance the TPB model by treating AI-driven media exposure as the higher-order construct. The use of the construct is expected to fill the gap of the absence of the higher-order construct (an advanced technique in structural equation models) in previous TPB studies (Kadel et al., 2024; Korsakiene et al., 2024; Samaniego-Arias et al., 2025), especially in boycott studies using the TPB model (Mady et al., 2025; Palacios-Florencio et al., 2021; Zejjari & Benhayoun, 2025). The present study contributes to the multidisciplinary approach to consumer behaviour, combining business management, psychology, and communication theories. The present study also contributes to the interplay between AI technology and TPB studies. The rest of this paper is structured as follows. The literature review is in the second section. The materials and methods are in the third section. The results are in the fourth section. The fifth section is media exposure. The sixth section covers the discussion, and the last section is the conclusion.

2. Literature Review

2-1. Product Boycott

The boycott originated from U.S. merchants' experience in protesting the adoption of the Stamp Act by the British Government in the time of revolution, according to previous studies (Friedman, 1999; Micheletti, 2003). In the boycott literature, there is disagreement over the timing of the Stamp Act boycott. One study argued that the boycott of British goods as a protest against the Stamp Act occurred in 1756 (Micheletti, 2003), while another argued that it occurred in 1765 (Friedman, 1999). A boycott is "an attempt by one or more parties to achieve certain objectives by urging individual consumers to refrain from making selected purchases in the marketplace" (Friedman, 1985, pp. 97-98). Boycott actions among consumers are embodied in some forms: feeling guilty about purchasing the products, the avoidance of purchasing, dislike of product ownership, substitution, infrequent purchasing (extent of purchasing), and extent of loyalty (Abosag & Farah, 2014; Sen et al., 2001). This study examines boycott behaviour using the TPB model discussed in the next section.

2-2. Theory of Planned Behaviour

The theory of planned behaviour (TPB) was introduced by Icek Ajzen in 1985 and was developed in 1991. The primary, straightforward TPB model was proposed in 1991 in a structural diagram. The basic TPB aims to predict and explain actual behaviour and the intention to perform it. According to the basic model, actual behaviour is explained by the intention to perform a given behaviour and the perception of behavioural control; in contrast, the intention is explained by attitude toward behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991).

Moreover, TPB evolved from the basic model to new following models: the first is basic TPB plus antecedents of attitude, subjective norms, and perceived behavioural control (broad model); the second is the comprehensive model plus background factors (i.e., personal, social, and information factors) (Ajzen, 2005). For simplification, the primary variables and background factors are presented in Figure 1. Media exposure is one of the background factors considered in this study. Some studies in several countries (McCreanor et al., 2024; Ng et al., 2025; Samaniego-Arias et al., 2025) found that media exposure affected purchasing behaviour.

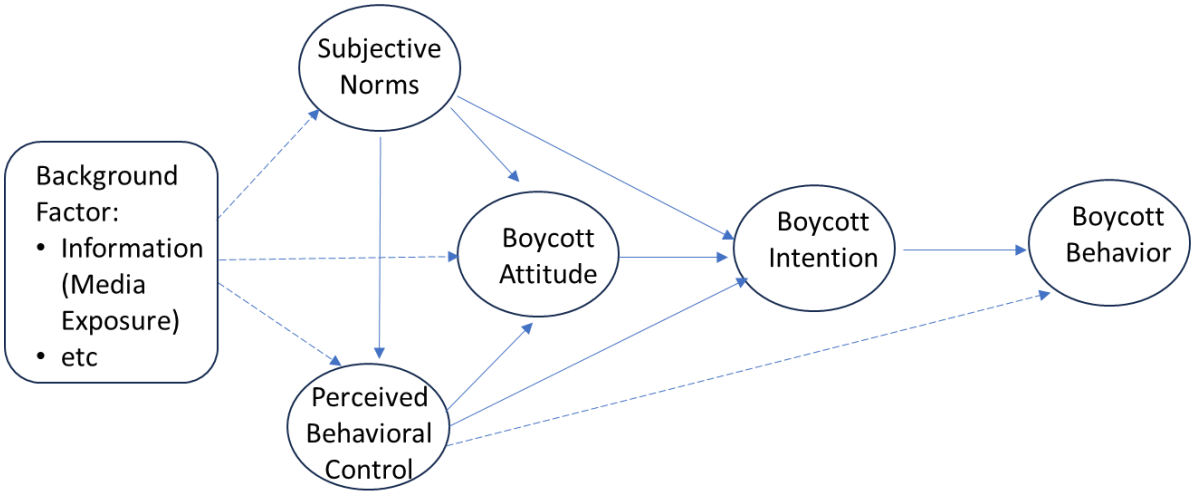


Fig. 1. The Model of the Theory of Planned Behaviour with Background Factors, Adapted from a Previous Study (Ajzen, 2005, p. 118, 135)

The TPB model with the background factor of media exposure was selected because the model was initially developed in psychology (Ajzen, 2005), which can be analysed using social cognitive theory (Bandura, 2002), cultivation theory (Morgan et al., 2016), and media exposure theory (Vreese & Neijens, 2016). Thus, adopting the TPB model with a media exposure background strengthens the psychological underpinnings of the findings and enriches the study's theoretical foundation. The role of media exposure in shaping behaviour under the TPB model, cultivation theory, and social cognitive theory is described in the later section.

2-3. The Boycott Behaviour under the TPB Model

Under the context of product boycott, some studies adopted TPB models (Asnawi et al., 2019; Delistavrou, 2022; Farah & Newman, 2010; Hamzah & Mustafa, 2019; Kim et al., 2023; Salma & Aji, 2023). Farah and Newman (2010) conducted a study on boycott intentions toward American products among Muslims and Christians in Lebanon. They found that boycott intentions were significantly affected by subjective norms, attitudes, and perceived behavioural control across the two groups. Asnawi et al. (2019) conducted a study on boycott intention toward products of pro-LGBT companies among domestic and international students in Indonesia. They found that subjective norms significantly affected boycott intention among domestic students, whereas attitude and perceived behavioural control affected it among international students. Hamzah and Mustafa (2019) conducted a study in Kuala Lumpur (Malaysia) about the intention to boycott Israeli supporting products under TPB (without background factor). They discovered that intention to participate in a product boycott was significantly affected by attitudes towards the boycott, subjective norms, and perceived behavioural control, but not by attitudes towards Israel. Delistavrou (2022) conducted a study on boycott intentions toward unethical supermarket products in Greece and found that boycott intentions were significantly affected by attitude, subjective norms, and perceived behavioural control. Kim et al (2023) investigated the effects of psychological and motivational factors on intention to participate in boycott products against Japanese products and actual purchasing behaviour in South Korea and found: first, boycott intention was positively and directly affected by subjective norms, attitude, and perceived behavioural control; second, actual purchasing behaviour (measured with: purchase

frequency, number of items purchased, and purchase amount) was negatively and directly affected by boycott intention and perceived behavioural control; and third, actual purchasing behaviour was negatively and indirectly affected by perceived behavioural control. A study on the boycott of French brands in Indonesia (Salma & Aji, 2023) revealed that subjective norms positively and significantly affected perceived efficacy, and that perceived efficacy, in turn, positively and significantly affected boycott intention. Those studies on boycott behaviour did not consider media exposure as a construct.

Based on the findings of the boycott studies under TPB above, the present study proposed some indicators of the primary constructs of TPB. Intention to boycott was measured using the likelihood of next-time boycott, definite boycott, and willingness to boycott (Tien et al., 2019; H. Yang, 2013). Perceived behavioural control was measured as freedom to boycott, ease of boycott, and control over ownership. Subjective norm was measured with other people's considerations (thoughts, willingness, and actions) (H. Yang, 2013). Attitude was measured by the likelihood of a boycott, dislike of boycotts, and a negative attitude towards boycotted products (H. Yang, 2013; H. Yang & Zhou, 2011).

2-4. Social Cognitive Theory: Media Exposure and the Process of Behavioural Change

Social cognitive theory "provides an agentic conceptual framework to examine the determinants and mechanism of the media/communication effect" on human thought, explains "psychological functioning in terms of triadic reciprocal causation" (i.e., personal, behavioural, and environmental determinants), and pays "much attention to the social origins of thought and mechanism through which social factors exert their influence on cognitive functioning" (Bandura, 2002, p. 121 & 123). Regarding media influence as the background factor in the present study's model, social cognitive theory suggests two pathways of media effect on behavioural change: the direct path from media influence to behavioural change, and the indirect path from media influence to behavioural change, mediated by connection to social systems. The present study then summarised the work of Bandura (2002) about the two pathways of behavioural change under media exposure (Figure 2), as follows: first, indirect pathway (socially mediated pathway) works under which media (mostly printed media having limited audiences) affect the opinion of the lead viewers/community leaders/influential persons and intermediaries who then affect others or diffuse information and point of view to others in their communities/social networks; and second, direct pathway works under ubiquitous media and the progress of communication technologies and global interconnectedness which many people are directly exposed to and affected by the media. The direct pathway is related to the TPB's components of behavioural control of the persons exposed to media affecting some other TPB's components (i.e., attitude, intention, behaviour); in contrast, the connection to social system under the indirect pathways is related to the TPB's component of subjective norms (the role of lead viewers/influential persons) affecting some other TPB's components (i.e., behavioural control, attitude, and intention) (Ajzen, 2005; Bandura, 2002).

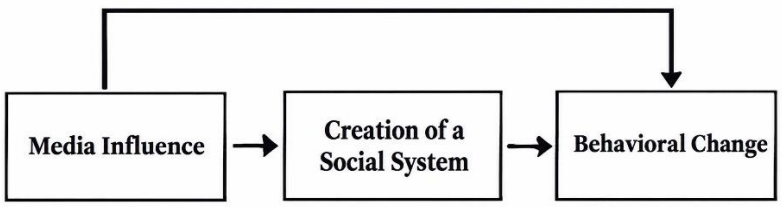


Fig. 2. Dual Pathways Between Media Exposure and Behavioural Change (Bandura, 2002, p. 141)

Socio-cognitive communication consists of three models for social change (i.e., theoretical model, translational and implementational model, and social diffusion model); the socio-cognitive theory only focuses on the analysis of the last model (social diffusion), analysing "new behaviour pattern in terms of the constituent processes" (acquisition of knowledge of innovative behaviour, adoption of behaviour, and the social network structure to spread the change) and "psychosocial factors governing them" (Bandura, 2002, p. 143 & 144).

The three processes and determinants of social diffusion of information from media promoting behavioural change are as follows (Bandura, 2002): first, the acquisition of knowledge of innovative behaviour is determined by the differences in required human competencies (e.g., knowledge,

resources, skills, and self-belief to use competencies) and physical proximity; second, the adoption of behaviour from what they have learned from media is determined by environmental inducements, incentive/benefit influences, self-evaluative reactions to the behaviour (approval for something valuable vs. resistance for something violating social and moral standards or conflicting with their self-conception), and the possibility to try the innovation; and third, the social network structure comprises clusters of varying density—from loosely knit to densely interconnected—whose direct and indirect ties enable the exchange of information and viewpoints; individuals with many ties are more likely to change their behavior because they diffuse more factual information and exert stronger social influence.

Based on the communication and psychological theories above, media exposure can include social media use and content that affects human behaviour. Some studies agreed that social media use and viral-recommended content affected human behaviour (Al-Maghaireh et al., 2024; McCreanor et al., 2024; Ng et al., 2025; Pescher et al., 2014; Tien et al., 2019; Ulo et al., 2025; H. Yang, 2013; T. Yang et al., 2023). Media exposure (measured by social media use and viral-recommended content in the present study) can be considered an antecedent of the basic TPB model. The following sections discuss the media exposure technology and the relationship between media exposure and other TPB components.

2-5. Technologies Facilitating Media Exposure

Background factors of media exposure are essential in the digital age. Media exposure refers to "the extent to which audience members have encountered specific messages or classes of messages/media content" (Slater, 2004, p. 168). Slater then proposed methods for measuring media exposure, namely self-reporting (asking the audience about their exposure to media messages), and estimating exposure likelihood (experimental manipulation in a laboratory or field setting). Vreese and Neijens (2016) also proposed measuring media exposure through self-reporting, passive measurement methods (passive registration systems, passive monitoring, and recording channel activities), and cross-media exposure (industry audience ratings), emphasising the importance of self-reporting. Vreese and Neijens (2016, p. 71) also proposed that the type of self-report can be free or unaided recall (inquiry about the number of days of watching TV or reading news, frequency of watching TV programs, time spent watching TV), aided recall (respondents are provided with a cue: question about the choice of TV program), confirmed or proven recall (respondents should prove what they have seen: "what was the ad/program about?"), recognition (the cue about the picture or footage of media content: showing the picture and asking "have you seen this?"), attention (the extent of attention paid to the news), and engagement (i.e., liking, sharing, forwarding, and discussing about the media contents). Moreover, the study described that self-reporting of media exposure is measured under a specific timeframe, such as "at this moment, today, yesterday/average day, last week/average week, last month/average month" (Vreese & Neijens, 2016, p. 72).

As media exposure is related to media, the cultivation theory, a theory in communication sciences, is discussed as bridging to psychological theory. The cultivation theory, initially developed by Gerbner and his colleagues between the 1960s and 1970s, refers to "the study on the contribution of mass-produced stories to audiences' conception of social reality," which initially focused on television (due to its role as dominant storytellers in the system of message production) and then developed to other media (e.g., digital video recorders, online streaming, on-demand videos, new networks, channels, and internet-based media which audiences can watch anytime and anywhere) (Morgan et al., 2016). The theory focuses on the effect of "long-term exposure to the complex system of messages among larger and heterogenous communities," concerns about "what is most broadly shared, in common, across program types and among large groups of otherwise heterogeneous viewers," and "what people would think about various aspects of reality (if they knew the issues or phenomena derived from media's dominant portrayals)," and examines the "independent contribution of media viewing to people's perception of the real world." The psychological theory of social cognition is then related to the theory of cultivation because cultivation is explained by cognitive processes, in which "the heuristic processing provides the cognitive key of understanding the cultivation" (Morgan et al., 2016, p. 3, 4, & 7).

3. Social Media Use

Some scholars (Vreese & Neijens, 2016; H. Yang, 2013) measured social media use with time spent on frequency and time spent (numbers of days or hours) for social media use in a typical timeframe (e.g., at this moment, today, yesterday, last week, and last month). Regarding social media use, Mortazavi et al. (2014) proposed some virtual social network attributes: social relationships, entertainment, information disclosure, and ease of use. The social relationship component was measured by improved social life performance, greater control over social interactions, improved quality of social relationships, greater effectiveness in maintaining social relationships, greater ease in maintaining social relationships, and greater usefulness in social life. In the present study, social media use was measured using the following indicators: multiple social media account ownership (the number of social media accounts), longer time spent using social media per day, improvement in social life performance, improvement in the quality of social relationships, effective maintenance of social relationships, and usefulness in social life (Lyons et al., 2024; Mortazavi et al., 2014; Vreese & Neijens, 2016; H. Yang, 2013).

The intensive use of social media enables exposure, which can affect human behaviour, as suggested by communication and psychological theories in the previous section. Lyons et al (2024) found that unhealthy-product consumers have multiple social media accounts and use them for many hours daily for entertainment, activism, social interaction, information discovery, information receiving, news searching, and boredom escape. In addition, social media is used to advertise products in the business sector. Another study in New Zealand (McCreanor et al., 2024) found that exposure to marketing through social media and advertising engagement affects alcohol purchasing behaviour.

During the Gaza crisis, many people used social media to access information about the situation in Gaza. For example, Jordanians spent many hours on social media following the Gaza situation, and high perceived stress was associated with longer time spent watching Gaza footage (Al-Maghaireh et al., 2024). In addition, frequent checks of social media (implying a longer time of social media use) on the Gaza situation caused severe health problems (i.e., fatigue and insomnia) among Jordanians (Gammoh et al., 2024). The use of social media among pro-humanitarian groups is discussed in a later section.

3-1. Artificial Intelligence in Social Media

Nowadays, social media platforms adopt AI for advertisement management, user experience, human emotion detection and analysis, content recommendation and moderation, creation and dissemination of information, learning and literacy, political and social mobilisation, business analytics, behavioural analysis, image analysis, and building reputation and relationships (Balaji et al., 2021; Saheb et al., 2024; Shah et al., 2020). Stryker & Kavlakoglu (2024) argued that AI refers to "a technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy." One such AI technology is machine learning (ML) (Balaji et al., 2021; Stryker & Kavlakoglu, 2024). As mentioned above, the AI can provide recommendations to its users.

The capability for recommendation provision is implemented in the recommendation engine and the recommendation system. Some scholars (Balaji et al., 2021; Caballar & Stryker, n.d.) used the terms interchangeably, but they may mean different things. The recommendation engine (recommender) refers to "an AI system suggesting items to a user," and the recommendation systems rely on "big data analytics and ML algorithms to find the patterns in behaviour data and recommend items based on the patterns to a user" (Caballar & Stryker, n.d.). The recommendation engine consists of three types: collaborative filtering, content-based filtering, and a hybrid recommendation system (Caballar & Stryker, n.d.; Maddodi & Prasad, 2019). Balaji et al. (2021) argued that the recommendation engine is an algorithm recommending the recommendation list to social media user based on collaborative filtering, content filtering, and geographical filtering and other users' preference while the recommendation system is the ML technology that can be used to perform an analysis based on user behaviour, run algorithm based on recommendation engine, and recommend the appropriate list to the user (Figure 3).

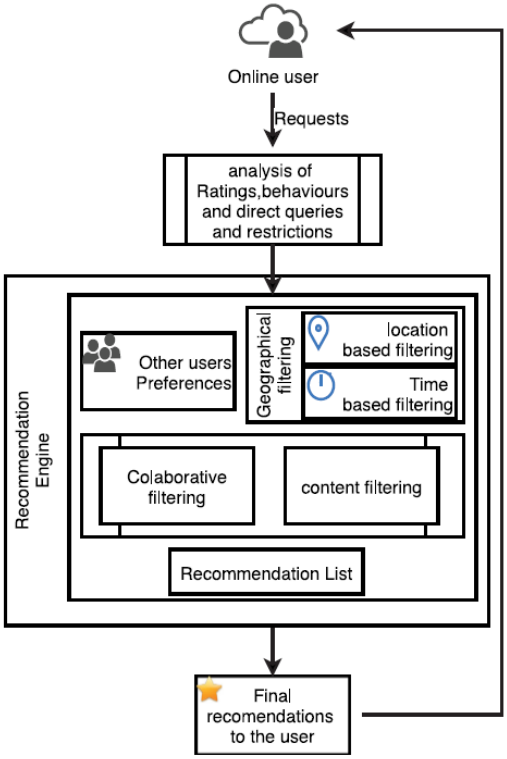


Fig. 3. The Recommender System Using Social Media (Balaji et al., 2021, p. 20)

In relation to the AI-powered technologies above, the social media algorithm is divided into two categories based on their function (Narayanan, 2023): content processing (e.g., face recognition, image filters, augmented and virtual reality, annotation, audio transcription, and language translation) and content propagation (e.g., search, recommendation/feeds, add delivery and targeting, content moderation, friend recommendation, notification, and trending). An AI-powered recommendation system in social media was used for propagation (Guinaudeau et al., 2022; Narayanan, 2023; Saheb et al., 2024). Social media-led information propagation is frequently driven by mixed social media platforms, including subscription-based, network-based, and algorithmic platforms, as presented in Table 1. The algorithm-led content propagation promotes the massive virality of social media content based on similar interests in past engagement (Narayanan, 2023). AI-powered social media can be used to disseminate information and mobilise support for humanitarian catastrophes. Some scholars (Balaji et al., 2021; Saheb et al., 2024) argued that AI-powered technologies can be used for crisis or disaster management.

Table 1. The Model of Information Propagation in Social Media

	Subscription	**Network**	**Algorithm**
What a user sees	Posts by those whom they have subscribed to	Posts by (or shared by) those that they have subscribed to	Posts that the algorithm predicts the user will like best
What impact does a post's reach have?	Poster's subscriber count	Both subscriber count and content	The content of the post
Example	Pre-2009 Facebook and pre-2022 Instagram	Pre-2016 Twitter	TikTok and YouTube

Source: Narayanan (2023)

3-2. The Role of Content Virality and Recommendation on Successful Propagation

Pro-humanitarian, religious groups, and even victims used social media to spread information and videos about the Israeli attacks and the Gaza situation to influence global support to deal with the Israel-Gaza crisis. The Israel-Gaza crisis since October 2023 had gone viral on social media (Al-Maghaireh et al., 2024; Darcy, 2023; Harwell & Lorenz, 2023; Kaur, 2024; Oremus & Nix, 2023) to inform the public and mobilise support. Previous conflicts between the Gaza militia and Israeli troops

were documented by Palestinian mobile phone activism and voluntary war journalism through social media, as follows. First, the Israel-Palestine conflict in July 2017, induced by the closure of the gate of Al-Aqsa, one of the Islamic holy sites, was also documented through social media (with some content, including photographs, videos/footage, illustrations, and infographics) to spread information and mobilise protest (A. M. A. Abushbak & Majeed, 2020). Second, during the Israel-Gaza conflict in May 2021 (or Operation Guardian of the Wall), Gazans of all ages recorded, documented, archived, and retrieved their content about terrific and deadly events that they experienced (embodied in videos, footage, pictures, and testimonies) to extend their mourning and other emotions to global society through social media so that the global society was aware of their situation, supported them and mobilised actions against the oppression (A. M. Abushbak et al., 2024).

The success of online movements in reaching many social media users depends on content virality and recommendations. Pescher et al (2014) then proposed the successive decision-making process of mobile viral campaigns (Figure 4) as follows: the first stage is "reading the message" (affected by entertainment value and the strength of the tie between sender and recipient); the second stage is "visiting the homepage or interested" (affected by entertainment value and purposive value/usefulness); and the third stage is "forwarding the message or decision to refer" (affected by entertainment value, purposive value/usefulness, usage intensity or the habit of writing a mobile text message, and the strength of the tie between sender and recipient).

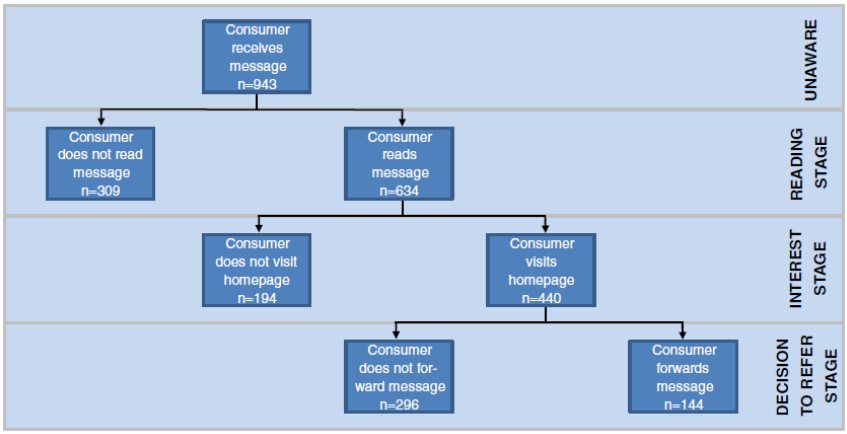


Fig. 4. Users' Decision-Making Process in a Viral Campaign (Pescher et al., 2014, p. 49)

In the AI era, content virality can work well when a user receives a feed or recommended content. How the recommendation works depends on the types of recommendation techniques adopted by the social media platforms (Balaji et al., 2021; Caballar & Stryker, n.d.; Maddodi & Prasad, 2019). Maddodi and Prasad (2019) exemplified how someone receives the recommendation in a schematic model (Figure 5).

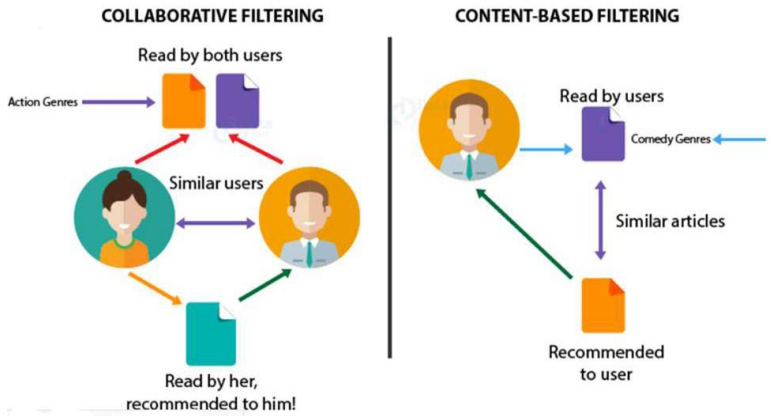


Fig. 5. The Process of AI-Powered Recommendation (Maddodi & Prasad, 2019, p. 45)

In a collaborative filtering, a user (e.g., user A: watching crime, horror, and action movies) will receive a recommended content based on the habits of other user (e.g., user B: watching crime, action, and comedy movies), who has watching profile in common, that is watching crime and action movies (Maddodi & Prasad, 2019). For example, user A receives a Netflix recommendation for a comedy movie that user B watched. In contrast, user B receives a recommendation of a horror movie that user A watched (Maddodi & Prasad, 2019). The recommendations generated by collaborative filtering could be described as viral. In content-based filtering, a user receives a recommended comedy movie because they watched similar comedy movies in the past (Maddodi & Prasad, 2019). In a hybrid recommendation system, user A receives a recommended movie because they watched a similar movie in the past, and the recommended movie was watched by another user with a similar profile to user A (Maddodi & Prasad, 2019). Narayanan (2023) confirmed that the recommendation of content to a user occurs due to a similar interest in past engagement. When a user receives a recommendation, it can go viral if the user shares the recommended content, as shown in Figure 4 (Pescher et al., 2014).

Some other scholars (Balaji et al., 2021; Berger & Milkman, 2012; Ulo et al., 2025; T. Yang et al., 2023) suggested that the adoption of viral content and content recommendations is affected by trustworthiness, usefulness, reliability, sentiment, and emotion. Online content attracts consumers' attention and goes viral because it evokes positive and negative sentiments, expresses specific emotions (e.g., awe, anger, anxiety, and sadness), and is informative (with practical utility) (Berger & Milkman, 2012). In addition, positive emotion (i.e., awe) is more viral than negative emotion (i.e., anger, sadness, and anxiety) (Berger & Milkman, 2012). Among the negative feelings, anger and anxiety are more prevalent than sadness (Berger & Milkman, 2012). Ulo et al. (2025) conducted a study in Indonesia and found that the adoption of healthy food recommendations on social media was directly influenced by the credibility and usefulness of the recommendations. A study among consumers in China (T. Yang et al., 2023) found that source credibility affected recommendation usefulness and credibility, that recommendation satisfaction was affected by recommendation usefulness and credibility, and that recommendation adoption was affected by recommendation satisfaction. Balaji et al. (2021) emphasised that content recommendations should be interesting and relevant to appropriate, trusted users.

In the context of the Gaza humanitarian crisis, the authors assumed that source trustworthiness and content credibility are essential. Source trustworthiness was measured using the following: reliable, trustworthy, sincere, honest, and dependable (Tien et al., 2019; T. Yang et al., 2023). Recommendation and viral content credibility were measured by their factualness, accuracy, and credibility (Tien et al., 2019; T. Yang et al., 2023). Because recommended content can go viral, as argued by some scholars (Narayanan, 2023; Pescher et al., 2014), the present study used the terms viral and recommended content (or viral-recommended content) to avoid confusion. Therefore, the present study measured the viral and recommended content with the following indicators: receiving the content (including reading), visiting the homepage, anger, sadness, being independent/undependable, honesty, reliability, sincerity, trustworthiness, being factual, accuracy, and credibility (Berger & Milkman, 2012; Pescher et al., 2014; Tien et al., 2019; T. Yang et al., 2023).

3-3. Relationship between the AI-Driven Media Exposure and Intention

Combining social media use and viral-recommended content into a single media exposure measurement makes sense, given the individual descriptions of media exposure indicators and their effects on behavioural change. The following argument describes some rationale for combining two lower-order components (LOCs) into a single media exposure construct. Combining media exposure into a single construct is warranted, as the measurement of media exposure in communication science inherently encompasses a combination of various media content—such as news, political comedy, images, advertising, and entertainment—encountered across platforms including television, billboards, videos, social networking sites, media footage, and games (Vreese & Neijens, 2016). Those represent social media use and viral-recommended content, enabling user engagement. The cultivation theory, which studies mass media and audiences' conception of social reality, can apply to any media and implies combined media exposure (Morgan et al., 2016). The social cognitive theory of mass communication, which studies media's effects on behavioural change, operates in both direct and

indirect ways (Bandura, 2002), and thus behavioural change can be affected by any media. It means the combination of constructs is possible.

Some scholars (Kadel et al., 2024; Korsakiene et al., 2024; Samaniego-Arias et al., 2025; Zejjari & Benhayoun, 2025) have adopted media exposure as a single aggregate construct for empirical research. For example, Korsakiene et al. (2024) studied the effect of media exposure on gambling intention and the problem severity of gambling in Lithuania using social cognitive theory and the theory of planned behaviour. They found that media exposure (measured with the frequency of watching gambling videos and movies, frequency of seeing gambling pictures and comments on social media, frequency of watching TV programs about gambling, frequency of seeing gambling advertisements in magazines and newspapers, frequency of hearing songs about gambling, and frequency of watching video games about gambling) had positive effect on attitude and perceived behavioural control (having positive effect on gambling intention) as well as subjective norms (having adverse effect on gambling intention). A study on veganism communication on Instagram, reflected through vegan hashtags (#vegan), using the TPB model (Kadel et al., 2024), revealed that Instagram's vegan posts gained engagement (liking, virality—sharing and forwarding—and discussion) among communities. Kadel et al. (2024) also found that media exposure (measured with the frequency of seeing veganism posts and frequency of sharing and reposting the veganism posts) significantly affected some TPB components (i.e., attitude, subjective norms, and perceived behavioural control), sharing the posts affected attitude and peer pressure, interaction significantly affected peer pressure, attitude and perceived behavioural control affected intention to adopt a vegan diet.

A study in Ecuador on social media use and intention to purchase organic products using the TPB model (Samaniego-Arias et al., 2025) found that social media use significantly and positively affected some TPB components (i.e., subjective norms, attitude, and perceived behavioural control) and had an indirect effect on purchase intention through the three TPB components. Moreover, a study on the boycott of Israel-linked products in Morocco (Zejjari & Benhayoun, 2025) found that subjective norms positively and significantly affected boycott intention, and that social media (not a higher-order construct) significantly and positively affected boycott intention, suggesting the role of social media use and virality.

All indicators of media exposure across studies (Kadel et al., 2024; Korsakiene et al., 2024; Samaniego-Arias et al., 2025; Zejjari & Benhayoun, 2025) fall into the social media use and virality categories. The media exposure constructs in those studies are not higher-order constructs (that is, they are ordinary, first-order constructs). Given the importance of media exposure as a background factor in affecting consumers' intention under the TPB model (Ajzen, 2005; Kadel et al., 2024; Korsakiene et al., 2024; Samaniego-Arias et al., 2025) and the importance of direct and indirect pathways (Figure 2) under social cognitive theory (Bandura, 2002), the present study proposed the following hypotheses:

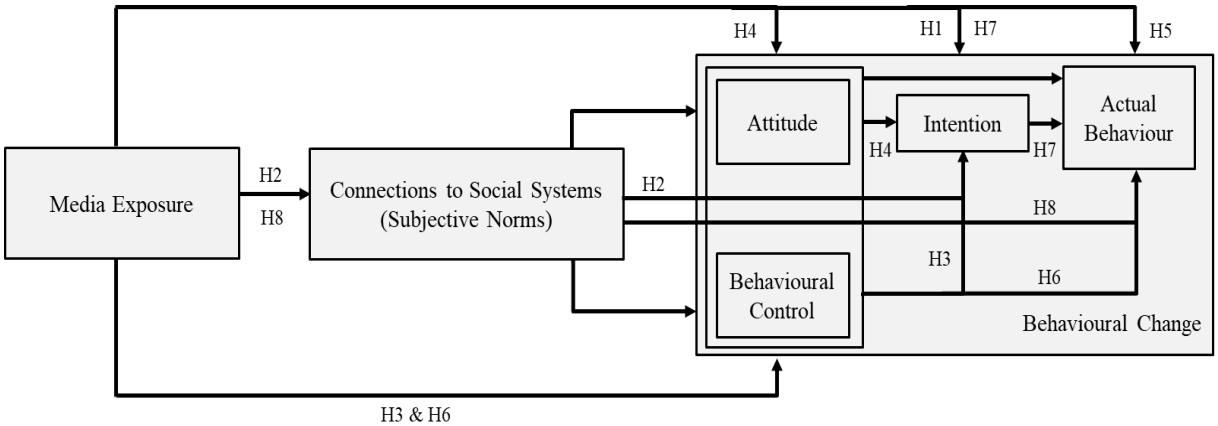


Fig. 6. Extended Dual Pathways between Media Exposure and Behavioural Change, Which was Used in This Study, based on Bandura (2002)

H_1: Boycott intention is directly affected by media exposure.
H_2: Boycott intention is indirectly affected by media exposure through subjective norms.

The social cognitive model (Figure 2) is unclear about whether or not it describes the relationship between media exposure and intention. Some other TPB components should be considered within the social cognitive model of media exposure. Thus, the present study proposed an extension of the social cognitive model of the media exposure effect (Figure 6). Based on the extended model, the present study then proposed some other hypotheses, as follows:

H_3: Boycott intention is indirectly affected by media exposure through perceived behavioural control.
H_4: Boycott intention is indirectly affected by media exposure through attitude.

3-4. Relationship between the AI-Driven Media Exposure and Behavioural Change

Given the debated relationship among variables in social cognitive theory (Bandura, 2002), the present study assumed a literal dual pathway between media exposure and behavioural change. The following study supported the assumption. A study in Spain on the boycott against Catalonian products and services (Palacios-Florencio et al., 2021) demonstrated that social influence negatively affected boycott behaviour, though this effect was insignificant. The social influence construct in the Catalonian boycott study was related to media exposure affecting behaviour. However, the study on the Catalonian boycott did not adopt a higher-order construct of social influence. Based on the literature, the present study proposed the following hypothesis:

H_5: Boycott behaviour is directly affected by media exposure.

Based on the extension of the dual pathways between media exposure and behavioural change in Figure 6, the present study proposed the following hypotheses:

H_6: Boycott behaviour is indirectly affected by media exposure through perceived behavioural control.
H_7: Boycott behaviour is indirectly affected by media exposure through boycott intention.

Palacios-Florencio et al. (2021) found that social influence was associated with boycott behaviour, although this association was not significant. The present study linked the findings of the previous study (Palacios-Florencio et al., 2021) with the social cognitive theory model (Bandura, 2002), which posits that media affect the social system, leading to behavioural change. Thus, the present study proposed the following hypothesis:

H_8: Boycott behaviour is indirectly affected by media exposure through subjective norms.

Based on the literature and hypotheses above, the present study proposed some constructs and their indicators, as presented in Table 2. The constructs in Table 2 were developed based on the conceptual model in Figure 6.

Table 2. Constructs and Their Indicators Used in the Present Study

Construct	Indicator	Source
Viral and Recommended Content	Receiving (including reading) Visit homepage Anger Sadness Independent/undependable Honest Reliable Sincere Trustworthy Factual Accurate Credible	(Berger & Milkman, 2012; Pescher et al., 2014; Tien et al., 2019; T. Yang et al., 2023)
Social Media Use	Number of social media accounts Longer time spent per day Improvement of social life performance Improvement of the quality of social relationships Effective maintenance of social relationships Usefulness in social life	(Lyons et al., 2024; Mortazavi et al., 2014; Vreese & Neijens, 2016; H. Yang, 2013)
Subjective Norms	Other people's consideration: thinking Other people's consideration: willingness Other people's actions	(H. Yang, 2013)
Perceived Behavioural Control	Free to boycott Easiness to boycott Own control	(H. Yang, 2013)
Boycott Attitude	Possibility to boycott Dislike boycotting (reverse coded) Negative Attitude towards boycotted products	(H. Yang, 2013; H. Yang & Zhou, 2011)
Boycott Intention	Likely to boycott Next-time boycott Definite boycott Willingness to boycott	(Tien et al., 2019; H. Yang, 2013)
Boycott Behaviour	Product Dislike Purchasing extent Disloyalty Feeling guilty about buying Avoid buying Substitution with others: neutral local products Substitution with others: neutral imported products	(Abosag & Farah, 2014; Sen et al., 2001)

4. Materials and Methods

The present study investigates the role of AI-driven media exposure in shaping boycott intention and boycott behaviour. The study adopted the TPB with background factors (Ajzen, 2005). A questionnaire survey was adopted (Saunders et al., 2019). An online questionnaire (using Google Forms) was distributed through social media in some Indonesian provinces from November 2023 to March 2024. Based on the distribution of the online questionnaire, 521 individuals completed it. However, nine observations were removed due to duplicate or uniform responses, and eight were removed due to non-smartphone ownership. The research on social media exposure can only efficiently work if respondents have smartphones. Thus, the total sample used in statistical analysis was 504 observations, scattered in 32 of 38 Indonesian provinces. The profile of the respondents is presented in Table 3.

Table 3 demonstrates that most of respondents are male (56.35%), highly educated (88.29%), employed (70.04%), medium- and high-income earners, that is above USD 306 (56.75%), urban residents (82.74%), of working age (74.01%), Muslim (96.83%), smartphone owners (100%), monthly data subscribers (95.04%), and holders of multiple social media accounts (96.03%). These characteristics of the respondents align with some facts about Indonesians in 2025, as follows: 54% of social media users was male, 62.7% of Indonesia population was social media users with the age of 18 and above, 67.3% of Indonesia's total internet users had at least one social media platforms, 74.38%

of total population was internet users, 96.4% mobile connections was broadband connected via 3G, 4G, or 5G mobile networks (Kemp, 2025). The urban residence of respondents accounted for 82.2% of internet penetration in urban areas, contributing to 69.5% of urban internet users in Indonesia (Machmudi & Nurcahyadi, 2024). Respondents' income sources are associated with telecommunication expenditure. According to statistical data (Indonesia Statistical Agency, 2024), the average of Indonesia's household consumption having telecommunication expenditure in 2023 was IDR 6.8 million (USD 417), with urban household consumption being IDR 7.1 million (USD 435) and rural household consumption being IDR 6.4 million (USD 392). The statistical data (Indonesia Statistical Agency, 2024) also revealed that the average of Indonesia's household consumption for telecommunication in 2023 was IDR 207 thousand or USD 13 (3.58% of total consumption), which urban telecommunication expenditure was IDR 247 thousand or USD 15 (3.71% of total consumption) and rural telecommunication expenditure was IDR 148 thousand or USD 9 (3.28% of total consumption). The data show that total urban household consumption and telecommunication consumption are above the national average.

Table 3. Demographic Characteristics of Respondents (*N* = 504)

No	Socio-Demographic Characteristics		Total (Person)	Proportion (%)	Type of Sample	Sample Measurement
1	Gender	Male	284	56.35	Categorical	Male (1) and female (0)
		Female	220	43.65		
2	Education	Senior high school or less	59	11.71	Categorical	Senior high school or less (1), vocational and undergraduate (2), and postgraduate (3)
		Vocational and undergraduate	230	45.63		
		Postgraduate	215	42.66		
3	Employment status	Student	121	24.01	Categorical	Student (1), employee (2), entrepreneur/self-employee (3), retired person (4), housewife (5)
		Employee	353	70.04		
		Entrepreneur/self-employee	21	4.17		
		Retired person	2	0.40		
		Housewife	7	1.39		
4	Income	No income/ not mentioned	104	20.63	Categorical	No incomes/not mentioned (0), < IDR 5 million or < USD 306 (1), IDR 5 – 10 million or USD 306 – 613 (2), and > IDR 10 million or > USD 613 (3)
		< IDR 5 million (< (USD 306) *	114	22.62		
		IDR 5 – 10 million (USD 306 – 613) *	203	40.28		
		> IDR 10 million (> USD 613) *	83	16.47		
5	Residence	Urban	417	82.74	Categorical	Non-urban (1), neutral (2), and urban (3)
		Non-urban	87	17.26		
6	Age	22 Y.O. or lower	109	21.63	Categorical	22 Y.O. or lower (1), > 22 Y.O. - < 55 Y.O. (2), and 55 Y.O. or higher (3)
		> 22 Y.O. – < 55 Y.O.	373	74.01		
		55 Y.O. or higher	22	4.37		
7	Religion	Muslim	488	96.83	Categorical	No answer (0), non-Muslim (1), and Muslim (2)
		Non-Muslim	14	2.78		
		No Answer	2	0.40		
8	Smartphone ownership	Yes	504	100	Categorical	Yes (1) and No (0)
		No**	-	-		
9	Monthly data subscription	Yes	479	95.04	Categorical	Yes (1) and No (0)
		No	25	4.96		
10	Multiple social media account ownership	Yes	484	96.03	Categorical	Yes (1) and No (0)
		No	20	3.97		

* 1 USD is equal to IDR 16.324.-; **Eliminated

Out of 504 respondents, most of them came from the following provinces: West Java (19.44%), Southeast Sulawesi (13.89%), Jakarta (9.52%), West Sumatera (7.94%), Yogyakarta (7.74%), Central Java (6.75%), Lampung (6.15%), South Sulawesi (5.16%), East Java (4.37%), and North Sumatera (3.77%). These provinces contributed 85.12% (429 observations). The rest of respondents came from

Banten (3.37%), South Sumatera (2.58%), Aceh (1.59%), West Kalimantan (0.79%), Riau (0.79%), South Kalimantan (0.60%), Bangka Belitung (0.60%), North Maluku (0.60%), West Nusa Tenggara (0.60%), Bali (0.40%), Jambi (0.40%), Central Kalimantan (0.40%), Maluku (0.40%), West Papua (0.40%), Gorontalo (0.20%), East Kalimantan (0.20%), North Kalimantan (0.20%), Riau Islands (0.20%), East Nusa Tenggara (0.20%), Papua (0.20%), South Papua (0.20%), and Central Sulawesi (0.20%). The majority of respondents (44.44%) came from Java island (i.e., Jakarta, West Java, Banten, Central Java, Yogyakarta, and East Java), which has the highest share of internet users (83.64% of the total population) among the main islands in Indonesia due to the availability of infrastructure (Machmudi & Nurcahyadi, 2024).

The respondents were asked questions about social media use, viral and recommended content, and product boycott behaviour (Table 4) using a 7-point Likert scale. The questions in Table 4 were formulated based on the indicators in Table 2. The use of the 7-Likert scale in the present study is consistent with previous studies on product boycotts (Abosag & Farah, 2014; Sen et al., 2001), and some of their variables were adopted in the present study. Most answers to questions used the 7-Likert scale: strongly disagree = 1, disagree = 2, somewhat disagree = 3, neutral = 4, somewhat agree = 5, agree = 6, and strongly agree = 7 (Busayo.longe, 2012). Some questions (i.e., Attitude_2, Behaviour_1, Behaviour_2, and Behaviour_3) adopted different 7-Likert scales (Bhandari & Nikolopoulou, 2023), as presented in Table 4. When asked about product boycotts, the respondents were presented with a picture of pro-Israeli products alleged to be under boycott since the attack in October 2023 (Alysherif, 2023).

Data obtained from the survey were analysed using Covariance-Based Structural Equation Modelling (CB-SEM; Dash & Paul, 2021; Hair, Babin, et al., 2017; Hair et al., 2019) with smartPLS 4. The CB-SEM is appropriate for testing the TPB model using the higher-order construct of media exposure as the background factor (Ajzen, 2005), as CB-SEM aims to confirm the theory (Dash & Paul, 2021).

The present study adopted a higher-order construct (Hair et al., 2022). Of the typologies of higher-order constructs, this study adopted the reflective-reflective type (Hair et al., 2022; Sarstedt et al., 2019). The reflective-reflective type was selected because the higher-order construct provides a simple measurement model: only reliability and validity tests (Sarstedt et al., 2019). In contrast, other types of higher-order construct require relatively more complicated measurement model tests. For example, the reflective-formative type requires a collinearity test for HOC (Sarstedt et al., 2019). Instead, adopting the fit test (Dash & Paul, 2021; Hair et al., 2017) sufficiently explains the fit of the structural model under the reflective-reflective type.

The reflective-reflective type consists of a higher-order component (HOC) (i.e., media exposure), reflecting lower-order components (LOCs) (Hair et al., 2022; Sarstedt et al., 2019). Hair, Matthews, et al. (2017) argued that performing a higher-order construct under CB-SEM requires at least three LOCs. The initial LOCs were Social Media Use, Electronic Word of Mouth (eWOM), and Viral Content. However, refocusing on viral and recommended content led the present study to reduce the number of LOCs from 3 to 2. Thus, the relevant LOCs are only social media use and viral-recommended content. Two LOCs are possible, as demonstrated by Hair et al. (2018).

The data were then analysed using CB-SEM methods under a reflective measurement model (e.g., validity and reliability test) and structural model (e.g., statistical inference and fit indices) (Dash & Paul, 2021; Hair et al., 2017, 2019). The criteria for judging the output of reflective measurement and structural model are presented in Table 5. Regarding fit indices, some scholars (Dash & Paul, 2021; Hair et al., 2017, 2017, 2019) differ in their thresholds, which can be confusing. Thus, the present study referred to Hair et al. (2019) for the thresholds and to Hair, Matthews, et al. (2017) for reporting the limited fit measures (e.g., chi-square, CMIN/df, GFI, AGFI, CFI, and RMSEA). Thus, the fit measures presented in Table 5 are also limited. Hair et al. (2019) proposed additional fit indices, namely Standardised Root Mean Square Residuals (SRMR) and the Relative Non-Centrality Index (RNI). However, RNI is not available in the CB-SEM output.

Table 4. Questions/Statements to Respondents by Constructs

Construct	Indicator	Question/Statement*
Content	Content_1	I have always *received* (and read) posts about Israeli Attacks against the Gaza Strip since October 2023.
	Content_2	I have always *visited* the website/link about Israeli Attacks against the Gaza Strip since October 2023.
	Content_3	I *felt anger* when reading content on Israeli Attacks against the Gaza Strip since October 2023.
	Content_4	I *felt sad* when reading content on Israeli Attacks against the Gaza Strip since October 2023.
	Content_5	Content on Israeli Attacks against the Gaza Strip since October 2023 came from *independent sources.*
	Content_6	Content on Israeli Attacks against the Gaza Strip since October 2023 came from *honest sources.*
	Content_7	Content on Israeli Attacks against the Gaza Strip since October 2023 was *reliable.*
	Content_8	Content on Israeli Attacks against the Gaza Strip since October 2023 was *sincere.*
	Content_9	Content on Israeli Attacks against the Gaza Strip since October 2023 was *trustworthy.*
	Content_10	Content on Israeli Attacks against the Gaza Strip since October 2023 was *factual.*
	Content_11	Content on Israeli Attacks against the Gaza Strip since October 2023 was *accurate.*
	Content_12	Content on Israeli Attacks against the Gaza Strip since October 2023 was *credible.*
Socmed	Socmed_1	I have multiple accounts on social media.
	Socmed_2	I spend much time on social media every day.
	Socmed_3	Using social media improved my social life performance (e.g., I often interact with others, get updated better, and keep social relationships stronger).
	Socmed_4	Using social media improved the quality of my social relationships.
	Socmed_5	Using social media improved my effectiveness in maintaining social relationships.
	Socmed_6	Overall, using social media was helpful in my social life.
Norms	Norms_1	Most people who are important me *think* it is *good to boycott* allegedly pro-Israeli products in order to reduce the humanitarian crisis.
	Norms_2	Most people who are important to me are *willing to boycott* allegedly pro-Israeli products to reduce the humanitarian crisis.
	Norms_3	Most people who are important to me *boycotted* allegedly pro-Israeli products to reduce the humanitarian crisis.
Control	Control_1	I *feel free to boycott* allegedly pro-Israeli products if I like to do it.
	Control_2	It is *easy* for me *to boycott* allegedly pro-Israeli products.
	Control_3	Boycotting pro-Israeli alleged products is entirely within my *control.*
Attitude	Attitude_1	Generally, I think that it is *good to boycott* allegedly pro-Israeli products to reduce the humanitarian crisis.
	Attitude_2	Honestly, I do not like to boycott allegedly pro-Israeli products (reverse-coded).
	Attitude_3	My *attitude* towards pro-Israeli alleged products is *negative.*
Intention	Intention_1	It is *likely* for me not to buy/reduce buying allegedly pro-Israeli products.
	Intention_2	I will not buy/will reduce buying allegedly pro-Israeli products *next time*, even if I need them.
	Intention_3	I will not buy/will reduce buying allegedly pro-Israeli products.
	Intention_4	I am *willing to boycott* allegedly pro-Israeli products to reduce humanitarian crises in Palestine.
Behaviour	Behaviour_1	How much do you *like* and *dislike* allegedly pro-Israeli products? **
	Behaviour_2	When you buy allegedly pro-Israeli products, to what *extent* do you *buy* the product? ***
	Behaviour_3	When you buy allegedly pro-Israeli products, to what extent are you *loyal*? ***
	Behaviour_4	I would *feel guilty* if I bought allegedly pro-Israeli products.
	Behaviour_5	Whenever possible, I *avoid buying* products that are allegedly pro-Israel.
	Behaviour_6	If local products were equal in quality to the allegedly pro-Israeli products, I would pay higher prices for *the local products.*
	Behaviour_7	If imported products were equal to pro-Israeli products in terms of quality and were politically neutral (ethical), I would be willing to pay higher prices *for them.*

* General response: Strongly disagree = 1, disagree = 2, somewhat disagree = 3, neutral = 4, somewhat agree = 5, agree = 6, and strongly agree = 7; **Dislike very much = 1; dislike = 2, somewhat dislike = 3, neutral = 4, somewhat like = 5, like = 6, and like very much = 7; ***Never = 1, rarely = 2, occasionally = 3, sometimes = 4, frequently = 5, usually = 6, and every time = 7

Table 5. Decision Criteria of CB-SEM

Evaluation Criteria	Thresholds
Reflective measurement model:	
Reflective indicator loadings	≥ 0.708 (0.40 for a sample size of > 200)
Internal consistency and reliability:	
• Cronbach's alpha/Rho_C/Rho_A	≥ 0.70 (0.60 in exploratory research)
Convergent validity: average variance extracted (AVE)	≥ 0.50
Discriminant validity: hetero-trait-monotrait ratio (HTMT)	< 0.90
Structural model:	
Significance and relevance of the path coefficients	Use bootstrapping under t-value for two-tailed test: ***2.57(α = 0.01), **1.96 (α = 0.05), and *1.65 (α = 0.10)
Explanatory power: R^2 value	0.75 (substantial), 0.50 (moderate), or 0.25 (weak)
Mediation Type:	
Complementary mediation (partial)	If P1*P2 (indirect) is significant, and P3 (direct) is significant, and P1*P2*P3 is positive
Competitive mediation (partial)	If P1*P2 is significant, P3 is significant, P1*P2*P3 is negative;
Full mediation (indirect only)	If P1*P2 is significant and P3 is insignificant;
No mediation (direct only)	If P1*P2 is insignificant, but P3 is significant; and
No mediation (no effect)	If P1*P2 is insignificant and P3 is insignificant as well.
Absolute Fit Measures:	
• The Chi-square of the estimated model	P value < 0.05 (for N > 250 and number of parameters > 30)
• CMIN/df or Chi-square/df or Normed Chi-square	3:1
• Goodness-of-fit index (GFI)	Fall between 0 and 1 (> 0.95 is better)
• Adjusted Goodness-of-fit index (AGFI)	Lower than GFI
• Root Mean Square Error of Approximation (RMSEA)	< 0.07
• Standardised Root Mean Square Residuals (SRMSR or SRMR)	0.08 or less
Incremental Fit Measures:	
• Comparative Fit Index (CFI)	Fall between 0 and 1 (> 0.92 is better)

Source: (Dash & Paul, 2021; Hair et al., 2017, 2017, 2019, 2022)

In line with the criteria in Table 5 and higher-order constructs of CB-SEM, Sarstedt et al. (2019) suggested that HOC and LOCs under reflective-reflective type (measurement model) were assessed using internal consistency and reliability, convergent validity, and discriminant validity, while the structural model was assessed using significance and relevance of the path coefficients and explanatory power. The fit test can assess the structural model results (Dash & Paul, 2021). The mediation analysis used the general criteria for structural model evaluation, along with additional criteria to determine the mediation type. Hair et al. (2022) suggested the criteria to determine the mediation type, as follows: first, it is complementary mediation (partial) if P1 (Y1→ Y2) * P2 (Y2 →Y3) is significant, P3 (Y1 → Y3) is significant, and P1*P2*P3 is positive; second, it is competitive mediation (partial) if P1*P2 is significant, P3 is significant, P1*P2*P3 is negative; third, it is complete mediation (indirect only) if P1*P2 is significant and P3 is insignificant; fourth, it is no mediation (direct only), if P1*P2 is insignificant, but P3 is significant; and fifth, it is no mediation (no effect) if P1*P2 is insignificant and P3 is insignificant as well.

When running CB-SEM, the present study ran a basic CB-SEM algorithm and CB-SEM bootstrapping, as provided by the PLS-SEM software. The basic CB-SEM algorithm was run to obtain the results of the reflective measurement model, R^2 value, absolute fit measure values, and incremental fit measure value using the default parameters: maximum iteration count was 10.000, stop criteria (gradient and function value) were 10^{-9} (very accurate), starting value strategy was checked for applying configured starting values (default), no special assumption was checked, and no mean-structure was used (default). The CB-SEM bootstrapping was used to produce significance and relevance of the path coefficient using some default criteria: subsamples were 500; parallel processing was checked; the number of results was the most important (faster); the confidence interval method

was percentile bootstrap; the test type was two-tailed under the 0.05 significance level; and the random number generator used a fixed seed.

5. Results

5-1. Reflective Model Evaluation

The statistical results of the reflective measurement model are presented in Tables 6 and 7. Most indicators of the constructs had standardised outer loadings above 0.708 (fulfilling the threshold), but some (mainly under the LOC of content and the construct of Behaviour) fell between 0.40 and 0.70. It is still tolerable (still fulfilling the threshold) because the sample size was large (> 200) and the reliability and validity values of the constructs fulfilled the thresholds (Hair et al., 2019, 2022). After the removal of the attitude construct (due to reliability and validity issues), all constructs fulfilled the requirements of reliability and validity (Cronbach's alpha and rho_C were > 0.70) and convergent validity (AVE was > 0.50) (Table 6). Regarding discriminant validity, all constructs and most LOCs met the validity requirements, in an HTMT ratio below 0.90 (Table 7). Therefore, the manifest and latent variables fulfilled the requirements of validity and reliability.

Table 6. Results of the Validity and Reliability Test

Construct (Latent Variable)	Indicator (Manifest Variable)	Indicator Loadings (Std)	Cronbach's Alpha (Std)	rho_C	AVE
Content (LOC)	Content_1	0.624	0.960	0.956	0.680
	Content_2	0.569			
	Content_3	0.583			
	Content_4	0.644			
	Content_5	0.838			
	Content_6	0.912			
	Content_7	0.896			
	Content_8	0.933			
	Content_9	0.929			
	Content_10	0.925			
	Content_11	0.939			
	Content_12	0.939			
Socmed (LOC)	Socmed_1	*	0.921	0.924	0.749
	Socmed_2	*			
	Socmed_3	0.793			
	Socmed_4	0.926			
	Socmed_5	0.934			
	Socmed_6	0.800			
Exposure (HOC)	-	-	0.000	0.000	0.000
Norms	Norms_1	0.933	0.960	0.961	0.890
	Norms_2	0.966			
	Norms_3	0.930			
Control	Control_1	0.814	0.868	0.867	0.683
	Control_2	0.886			
	Control_3	0.776			
Attitude	Attitude_1	*	*	*	*
	Attitude_2	*			
	Attitude_3	*			
Intention	Intention_1	0.810	0.939	0.941	0.797
	Intention_2	0.937			
	Intention_3	0.870			
	Intention_4	0.948			
Behaviour	Behaviour_1	*	0.870	0.858	0.611
	Behaviour_2	*			
	Behaviour_3	*			
	Behaviour_4	0.839			
	Behaviour_5	0.942			
	Behaviour_6	0.691			
	Behaviour_7	0.612			

Note: *Dropped from analysis because the reliability and validity values were out of the thresholds.

Table 7. Results of Discriminant Validity: HTMT Ratio

	Behaviour	Intention	Control	Socmed (LOC)	Norms	Content (LOC)
Behaviour	.	.	.	.	.	.
Intention	0.756	.	.	.	.	.
Control	0.650	0.809	.	.	.	.
Socmed (LOC)	0.206	0.135	0.167	.	.	
Norms	0.602	0.752	0.833	0.170	.	.
Content (LOC)	0.604	0.600	0.617	0.371	0.637	.

5-2. The Structural Model Evaluation

The structural model evaluation results provided explanatory power for in-sample predictive power (R^2) and for absolute and incremental fit measures. After removing the Attitude construct, the modified version showed moderate to substantial explanatory power (0.60–0.75) for Behaviour (0.662), Intention (0.674), and Control (0.713). It means that 66.2% of variance of Behaviour was explained by the existing exogenous constructs (i.e., Intention, Control, Norms, and Exposure), 67.4% of variance of Intention was explained by the existing exogenous constructs (i.e., Norms, Control, and Exposure), and 71.3% of the variance of Control was explained by the existing exogenous constructs (i.e., Norms and Exposure). In contrast, the Norm construct had 0.304 explanatory power, which fell within the low-to-moderate range (0.25-0.50). This means that 30.4% of the variance in Norms was explained by Exposure. Moreover, one LOC (i.e., Viral) had substantial explanatory power (1.265), and the rest of the LOC (i.e., Socmed) had low explanatory power (0.083). However, the LOCs are not part of the structural model (Sarstedt et al., 2019). The explanatory power values are presented in Figure 7.

The last results of the structural model are the fit parameters. The evaluation results of the absolute fit measures are described as follows. The chi-square value was 2090.67 ($P < 0.05$) for 72 significant parameters and a sample size of $N = 504$. The value of the degree of freedom was 393, Chi-square/df value was 5.320, and RMSEA was 0.093 (larger than 0.07), both of which were outside the threshold. The GFI value was 0.769 (between 0 and 1), and AGFI was 0.727 (lower than GFI), indicating that it is still a good fit. SRMR was 0.054 (fulfilling the threshold: lower than 0.08), indicating a good fit. Moreover, the incremental fit measure (CFI) was 0.899 (between 0 and 1), indicating a good fit.

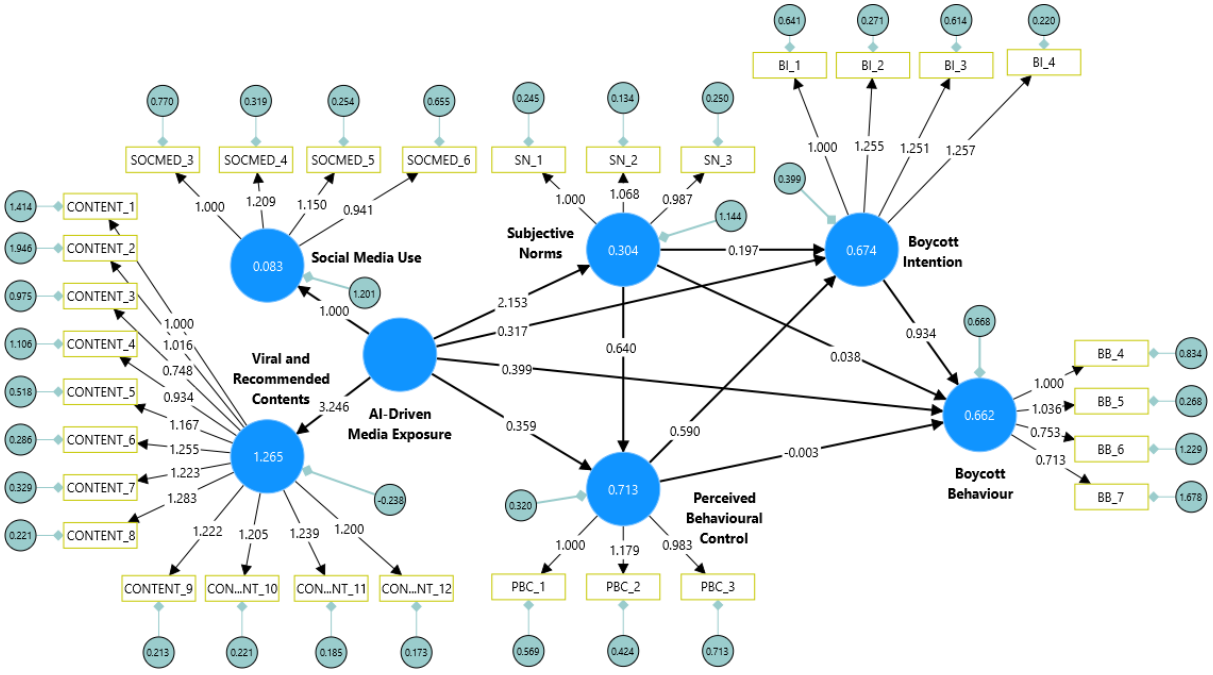


Fig. 7. CB-SEM Output: The Schematic Relationship among TPB's Components in the Boycott Study

5-3. Direct Path Analysis

Because the manifest and latent variables were valid and reliable, this study reports the results of the structural model evaluation in Table 8. The direct path coefficient from Exposure to Control was 0.359 (t-stat = 2.132), significant at α = 0.05 (t-value = 1.96) for a two-tailed test. The direct path coefficient from Exposure to Norm was 2.153 (t-stat = 4.989), significant at α = 0.01 (t-value = 2.57). The direct path coefficient from Control to Intention was 0.590 (t-stat = 4.012), significant at α = 0.01. The direct path coefficient from Norm to Intention was 0.197 (t-stat = 1.767), significant at α = 0.10 (t-value = 1.65). The direct path coefficient from Norm to Control was 0.640 (t-stat = 9.971), significant at α = 0.01. The direct path coefficient from Intention to Behaviour was 0.934 (t-stat = 8.466), significant at α = 0.01.

The direct path coefficient from Exposure to Intention was 0.317 (t-stat = 2.040), which is significant at α = 0.05. Thus, H1 (boycott intention is directly affected by media exposure) is confirmed. The direct path coefficient from Exposure to Behaviour was 0.399 (t-stat = 1.670), which is significant under α = 0.10. Thus, the H5 (boycott behaviour is directly affected by media exposure) is accepted.

The direct path results also demonstrated the significance of the path from HOC to LOC, except for the path from HOC to Socmed, as follows: the direct path coefficient from Exposure to Content was 3.246 (t-stat = 2.797, significant at α = 0.01).

Table 8. Results of Path Coefficient under the Structural Model (Unstandardised)

Nr	Path Direction	Original Sample Est	Sample Mean	Std Dev	T-Stat	Remarks	Hypothesis
A	**Direct path**						
1	Intention → Behaviour	0.934***	0.936	0.110	8.466	Supported	-
2	Exposure → Behaviour	0.399*	0.427	0.239	1.670	Supported	H5
3	Exposure → Intention	0.317**	0.318	0.155	2.040	Supported	H1
4	Exposure → Control	0.359**	0.383	0.168	2.132	Supported	-
5	Exposure → Socmed	1.000	1.000	0.000	n/a	*Unsupported*	HOC → LOC
6	Exposure → Norms	2.153***	2.202	0.432	4.989	Supported	-
7	Exposure → Content	3.246***	3.457	1.161	2.797	Supported	HOC → LOC
8	Control → Behaviour	-0.003	-0.014	0.147	0.023	*Unsupported*	-
9	Control → Intention	0.590***	0.601	0.147	4.012	Supported	-
10	Norm → Behaviour	0.038	0.039	0.104	0.363	*Unsupported*	-
11	Norm → Intention	0.197*	0.187	0.112	1.767	Supported	-
12	Norm → Control	0.640***	0.633	0.064	9.971	Supported	-
13	Exposure → Attitude	-	-	-	-	*Dropped*	-
14	Control → Attitude	-	-	-	-	*Dropped*	-
15	Norms → Attitude	-	-	-	-	*Dropped*	-
16	Attitude → Intention	-	-	-	-	*Dropped*	-
B	**Indirect path**						
1	Exposure → Intention → Behaviour	0.296*	0.302	0.155	1.912	Supported	H7
2	Control → Intention → Behaviour	0.551***	0.560	0.143	3.845	Supported	-
3	Norm → Control → Intention	0.378***	0.380	0.101	3.739	Supported	-
4	Exposure → Norms → Intention	0.425	0.419	0.272	1.561	*Unsupported*	H2
5	Exposure → Control → Behaviour	-0.001	-0.006	0.062	0.019	*Unsupported*	H6
6	Exposure → Control → Intention	0.212*	0.235	0.125	1.693	Supported	H3
7	Exposure → Norm → Control	1.379***	1.395	0.309	4.457	Supported	-
8	Exposure → Norm → Behaviour	0.082	0.089	0.234	0.348	*Unsupported*	H8
9	Norm → Intention → Behaviour	0.184*	0.174	0.107	1.726	Supported	-
10	Norm → Control → Behaviour	-0.002	-0.009	0.095	0.022	*Unsupported*	-
11	Exposure → Attitude → Intention	-	-	-	-	*Dropped*	H4
12	Exposure → Norm → Attitude	-	-	-	-	*Dropped*	-
13	Exposure → Control → Attitude	-	-	-	-	*Dropped*	-
14	Control → Attitude → Intention	-	-	-	-	*Dropped*	-

Note: t-value for two-tailed test: ***2.57 (α = 0.01), **1.96 (α = 0.05), and *1.65 (α = 0.10)

5-4. The Mediation Effect

Table 8 also presents the results of the indirect path (mediation) analysis among the constructs under TPB, as follows. The coefficient of the indirect path from Control to Behaviour through Intention ([P1: Control → Intention] * [P2: Intention → Behaviour]) was 0.551 (t-stat = 3.845), significant at α

= 0.01. The direct effect (P3: Control → Behaviour) was insignificant even under α = 0.10. Thus, the mediation type is complete (indirect-only).

The coefficient of the indirect path from Norms to Intention through Control ([P1: Norms → Control] * [P2: Control → Intention]) was 0.378 (t-stat = 3.739), significant at α = 0.01. The direct effect (P3: Norms → Intention) was significant under α = 0.10. The multiplication of P1*P2*P3 was 0.074 (positive). Thus, the mediation type is complementary mediation (partial).

The coefficient of the indirect path from Exposure to Control through Norms ([P1: Exposure → Norms] * [P2: Norms → Control]) was 1.379 (t-stat = 4.457), significant at α = 0.01. The direct effect (P3: Exposure → Control) was significant at α = 0.05. The multiplication of P1*P2*P3 was 0.495 (positive). Thus, the mediation type is complementary mediation (partial).

The coefficient of the indirect path from Norms to Behaviour through Intention ([P1: Norms → Intention] * [P2: Intention → Behaviour]) was 0.184 (t-stat = 1.726), significant at α = 0.10. The direct effect (P3: Norms → Behaviour) was insignificant even under α = 0.10. The multiplication of P1*P2*P3 was 0.007 (positive). Thus, the mediation type is complementary mediation (partial).

The coefficient of the indirect path from Exposure to Intention through Control ([P1: Exposure → Control] * [P2: Control → Intention]) was 0.212 (t-stat = 1.693), significant at α = 0.10. The direct effect (P3: Exposure → Intention) was significant at α = 0.05. The multiplication of P1*P2*P3 was 0.067 (positive). Thus, the mediation type is complementary mediation (partial). Thus. H3 (boycott intention is indirectly affected by media exposure through perceived behavioural control) is accepted.

The coefficient of the indirect path from Exposure to Behaviour through Intention ([P1: Exposure → Intention] * [P2: Intention → Behaviour]) was 0.296 (t-stat = 1.912), significant at α = 0.10. The direct effect (P3: Exposure → Behaviour) was significant at α = 0.10. The multiplication of P1*P2*P3 was 0.118 (positive). Thus, the mediation type is complementary mediation (partial). Thus, H7 (boycott behaviour is indirectly affected by media exposure through boycott intention) is confirmed.

5-5. Media Exposure

Media exposure here is related to the use of social media (e.g., Facebook, Instagram, X, WhatsApp, Telegram, YouTube, and TikTok). Indonesians generally have multiple social media accounts, and 96% of the respondents in this study confirmed owning multiple accounts and using them for many hours a day (Figure 8). The most common social media platforms among Indonesians are Instagram and Facebook (Figure 9). The average time spent on social media was 4.25 hours per day, as shown in Figure 9. Some Indonesians use social media because it is helpful in their social life, effective in maintaining their social relationships, and can improve their social life performance and the quality of their social relationships (Figure 8). The reasons for using social media can be entertainment and information disclosure (Mortazavi et al., 2014).

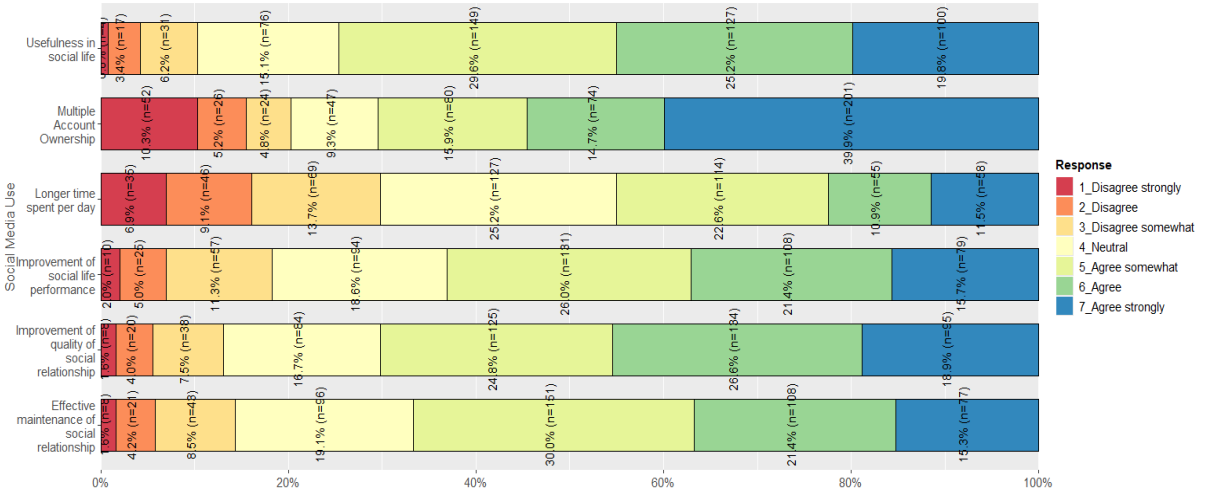


Fig. 8. The Use of Social Media

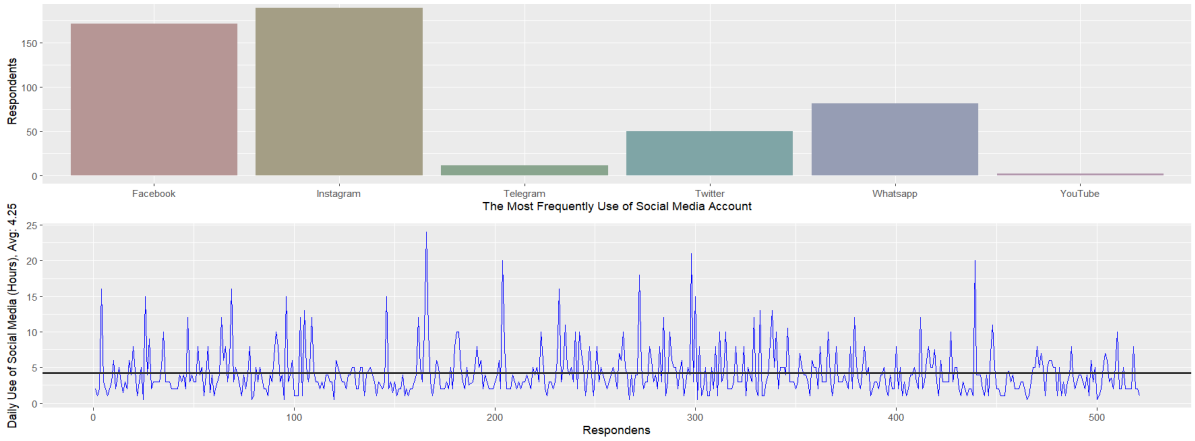


Fig. 9. Social Media Use among Respondents

Information propagation and support mobilisation were diffused through viral and recommended content. Indonesians mostly found the viral content about the attacks and then visited the links/pages/websites associated with it. When social media users received the viral and recommended content, they responded by showing angry and sad feelings because they believed that the videos/footage really happened (credible), as presented in Figure 10. The present study demonstrates that social media content depicting relentless military attacks and considerable casualties potentially evoked people's negative emotions (such as anger and sadness) and led to the virality and recommendations of the videos/footage among other social media users. The more negative the emotions, the greater the virality of social media content. Therefore, many Indonesians received the social media content about the Palestinian-Israeli war. The findings of the present study confirm the study by Berger and Milkman (2012), who argued that, first, content with more positive emotion was more viral than harmful content; second, content with high sadness was less likely to go viral than content with lower sadness; third content with high anger was more likely to go viral than that with low anger; fourth, valuable and informative content was more likely to be shared. The great suffering of Gazans, released by the media, led to the adverse self-evaluation reaction among media audience by resisting and protesting Israel's violent behaviour (Bandura, 2002).

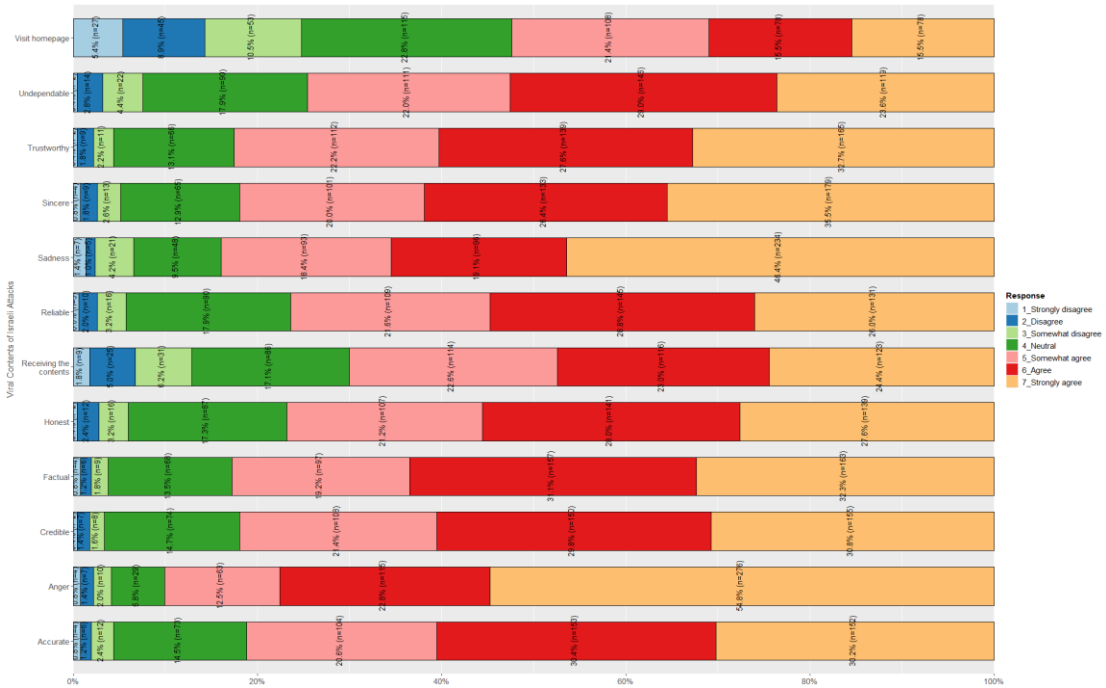


Fig. 10. Viral and Recommended Social Media Content of Israeli Attacks since October 2023

High casualties in Gaza and other Palestinian communities brought about high anger and sadness among people in Indonesia. The social media content of Palestine's situation since October 2023 had been necessary to people so that they could express solidarity and support for the victims. The present study also aligns with previous studies (Berger & Milkman, 2012; Pescher et al., 2014; Ulo et al., 2025; T. Yang et al., 2023) that found that anger, practical usefulness, and content credibility affected the adoption of recommendations and viral content. González-Esteban et al. (2024) examined the virality and recommendation of videos about the Gaza situation on TikTok, and the videos then led to hate speech among pro-Palestine and pro-Israel in Spain. In addition, a study in Jordan confirmed that the Gaza situation went viral. Al-Maghaireh et al. (2024) also found that much time spent watching Gaza news footage on social media platforms caused high levels of stress and extreme emotional responses (e.g., sadness, shock, and hopelessness) among Jordanian adolescents.

6. Discussion

This section discusses the interpretation of statistical results in CB-SEM, as covered in the previous section. The CB-SEM results provided evidence on the role of media exposure in shaping boycott intention and behaviour.

Factors affecting perceived behavioural control. The direct effect of subjective norm on perceived behavioural control was significant and is supported by the root theory of TPB (Ajzen, 2005). However, it does not align with social cognitive theory (Bandura, 2002). The extended model of social cognitive theory runs from social media exposure to the social system/subjective norm to behaviour (including perceived behavioural control), with mediation effects.

The perceived behavioural control was directly affected by media exposure. The present study aligns with a previous study on the boycott of Israel-related products, which found a significant effect of social media on perceived behavioural control (Mady et al., 2025). A non-boycott study (Samaniego-Arias et al., 2025) found a significant effect of social media on perceived behavioural control, which the present study also confirms. Other studies on non-boycott (Kadel et al., 2024; Korsakiene et al., 2024), which found a significant effect of media exposure on perceived behavioural control, aligned with the present study.

Perceived behavioural control was also indirectly affected by media exposure via subjective norms. The present study aligns with the core theory of TPB (Ajzen, 2005) and is supported by the extended social cognitive model of media exposure, as outlined in Bandura (2002).

Factors affecting boycott intention. Before discussing the determinants, the boycott intention is explained. The intention to boycott pro-Israeli products took the following forms: likely to boycott, next-time boycott action, willingness to boycott, and definite action to boycott the alleged products, with almost all respondents agreeing with the intention (Figure 11).

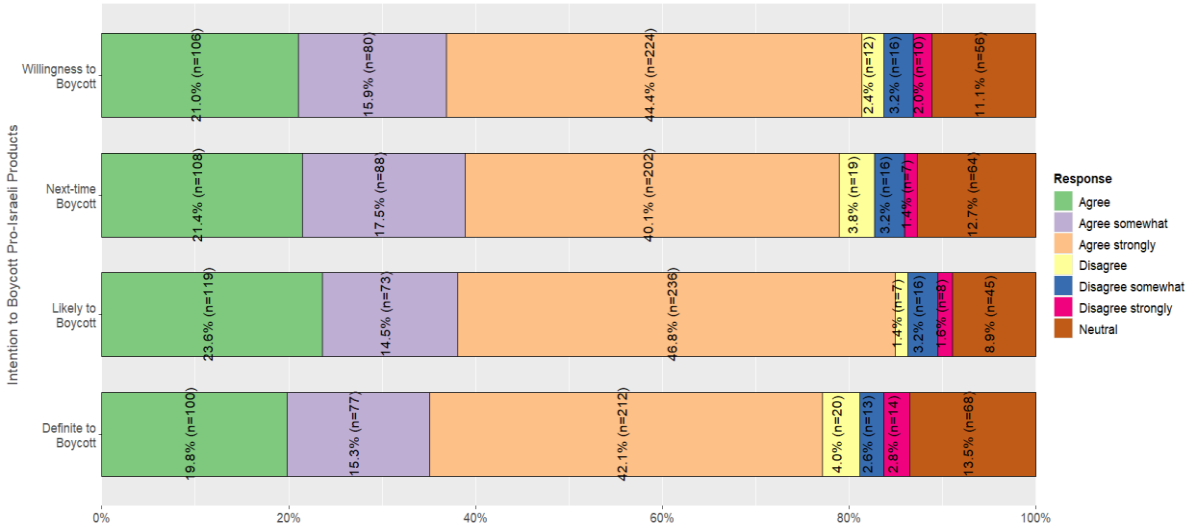


Fig. 11. Intention to Boycott Pro-Israeli Products

The intention to boycott allegedly pro-Israeli products was directly affected by perceived behavioural control. The present study is supported by the previous studies in Egypt (Mady et al., 2025), Greece (Delistavrou, 2022; Delistavrou et al., 2020), Malaysia (Hamzah & Mustafa, 2019), Indonesia (Asnawi et al., 2019), South Korea (Kim et al., 2023), and Lebanon (Farah & Newman, 2010) about the effect of perceived behavioural control on boycott intention.

Both the direct effect and indirect effect of the subjective norm (through perceived control) on boycott intention were significant. The role of subjective norms in shaping boycott intention is supported by some studies on the effect of subjective norm on intention to boycott some products in some countries (Asnawi et al., 2019; Delistavrou, 2022; Delistavrou et al., 2020; Farah & Newman, 2010; Hamzah & Mustafa, 2019; Kim et al., 2023; Salma & Aji, 2023; Zejjari & Benhayoun, 2025). The present study aligns with a non-boycott study in Ecuador, which confirmed the significant effect of the subjective norm on purchasing intention (Samaniego-Arias et al., 2025). In contrast, the present study does not align with a non-boycott study in Lithuania, which rejected the effect of the subjective norm on intention (Korsakiene et al., 2024). However, the direct and indirect effects of subjective norms on boycott intention are irrelevant under social cognitive theory, which analyses the pathway from media influence to the social system/subjective norm and then to behavioural change (Bandura, 2002).

The present study rejects the hypothesis that the media exposure indirectly affects boycott intention through subjective norms. The present study's findings do not align with those of Samaniego-Arias et al. (2025), which found an indirect effect of social media use (via subjective norm) on purchasing intention. The present findings also do not align with the roots of TPB and social cognitive theory (Ajzen, 2005; Bandura, 2002), which argue that media exposure indirectly affects behaviour (here, intention) through the subjective norm or social system. In this case, the social system or subjective norms play the minimum role in shaping boycott intention. The role of lead viewers/influential persons in affecting the behaviour of other people in a social system is not as strong as the role of AI-powered recommendations. It is also possible that the collaborative filtering-based content recommendation (recommendation based on the previous preferences of other persons with similar profiles), applies, as Maddodi and Prasad (2019) argued. The other possibility is that the direct effect of media exposure on boycott intention is more powerful.

The intention to boycott allegedly pro-Israeli products was directly affected by media exposure. The present study is supported by studies on boycotts of Israel-related products in Egypt and Morocco (Mady et al., 2025; Zejjari & Benhayoun, 2025), which found a significant effect of social media on boycott intention. A study on a non-boycott case in Ecuador (Samaniego-Arias et al., 2025) found a significant effect of social media use on purchasing intention, confirming the present study’s findings. The media exposure is enabled here not only by traditional virality methods (Pescher et al., 2014) but also by an advanced virality methods driven by AI (Balaji et al., 2021; Maddodi & Prasad, 2019; Narayanan, 2023). Under an AI-powered algorithm, the content recommendation based on the user's past habit of watching Gaza footage implies that the direct effect of media is more influential. The direct effect of media exposure on intention is related to the content-based filtering (Caballar & Stryker, n.d.; Maddodi & Prasad, 2019). The role of media exposure in directly affecting boycott intention confirms the workability of the dual pathways of change in intention, as social cognitive theorist argued (Bandura, 2002). As the Palestine-Israel conflict is a long-term one, the findings of the study confirm the cultivation theory (Morgan et al., 2016), arguing that the long-term effect of media exposure had an impact on the formation of the audience's social reality conception.

In addition, the boycott intention was also indirectly affected by media exposure through perceived behavioural control. Mady et al. (2025) discovered the indirect effect of social media use on boycott intention (through control), confirming the present study's findings. The non-boycott study (Samaniego-Arias et al., 2025), which found an indirect effect of social media use on purchase intention (through control), also confirmed the present study. The indirect effect confirms the extended model of social cognitive theory developed in the present study, which suggests that perceived control is initially affected by media exposure. This means that consumers of the product—social media users—received viral and recommended content based on their own past habits and those of others in watching Gaza footage. In this case, the indirect effect of media exposure on boycott intention is mediated by the hybrid recommendation system (Caballar & Stryker, n.d.; Maddodi & Prasad, 2019).

Factors affecting boycott behaviour. Before discussing its determinants, boycott behaviour is first explained. Boycott behaviour against allegedly pro-Israeli products in Indonesia took various forms, such as dislike, infrequent purchasing, product disloyalty, purchase avoidance, feelings of guilt about purchasing, and substitution with local and imported products (Figure 12). The present study confirms that some boycott indicators employed in previous studies (Abosag & Farah, 2014; Sen et al., 2001) are relevant to the boycott of allegedly pro-Israeli products.

The behaviour of boycotting allegedly pro-Israeli products was directly shaped by boycott intention. The present study is strengthened by a study in Spain (Palacios-Florencio et al., 2021), which found the positive effect of boycott intention on boycott behaviour.

The present study rejects the notion that perceived behavioural control directly affected boycott behaviour. However, the boycott behaviour was also indirectly affected by perceived behavioural control through boycott intention. A study in South Korea (Kim et al., 2023) that found an indirect effect of perceived behavioural control on product purchasing via boycott intention did not confirm the findings of the present study.

The present study rejects the hypotheses that boycott behaviour was indirectly affected by media exposure through perceived behavioural control and subjective norm. The mediating roles of perceived behavioural control and subjective norm are necessary but not sufficient to affect boycott behaviour. Thus, the present findings align with previous ones (Palacios-Florencio et al., 2021) in that social influence did not affect boycott behaviour. However, they do not align with social cognitive theory, which holds that media affect behaviour through the social system (Bandura, 2002). The present study assumes that the influence of lead viewers/influential persons in the social system is not as strong as the direct effect of media exposure on behaviour driven by content-based filtering.



Fig. 12. Boycotting Allegedly Pro-Israeli Products

The boycott behaviour was significantly affected by subjective norms, as reflected in boycott intention. Kim et al. (2023) in Korea confirmed that subjective norms negatively affected purchasing, resulting in reduced purchasing. The present study rejects the indirect effect of subjective norms on boycott behaviour through perceived behavioural control. However, both violate the model under the social cognitive theory (Bandura, 2002).

The behaviour of boycotting allegedly pro-Israeli products was directly shaped by media exposure. The present findings align with the social cognitive theory model, which posits that media affect behavioural change (Bandura, 2002). The direct effect of media exposure on boycott behaviour in the present findings is attributed to AI-powered content recommendations (Balaji et al., 2021; Caballar & Stryker, n.d.; Maddodi & Prasad, 2019). For example, content-based filtering enabled social media user to receive content recommendation related to the Gaza situation, leading them to boycott the products. Consumers adopt viral and recommended content, as they trust the source and perceive the AI-powered content as useful and credible (Tien et al., 2019; Ulo et al., 2025; T. Yang et al., 2023).

The boycott behaviour was also indirectly affected by media exposure through boycott intention. It is also related to the extended model of social cognitive theory, as the present study suggests. Thus, the present findings align with the principle of social cognitive theory (Bandura, 2002). In the context of AI technology (Balaji et al., 2021; Caballar & Stryker, n.d.; Maddodi & Prasad, 2019), media exposure first shaped users' intention to boycott, leading them to boycott the products. It possibly worked under a hybrid recommendation system, in which social media users received viral and recommended content based on their own past behaviour and that of others in watching Gaza footage.

The present findings imply that boycott actions erode consumer loyalty to the boycotted products. It is true that boycott action negatively affected customers' loyalty (Abosag & Farah, 2014). The boycott is one of the strategies among Muslim consumers in response to unintended adverse events encountered by other Muslim groups (Farah & Newman, 2010; Ghazali et al., 2019; Hamzah & Mustafa, 2019; Heilmann, 2016; Kaikati, 1978; Losman, 1972; Roswinanto & Suwanda, 2023; Salma & Aji, 2023). It is supported by the fact that Muslim respondents were eager to participate in this study (Table 3). The boycott occurs in the case of the weak power of political elites in response to unintended events/unethical practices and weak individuals in dealing with business involvement in unintended events/unethical practices. The boycott of allegedly pro-Israeli products is a long-standing struggle among Muslim society in response to oppression in Palestine, as Muslim society boycotted Israeli or allegedly pro-Israeli products long before the *Nakba* of October 2023 (Ghazali et al., 2019; Hamzah & Mustafa, 2019; Heilmann, 2016; Kaikati, 1978; Losman, 1972).

The findings of the present study confirm three determinants of the social diffusion of information leading to behavioural change, from the perspective of social cognitive theory: the acquisition of knowledge about innovative behaviour, the adoption of the behaviour, and the social network structure (Bandura, 2002), as explained below. The knowledge acquisition of innovative behaviour in the present study is possibly determined by the knowledge, resources, physical proximity, and faith (Table 3). Knowledge is related to respondents' educational level, with most being educated. The resources include smartphone ownership, which facilitates access to information through various media channels; sufficient income to afford monthly data subscriptions; and multiple social media accounts, which enable continuous exposure to information from diverse sources. Physical proximity here refers to respondents' residences. Most live in urban areas with relatively high internet penetration (Machmudi & Nurcahyadi, 2024), enabling intensive exposure to information and content recommendations, as well as the intensive influence of lead viewers/influential persons. A Muslim social media user received a recommendation for content related to the situation in Gaza based on the viewing histories of other Muslim social media users who had previously watched similar content, using collaborative filtering. The adoption behaviour is possibly determined by environmental inducements and adverse self-evaluative reactions to the sadistic behaviour of Israeli troops going viral on the social media. The negative behaviour of the troops drove people to propagate the information and mobilise a protest to deal with the Gazan situation. The last determinant of the social diffusion of information is the role of social network structure, which social media, with varying degrees of social ties, contributed to the virality and recommendations of Gaza situation content.

The determinants of the social diffusion of the information above include mobile phone activism, voluntary war journalism (mainly by Gazans), and AI development. Mobile phone activism and

voluntary war journalism (mainly by Gazans) played the significant roles in spreading information through social media and in mobilising support for Gaza (Abushbak et al., 2024; Abushbak & Majeed, 2020; Kaur, 2024). Following October 7, 2023, some Gazans documented the situation in Gaza to inform the international community about conditions on the ground and mobilize global support, amid restricted access for journalists to Gaza and Israeli restrictions on journalists (Kaur, 2024).

Based on the above, the refined extended model of media exposure-induced behavioural change under social cognitive theory is depicted in Figure 13.

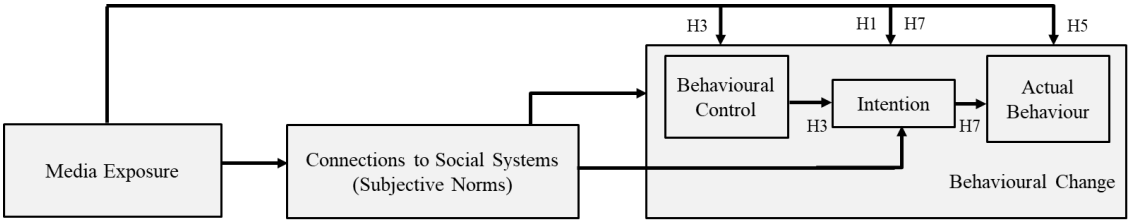


Fig. 13. Boycott Behaviour of Allegedly Pro-Israeli Products

7. Conclusion

The present study has investigated the role of AI-driven media exposure in shaping boycott intention and boycott behaviour. The present study presents the following statistical results. Boycott intention was affected directly by media exposure (H_1) and indirectly by media exposure through perceived behavioural control (H_3). In addition, boycott behaviour was affected directly by media exposure (H_5) and indirectly by media exposure through boycott intention (H_7). The boycott behaviour was successful because of the development of AI technology that supports content recommendations for social media users (e.g., content-based filtering, collaborative filtering, and hybrid recommendation systems). The viral and recommended content also supports the behavioural change. The present study demonstrates that consumers are successfully moving outside the political system to address unethical business practices by corporate companies. The present study confirms the extended model of social cognitive theory of media exposure, in which the role of the social system in affecting behavioural change is not well established.

Although the present studies successfully initiated TPB research by incorporating media exposure as a background factor, they have some limitations. The present study did not investigate other background factors of TPB, such as social and personal factors (Ajzen, 2005), as it focused only on media exposure (a higher-order component) and two lower-order components. This study also did not adopt other social media attributes due to concerns about the use of too many indicators, as Mortazavi et al. (2014) suggested, which may affect the performance of lower-order components of social media use. The present study did not fully consider measuring media exposure using self-report methods, as suggested by scholars in the communication field (Vreese & Neijens, 2016). The lower-order components of social media use were poorly designed, resulting in a poor coefficient (the value was one) and the absence of a t-value for the path from Exposure to Socmed (Table 8). The present study has limitations in measuring attitude, possibly due to the use of reverse coding, which distorted the attitude construct and affected the prediction of boycott intention. The present study lacks sufficient and relevant literature on TPB, and background factors related to media exposure have not been investigated to examine the indirect effects of TPB's components due to selection bias. When the questionnaire was distributed, it obtained limited feedback from non-Muslim respondents, raising the assumption that the boycott movement was promoted only by Muslims due to the religious attachment. The present study faced difficulties in analysing the reflective-formative type of the higher-order construct, so it failed to detect collinearity among the constructs and the higher-order construct.

7-1. Managerial and Policy Implications

The findings of this study have practical implications for activists, media, lead viewers, influential persons/influencers, the business sector, policymakers, social media users, and consumers, as follows: Regarding activism, activists can change the behaviour of other people regarding the intended and concerned social reality by taking the advantage of AI development to propagate the information

through social media platforms. The platforms then move on to social media content, run by algorithms that recommend it to appropriate users, employing various recommendation techniques. Activists should equip themselves with the skills to create innovative, creative content so they can disseminate information through social media. Activists should maintain their integrity and credibility to disseminate reliable social media content and encourage social media users to engage with credible content recommendations.

Media exposure plays an important role in shaping the behaviour of media users/consumers in direct and indirect ways under the social cognitive model. Media (including online media and social media platforms) should stand in a neutral/ethical position when broadcasting/ disseminating information. Media organizations can employ AI-assisted content moderation to manage the overwhelming volume of information and content related to unethical practices by stakeholders. Accordingly, media organizations should maintain their integrity and credibility to promote and enforce ethical conduct.

Lead viewers and influential persons/influencers play an important role in the successful campaign against unethical practices through socially mediated pathways of information diffusion and the functioning of subjective norms. The lead viewers and influential persons/influencers catalyse the formation of others' behavioural control through their exposure to media. They should also maintain their integrity and credibility so they can only work ethically. They should also be able to detect and eliminate fake and unethical information and content across any media.

The brands/products of national and multinational corporations are subject to negative sentiments and boycotts among consumers in Muslim-majority countries. Thus, corporations must enforce business ethics and avoid investment in conflict regions and disputed territories. Avoiding involvement with or cooperation with entities that violate ethical standards can help corporations maintain a positive reputation and potentially protect them from negative public sentiment and consumer boycott behavior. The business sector that intends to increase sales can leverage media influence with credible content and increase consumers' media exposure using AI to retain current customers and attract new ones. The business sector should actively implement some programs on human rights and ethics promotion, leading to an increase in corporate reputation. The companies should defend their good reputation and participate in business networks, including ethical business networks, to counter allegations of supporting unethical business practices and to boost ethical campaigns and information diffusion through socially mediated pathways.

On the governmental side, the government should consider the ethical implications and the impact on business sector development before adopting a new policy. If possible, a nation needs to remain neutral in geopolitical tensions to avoid adverse effects on its business sector.

Social media users should be selective in adopting viral and recommended content. They should be able to detect, adopt, and disseminate credible content. On the consumer side, consumers worldwide can use boycotts to reduce or eliminate unethical practices by any party. Consumers should verify the information disseminated through media (acquired directly from media under direct pathways) to stand on the right side and promote justice, ethics, and human rights. As individuals in a society, consumers should also consult their communities when facing ethical campaigns in the media to determine their self-evaluative reactions: resistance or approval of the campaign messages. The consultation can relate to indirect pathways of information diffusion shaping consumers' behaviour.

7-2. Theoretical Implications

The present study makes the following scientific contributions. This study demonstrates how TPB operates in the context of media exposure as a background factor, as suggested by Ajzen (2005), thereby addressing a limitation in the existing TPB literature. This study successfully addresses the slow progress of TPB studies in the digital era, challenging academia to investigate the media effect within the complete TPB model. New perspectives on the boycott and planned behaviour studies, with a nearly comprehensive media exposure construct, are provided. Thus, the present study has closed the gap in boycott studies by extending the incomplete TPB model with media exposure (Mady et al., 2025; Palacios-Florencio et al., 2021; Zejjari & Benhayoun, 2025). The findings of the present study contribute to filling the scientific gap in boycott studies by using the TPB model with AI-driven media exposure as a background factor.

This study contributes to the long-standing literature on product boycotts to end humanitarian crises in Palestine, consolidated by foreigners (Dekhil et al., 2017; Ghazali et al., 2019; Hamzah & Mustafa, 2019; Kaikati, 1978; Losman, 1972; Mady et al., 2025; Zejjari & Benhayoun, 2025). Given the significant interrelationships among TPB's components, the present study contributes to AI-powered disaster/crisis management research and consolidating the collective action of external parties in reducing or terminating human-made catastrophes.

A *fatwa* from the Indonesia Ulema Council (MUI, 2023) emphasises the prohibition on consuming products that support the human-made crisis. The present study investigated one of the Muslim consumer behaviours requiring a good reputation of products that are free from human rights violations. It contributes to studying the Islamic economy under the specific marketing branch and responsible/ethical consumption.

The present study contributes to TPB research by applying advanced multivariate statistics along with the study conducted by Zejjari and Benhayoun (2025). The use of a higher-order construct in this study fills a gap in the application of advanced SEM to the TPB model in boycott and non-boycott studies. Some previous studies on boycott mostly used ordinary SEM techniques (Delistavrou, 2022; Delistavrou et al., 2020; Kadel et al., 2024; Kim et al., 2023; Korsakiene et al., 2024; Mady et al., 2025; Palacios-Florencio et al., 2021; Samaniego-Arias et al., 2025), while others used regression and other techniques (Asnawi et al., 2019; Farah & Newman, 2010; Hamzah & Mustafa, 2019; Roswinanto & Suwanda, 2023). Employing higher-order construct in the present study helps reduce the number of variables related to media exposure in the TPB model. It helps overcome the bandwidth-fidelity dilemma ("trade-off between a variety of information and the thoroughness of test for more certain information") under the TPB model (Hair et al., 2022). Without the present study, the higher-order construct of media exposure within the TPB framework would remain unexplored, potentially resulting in less efficient structural models with numerous interrelated constructs and leaving unresolved the question of whether multiple dimensions of media exposure, such as social media use and exposure to viral and recommended content, simultaneously influence behavioral change. CB-SEM in this study contributes to testing and confirming social cognitive theory and TPB using the boycott behaviour case, as argued by scholars in SEM (Dash & Paul, 2021).

More specifically, the present study successfully integrated the social cognitive theory of mass communication (Bandura, 2002) and the TPB model (Ajzen, 2005), providing detailed insights into the dual paths of media influence (direct and indirect) in affecting behavioural change. The present study also emphasises that socially mediated pathways in social cognitive theory operate through social media powered by AI. Initially, the theory argues that the dual pathways operate primarily through print and offline media. Despite focusing on media exposure and behavioural change, the present study reinforces the need for the social system to function in order to pave the way for socially mediated pathways of media effects on behavioural change. The present study also reinforces the role of subjective norms (peer and social systems) in the diffusion of information affecting the behaviour of social media audiences and users. Moreover, the present study extended the social cognitive model, positing that behavioural change involves TPB components, including perceived behavioural control, intention, and actual behaviour.

The present study also integrated communication, psychology, and marketing studies. This study emphasises that media exposure measurement through self-report (Slater, 2004; Vreese & Neijens, 2016) is important because many people use social media, so the measurement is based on self-reports of social media exposure. Moreover, the present study demonstrates that media exposure is essential in the cognitive process (e.g., perception and conception formation) of online media audiences and social media users, as the cultivation theory scholars (Morgan et al., 2016) argued. Long media exposure of oppression in Palestine helped form the conception and perception of the social media audience and users about the suffering that should be ended. The present study also contributes to knowledge by demonstrating that cultivation theory also operates in online and social media contexts.

The present study provides new insights into TPB research by considering AI technology, enhancing the effectiveness of media exposure driven by AI-based content recommendation algorithms, such as content-based filtering, collaborative filtering, and hybrid recommendation systems. Media exposure should not only rely on conventional viral content. Content virality should be driven by an algorithm for effectiveness, leading to the new terms of viral and recommended content.

However, the content should be credible and useful to achieve widespread consumer adoption. Content creators should be credible and innovative so that social media users can trust and adopt their recommendations. The present study also contributes to the mobile viral-based and AI-based marketing studies, which examine the characteristics of social media content (e.g., anger, sadness, trustworthiness, usefulness, and credibility) to determine the virality and adoption of the recommended content (Berger & Milkman, 2012; Pescher et al., 2014; Ulo et al., 2025; T. Yang et al., 2023).

8. Ideas for Future Research

The present study suggests the following future studies. Some mixed-methods research (combining quantitative and qualitative methods) on boycott studies in the AI era is necessary to explain the causes and effects of boycotts and their impact on business performance. A comprehensive concept of the boycott, with several characteristics (e.g., different scales, time duration and dimensions, completeness, sponsors, escalation, area, and offending action) (Friedman, 1985, 1991, 1999), is proposed for future research. The boycott study should consider several characteristics, including the adoption of advanced multivariate statistics (e.g., advanced SEM), comprehensive background factors and their comprehensive measurement, several theoretical perspectives, and technological progress. A study of product boycotts against the allegedly pro-Israeli products is suggested by comparing incidents in Gaza and other Middle Eastern country (e.g., Iran, Syria, or Lebanon) to reveal the different effects of boycotts and the extent of attachment to different countries/regions. Moreover, research on boycotts can also be investigated by comparing the behaviour of Muslim and non-Muslim consumers in different countries to reveal their attachment and solidarity to the *Nakba*. The present study suggests further research on consumers' willingness to shift from unethical to ethical products, including the willingness to pay for ethical products and the demand elasticity for unethical products.

Future studies on TPB (both boycott and non-boycott studies) should consider additional background factors and draw on theoretical perspectives from various scientific fields. The background factors of TPB can be considered advanced multivariate statistical techniques, including higher-order constructs of all background factors, to achieve robust statistical results. For those interested in media exposure studies, future studies on boycott and non-boycott under TPB are also expected to incorporate media exposure factors, using a comprehensive self-report measure that combines several media types assisted by AI and similar technologies. Further study of the interplay among TPB components, background factors, AI, and other algorithmic and analytics technologies will provide new insights into how consumers behave across different technologies and settings.

Studies on the dual pathways of media effects on behavioural change under the social cognitive theory of mass communication should be conducted in greater detail for both boycott and non-boycott studies. The dual pathways are important because social systems facilitate media influence, and behavioural change is influenced by determinants such as the extent of social ties, human competencies, and environmental inducements (Bandura, 2002).

As the present study focuses on the negative emotions of virality regarding humanitarian crises and product boycotts (adverse action), future studies should investigate the effects of negative emotions of virality regarding human-made crises on positive actions such as collective prayers and donations/fundraising. Humanitarian crises (e.g., the Gaza crisis) attracted the attention of some communities by raising funds to help the crisis's victims (Islamic Relief Worldwide, n.d.). AI and similar technologies possibly power social action; therefore, it is essential to investigate their effectiveness using consumer behaviour theories.

Future studies should not only focus on negative actions against the alleged products but also on corporate reputation and business ethics, given their support for the human-made crisis. This is essential because a company's reputation is shaped by its past ethical actions. Modern and ethical consumers require a reputation and ethical compliance in purchasing products. Companies that do not fulfil the ethical and reputational requirements are at risk of consumer disloyalty. Thus, the recommended research will provide insight into the antecedents of boycott and other kinds of consumer disloyalty.

References

Abosag, I., & Farah, M. F. (2014). The influence of religiously motivated consumer boycotts on brand image, loyalty and product judgment. *European Journal of Marketing*, *48*(11/12), 2262–2283. https://doi.org/https://doi.org/10.1108/EJM-12-2013-0737

Abushbak, A. M. A., & Majeed, T. (2020). The Role of Social Media in Mobilizing Crowd Protest – A Case Study of Palestinian Anger Against Israel's Military Measures at Al-Aqsa Compound on Instagram. *JTA Multidisciplinary International Conference*, *40*(10), 511–526.

Abushbak, A. M., Majeed, T., & Kusuma, K. S. (2024). Mobile phone activism during Israel's 'Operation Guardian of the Wall' in Gaza. *Media, War & Conflict*, 1–18. https://doi.org/https://doi.org/10.1177/17506352241249063

Aish, E. A., McKechnie, S., Abosag, I., & Hassan, S. (2013). The mystique of macro-boycotting behaviour: A conceptual framework. *International Journal of Consumer Studies*, *37*(2), 165–171. https://doi.org/10.1111/j.1470-6431.2012.01108.x

AJLabs. (2024, July 28). Israel-Gaza war in maps and charts: Live tracker. *Aljezeera*. https://www.aljazeera.com/news/longform/2023/10/9/israel-hamas-war-in-maps-and-charts-live-tracker

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2005). *Attitudes, Personality and Behavior* (2nd ed.). Open University Press.

Allam, H., & Chamaa, M. E. (2023, November 23). Many in Middle East blame United States for devastation in Gaza. *The Washington Post*. https://www.washingtonpost.com/world/2023/11/23/israel-gaza-war-america-middle-east/

Al-Maghaireh, D., Shawish, N. S., Alsaqer, K., Kawafha, M., Sheyab, H. S., Mushasha, R. A. A., & Kofahi, A. A. (2024). Acute Stress Disorders Among Jordanian Adolescents After Watching Gaza News Footage on Social Media. *Journal of Multidisciplinary Healthcare*, *17*, 2521–2533. https://doi.org/10.2147/JMDH.S461333

Alysherif. (2023). *How boycotting Israeli supporting products did benefit local brands*. Medium. https://medium.com/@alysherif2/how-boycotting-israeli-supporting-products-did-benefit-local-brands-6e831cb02857

Asnawi, N., Dwisetyaningsih, N., & Djakfar, M. (2019). Predicting Muslim consumer intention to boycott a product—A test of the theory of planned behavior. *International Journal of Innovation, Creativity and Change*, *5*(2), 1534–1550.

Balaji, T. K., Annavarapu, C. S. R., & Bablani, A. (2021). Machine learning algorithms for social media analysis: A survey. *Computer Science Review*, *40*, 1–32. https://doi.org/https://doi.org/10.1016/j.cosrev.2021.100395

Bandura, A. (2002). Social Cognitive Theory of Mass Communication. In *Media Effects: Advances in Theory and Research* (2nd ed.). Lawrence Erlbaum Associates, Inc., Publishers.

Bedi, R. S., Haizan, R. Y. A., & Armandhanu, D. (2023, November 10). Pro-kontra warnai boikot anti-Israel yang marak di Malaysia dan Indonesia. *Channel News Asia*. https://www.channelnewsasia.com/indonesia/indonesia-malaysia-palestina-boikot-produk-perusahaan-pro-israel-perang-gaza-3912056

Berger, J., & Milkman, K. L. (2012). What Makes Online Content Viral? *Journal of Marketing Research*, *49*(2), 192–205. https://doi.org/https://doi.org/10.1509/jmr.10.0353

Bhandari, P., & Nikolopoulou, K. (2023). *What Is a Likert Scale? Guide & Examples*. Scribbr. https://www.scribbr.com/methodology/likert-scale/

Busayo.longe. (2012). *The 4,5, and 7 Point Likert Scale + [Questionnaire Examples]* [Formplus]. https://www.formpl.us/blog/point-likert-scale

Caballar, R. D., & Stryker, C. (n.d.). *What is a recommendation engine?* IBM. Retrieved https://www.ibm.com/think/topics/recommendation-engine

Darcy, O. (2023, October 13). Explosive claims about the Israel-Hamas war are going viral. But the truth is not always so simple. *CNN*. https://edition.cnn.com/2023/10/13/media/israel-hamas-claims-reliable-sources/index.html

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting & Social Change*, *173*, 1–11. https://doi.org/https://doi.org/10.1016/j.techfore.2021.121092

Dekhil, F., Jridi, H., & Farhat, H. (2017). Effect of religiosity on the decision to participate in a boycott: The moderating effect of brand loyalty – the case of Coca-Cola. *Journal of Islamic Marketing*, *8*(2), 309–328. https://doi.org/https://doi.org/10.1108/JIMA-01-2013-0008

Delistavrou, A. (2022). Theory of planned behaviour and boycotting: The moderating role of socio-political control and demographics. *EuroMed Journal of Business*, *17*(2), 270–287. https://doi.org/10.1108/EMJB-02-2021-0020

Delistavrou, A., Athanasios Krystallis, & Tilikidou, I. (2020). Consumers' decision to boycott "unethical" products: The role of materialism/post materialism. *International Journal of Retail & Distribution Management*, *48*(10), 1121–1138. https://doi.org/https://doi.org/10.1108/IJRDM-04-2019-0126

Detikcom Team. (2021). Palestina Mengakui Kedaulatan Indonesia Pada 1944. *DetikNews*. https://news.detik.com/internasional/d-5588577/palestina-mengakui-kedaulatan-indonesia-pada-1944-ini-sejarahnya

Farah, M. F., & Newman, A. J. (2010). Exploring consumer boycott intelligence using a socio-cognitive approach. *Journal of Business Research*, *63*(4), 347–355. https://doi.org/10.1016/j.jbusres.2009.03.019

Friedman, M. (1985). Consumer Boycotts in the United States, 1970-1980: Contemporary Events in Historical Perspective. *The Journal of Consumer Affairs*, *19*(1), 96–117.

Friedman, M. (1991). Consumer Boycotts: A Conceptual Framework and Research Agenda. *Journal of Social Issues*, *47*(1), 149–168. https://doi.org/https://doi.org/10.1111/j.1540-4560.1991.tb01817.x

Friedman, M. (1999). *Consumer Boycotts: Effecting Change through the Marketplace and the Media*. Routledge - the Taylor & Francis Group.

Gammoh, O. S., Alqudah, A., Qnais, E., & Badriyah S. Alotaibi. (2024). Factors associated with insomnia and fatigue symptoms during the outbreak of Oct.7th war on Gaza: A study from Jordan. *Preventive Medicine Reports*, *41*, 1–5. https://doi.org/https://doi.org/10.1016/j.pmedr.2024.102685

Ghazali, E. M., Mutum, D. S., Sundramohana, M., & Valdivieso, P. (2019). Was the Boycott of McDonald's Malaysia Religiously Motivated? In *Management of Shari'ah Compliant Businesses, Management for Professionals* (pp. 155–161). Springer Nature. https://doi.org/10.1007/978-3-030-10907-3_13

Guinaudeau, B., Munger, K., & Votta, F. (2022). Fifteen Seconds of Fame: TikTok and the Supply Side of Social Video. *Computational Communication Research*, *4*(2), 463–485. https://doi.org/https://doi.org/10.5117/CCR2022.2.004.GUIN

Hair, J. F., Babin, B. J., & Krey, N. (2017). Covariance-Based Structural Equation Modeling in the Journal of Advertising: Review and Recommendations. *Journal of Advertising*, *46*(1), 163–177. https://doi.org/http://dx.doi.org/10.1080/00913367.2017.1281777

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th ed.). Cengage Learning EMEA.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (3rd ed.). Sage Publications.

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107–123. https://doi.org/https://doi.org/10.1504/IJMDA.2017.087624

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). *Advanced Issues in Partial Least Squares Structural Equation Modeling*. Sage Publications.

Hamzah, H., & Mustafa, H. (2019). Exploring consumer boycott intelligence towards Israel-related companies in Malaysia: An integration of the theory of planned behaviour with transtheoretical stages of change. *Journal of Islamic Marketing*, *10*(2), 208–226. https://doi.org/https://doi.org/10.1108/JIMA-06-2017-0070

Harwell, D., & Lorenz, T. (2023, November 2). Israel-Gaza war sparks debate over TikTok's role in setting public opinion. *The Washington Post*. https://www.washingtonpost.com/technology/2023/11/02/tiktok-israel-hamas-video-brainwash/

Heilmann, K. (2016). Does political conflict hurt trade? Evidence from consumer boycotts. *Journal of International Economics*, *99*, 179–191. https://doi.org/http://dx.doi.org/10.1016/j.jinteco.2015.11.008

Indonesia Statistical Agency. (2024, October 2). *Statistik menurut Subjek: Masyarakat Informasi*. Badan Pusat Statistik (BPS)/Indonesia Statistical Agency. https://www.bps.go.id/id/statistics-table?subject=565

Islamic Relief Worldwide. (n.d.). *Palestine Emergency Appeal*. Retrieved https://islamic-relief.org/appeals/palestine-emergency-appeal/

Kadel, P., Heist, N., Paulheim, H., & Mata, J. (2024). From Pixels to Palate: Communication around #vegan on Instagram and its relation with eating intentions. *Appetite*, *200*, 1–10. https://doi.org/https://doi.org/10.1016/j.appet.2024.107518

Kaikati, J. G. (1978). The Arab Boycott: Middle East Business Dilemma. *California Management Review*, *20*(3), 32–46. https://doi.org/https://doi.org/10.2307/41165280

Kaur, H. (2024, January 19). Palestinians are documenting the war for millions on social media. Their followers have come to see them as family. *CNN*. https://edition.cnn.com/2024/01/19/world/palestinians-x-tiktok-instagram-gaza-cec/index.html

Kemp, S. (2015, January 22). *Digital 2015: Indonesia*. Datareportal. https://datareportal.com/reports/digital-2015-indonesia

Kemp, S. (2025, February 25). *Digital 2025: Indonesia*. Datareportal. https://datareportal.com/reports/digital-2025-indonesia

Kim, C., Yan, X., & Park, S. (2023). Do consumer boycotts really matter with global companies? The moderating effect of gender differences. *International Journal of Emerging Markets*, *18*(12), 5707–5726. https://doi.org/10.1108/IJOEM-03-2021-0312

Korsakiene, R., Vilkaite-Vaitone, N., & Jeseviciute-Ufartiene, L. (2024). Exposed to the Media: Intentions to Gamble and Problem Gambling. *SAGE Open*, *14*(4), 1–13. https://doi.org/https://doi.org/10.1177/21582440241298812

Losman, D. L. (1972). The Arab Boycott Of Israel. *International Journal of Middle East Studies*, *3*(2), 99–122. https://doi.org/10.1017/S0020743800024831

Lyons, A., Barnes, A. M., McCreanor, T., Goodwin, I., Young, J., & Carah, N. (2024). *Te Ngāngara Limbic capitalism in Aotearoa: Young people, social media and unhealthy product marketing*. University of Auckland. https://researchspace.auckland.ac.nz/items/27354619-a66f-40bc-9330-df0690d6e8bb

Machmudi, M. I. A., & Nurcahyadi, G. (2024, January 31). Hampir 70% Pengguna Internet di Indonesia ada di Daerah Urban. *Media Indonesia*. https://mediaindonesia.com/teknologi/648089/hampir-70-pengguna-internet-di-indonesia-ada-di-daerah-urban

Maddodi, S., & Prasad, K. (2019). Netflix Bigdata Analytics: The Emergence of Data Driven Recommendation. *International Journal of Case Studies in Business, IT, and Education (IJCSBE)*, *3*(2), 41–51. https://doi.org/https://doi.org/10.5281/zenodo.3510315

Mady, K., Salaheldeen, M., Refaat, H., & Battour, M. (2025). The impact of social media on consumer boycotts: Mediating roles of animosity, behavioral control, and efficacy. *Social Sciences & Humanities Open*, *12*, 1–13. https://doi.org/https://doi.org/10.1016/j.ssaho.2025.102041

McCreanor, T., Moewaka Barnes, A., Goodwin, I., Carah, N., Young, J., Spicer, J., & Lyons, A. C. (2024). Alcohol marketing on social media: Young people's exposure, engagement and alcohol-related behaviors. *Addiction Research & Theory*, 1–11. https://doi.org/10.1080/16066359.2024.2373145

Micheletti, M. (2003). *Political virtue and shopping: Individuals, consumerism, and collective action*. Palgrave Macmillan.

Morgan, M., Shanahan, J., & Signorielli, N. (2016). Cultivation Theory. In *The International Encyclopedia of Communication Theory and Philosophy* (1st ed., pp. 1–10). John Wiley & Sons, Inc. https://doi.org/10.1002/9781118766804.wbiect015

Mortazavi, M., Esfidani, M. R., & Barzoki, A. S. (2014). Influencing VSN users' purchase intentions: The roles of flow, trust and eWOM. *Journal of Research in Interactive Marketing*, *8*(2), 102–123. https://doi.org/https://doi.org/10.1108/JRIM-08-2013-0057

MUI. (2023, November 8). *Fatwa Majelis Ulama Indonesia Nomor: 83 Tahun 2023 Tentang Hukum Dukungan Terhadap Perjuangan Palestina*. Majelis Ulama Indonesia (MUI).

Narayanan, A. (2023). *Understanding Social Media Recommendation Algorithms: Towards a better informed debate on the effects of social media*. Knight First Amendment Institute at Columbia University. https://knightcolumbia.org/content/understanding-social-media-recommendation-algorithms

Ng, P. M. L., Chan, J. K. Y., Lit, K. K., Cheung, C. T. Y., Lau, M. M., Wan, C., & Choy, E. T. K. (2025). The impact of social media exposure and online peer networks on green purchase behavior. *Computers in Human Behavior*, *165*, 108517. https://doi.org/10.1016/j.chb.2024.108517

Oremus, W., & Nix, N. (2023, October 11). Graphic war videos go viral, testing social media's rules. *The Washington Post*. https://www.washingtonpost.com/technology/2023/10/11/tiktok-youtube-israel-hamas-content-moderation/

Palacios-Florencio, B., Revilla-Camacho, M.-A., Garzón, D., & Prado-Román, C. (2021). Explaining the boycott behavior: A conceptual model proposal and validation. *Journal of Consumer Behaviour*, *20*(5), 1313–1325. https://doi.org/https://doi.org/10.1002/cb.1937

Pescher, C., Reichhart, P., & Spann, M. (2014). Consumer Decision-making Processes in Mobile Viral Marketing Campaigns. *Journal of Interactive Marketing*, *28*, 43–54. https://doi.org/http://dx.doi.org/10.1016/j.intmar.2013.08.001

PEW Research Center. (2015). *The Future of World Religions: Population Growth Projections, 2010-2050*. https://www.pewforum.org/2015/04/02/religious-projections-2010-2050/ (accessed on 25 December 2022)

Rachmahyanti, S. (2021). Seruan Boikot Produk Israel Mulai Ramai, Apa Saja Produknya di Indonesia? *Sindo News*. https://ekbis.sindonews.com/read/433686/34/seruan-boikot-produk-israel-mulai-ramai-apa-saja-produknya-di-indonesia-1621587956

RachmawatiI, D. (2024, June 12). Boikot Israel dan Geruduk Starbucks Cs, Waralaba Merugi Picu PHK Massal. *Bisnis.Com*. https://ekonomi.bisnis.com/read/20240612/12/1773537/boikot-israel-dan-geruduk-starbucks-cs-waralaba-merugi-picu-phk-massal

Rahmawati, L., & Marboen, A. P. (2014). Boikot produk Israel tidak berdampak luas. *Antara News*. https://www.antaranews.com/berita/449640/boikot-produk-israel-tidak-berdampak-luas

Roswinanto, W., & Suwanda, S. N. (2023). Religious boycott in Indonesia: Investigation of antecedents and the effect of religiosity dimensions. *Journal of Islamic Marketing*, *14*(1), 174–195. https://doi.org/https://doi.org/10.1108/JIMA-08-2020-0246

Saheb, T., Sidaoui, M., & Schmarzo, B. (2024). Convergence of artificial intelligence with social media: A bibliometric & qualitative analysis. *Telematics and Informatics Reports*, *14*, 1–14. https://doi.org/https://doi.org/10.1016/j.teler.2024.100146

Salma, S. Y., & Aji, H. M. (2023). What drives Muslims to boycott French brands? The moderating role of brand judgement and counterargument. *Journal of Islamic Marketing*, *14*(5), 1346–1368. https://doi.org/https://doi.org/10.1108/JIMA-04-2021-0128

Samaniego-Arias, M., Chávez-Rojas, E., García-Umaña, A., Carrión-Bósquez, N., Ortiz-Regalado, O., Llamo-Burga, M., Ruiz-García, W., Guerrero-Haro, S., & Cando-Aguinaga, W. (2025). The Impact of Social Media on the Purchase Intention of Organic Products. *Sustainability*, *17*(6), 1–16. https://doi.org/https://doi.org/10.3390/su17062706

Sari, D. K., Mizerski, D., & Liu, F. (2017). Boycotting foreign products: A study of Indonesian Muslim consumers. *Journal of Islamic Marketing*, *8*(1), 16–34. https://doi.org/https://doi.org/10.1108/JIMA-12-2014-0078

Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, *27*(3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.). Pearson.

Schwalb, M., García-Arrizabalaga, I., & Gibaja-Martíns, J.-J. (2023). Profile of the Political Consumer: An International Comparative Study. *Journal of International Consumer Marketing*, *35*(3), 296–313. https://doi.org/https://doi.org/10.1080/08961530.2022.2103866

Scopus. (n.d.). *Scopus Database* [Database]. Retrieved https://www.scopus.com/search/form.uri?display=basic&zone=header&origin=#basic (accessed on 15 December 2022)

Scott, M., Coi, G., & Poloni, G. (2024, May 7). Anatomy of a scroll: Inside TikTok's AI-powered algorithms. *Politico*. https://www.politico.eu/article/anatomy-scroll-inside-tiktok-ai-powered-algorithm-israel-palestine-war/

Sen, S., Gürhan-Canli, Z., & Morwitz, V. (2001). Withholding Consumption: A Social Dilemma Perspective on Consumer Boycotts. *Journal of Consumer Research*, *28*(3), 399–417.

Shah, N., Engineer, S., Bhagat, N., Chauhan, H., & Shah, M. (2020). Research Trends on the Usage of Machine Learning and Artificial Intelligence in Advertising. *Augmented Human Research*, *5*(19), 1–15. https://doi.org/https://doi.org/10.1007/s41133-020-00038-8(0123456789().,-volV)(0123456789,-().volV)

Slater, M. D. (2004). Operationalizing and Analyzing Exposure: The Foundation of Media Effects Research. *Journalism & Mass Communication Quarterly*, *81*(1), 168–183. https://doi.org/https://doi.org/10.1177/107769900408100112

Stryker, C., & Kavlakoglu, E. (2024, August 9). *What is artificial intelligence (AI)?* IBM. https://www.ibm.com/think/topics/artificial-intelligence

Suhud, U., Hajat, N., & Griandini, D. (2017). *Animosity of Indonesian Consumers Against Foreign Products*. 358–369. https://www.researchgate.net/publication/341322091_Animosity_of_Indonesian_Consumers_Against_Foreign_Products

The Editors of EB. (2023a, December 6). *Yom Kippur War: Middle East 1973*. Encyclopaedia Britannica (EB). https://www.britannica.com/topic/human-body-systems-2237111

The Editors of EB. (2023b, December 19). *Israel-Hamas War of 2023*. Encyclopaedia Britannica (EB). https://www.britannica.com/event/Israel-Hamas-War-of-2023

Tien, D. H., Rivas, A. A. A., & Liao, Y.-K. (2019). Examining the influence of customer-to-customer electronic word-of-mouth on purchase intention in social networking sites. *Asia Pacific Management Review*, *24*(3), 238–249. https://doi.org/https://doi.org/10.1016/j.apmrv.2018.06.003

Ulo, K. L. M., Novrialdi, A., Hidayatulloh, F. A., Yusmananda, H. R., Gaol, N. R. L., & Wibowo, W. C. (2025). From Likes to Lifestyle: Exploring the Adoption of Healthy Food Recommendations on Social Media. *2025*

16th International Conference on E-Education, E-Business, E-Management and E-Learning (IC4e), 471–475. https://doi.org/https://doi.org/10.1109/IC4e65071.2025.11075420

Vreese, C. H. de, & Neijens, P. (2016). Measuring Media Exposure in a Changing Communications Environment. *Communication Methods and Measures*, *10*(2–3), 69–80. https://doi.org/https://doi.org/10.1080/19312458.2016.1150441

WPR. (2025). *Social Media Users by Country 2025*. World Population Review (WPR). https://worldpopulationreview.com/country-rankings/social-media-users-by-country#title

Yang, H. (2013). Market Mavens in Social Media: Examining Young Chinese Consumers' Viral Marketing Attitude, eWOM Motive, and Behavior. *Journal of Asia-Pacific Business*, *14*(2), 154–178. https://doi.org/https://doi.org/10.1080/10599231.2013.756337

Yang, H., & Zhou, L. (2011). Extending TPB and TAM to mobile viral marketing: An exploratory study on American young consumers ' mobile viral marketing attitude, intent and behavior. *Journal of Targeting, Measurement and Analysis for Marketing*, *19*(2), 85–98. https://doi.org/https://doi.org/10.1057/jt.2011.11

Yang, T., Yang, F., & Men, J. (2023). Recommendation content matters! Exploring the impact of the recommendation content on consumer decisions from the means-end chain perspective. *International Journal of Information Management*, *68*, 1–13. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2022.102589

Zejjari, I., & Benhayoun, I. (2025). Predicting the determinants of consumer's intention to boycott surrogate Israeli products – evidence on nonlinear relationships fromMorocco. *Journal of Islamic Marketing*. https://doi.org/https://doi.org/10.1108/JIMA-02-2024-0096