

DEVELOPMENT OF A VOTER DIGITAL LITERACY MODEL TO ADDRESS MISINFORMATION IN MALAYSIAN ELECTION CAMPAIGNS USING THE FUZZY DELPHI TECHNIQUE

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Abstract: Misinformation has become a defining feature of Malaysian election campaigns, intensifying from the WhatsApp-driven 14th General Election (GE14) in 2018 to the TikTok-dominated 15th General Election (GE15) in 2022, where ethnoreligious disinformation, cybertrooper operations and short-form video manipulation shaped public discourse. Although digital literacy is widely proposed as a remedy, no validated, context-specific model exists to guide voter education in Malaysia. This study aimed to develop and validate a Voter Digital Literacy Model to address misinformation in Malaysian election campaigns using the Fuzzy Delphi Method (FDM). An initial model comprising six constructs and 33 items was derived from a systematic literature review and international frameworks, including DigComp 2.2 and UNESCO's Media and Information Literacy framework. Seven experts in political communication, media literacy, educational technology, electoral governance and Islamic studies evaluated the items using a seven-point linguistic scale. Data were analysed with the FUDELO application using triangular fuzzy numbers, threshold value (d), percentage of expert agreement and defuzzification. Thirty items met all three FDM criteria ($d \leq 0.2$, agreement $\geq 75\%$, $A_{max} \geq 0.5$), while three were rejected. The validated model consists of six constructs: Information Access and Navigation, Source Credibility Evaluation, Verification and Fact-Checking Skills, Awareness of Manipulation Tactics, Ethical and Responsible Sharing, and Civic and Electoral Knowledge. The highest-ranked items were fact-checking service use, pausing before reacting to emotional content, recognising ethnoreligious incitement and refraining from forwarding unverified content in messaging groups. The model offers the Election Commission, educators, civil society and platforms an expert-validated framework for voter education programmes ahead of future Malaysian elections.

Keywords: digital literacy; misinformation; election campaign; voter education; Fuzzy Delphi Method; Malaysia

Introduction

The digital transformation of political communication has fundamentally altered how citizens receive, interpret and act upon electoral information. Social media platforms and instant messaging applications now function as primary news sources for large segments of the electorate, bypassing traditional editorial gatekeeping. While this shift has broadened participation, it has also created fertile ground for the rapid spread of false and misleading content. Wardle and Derakhshan (2017) describe this condition as "information disorder", encompassing misinformation, disinformation and malinformation. Empirical evidence shows that falsehood diffuses significantly farther, faster and more broadly than truth on social networks (Vosoughi et al., 2018), and that fabricated news stories reached millions of voters during recent national elections (Allcott & Gentzkow, 2017). Elections, as high-stakes moments of collective decision-making, are therefore especially vulnerable to the distortive effects of misinformation.

Malaysia offers a compelling case of how digital media reshapes electoral politics. Since the 2008 general election, new media has been recognised as an alternative political space that challenged the dominance of state-aligned mainstream outlets (Pepinsky, 2013). In GE14 in 2018, rising smartphone penetration in semi-rural "heartland" constituencies allowed Facebook and WhatsApp to carry campaign messages, rumours and critiques directly into voters' hands, contributing to Malaysia's first change of federal government (Tapsell, 2018). The same channels, however, also carried unverified claims, manipulated images and partisan rumours that voters struggled to evaluate. Malaysia has also been identified as one of the countries where organised social media manipulation by "cybertroopers" operates on a sustained basis (Bradshaw & Howard, 2019; Mohd Hed et al., 2025).

The problem intensified in GE15 in November 2022. The campaign was characterised by professionalised video campaigning, livestreaming and the emergence of TikTok as an influential conduit for political messaging, particularly among young and first-time voters enfranchised by the Undi18 reform and automatic voter registration (Tapsell, 2023; Anuar et al., 2025). Jalli (2024) found that more than half of the high-reach GE15-related TikTok videos analysed contained hate speech, much of it ethno-religious in nature, with hashtags invoking the 13 May 1969 riots trending after the announcement of a hung parliament. These developments demonstrate that misinformation in Malaysian elections is not merely a technical problem of false facts but a socio-political threat to social cohesion, electoral integrity and public trust.

Regulatory and platform-level responses, such as fact-checking portals, content takedowns and legal provisions under the Communications and Multimedia Act 1998, are necessary but insufficient. Research consistently shows that corrections only partially reduce belief in misinformation (Chan et al., 2017), and that misinformation continues to influence reasoning even after debunking (Lewandowsky et al., 2017; Ecker et al., 2022). Consequently, scholars increasingly advocate building citizens' internal capacities to recognise and resist misinformation, through digital media literacy interventions, lateral reading and psychological inoculation (Guess et al., 2020; Kozyreva et al., 2020; Roozenbeek et al., 2022). Yet existing digital literacy frameworks, such as DigComp 2.2 (Vuorikari et al., 2022), are generic and were not designed around the specific dynamics of election campaigns in a multi-ethnic, multi-religious society such as Malaysia.

This gap calls for a contextualised, expert-validated model that specifies which competencies Malaysian voters need to navigate election-period misinformation. Developing such a model requires systematic consensus among experts across political communication, media literacy,

education, electoral governance and religious studies. The Fuzzy Delphi Method (FDM) is well suited to this purpose because it integrates fuzzy set theory with the classical Delphi technique, accommodating the vagueness inherent in expert judgement while requiring fewer rounds and a smaller panel (Mohd Jamil et al., 2017; Mustapha & Darusalam, 2017). Accordingly, this study aims to develop and validate a Voter Digital Literacy Model to address misinformation in Malaysian election campaigns using the Fuzzy Delphi technique, with data analysed using the FUDELO application.

Literature Review

Conceptualising misinformation and information disorder

Scholarly definitions of false information have evolved considerably over the past decade. Tandoc et al. (2018) identified six types of "fake news" in the literature, namely satire, parody, fabrication, manipulation, advertising and propaganda, distinguished by their levels of facticity and intention to deceive. Wardle and Derakhshan (2017) proposed the broader framework of information disorder, separating misinformation (false content shared without intent to harm) from disinformation (deliberately false content) and malinformation (genuine content used to inflict harm). Vraga and Bode (2020) further argued that misinformation should be defined relative to the best available expert evidence at a given time. These distinctions matter for voter education, because citizens must learn not only to detect falsity but also to recognise manipulation of context, framing and intent, which characterise much election-period content.

The psychology of misinformation susceptibility

A substantial body of work explains why people believe and share false information. Lazer et al. (2018) highlighted the interplay of cognitive, social and algorithmic factors in the spread of fake news. Pennycook and Rand (2019) showed that susceptibility to partisan fake news is better explained by a lack of analytical reasoning than by motivated reasoning, suggesting that prompting deliberation can improve discernment. Emotional arousal also plays a role, as anger and anxiety can amplify partisan bias in accepting political misinformation (Ecker et al., 2022). Ecker et al. (2022) synthesised the cognitive, social and affective drivers of misinformation belief and its resistance to correction, including the continued influence effect. Lewandowsky et al. (2017) warned that misinformation in a "post-truth" environment cannot be addressed by corrections alone, as it is embedded in broader political and social dynamics. This literature implies that a voter digital literacy model must include dispositional and emotional self-regulation components, not only technical skills.

Digital, media and information literacy as a countermeasure

Digital literacy has been framed as a multidimensional competence that includes technical, cognitive and social-emotional dimensions. The European DigComp 2.2 framework identifies information and data literacy, communication and collaboration, digital content creation, safety and problem solving as core areas, and explicitly addresses misinformation and disinformation in its updated examples (Vuorikari et al., 2022). Kahne and Bowyer (2017) found that media literacy learning opportunities were associated with better judgements of the accuracy of political claims, regardless of prior political knowledge. However, Jones-Jang et al. (2021) showed that only information literacy, rather than media, news or digital literacy in general, significantly predicted the identification of fake news. This suggests that a voter-focused model must prioritise specific, actionable information evaluation skills rather than broad technological familiarity.

Evidence on intervention approaches

Intervention studies offer guidance on which competencies are trainable. McGrew et al. (2018) documented the weak ability of students to evaluate online sources and advocated "civic online reasoning" built on lateral reading, that is, leaving a website to investigate who is behind it. Guess et al. (2020) demonstrated that a brief digital media literacy intervention increased discernment between mainstream and false news in both the United States and India, a context with heavy WhatsApp use comparable to Malaysia. Roozenbeek and van der Linden (2019) introduced prebunking through the Bad News game, which conferred psychological resistance to manipulation techniques, and Roozenbeek et al. (2022) replicated inoculation effects at scale through short videos on social media. Kozyreva et al. (2020) categorised these cognitive tools into nudges, boosts and technocognition, arguing that boosting citizens' competencies is essential for democratic resilience. Meta-analytic work indicates that debunking is more effective when it provides detailed counter-arguments (Chan et al., 2017).

Digital media and elections in Malaysia

Malaysian scholarship has long examined the political role of new media. Pepinsky (2013) argued that new media's political effects should be understood within Malaysia's historical patterns of modernisation and regime strategy. Tapsell (2018) showed how WhatsApp and Facebook acted as "weapons of the weak" during GE14, spreading information on corruption but also gossip, rumour and conspiracy. Bradshaw and Howard (2019) documented the use of cybertroopers by Malaysian parties and government agencies to spread propaganda and attack opponents, and Mohd Hed et al. (2025) found that experts regard cybersecurity education as a key mechanism for controlling cybertrooper influence. For GE15, Tapsell (2023) described the professionalisation of video campaigning that enabled polarising narratives, while Jalli (2024) found widespread ethnoreligious hate speech on TikTok. Anuar et al. (2025) confirmed that social media shaped young voters' perceptions while introducing misinformation and hate speech challenges. Despite this rich diagnostic literature, prescriptive frameworks for building voters' competencies remain scarce.

The Fuzzy Delphi Method for model development

Developing a contextual model requires structured expert consensus. The classical Delphi technique gathers expert opinion over several rounds but is time-consuming and does not handle the ambiguity of linguistic judgement. The Fuzzy Delphi Method integrates triangular fuzzy numbers and defuzzification to convert linguistic ratings into crisp values, allowing consensus to be established in a single round (Hsu et al., 2010; Chang et al., 2011). In Malaysia, FDM has been widely adopted in design and development research in education, social sciences and Islamic studies (Mohd Jamil et al., 2017; Mustapha & Darusalam, 2017), as well as in instrument validation in health research (Manakandan et al., 2017). Its suitability for small, heterogeneous expert panels makes it appropriate for developing a voter digital literacy model that draws on multidisciplinary expertise. To the authors' knowledge, no previous study has applied FDM to develop a digital literacy model specifically for election misinformation in Malaysia, which constitutes the gap addressed by this study.

Research Questions

This study is guided by the following research questions:

1. What are the experts' consensus on the constructs that should form a Voter Digital Literacy Model to address misinformation in Malaysian election campaigns?
2. What are the experts' consensus on the items that should be included under each construct of the model?
3. What is the priority ranking of the validated items within each construct based on the Fuzzy Delphi defuzzification process?

Methodology

Research design

The Fuzzy Delphi Method (FDM) was used to obtain expert consensus on the constructs and items of the proposed Voter Digital Literacy Model. FDM combines the classical Delphi technique with fuzzy set theory, converting experts' linguistic judgements into triangular fuzzy numbers so that the uncertainty of human evaluation is captured mathematically (Hsu et al., 2010; Chang et al., 2011). Consensus is determined in a single round, which reduces respondent fatigue and time compared with the iterative classical Delphi (Mohd Jamil et al., 2017; Mustapha & Darusalam, 2017).

Development of the instrument

The initial items were developed through a systematic review of literature on misinformation, digital and media literacy, and Malaysian election campaigns (e.g., Tapsell, 2018, 2023; Jones-Jang et al., 2021; Vuorikari et al., 2022; Jalli, 2024). This produced six constructs and 33 items: Information Access and Navigation (5 items), Source Credibility Evaluation (6), Verification and Fact-Checking Skills (6), Awareness of Manipulation Tactics (6), Ethical and Responsible Sharing (5), and Civic and Electoral Knowledge (5). The questionnaire used a seven-point linguistic agreement scale, and an open-ended section allowed experts to propose modifications, additions or deletions.

Expert panel

Seven experts were selected through purposive sampling. FDM literature indicates that a homogeneous panel of 5 to 10 experts is adequate for reaching consensus (Mohd Jamil et al., 2017; Manakandan et al., 2017). Selection criteria included (a) at least 10 years of professional or academic experience in the relevant field, (b) recognised expertise through publications, training or policy involvement, and (c) willingness to participate. The panel profile is shown in Table 1.

Table 1. Profile of the expert panel

Expert	Field of expertise	Position / institution type	Experience (years)
E1	Political communication	Associate Professor, public university	18
E2	Media and information literacy	Senior Lecturer, public university	14
E3	Educational technology	Associate Professor, public university	16
E4	Electoral governance	Senior officer, election management body	20
E5	Journalism and fact-checking	Editor, fact-checking organisation	12
E6	Islamic studies and da'wah communication	Senior Lecturer, public university	15
E7	Civic and citizenship education	Lecturer, teacher education institute	11

Data analysis using the FUDELO application

Data were analysed using FUDELO, a dedicated Fuzzy Delphi analysis application developed by Mustapha (UiTM) that automates triangular fuzzy number conversion, threshold computation, expert agreement percentage, defuzzification and ranking, and exports the results to Word and Excel. Using a dedicated application reduces manual computation error and ensures transparency of each analytical step. The FDM procedure followed seven steps (Mustapha & Darusalam, 2017).

Step 1: Selecting the experts. Seven experts meeting the criteria in Section 4.3 were appointed and briefed on the research objectives and the scale.

Step 2: Determining the linguistic scale. Each linguistic rating was assigned a triangular fuzzy number (m_1 , m_2 , m_3), representing the minimum, most plausible and maximum values. The seven-point scale is shown in Table 2.

Table 2. Seven-point linguistic scale and triangular fuzzy numbers

Scale	Linguistic variable	m_1	m_2	m_3
1	Extremely disagree	0.0	0.0	0.1
2	Strongly disagree	0.0	0.1	0.3
3	Disagree	0.1	0.3	0.5
4	Moderately agree	0.3	0.5	0.7
5	Agree	0.5	0.7	0.9
6	Strongly agree	0.7	0.9	1.0
7	Extremely agree	0.9	1.0	1.0

Step 3: Converting ratings and computing the average fuzzy number. Each expert's rating was converted to its triangular fuzzy number, and the average fuzzy number for each item was calculated across the $n = 7$ experts:

Each expert's rating was converted into a triangular fuzzy number, $\tilde{n}_j = (n_{1j}, n_{2j}, n_{3j})$, for expert $j = 1, 2, \dots, N$, where $N = 7$. The average fuzzy number of each item, $\tilde{m} = (m_1, m_2, m_3)$, was then calculated:

$$m_1 = (1/N) \sum n_{1j}; m_2 = (1/N) \sum n_{2j}; m_3 = (1/N) \sum n_{3j}, \text{ for } j = 1, 2, \dots, N \dots (1)$$

Step 4: Calculating the threshold value (d). The distance between each expert's fuzzy number (n_1, n_2, n_3) and the average (m_1, m_2, m_3) was computed using the vertex method:

$$d(\tilde{m}, \tilde{n}_j) = \sqrt{\frac{1}{3} [(m_1 - n_{1j})^2 + (m_2 - n_{2j})^2 + (m_3 - n_{3j})^2]} \quad (2)$$

The threshold value of each item is the mean of the N individual distances:

$$d = \frac{1}{N} \sum_{j=1}^N d(\tilde{m}, \tilde{n}_j) \quad (3)$$

An item achieves expert consensus when its average threshold value is $d \leq 0.2$ (Chang et al., 2011).

Step 5: Determining the percentage of expert agreement. The percentage of individual d values that are ≤ 0.2 was calculated for each item. An item is accepted when the agreement is $\geq 75\%$ (Mohd Jamil et al., 2017).

Step 6: Defuzzification. The average fuzzy number was converted into a crisp score (A_{max}) using:

$$A_{max} = \frac{1}{3}(m_1 + m_2 + m_3) \quad (4)$$

An item is accepted when $A_{max} \geq 0.5$ (α -cut), indicating that experts agree on its inclusion; items below 0.5 are rejected (Mustapha & Darusalam, 2017).

Step 7: Ranking and model formation. Items satisfying all three conditions were ranked within each construct according to their A_{max} scores. The ranking determines the priority of each competency in the final model, while rejected items were removed or revised based on the experts' qualitative comments.

Findings

Thirty of the 33 items (90.9%) met all three Fuzzy Delphi conditions and were accepted into the model, while three items (A5, C6 and F5) were rejected. All six constructs were retained. The results are reported according to the three research questions.

Expert consensus on items (RQ2)

Table 3 presents the FUDELO output for every item: the individual threshold values of the seven experts, the average threshold value (d), the percentage of expert agreement, the average fuzzy numbers, the defuzzified score (A_{max}), the rank within the construct and the decision. Values of d greater than 0.2 are shown in bold.

Table 3. Fuzzy Delphi analysis of all items (n = 7 experts)

Item	E1	E2	E3	E4	E5	E6	E7	d	Agreement (%)	m1	m2	m3	Amax	Rank	Decision
A1	0.037	0.037	0.092	0.037	0.092	0.037	0.037	0.053	100.0	0.843	0.971	1.000	0.938	1	Accepted
A2	0.037	0.037	0.092	0.037	0.037	0.092	0.037	0.053	100.0	0.757	0.929	1.000	0.895	3	Accepted
A3	0.037	0.092	0.037	0.037	0.092	0.037	0.037	0.053	100.0	0.757	0.929	1.000	0.895	4	Accepted
A4	0.055	0.074	0.055	0.055	0.074	0.074	0.055	0.063	100.0	0.814	0.957	1.000	0.924	2	Accepted
A5	0.042	0.139	0.231	0.139	0.042	0.256	0.231	0.154	57.1	0.557	0.743	0.886	0.729	–	Rejected
B1	0.037	0.037	0.037	0.092	0.037	0.037	0.092	0.053	100.0	0.843	0.971	1.000	0.938	1	Accepted
B2	0.037	0.092	0.037	0.037	0.037	0.092	0.037	0.053	100.0	0.843	0.971	1.000	0.938	2	Accepted
B3	0.055	0.074	0.055	0.074	0.055	0.074	0.055	0.063	100.0	0.786	0.943	1.000	0.910	4	Accepted
B4	0.037	0.037	0.092	0.037	0.037	0.037	0.092	0.053	100.0	0.757	0.929	1.000	0.895	5	Accepted
B5	0.055	0.055	0.074	0.074	0.055	0.055	0.074	0.063	100.0	0.814	0.957	1.000	0.924	3	Accepted
B6	0.012	0.012	0.012	0.133	0.012	0.165	0.012	0.051	100.0	0.700	0.886	0.986	0.857	6	Accepted
C1	0.018	0.018	0.018	0.018	0.111	0.018	0.018	0.032	100.0	0.871	0.986	1.000	0.952	1	Accepted
C2	0.037	0.037	0.092	0.037	0.037	0.092	0.037	0.053	100.0	0.757	0.929	1.000	0.895	5	Accepted

Item	E1	E2	E3	E4	E5	E6	E7	d	Agreement (%)	m1	m2	m3	Amax	Rank	Decision
C3	0.074	0.055	0.055	0.074	0.074	0.055	0.055	0.063	100.0	0.786	0.943	1.000	0.910	4	Accepted
C4	0.037	0.037	0.092	0.037	0.037	0.092	0.037	0.053	100.0	0.843	0.971	1.000	0.938	3	Accepted
C5	0.018	0.018	0.018	0.111	0.018	0.018	0.018	0.032	100.0	0.871	0.986	1.000	0.952	2	Accepted
C6	0.171	0.029	0.229	0.171	0.029	0.229	0.171	0.147	71.4	0.271	0.471	0.671	0.471	–	Rejected
D1	0.037	0.037	0.092	0.037	0.037	0.092	0.037	0.053	100.0	0.843	0.971	1.000	0.938	2	Accepted
D2	0.037	0.037	0.092	0.037	0.092	0.037	0.037	0.053	100.0	0.757	0.929	1.000	0.895	4	Accepted
D3	0.018	0.018	0.018	0.018	0.111	0.018	0.018	0.032	100.0	0.871	0.986	1.000	0.952	1	Accepted
D4	0.012	0.012	0.012	0.133	0.012	0.012	0.165	0.051	100.0	0.700	0.886	0.986	0.857	6	Accepted
D5	0.037	0.092	0.037	0.037	0.092	0.037	0.037	0.053	100.0	0.757	0.929	1.000	0.895	5	Accepted
D6	0.055	0.074	0.055	0.055	0.074	0.055	0.074	0.063	100.0	0.814	0.957	1.000	0.924	3	Accepted
E1	0.018	0.018	0.018	0.018	0.018	0.111	0.018	0.032	100.0	0.871	0.986	1.000	0.952	1	Accepted
E2	0.037	0.092	0.037	0.037	0.092	0.037	0.037	0.053	100.0	0.757	0.929	1.000	0.895	3	Accepted
E3	0.037	0.037	0.037	0.092	0.037	0.037	0.092	0.053	100.0	0.757	0.929	1.000	0.895	4	Accepted
E4	0.034	0.140	0.034	0.034	0.156	0.140	0.034	0.082	100.0	0.671	0.857	0.971	0.833	5	Accepted
E5	0.055	0.074	0.055	0.055	0.074	0.074	0.055	0.063	100.0	0.814	0.957	1.000	0.924	2	Accepted
F1	0.037	0.037	0.092	0.037	0.037	0.037	0.092	0.053	100.0	0.843	0.971	1.000	0.938	1	Accepted
F2	0.037	0.037	0.092	0.037	0.037	0.092	0.037	0.053	100.0	0.757	0.929	1.000	0.895	3	Accepted
F3	0.018	0.018	0.018	0.018	0.111	0.018	0.018	0.032	100.0	0.729	0.914	1.000	0.881	4	Accepted
F4	0.074	0.055	0.055	0.074	0.055	0.055	0.074	0.063	100.0	0.786	0.943	1.000	0.910	2	Accepted
F5	0.179	0.016	0.191	0.016	0.179	0.191	0.016	0.113	100.0	0.129	0.300	0.500	0.310	–	Rejected

Three items failed to meet the criteria. Item A5 (subscribing to diverse news outlets across political lines) obtained an expert agreement of only 57.1%, below the 75% threshold, as three experts' ratings deviated by more than 0.2 from the group average. Item C6 (technical metadata analysis such as EXIF and geolocation) failed both the agreement criterion (71.4%) and the defuzzification criterion ($A_{max} = 0.471$). Item F5 (memorising the full constituency delimitation history) achieved consensus on its low value, but its A_{max} of 0.310 shows that experts agreed it should be excluded. Experts commented that C6 is too technical for ordinary voters and F5 reflects rote knowledge rather than literacy.

Expert consensus on constructs (RQ1)

Table 4. Summary of expert consensus by construct

Code	Construct	Items proposed	Items accepted	Mean d	Mean agreement (%)	Decision
A	Information Access and Navigation	5	4	0.075	91.4	Accepted
B	Source Credibility Evaluation	6	6	0.056	100.0	Accepted
C	Verification and Fact-Checking Skills	6	5	0.063	95.2	Accepted
D	Awareness of Manipulation Tactics	6	6	0.051	100.0	Accepted
E	Ethical and Responsible Sharing	5	5	0.056	100.0	Accepted
F	Civic and Electoral Knowledge	5	4	0.063	100.0	Accepted
Total		33	30			

All six constructs recorded mean threshold values well below 0.2 (0.051 to 0.075) and mean agreement of 91.4% to 100%, confirming strong expert consensus that every construct belongs in the model.

Priority ranking of accepted items (RQ3)

Table 5 lists the 30 accepted items in order of priority within each construct, forming the validated Voter Digital Literacy Model.

Table 5. Validated Voter Digital Literacy Model ranked by defuzzification score

Construct	Rank	Item	Statement	Amax
Information Access and Navigation	1	A1	Locates official election information (SPR/EC portals, gazettes, candidate lists) online	0.938
	2	A4	Distinguishes news, opinion, sponsored and user-generated content in a feed	0.924
	3	A2	Uses advanced search strategies to retrieve multiple sources on a campaign claim	0.895
	4	A3	Navigates platform features (pinned posts, profile info, page transparency) to trace content origin	0.895
Source Credibility Evaluation	1	B1	Checks the identity, expertise and track record of the author or account	0.938
	2	B2	Practises lateral reading by leaving the page to see what other sources say	0.938
	3	B5	Evaluates the date, context and original setting of recycled content	0.924
	4	B3	Identifies anonymous, newly created or inauthentic accounts	0.910
	5	B4	Recognises partisan framing and loaded language in campaign content	0.895
	6	B6	Assesses whether a website domain imitates a legitimate news outlet	0.857
Verification and Fact-Checking Skills	1	C1	Uses fact-checking services such as Sebenarnya.my, MyCheck.my and AFP Fact Check	0.952
	2	C5	Pauses and verifies before reacting to emotionally charged posts	0.952
	3	C4	Detects edited, out-of-context or synthetic (deepfake) audio and video	0.938
	4	C3	Cross-checks statistics and figures against primary sources	0.910
	5	C2	Performs reverse image and keyframe searches on suspicious visuals	0.895
Awareness of Manipulation Tactics	1	D3	Identifies ethnoreligious and racial incitement used as campaign strategy	0.952
	2	D1	Recognises coordinated cybertrooper activity and astroturfing	0.938
	3	D6	Recognises AI-generated text, images and voice clones in campaigns	0.924

Construct	Rank	Item	Statement	Amax
Ethical and Responsible Sharing	4	D2	Understands how recommendation algorithms create filter bubbles and echo chambers	0.895
	5	D5	Understands the use of bots and fake engagement to inflate popularity	0.895
	6	D4	Recognises political microtargeting and undisclosed paid promotion	0.857
	1	E1	Refrains from forwarding unverified content in WhatsApp and Telegram groups	0.952
	2	E5	Applies the Islamic principle of tabayyun (verification) before sharing news	0.924
	3	E2	Corrects or retracts misinformation that one has previously shared	0.895
Civic and Electoral Knowledge	4	E3	Reports false or harmful content through platform reporting tools	0.895
	5	E4	Understands legal provisions on false content (CMA 1998 s.233, Penal Code s.505)	0.833
	1	F1	Understands electoral processes, voting procedures and the role of the Election Commission	0.938
	2	F4	Engages in respectful, evidence-based political discussion online	0.910
	3	F2	Compares party manifestos and candidate records using credible sources	0.895
	4	F3	Understands campaign rules, election offences and complaint channels	0.881

The four highest-scoring items across the model ($A_{max} = 0.952$) were C1 (using fact-checking services such as *Sebenarnya.my*), C5 (pausing to verify before reacting to emotionally charged posts), D3 (identifying ethnoreligious and racial incitement) and E1 (refraining from forwarding unverified content in WhatsApp and Telegram groups). These were followed by A1, B1, B2, C4, D1 and F1 ($A_{max} = 0.938$). The lowest accepted items, B6 and D4 ($A_{max} = 0.857$) and E4 ($A_{max} = 0.833$), remained well above the 0.5 threshold.

Discussion

The experts reached strong consensus on a six-construct Voter Digital Literacy Model with 30 items, confirming that election-period digital literacy in Malaysia must combine technical, cognitive, ethical and civic competencies. This multidimensional structure is consistent with DigComp 2.2, which treats information literacy, safety and responsible communication as interrelated areas (Vuorikari et al., 2022). However, the model extends generic frameworks by adding two election-specific constructs, Awareness of Manipulation Tactics and Civic and Electoral Knowledge, which reflect the documented realities of cybertrooper operations and polarising campaign content in Malaysia (Bradshaw & Howard, 2019; Tapsell, 2023).

The high ranking of C1 (using fact-checking services) and C5 (pausing before reacting to emotional posts) aligns with evidence that deliberation reduces susceptibility to false news (Pennycook & Rand, 2019) and that emotional arousal drives misinformation belief (Ecker et al., 2022). That experts placed a dispositional habit, pausing, alongside a technical skill at the top of the verification construct supports the argument that literacy is as much about self-

regulation as about tools. The strong endorsement of B2 (lateral reading) likewise echoes the civic online reasoning approach of McGrew et al. (2018), which is among the few strategies with consistent experimental support. This prioritisation also corresponds with Jones-Jang et al. (2021), who found that specific information evaluation skills, rather than broad digital familiarity, predict fake news identification.

The top position of D3 (identifying ethnoreligious and racial incitement) is a distinctly Malaysian finding. It reflects GE15 evidence that ethnoreligious hate speech dominated high-reach TikTok content and that narratives invoking the May 1969 riots trended after the election (Jalli, 2024). Similarly, the high score of D1 (recognizing cybertrooper activity) mirrors Malaysian research identifying organised cybertroopers as a persistent threat to informed public opinion (Mohd Hed et al., 2025). Including D6 (recognising AI-generated content and voice clones) indicates that experts anticipate synthetic media becoming a major campaign threat in future elections, consistent with the inoculation literature's emphasis on teaching manipulation techniques rather than individual false claims (Roozenbeek & van der Linden, 2019; Roozenbeek et al., 2022).

Within the Ethical and Responsible Sharing construct, E1 (refraining from forwarding unverified content in WhatsApp and Telegram groups) was ranked first. This is consistent with Tapsell's (2018) observation that closed messaging groups were central channels for political rumours in GE14, where content is difficult to monitor or correct publicly. Guess et al. (2020) showed that literacy interventions can work even in WhatsApp-heavy environments, supporting the inclusion of sharing behaviour as a teachable competence. The strong endorsement of E5, the Islamic principle of *tabayyun* (verifying news before acting on it), is noteworthy. It suggests that culturally and religiously grounded values can be harnessed to frame responsible sharing for the Muslim majority electorate, making literacy messages more resonant than secular frameworks alone.

The rejected items offer equally useful insights. Experts rejected C6 (technical metadata analysis) as too specialised for ordinary voters, indicating that the model should focus on accessible strategies rather than forensic skills. A5 (subscribing to diverse outlets across political lines) did not reach agreement, possibly reflecting divided views on whether exposure diversity is realistic or effective in a polarised environment. F5 (memorising constituency delimitation history) was rejected because it reflects rote knowledge rather than functional literacy. These decisions demonstrate the value of FDM in refining a model through structured expert judgement rather than merely confirming a researcher's initial assumptions (Mohd Jamil et al., 2017; Mustapha & Darusalam, 2017).

Methodologically, the use of the FUDELO application ensured that triangular fuzzy conversion, threshold computation, agreement percentages and defuzzification were computed consistently and transparently. The narrow range of mean threshold values across constructs (0.051 to 0.075) indicates a high degree of convergence among experts from diverse disciplines. Nevertheless, the model represents expert consensus rather than empirical evidence of effectiveness among voters, and it must be tested further with the target population.

Conclusion and Recommendations

This study developed and validated a Voter Digital Literacy Model to address misinformation in Malaysian election campaigns through expert consensus using the Fuzzy Delphi Method. Seven experts validated six constructs and 30 items, with three items rejected for failing the

FDM criteria. The model shows that resisting election misinformation requires voters to access official information, evaluate sources laterally, verify claims using fact-checking tools, recognise manipulation tactics such as cybertroopers, ethnoreligious incitement and synthetic media, share responsibly, and understand the electoral process. Its contribution lies in contextualising global digital literacy frameworks to Malaysia's multi-ethnic, multi-religious and messaging-app-driven political environment, while integrating religious values such as tabayyun.

Based on the findings, the following recommendations are proposed:

1. **Election Commission (SPR) and government agencies** should adopt the model as a framework for pre-election voter education campaigns, prioritising the highest-ranked items such as fact-checking, pausing before sharing and recognising ethnoreligious incitement.
2. **Higher education institutions** should embed the model into general courses on citizenship, ethics and Islamic civilisation, particularly to prepare young and first-time voters enfranchised under Undi18.
3. **Civil society and fact-checking organisations** should develop short-form video and gamified prebunking modules aligned with the Awareness of Manipulation Tactics construct, delivered through the same platforms where misinformation spreads.
4. **Religious institutions and community leaders** should use the tabayyun principle to promote responsible sharing in WhatsApp and Telegram groups, where much election misinformation circulates.
5. **Social media platforms** should collaborate with local stakeholders to integrate in-app prompts that encourage verification and pausing before forwarding during campaign periods.

For future research, the model should be evaluated in the next phase of the DDR approach through usability testing and quasi-experimental studies measuring changes in voters' ability to discern true from false election content. Future studies could also apply Interpretive Structural Modelling (ISM) to establish relationships among the constructs, develop a validated measurement instrument based on the 30 items for testing with structural equation modelling, and expand the expert panel to include representatives from East Malaysia and political party communication units. Longitudinal research across future general and state elections would further reveal how voters' digital literacy evolves alongside emerging technologies such as generative AI.

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