

Pathways towards social license for offshore wind energy: Modelling strategies to reduce conflict and increase acceptability

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ABSTRACT

While the global expansion of offshore wind energy is essential to achieving net-zero emissions targets, opposition from local communities and other stakeholders is often a major barrier to implementation. The response to planned developments around the Australian coastline have shown divergent trajectories ranging from a relatively mild public response in Tasmania to sometimes vitriolic debate in New South Wales (NSW). This study uses a novel social influence model to simulate the evolution of community and other stakeholder attitudes toward offshore wind developments in both Tasmania and NSW. Results presented as Social License Graphs (SLGs) show that without intervention, Tasmania is likely to maintain an even balance between support and opposition, whereas opposition may become more entrenched in NSW. Simulated communication strategies, such as collaborative learning across key stakeholder groups and ocean literacy campaigns targeted at the broader public, provided modest reduction in the levels of community conflict, whereas traditional persuasive advertising by the offshore wind energy sector tended to increase conflict. Improving perceptions of environmental, governance and economic performance markedly improved social acceptability, potentially shifting mean attitudes in NSW from strongly negative to positive. This work demonstrates the utility of agent-based modelling for understanding and managing the social dynamics of renewable energy transitions, with findings supporting a set of policy recommendations focused on media monitoring and improving perceptions of industry performance through targeted reforms and effective communications.

1. Introduction

Global carbon emission targets are accelerating the planning and construction of renewable energy infrastructure, including coastal and offshore wind energy (Gonzalez et al., 2024; Veers et al., 2022). The global wind energy market is projected to experience compound growth of 14% to at least 2030 (Swadi et al., 2024). However, new proposals are increasingly being contested by local communities, as well as national and international advocacy groups (Cashmore et al., 2022; Colvin et al., 2016; Gonyo et al., 2021). It has been suggested that low levels of local acceptance may ultimately constrain our ability to achieve renewable energy targets (Wüstenhagen et al., 2007), particularly in relation to wind energy (Landeta-Manzano et al., 2018; Rand and Hoen, 2017). At the same time, research to support the transition continues to be

overwhelmingly focused on technological issues rather than the underlying social constraints (Bidwell and Sovacool, 2023; Boudet, 2019; Conde and Takano-Rojas, 2025; Sovacool, 2014; Van Veelen et al., 2019).

While opposition to new wind energy developments often centres on visual impacts to landscapes and seascapes (Colvin et al., 2016; Cousse et al., 2020; Fast et al., 2016), public acceptance is also shaped by a broad set of social, economic, environmental and governance factors. These include proximity to turbines (Ki et al., 2022), the quality of community engagement and planning processes (Colvin et al., 2016), the distribution of economic benefits (Bidwell, 2013), interactions with existing ocean users such as commercial fisheries (Bidwell et al., 2023; Chaji and Werner, 2023; Helene et al., 2022; Stelzenmüller et al., 2022), and the stage of project development with opposition often strongest

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during the planning and approval phases (Bidwell, 2023; le Maitre et al., 2024; Penneman et al., 2023; Wolsink, 2007). Attitudes are further influenced by previous experiences with the wind energy sector, which can shape perceptions of new developments and ongoing operations (Ellis et al., 2023; Windemer, 2023). These factors interact across local communities and broader regional networks (Kirkegaard et al., 2023), with attitudes continuously evolving through interpersonal communication, community debate, and media exposure (Deignan et al., 2013; Gearhart et al., 2019; Heidenreich, 2016).

Evidence suggests support for renewable energy is often grounded in relatively stable values and beliefs, whereas opposition can be more contingent and responsive to new information and experiences (Bingaman et al., 2023). The growing influence of misinformation (Ermarth and Chang, 2026; Howley et al., 2025), including confounding issues associated with different types of renewable energy (Wiersma and Devine-Wright, 2014), combined with a lack of longitudinal studies of attitudinal change (Bingaman et al., 2023) continue to limit our understanding of how social acceptance evolves over time and how it may respond to policy and management interventions.

We have developed a social influence model to both track the evolution of community and stakeholder attitudes (opinions) to offshore wind developments and project alternative future pathways. Social influence models represent people as connected agents who influence one another over time and allow attitudes to spread through populations. By simulating these interactions, social influence models can provide insights into processes such as the diffusion of information and misinformation, and development of consensus or polarisation. While there is a large body of literature devoted to theoretical aspects of social influence models (Flache et al., 2017; Hegselmann and Krause, 2002; Lorenz, 2007; Perc, 2019), there are relatively few previous examples of applications utilising issue and place specific data (Condie et al., 2022a; Lee et al., 2019; Sobkowicz, 2009) and none that we are aware of relating to the renewable energy sector. The model described here has been used to evaluate strategies aimed at mitigating conflict surrounding offshore wind energy in Australia, contrasting a region characterized by low

existing conflict (Tasmania) with another characterized by high existing conflict (New South Wales, NSW).

2. Methods

2.1. Study regions

The study models community and other stakeholder responses to declarations of offshore wind areas in Australian Commonwealth waters. The Bass Strait Offshore Wind Area is situated 20 km offshore of northern Tasmania, while the Hunter Offshore Wind Area and the Illawara Offshore Wind Area are both situated 20 km offshore of the central coast of NSW (Fig. 1). These two areas were selected for study because of their strongly contrasting community responses to the proposed developments. Characteristics of the Tasmanian offshore wind area and the two NSW offshore wind areas are summarised in Table 1. When public submissions were invited, the Hunter and Illawara proposals received more than 50 times the number of submissions received for the Bass Strait proposal (Table 1). The number of submissions per

Table 1
Characteristics of the declared Bass Strait, Hunter and Illawara offshore wind areas (<https://www.dcccew.gov.au/energy/renewable/offshore-wind/areas>).

Offshore wind area	Bass Strait	Hunter	Illawara
Area	7104 km ²	1854 km ²	1022 km ²
Minimum distance offshore	20 km	20 km	20 km
Potential power generation	20 GW	5.0 GW	2.9 GW
Potential construction jobs	12,000	3000	1740
Potential ongoing jobs	6000	1560	870
Public submissions	270	1916	14,211
Dates of public consultation	Oct 2023 – Jan 2024	Feb 2023 – Apr 2023	Aug 2023 – Nov 2023

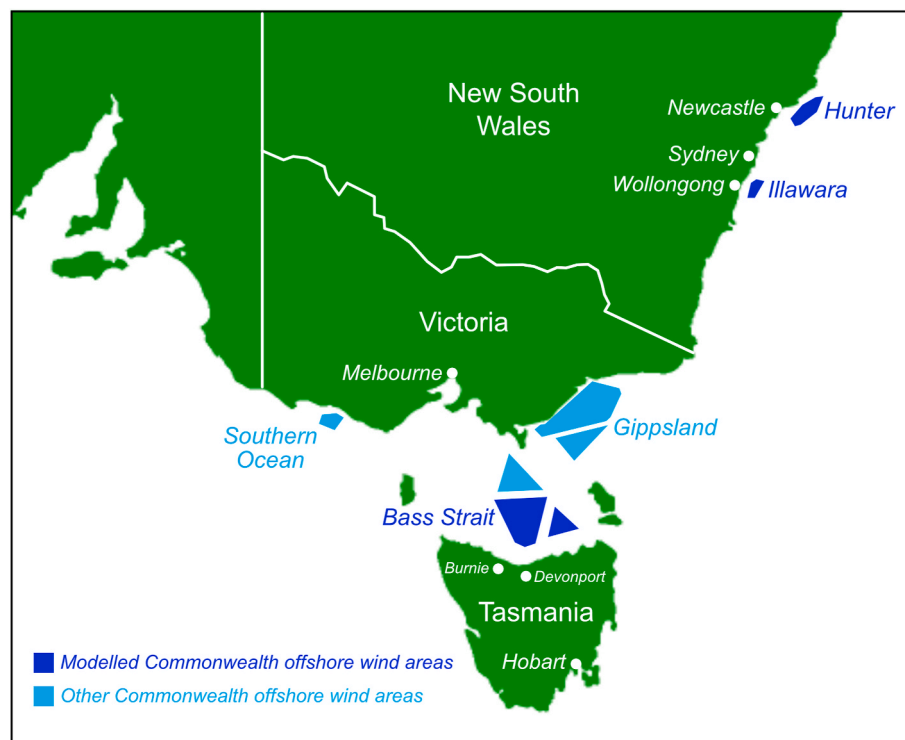


Fig. 1. Declared offshore wind areas in Commonwealth waters around southeastern Australia. The Bass Strait, Hunter and Illawara areas (dark blue) provide the focus for the current study. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

unit of local population was also much higher (at least an order of magnitude) for the Hunter and Illawara regions, indicative of strongly contrasting levels of debate.

The Bass Strait offshore wind area is a large zone off the northern coast of the island state of Tasmania (Fig. 1). The total population of Tasmania is around 575,000 and the northern region is largely agricultural with two small coastal cities (Devonport and Burnie). A large portion of the island is listed as conservation area and the state has a well-documented history of environmental campaigning in response to industries such as hydro-power generation (Bandler, 1987), forestry (Gale, 2013), trawler fishing (Tracey et al., 2013), salmon aquaculture (Condie et al., 2022b; Cullen-Knox et al., 2019), and onshore wind-energy (Colvin et al., 2016).

The Hunter and Illawara offshore wind areas are smaller zones off the central coast of NSW (Fig. 1). They are adjacent to some of the most heavily populated areas of Australia with over 6 million residents across the coastal region. Environmental campaigning in this region has traditionally focused on mining (Laurence, 2021), climate (Marshall, 2023), and to a lesser extent fishing (Voyer et al., 2017), with offshore wind gaining recent prominence (Larkin et al., 2024).

2.2. The PAX social influence model

PAX (People's Attitudes eXplained; also Latin for peace or harmony) is an agent-based social influence model implemented within the Net-Logo environment (version 6.4.0) (Wilensky, 1999). It represents a network of agents that includes individuals from multiple stakeholder groups, who each have potential to influence other's attitudes in relation to specific issues. Influence can occur through personal interactions, social media, exposure to broadcast media, or in response to purposeful interventions aimed at modifying attitudes (Fig. 2a). Definitions of all PAX model parameters are provided in Table A.1 and model equations in Table A.2. This modelling approach has been demonstrated in other sectors to accurately hindcast surveyed community attitudes at the population level, including historical tipping points (Condie et al., 2024a; Condie and Condie, 2021).

2.3. Stakeholder traits

PAX extends traditional bounded confidence models to explicitly represent stakeholder groups with different traits (Fig. 2b) (Condie et al., 2024a). Key stakeholder groups in relation to offshore wind energy were identified using stakeholder submissions to the Bass Strait, Hunter and

Illawara Offshore Renewable Energy Declarations (<https://www.dcccew.gov.au/energy/renewable/offshore-wind/areas>) and responses to the CSIRO 2023 Survey of Australian Attitudes to the Energy Transition (McCrea et al., 2024). These groups include general public, local public (living adjacent to declared offshore wind areas), blue public (regular users of coasts and oceans for recreation), advocacy groups (social and environmental), marine scientists, government, the offshore wind sector, the tourism sector, and the commercial fishing sector.

Information on key traits relating to attitudes and influences were extracted from results of a recent Tasmanian survey (Condie et al., 2024b) that included questions specifically designed to support model parameterisation (Table A.3). Trait values were then adapted for the NSW population using data from a recent national survey (McCrea et al., 2024). These traits are defined as follows and mean values for each stakeholder group are listed in Table A.4.

- (i) The underlying attitude *bias* of individuals, usually associated with beliefs or vested interests, where extreme opposition is represented by a score of -1 and extreme support by a score of 1 .
- (ii) The *certainty* that individuals have in their own attitude, usually associated with interest, knowledge, education or self-confidence, where complete unfamiliarity is represented by a score of 0 and absolute belief by a score of 1 .
- (iii) The *trustworthiness* of individuals as perceived by others (Colquitt and Rodell, 2011), where absolute distrust is represented by a score of 0 and absolute trust by a score of 1 .
- (iv) The *reach* of individuals within the broader social network, where complete isolation is represented by a score of 0 and connection to all other individuals by a score of 1 (note that a connection does not necessarily imply influence between individuals).
- (v) The *influence* of individuals, defined here as the product of their certainty and their trustworthiness, where zero potential to influence is represented by a score of 0 and an extremely high potential to influence by a score of 1 . For example, individuals with low levels of interest and knowledge in relation to the debate (e.g. general public) typically have low certainty and low perceived trustworthiness resulting in low influence; whereas those with a strong vested interest (e.g. industry representatives) typically have high certainty and low perceived trustworthiness resulting in intermediate influence; whereas those with non-vested expertise (e.g. independent scientists) typically have high certainty and high perceived trustworthiness resulting in high influence.

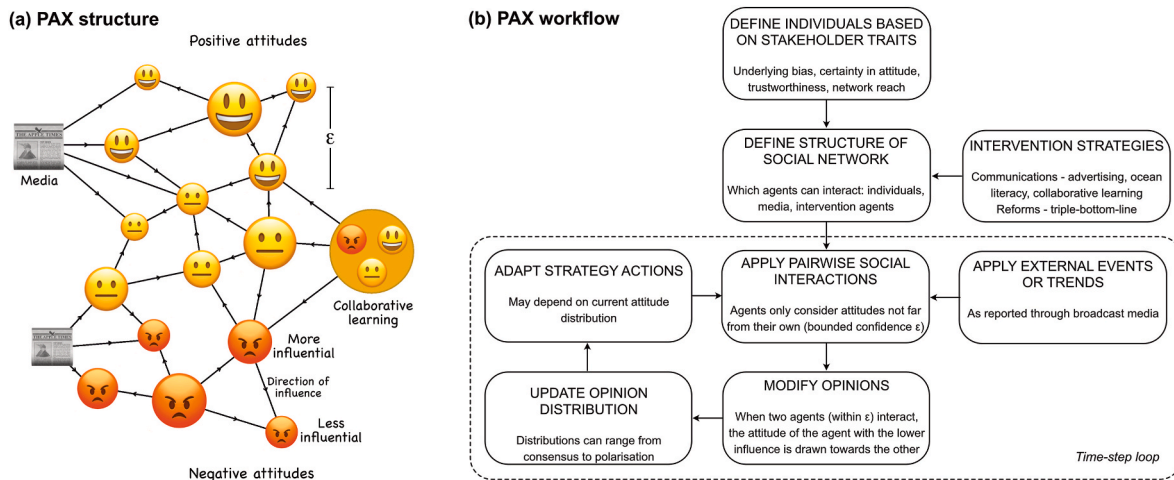


Fig. 2. (a) Schematic of the PAX model social network structure, including media influences and an example intervention in the form of collaborative learning across stakeholder groups. Larger symbols represent more influential agents and vertical position indicates their attitude to offshore wind (more positive attitudes towards the top). Homophily ensures that there is no effective influence between agents with very different attitudes (i.e. large vertical separation relative to the confidence threshold ϵ). (b) Computational workflow of PAX, including setup (upper two rows of boxes) and run iterations (lower two rows of boxes).

2.4. Social influence mechanisms

Social influence in PAX is assumed to occur through pairwise interactions on a network whose links changed randomly at every timestep (Fig. 2b). The pairwise nature of these interactions categorises PAX as an asynchronised model (Deffuant et al., 2000), differentiating it from models where the attitudes are synchronously influenced by the average attitude of all network neighbours at every timestep (Hegselmann and Krause, 2002). The fraction of the total population that the combined members of any stakeholder group can reach within a single timestep is selected randomly between zero and twice the group's long-term reach (giving a mean value equal to the reach in Table A.1).

Network interactions are also limited by the *bounded confidence* assumption, whereby individuals can only be influenced by attitudes that are not too far from their own (Fig. 2a and b). This characteristic is referred to as *homophily*, with the threshold separation of attitudes referred to as the *confidence threshold* (denoted by ϵ). Low levels of homophily ($\epsilon \sim 1$) typically lead toward consensus, whereas high levels of homophily ($\epsilon \ll 1$) typically lead toward attitude clustering and sometimes polarisation of attitudes (Deffuant et al., 2000; Flache et al., 2017). Representation of homophily in PAX differs from traditional bounded confidence models in that the probability of an influential interaction is a continuous function of attitude difference rather than a step-function based on a fixed threshold (Table A.2). While both representations support attitude clustering, a continuous function acknowledges variations in both the communication abilities of individuals and the context of interactions.

When there is an influential interaction between any two individuals, the individual with the lesser *influence* is assumed to shift their attitude to a value selected randomly between the attitudes of the two individuals. The net effect is convergence of attitudes that are not too dissimilar around the attitudes of more influential individuals. In the absence of other influences, the attitudes of all individuals eventually converge. However, including influences such as broadcast media in the model has been shown to negate attitude drift and allow polarisation to persist indefinitely (Condie and Condie, 2021).

2.5. Media influences

The influence of broadcast media is included in the model by allowing each media story to influence individuals in the same way that individuals influenced each other, with media agents differing from individuals only in their ability to simultaneously influence a larger fraction of the population within a single timestep (Fig. 2a). Representing media influences in this way has successfully replicated community attitudes in other sectors such as aquaculture (Condie et al., 2022a). Because newspapers are widely read within the Tasmanian and NSW populations and are known to be highly influential across the broad community (Condie et al., 2022c), newspaper articles relating to offshore wind (including news stories, editorials, and other opinion pieces) were used as a proxy for broader media influences.

Articles from national and regional newspapers from the 5-year period of January 2020 to December 2024 were identified using ProQuest online searches of rights-cleared articles (Table B.1). The framing of each article was scored between -1 (extremely negative) and 1 (extremely positive) using the AI sentiment analysis functionality within ProQuest TDM Studio (Appendix B). A total of 241 unique articles were scored for Tasmania and 1037 for NSW. The reliability of the AI scoring was checked using the *content analysis trustworthiness check* list (Elo and Kyngäs, 2008) that included: an external audit and review of the coding rules used for sentiment scoring and the use of a single coder experienced in reviewing media articles to independently score and verify 88 randomly selected articles. Chi-square test of homogeneity indicated no evidence of a difference between the distributions generated by the AI sentiment analysis and the human sentiment analysis (Figure B.1).

AI generated media sentiment scores were used in all model sce-

narios for the historical period January 2020 to December 2024. The projections period (January 2025 to December 2030) then used sentiment scores from articles randomly selected from the 3-year period January 2022 to December 2024, with the number of articles in any given month set at $500U(\Delta O_t)^2$, where ΔO_t was the level of community conflict in that month (as defined in Table A.1) and U denotes a random number in $[0, 1]$. This simple relationship reflects an increase in media coverage often associated with increasing community conflict and generates monthly article numbers that are broadly consistent with recent historical patterns in Tasmania and NSW. However, it should be emphasised that the relationship is not intended to be predictive, its only purpose being to generate plausible scenarios within which the efficacy of interventions can be compared.

2.6. Influences of targeted communication campaigns

In addition to influences from other individuals and the broadcast media, individuals may also be influenced by targeted communications campaigns deployed by one or more of the stakeholder groups in the debate. These campaigns typically attempt to change perceptions with the aim of either shifting attitudes or reducing levels of conflict. Campaigns based on three distinct communication strategies were modelled in the context of offshore wind energy (parameter values are given in Table 2):

- (i) Persuasive advertising uses media advertising to nudge attitudes towards a partisan viewpoint (Barnard and Ehrenberg, 1997).

Table 2

Definitions of model scenarios applied from January 2026. It was assumed that purposeful interventions could achieve a mean reach of 0.5 on the basis that reach of offshore wind media stories in Tasmania is already near 0.4 (Condie et al., 2024b). The mean influence of advertising was set to the wind sector monthly value of 0.17, the mean influence of ocean literacy was set to the scientist monthly value of 0.48 (Table A.4), and the mean influence of collaborative learning was set at 0.6 to reflect high levels of consultation across stakeholder groups. Campaigns and reforms had zero attitude bias apart from persuasive advertising, which assumed a positive attitude bias of 0.8.

Category	Name	Attitude of intervention agent
Counterfactual Campaigns	No intervention	
	Persuasive advertising	Set each month to the model mean attitude of the wind sector with an additional positive bias of 0.8 $[-1, 1]$
	Ocean literacy	Set each month to the model mean attitude of scientists
Reforms	Collaborative learning	Set each month to the model mean attitude of all stakeholders
	Economic reform	Set to a positive value of 0.6, then weighted by importance of economic reform to each stakeholder group (from survey)
	Governance reform	Set to a positive value of 0.6, then weighted by importance of governance reform to each stakeholder group (from survey)
	Environmental reform	Set to a positive value of 0.6, then weighted by importance of environmental reform to each stakeholder group (from survey)
	Triple-bottom-line reform	Set to a positive value of 0.6, then weighted by importance of each reform to each stakeholder group (from survey)
Combination	Deteriorating performance	Set to a negative value of 0.6, then weighted by importance of each reform to each stakeholder group (from survey)
	Collaborative learning combined with triple-bottom-line reform	As described above for collaborative learning and triple-bottom-line reform

PAX models this type of influence by introducing a campaign agent for the offshore wind industry. To reflect the stronger messaging typical of persuasive advertising, attitudes of the campaign agents were respectively set at the mean industry attitude plus an additional positive attitude bias.

- (ii) Ocean literacy builds understanding of the impacts of offshore wind systems among all stakeholders, providing them with a more informed view based on the best available science (Spitzer and Fraser, 2020). This was modelled by introducing a campaign agent that adopted the monthly mean attitude, monthly maximum influence, and reach of the scientist group.
- (iii) Collaborative learning brings together key stakeholder groups to work together (potentially with professional mediators) to define the parameters of the conflict and agree on a common language and set of expectations in relation to indicators, benchmarks, and reporting processes (Peterson et al., 2004). This process was modelled by introducing a collaborative agent that adopted the mean attitude of all stakeholder groups (any subset of stakeholder groups could have been selected).

Parameter values representing each of these communication strategies and their rationale are listed in Table 2.

2.7. Influences of targeted reforms that change perceptions of sector performance

A second set of strategies were based on sector reforms aimed at changing community perceptions of offshore wind sector activities in relation to:

- (i) economic performance;
- (ii) social and governance performance; and
- (iii) environmental performance.

In each case, the influence of a reform on members of a stakeholder group was dependent on its importance to that group as measured in a recent survey (Condie et al., 2024b) using the survey questions listed in Table A.3 and values documented in Table A.4. Performance scenarios also considered the effect of triple-bottom-line reforms by applying all three reforms together or, conversely, a deteriorating triple-bottom-line where performance declined in all three areas.

2.8. Model scenarios

All model scenarios covered the period January 2016 to December 2030 with a monthly timestep. There was almost no media coverage on offshore wind over the period 2016–2019, which allowed the model to equilibrate stakeholder attitudes. Historical media was used for the 5-year period January 2020 to December 2024, switching to media projections for the next 6-year period 2025–2030 (as described above). Campaigns and reforms (Table 2) were applied over the period January 2026 to December 2030. Stochastic variability in model responses was captured by running each scenario 50 times to form a statistical ensemble.

2.9. Evolution of attitudes and conflict

Two key metrics were used to track changes in attitudes through time:

- (i) The mean attitudes of each stakeholder group and the mean attitude of the entire community. Attitudes could range from -1 (unanimous opposition) to 1 (unanimous support).
- (ii) Following previous studies (Condie et al., 2024a; Condie and Condie, 2021), community conflict was defined as the standard deviation in community attitudes at any time. This provides a

simple measure of the distribution of attitudes that can range from 0 (consensus) to 1 (extreme polarisation), without assuming anything about the shape of the distribution. This distinguishes community conflict from indicators that focus specifically on polarisation by measuring the clustering of attitudes within the broader distribution (Adams et al., 2022; Fiorina and Abrams, 2008).

Metrics were tracked on a monthly timestep for every run within the 50-run ensemble. Ensemble statistics were then used to plot time-series of ensemble medians (with 5th and 95th percentiles) for stakeholder attitudes and community conflict levels. Ensemble mean attitudes were also plotted against ensemble mean conflict (with 5th and 95th percentiles). This representation is referred to as the *Social License Graph* (SLG) and can be used to map the trajectory of community attitudes over time in terms of both community interest and social acceptability (Condie and Condie, 2025). This approach also allows any distribution of community attitudes to be categorised as a *social license* to operate, *contested* operations, a *social obligation* to modify operations, or *indifference* to operations. More detailed descriptions of each of these categories are provided in Table 3.

3. Results

The ensemble model results broadly reflect the patterns observed in survey data for Tasmania in 2023, 2024 and 2025 (Fig. 3c) and NSW in 2023 (Fig. 3d), including the attitudes of individual Tasmanian stakeholder groups in 2024 (Fig. 3a). Between 2020 and 2024, media coverage played a key role in shaping modelled public sentiment, which fluctuated markedly between positive and negative in the general community and some stakeholder groups. While Tasmania continued to be volatile, NSW showed a consistent trend towards more negative attitudes throughout 2022–2024. Conflict levels throughout 2024 were also higher in NSW (~ 0.5 , Fig. 3f) than in Tasmania (~ 0.3 , Fig. 3e). Modelled attitudes from both Tasmania and NSW were generally in good agreement with the available survey results, although it should be emphasised that the 2024 stakeholder results contributed to setting some of the model parameters (Table A.4).

Conflict around offshore wind energy was hindcast to be low in both regions before 2021 (< 0.2), then climbed rapidly through 2021–2023 (0.4 – 0.6) following initiation of the government-run public consultation process on the newly declared offshore wind areas (Fig. 3e and f). However, pathways within the two regions then diverged, with conflict in Tasmania falling through most of 2024 (0.2 – 0.3), while NSW remained in a state of relatively high conflict (0.4 – 0.6). The model generated both attitudes and conflict levels that were consistent with those estimated from the 2023 national survey in both Tasmania and NSW, as well as those estimated from the 2024 and 2025 Tasmanian

Table 3

Categorisation of community attitudes to offshore wind energy as used in the Social License Graphs (Condie and Condie, 2025).

Category	Description of stakeholder attitudes	Interest	Social acceptability
Social license	Stakeholders falling within this category accept and approve of offshore wind energy.	High	High
Contested	Stakeholders falling within this category are strongly divided in their views on offshore wind energy.	High	Intermediate
Social obligation	Stakeholders falling within this category disapprove of offshore wind energy.	High	Low
Indifference	Stakeholders falling within this category have a low level of interest and no strong opinions relating to offshore wind energy.	Low	Uncertain

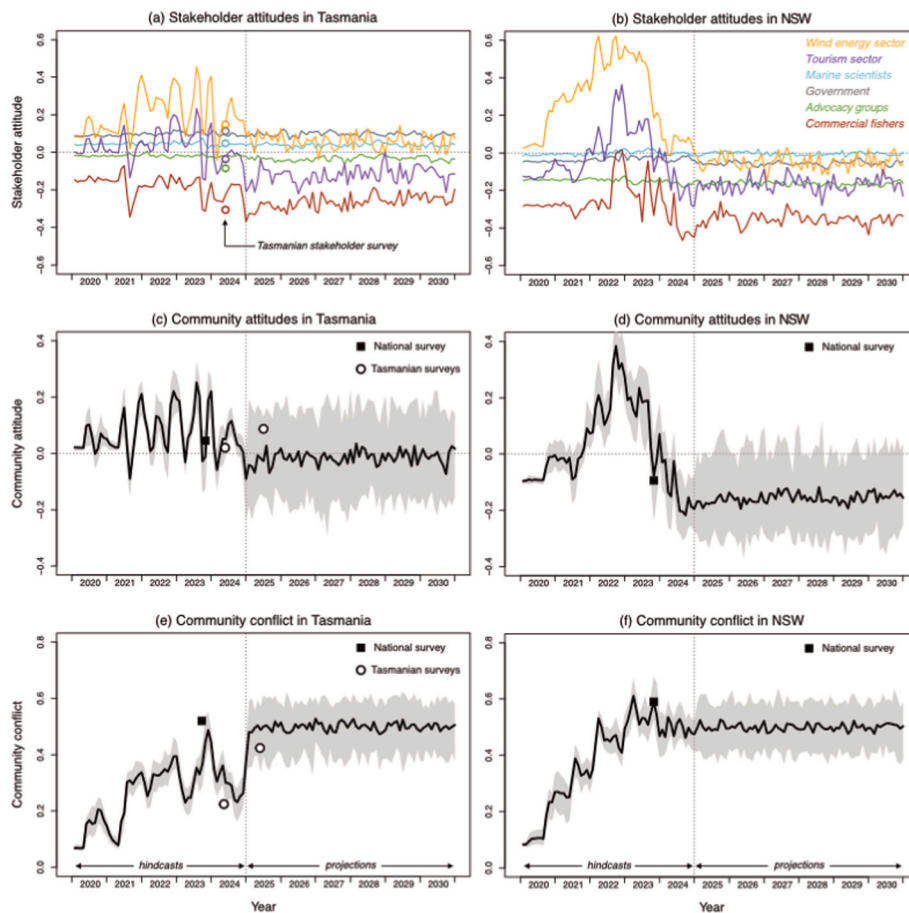


Fig. 3. Model time series (January 2020–December 2030) of model results from Tasmania (left column) and NSW (right column): (a–b) stakeholder attitudes colour coded by stakeholder group; (c–d) community attitudes; and (e–f) community conflict. For (c–f) ensemble medians are indicated by black lines and the 5th to 95th percentile ensemble range by grey shading. The hindcast period (2020–2024) used historical media, whereas the projection period used modelled media projections that varied with each run in the ensemble (Appendix B). Results from a national survey conducted in 2023 (134 respondents in Tasmania and 2077 respondents in NSW), a Tasmanian survey conducted in 2024 (557 respondents) and a second Tasmanian survey conducted in 2025 (930 respondents) are shown for comparison. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

surveys (noting that 2025 falls within the model projection period rather than the hindcast). While the temporal coverage of the surveys is very limited, the level of agreement is very satisfactory given differences in survey methods (online research panel with an online questionnaire in 2023 versus stratified purposive sampling with a paper questionnaire in 2024 and 2025) and sample sizes (135 respondents in 2023 versus 557 respondents in 2024 and 930 respondents in 2025).

Variability across the ensemble results rose sharply when historical media sentiment was replaced by multiple media projections from January 2025 (grey shading in Fig. 3c–f). At the same time, median attitude and median conflict stabilised as ensemble statistics tended to dampen fluctuations in median values. While these results are not informative as a prediction (as expected for any chaotic system), they suggest high levels of uncertainty in future attitudes and levels of conflict. Attitudes in NSW were consistently more negative than in Tasmania (cf. 3c and 3d), whereas conflict levels were comparable (cf. 3e and 3f). These trends were generally consistent across stakeholder groups, with government and the offshore wind sector being the most positive and fishers being most negative. However, a notable difference between Tasmania and NSW was that advocacy groups in NSW were substantially more negative in their attitudes than their Tasmanian counterparts (cf. 3a and 3b, green lines).

Social License Graphs (Fig. 4a) for the 5-year period 2026–2030 indicate that without intervention, the Tasmania community is likely to oscillate between indifference and contested (Fig. 4b), whereas the NSW community is likely to be more volatile with offshore wind energy

continuing to be quite strongly contested (Fig. 4c). A key difference between the two regions was that mean attitudes were very negative in NSW compared to the relatively neutral attitudes in Tasmania, resulting in lower social acceptability (cf. 4b and 4c).

Interventions in the two regions usually shifted them in a similar direction on the SLG, although the magnitude of this shift could be quite different:

Persuasive advertising increased interest and shifted attitudes in the positive direction (Fig. 4b and c). However, because homophily precluded positive advertising from influencing individuals with more negative attitudes, this change was accompanied by increased conflict and a shift towards more contested space.

Ocean literacy and *collaborative learning* had very similar influences, both reducing conflict with mean attitudes becoming slightly more positive (Fig. 4b and c).

Single reforms in relation to the economic, social, or environmental performance of the offshore wind industry had almost identical effects because of their very similar survey weightings (Table A.4). Conflict levels decreased and attitudes shifted in the positive direction (Fig. 4b and c), which was particularly important in NSW where mean attitudes moved from negative to neutral (Fig. 4c).

Triple-bottom-line reforms had a larger influence than single reforms, with positive shifts in mean attitudes resulting in substantially higher levels of social acceptability (Fig. 4b and c).

Triple-bottom-line deterioration had the opposite effect to reforms, with sharp falls in social acceptability (Fig. 4b and c) and, in the case of

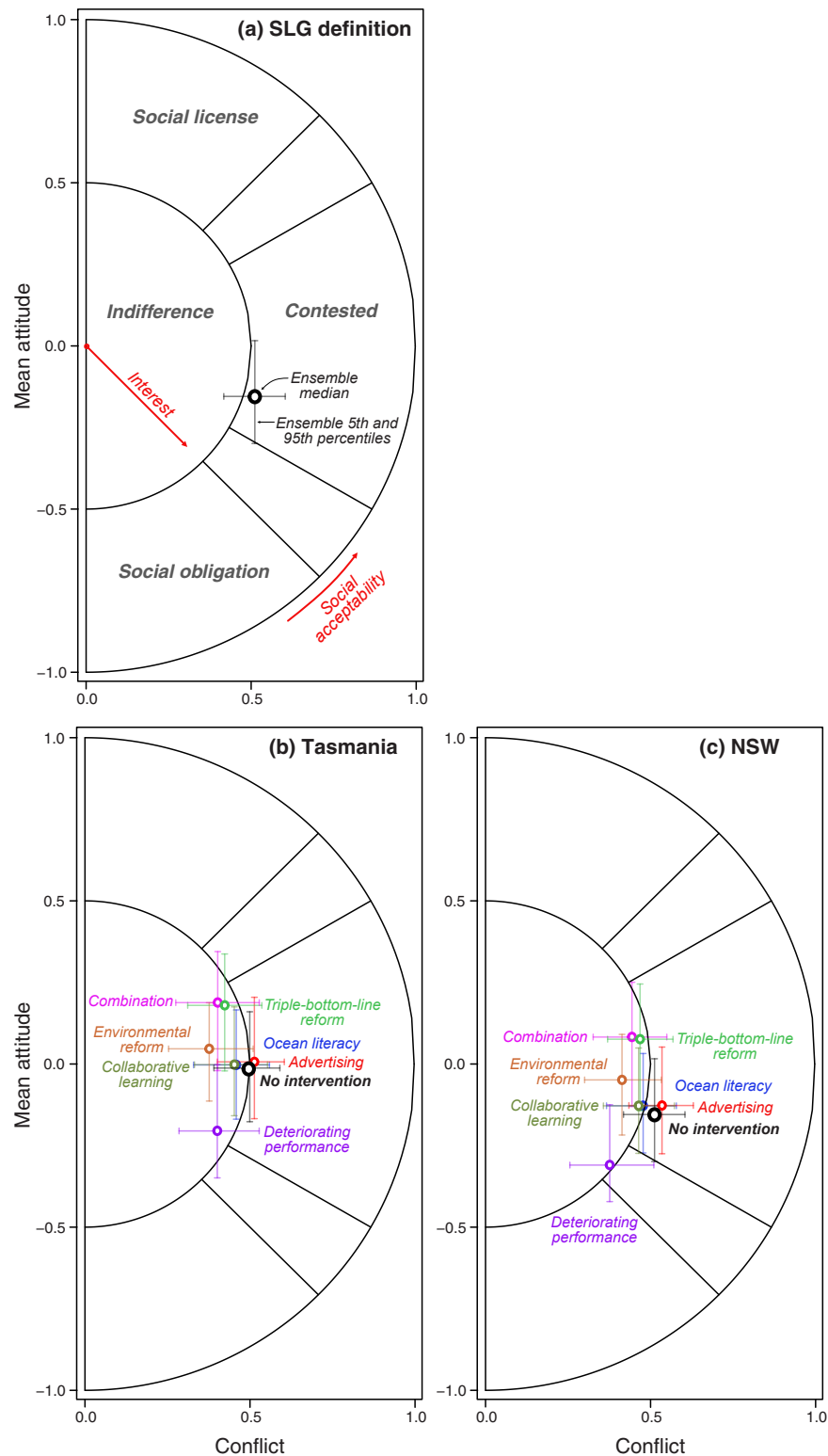


Fig. 4. Social license graphs (SLGs) for (a) Tasmanian attitudes to the Bass Strait Offshore Wind Area and (b) NSW attitudes to the Hunter and Illawara Offshore Wind Areas for the 5-year period 2026–2030. Each graph contrasts the no intervention counterfactual (larger black symbol) with interventions based on the campaigns and reforms listed in Table 2. Circles coincide with the ensemble median of community conflict and the ensemble median of mean community attitude, with crossbars indicating the 5th and 95th percentiles.

NSW, a growing risk of social obligation to moderate operations (Fig. 4c).

Considering the relative performance of intervention options (Table 4), it is apparent that communication strategies such as collaborative learning and enhancing ocean literacy helped moderate conflict,

but had little impact on social acceptability. In contrast, reforms that changed perceptions provided substantial increases in social acceptability. Combining triple-bottom-line reforms with improved communications provided only a small further reduction in conflict levels.

Table 4

Social license graph statistics from the counterfactual and intervention scenarios for Tasmania and NSW. The most substantial changes in mean attitude and conflict (i.e. outside of the 5th and 95th percentiles) are indicated by an asterisk.

	TASMANIA				NEW SOUTH WALES			
	Mean attitude	Conflict	Interest	Acceptability	Mean attitude	Conflict	Interest	Acceptability
Counterfactual ensemble median	−0.01	0.50	0.50	−0.02	−0.15	0.50	0.52	−0.19
Change in ensemble median relative to the counterfactual:								
Industry advertising	0.02	0.01	0.1	0.03	0.02	0.02	0.01	0.04
Ocean literacy	0.01	−0.04	−0.04	0.02	0.02	−0.04	−0.04	0.02
Collaborative learning	0.01	−0.05	−0.05	0.02	0.02	−0.05	−0.05	0.01
Economic reform	0.06	−0.12	−0.12	0.10	0.09	−0.10	−0.12	0.10
Governance reform	0.06	−0.12	−0.12	0.11	0.10	−0.10	−0.12	0.11
Environmental reform	0.06	−0.12	−0.12	0.10	0.10	−0.10	−0.12	0.11
Triple-bottom-line reform	0.19*	−0.08	−0.04	0.28	0.23*	−0.04	−0.06	0.30
Triple-bottom-line deterioration	−0.20	−0.10	−0.05	−0.28	−0.15	−0.12*	−0.03	−0.24
Collab. learning plus triple-bottom-line	0.20*	−0.10	−0.06	0.30	0.24*	−0.06	−0.07	0.31

4. Discussion and policy recommendations

This study demonstrates the utility of a social influence model (PAX) in understanding and managing the evolving dynamics of public attitudes toward offshore wind energy. By simulating stakeholder interactions, media influences and strategic interventions, the model provides a robust framework for anticipating conflict and identifying effective pathways towards social license. Social license graphs have helped visualise the interplay between mean public attitude and conflict (Condie and Condie, 2025). While the levels of conflict in Tasmania and NSW are comparable (in both survey results and projections), differences in mean attitudes (neutral in Tasmania versus substantially negative in NSW) suggest that social license risks in the two regions may continue to diverge. Without proactive strategies, Tasmania is likely to move toward a contested state, whereas NSW risks entering a state of social obligation to modify their operations.

The contrasting trajectories of Tasmania and NSW underscore the importance of regional context and the associated history of the debate. Tasmania, with relatively low media intensity and limited public interest, exhibits relatively stable attitudes ranging from neutral to positive. A notable exception is the commercial fishing sector, which has very specific concerns relating to potential impacts on their operations in Bass Strait (Condie et al., 2024b). NSW provides a strong contrast to Tasmania, experiencing high levels of media-driven volatility and stakeholder polarisation, with advocacy groups adopting a far more negative viewpoint. These findings reinforce the need for tailored engagement strategies that reflect local histories, values, and trust dynamics.

Amongst the tested interventions, collaborative learning and ocean literacy campaigns help reduce conflict by fostering mutual understanding and trust, leading to better alignment of stakeholder attitudes. While persuasive advertising can raise interest and shift mean attitudes in a positive direction, it also has the potential to increase conflict, suggesting that overtly promotional messaging may increase social risks in contested settings.

Economic, environmental or governance reforms can lead to increased support for offshore wind energy, while also reducing conflict. When combined as triple-bottom-line reforms, levels of acceptability can increase markedly, as shown for NSW where mean attitudes shifted from negative to positive. Any tendencies for interest and conflict to increase can be largely offset by simultaneously engaging key stakeholders in collaborative learning processes. These findings highlight the value of integrated, multi-pronged strategies.

As in any complex system, there are high levels of uncertainty associated with PAX future projections that cannot be reduced by increasing model complexity (Robinson, 2023). While agreement with available survey data is encouraging, the limited availability of longitudinal attitudinal data means that model calibration and evaluation remain partial and should be strengthened through future repeated

surveys designed independently of model development. In its current form, the utility of PAX is not in detailed prediction, but rather the understanding and heuristics that emerge from scenario modelling within an agent-based framework (Bodin et al., 2019; Macy and Willer, 2002).

Based on the scenario findings, we can offer the following recommendations for policymakers seeking to build and maintain social license for offshore wind energy:

- i. Large differences in stakeholder attitudes underline the need to invest in collaborative processes that facilitate structured, multi-stakeholder dialogues that include industry, government, scientists, advocacy groups, and affected communities. These processes help align expectations, build shared understanding, and reduce conflict. They can be effective even in regions such as NSW where conflict has become entrenched. On the other hand, consultation processes with little ability to modify development pathways can be counterproductive (Colvin et al., 2016).
- ii. Promote ocean literacy initiatives led by trusted independent experts. Ocean literacy campaigns can increase certainty and foster informed public discourse without exacerbating polarisation. While sustained campaigns can also help inoculate communities against misinformation, the underlying social dynamics driving the promulgation of misinformation are complex and often unpredictable (Howley et al., 2025; Winter et al., 2022),
- iii. Prioritise reforms that address public concerns about governance, environmental and economic performance. For example, improving transparency, accountability, and responsiveness in planning and regulatory processes. Similar findings have reported from Europe (Wolsink, 2007) and North America (Bidwell and Sovacool, 2023)
- iv. Avoid overreliance on persuasive advertising, which while increasing awareness, may also intensify opposition if perceived as one-sided. Messaging should be balanced, evidence-based, and sensitive to local concerns.
- v. Policymakers should monitor media narratives, which have a powerful role in shaping public attitudes (Heidenreich, 2016) and potentially increasing conflict and reducing the scope for meaningful community participation (Howley et al., 2025). They should be prepared to respond with timely and factual information to counteract misinformation and reduce volatility.
- vi. Design integrated engagement and reform strategies. Model results suggest that inclusion of targeted engagement can help reduce the risk that the heightened interest in reforms will intensify debate.
- vii. Considering the limitations of the current model structure, it is also recommended that future survey and modelling approaches more explicitly include the viewpoints of rightsholders, such as

Indigenous communities. This will generate more comprehensive research findings and help improve the legitimacy and equity of decision-making processes.

5. Conclusion

Using a novel agent-based social influence model, this study demonstrates how stakeholder interactions, media narratives, and targeted interventions can shape the evolution of community attitudes and conflict around offshore wind developments. The contrasting trajectories observed in Tasmania and New South Wales highlight that social acceptance is context dependent, reflecting differences in local histories, stakeholder networks, and existing levels of trust and controversy.

Model results suggest that communication-based interventions such as collaborative learning and ocean literacy initiatives can help moderate conflict and foster more constructive dialogue, although their influence on overall acceptability may be limited. In contrast, reforms that improve perceptions of environmental stewardship, governance quality, and economic benefits have the potential to substantially increase social acceptance while also reducing conflict. The strongest outcomes were achieved through integrated approaches that combined meaningful stakeholder engagement with credible improvements in sector performance.

While the model is not intended as a predictive tool, it provides valuable insights into the mechanisms that drive support, opposition, and polarisation. More broadly, the study demonstrates how social influence modelling can support evidence-based policy development by identifying pathways that reduce conflict and strengthen social license. When combined with AI-based media tracking, the model also has future potential to be developed as an operational platform, estimating current community attitudes and conflict levels to help inform decision-making. These capabilities are also transferable to other communities, regions, and countries, requiring collection of region-specific data describing underlying attitude distributions, trust relationships, and social network characteristics of local stakeholders, as well as longitudinal data on media sentiment. As offshore wind deployment accelerates globally, understanding and proactively managing social dynamics will be essential to achieving an effective, equitable, and durable energy transition.

Appendix A. Model equations and parameterisation

Table A.1

Definitions and values of PAX model variables.

Variable	Definition	Estimation	Range
Individual characteristics			
$O_{i,s,t}$	Attitude of individual i from stakeholder group s at time t	Equation A.1	[-1 1]
O_s	Attitude bias of stakeholder group s associated with underlying ideology or vested interest	Table A.4 (survey results)	[-1 1]
$I_{i,s,t}$	Influence of individual i from stakeholder group s at time t	Equation A.5	[0 1]
I_s	Baseline influence of stakeholder group s	Table A.4, $I_s = (C_s T_s)^{0.5}$	[0 1]
R_s	Mean reach of stakeholder group s to other individuals	Table A.4 (survey results)	[0 1]
C_s	Mean certainty of stakeholder group s in their own attitude	Table A.4 (survey results)	[0 1]
T_s	Mean trust in individuals from stakeholder group s	Table A.4 (survey results)	[0 1]
Media characteristics			
$M_{k,t}$	Framing (attitude) of media story k at time t	Newspaper data (2016–2024) then media model (2025–2040) (Figure B.1)	[-1 1]
I_k	Baseline influence of media	Previous model calibration (Condie et al., 2024a)	0.30
R_m	Mean reach of media articles to individuals	Previous model calibration (Condie et al., 2024a)	0.17
Intervention strategy characteristics			
$S_{l,t}$	Setting (attitude) of strategy l at time t	Table 2	[-1 1]

(continued on next page)

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used TDM Studio (ProQuest) with GPT-4o-mini large language model (LLM) via the OpenAI Chat Completions API to assess sentiment toward offshore wind energy of newspaper articles. After using this tool, the authors checked the reliability of the GPT-4o-mini sentiment scores by comparing a subsample with human generated scores (Appendix B). The authors take full responsibility for the content of the published article.

CRediT authorship contribution statement

Scott A. Condie: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Corrine M. Condie:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Matthew Andreotta:** Formal analysis, Writing – review & editing. **Rod McCrea:** Methodology, Resources, Validation, Writing – review & editing. **Jess Melbourne-Thomas:** Investigation, Project administration, Writing – review & editing. **Scott Spillias:** Data curation, Formal analysis, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table A.1 (continued)

Variable	Definition	Estimation	Range
I_l	Baseline influence of strategy	Table 2	[0 1]
R_l	Mean reach of strategies to individuals	Table 2	[0 1]
System characteristics			
N	Total number of individuals	$N = \sum_s N_s$	220
ϵ	Confidence threshold (describing homophily)	Previous model calibration (Condie et al., 2022a)	0.3
$\Delta\epsilon$	Confidence transition scale (inverse logistic function)	Intermediate between traditional step-function ($\Delta\epsilon < 0.01$) and a connected network ($\Delta\epsilon > 0.1$)	0.03
ΔO_t	Conflict level at time t	Standard deviation of $O_{i,t}$	[0 1]

Condie, C. M., K. A. Alexander, E. A. Fulton, J. Vince, and S. A. Condie. 2022a. Reducing socio-ecological conflict using social influence modelling. *Scientific Reports* 12:22002.

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Table A.2

PAX model equations with bounded confidence described by an inverse logistic function. Here U denotes a random number in [0 1].

Equation	Definition	No.
$O_{i,s,t+1} = O_{i,s,t} + U \sum_{j \in J_{i,t}} (2O_{j,s,t} - O_{i,s,t} - O_s) + U \sum_{k \in K_t} (M_{k,t} - O_{i,s,t}) + U \sum_{l \in L_t} (S_{l,t} - O_{i,s,t}) + \xi$	Attitude equation describing influences on individual i from other individuals j , media articles k , and intervention strategies l .	A.1
$J_{s,t} = \{j \in \mathbb{Z}^+ \mid (j < 2UR_s N) \cap ((1 + e^{(0.5 O_{i,s,t} - O_{j,s,t} - \epsilon)/\Delta\epsilon})^{-1} > U) \cap (I_{i,s,t} < I_{j,s,t})\}$	Bounded confidence and influence assumptions for individuals.	A.2
$K_t = \{k \in \mathbb{Z}^+ \mid (k < 2UR_m N) \cap ((1 + e^{(0.5 O_{i,s,t} - M_{k,t} - \epsilon)/\Delta\epsilon})^{-1} > U) \cap (I_{i,s,t} < I_k)\}$	Bounded confidence and influence assumptions for media.	A.3
$L_t = \{l \in \mathbb{Z}^+ \mid (l < 2UR_l N) \cap ((1 + e^{(0.5 O_{i,s,t} - S_{l,t} - \epsilon)/\Delta\epsilon})^{-1} > U) \cap (I_{i,s,t} < I_l)\}$	Bounded confidence and influence assumptions for strategies based on campaigns or reforms.	A.4
$I_{i,s,t+1} = I_{i,s,t} + U(I_s - I_{i,s,t}) + \xi$	Influence of any individual i is constrained by the underlying certainty and trustworthiness of their stakeholder group s .	A.5
$\xi = 0.1\epsilon$	Random noise applied to attitudes and influences at each timestep.	A.6

Table A.3

Survey questions used to estimate PAX model parameters for each stakeholder group. Parameter values were based on the mean response from stakeholder group members.

PAX model parameter	Parameter components	Survey questions requiring responses on a 5-point Likert scale.
Attitude bias = importance x performance x certainty	Importance to individuals	<i>Economic opportunities - how important is it to you that the proposed Bass Strait offshore wind farm project provides economic opportunities in Tasmania's regional areas?</i> <i>Closely regulated - how important is it to you that the proposed Bass Strait offshore wind farm project is closely regulated and monitored by government?</i> <i>Environmentally sustainable - how important is it to you that the proposed Bass Strait offshore wind farm project is an environmentally sustainable project?</i>
	Individual's perceptions of performance	<i>Economic opportunities - the proposed Bass Strait wind farm development will:</i> • provide an economic boost to surrounding areas • create more jobs in regional areas • reduce the value of properties that are close by • bring more services and facilities to local communities <i>Closely regulated - the proposed Bass Strait wind farm development will:</i> • be effectively regulated by government • still allow me to access my usual spots to fish, sail or dive • be a danger to shipping and fishing boats <i>Environmentally sustainable - the proposed Bass Strait wind farm development will:</i> • reduce the scenic and natural beauty of the coast • not be located in an area of ecological significance • create artificial marine reefs • be harmful to migratory birds
	Individual's certainty in their views of performance	<i>For each of the performance measures above</i>
Reach		<i>I get information about offshore wind farms from [list of stakeholder groups].</i>
Trustworthiness		<i>I trust information about offshore wind farms from [list of stakeholder groups].</i>

Table A.4

Parameter values for stakeholder groups identified in a recent survey (Condie et al., 2024b) and utilised in the model. Values are based on responses to survey questions (Table A.3) except for *influence*, which is defined as a function of *certainty* and *trust* in: $I_s = (C_s T_s)^{0.5}$. The final three columns correspond to the perceived economic, social and governance, and environmental performance of the offshore wind sector (Table A.3). The *local public* group lived adjacent to a declared offshore wind area and the *blue public* group used coasts and oceans for recreation at least once per week.

Stakeholder group	Size A	Bias: TAS $B_s \in [-1 \ 1]$	Bias: NSW $B_s \in [-1 \ 1]$	Reach $R_s \in [0 \ 1]$	Certainty $C_s \in [0 \ 1]$	Trust $T_s \in [0 \ 1]$	Influence $I_s \in [0 \ 1]$	Economic [0 1]	Social [0 1]	Environ. [0 1]
General public	60	0.06	−0.08	0.40	0.32	0.08	0.16	0.85	0.90	0.93
Local public	30	0.07	−0.07	0.28	0.44	0.07	0.18	0.83	0.92	0.89
Blue public	70	−0.02	−0.16	0.28	0.37	0.07	0.16	0.85	0.95	0.97
Advocacy groups	10	−0.07	−0.21	0.39	0.46	0.24	0.33	0.69	0.99	1.00
Marine scientists	10	0.06	0.06	0.47	0.34	0.68	0.48	0.83	0.97	0.99
Government	10	0.13	0.13	0.31	0.32	0.30	0.31	0.87	0.90	0.96
Offshore wind sector	10	0.16	0.02	0.15	0.36	0.08	0.17	0.92	0.94	0.99
Tourism sector	10	−0.02	−0.02	0.15	0.48	0.08	0.20	0.85	0.84	0.96
Commercial fishing	10	−0.30	−0.30	0.15	0.59	0.08	0.22	0.88	0.95	0.98

Appendix B. Analysis and modelling of newspaper media

Articles from pertinent national and regional newspapers within the 5-year period January 2020 to December 2024 were first identified through ProQuest online searches of rights-cleared articles using the key word searches defined in Table B.1. This process identified articles related to Tasmanian offshore wind developments from 6 newspapers and articles related to NSW offshore wind developments from 9 newspapers (Table B.1).

Table B.1

Printed and online newspapers included in the media analysis for Tasmania and NSW discovered through ProQuest databases. Only newspapers with at least 30 relevant articles over the 5-year period (1 January 2020 to 31 December 2024) were included. Where available, average readership (1000s) for each paper is given for the 12 months prior to March 2021 within Tasmania (<https://www.statista.com/statistics/944757/newspaper-readership-tasmania-australia/>) and within NSW (<https://www.statista.com/statistics/944616/newspaper-readership-new-south-wales/>).

Region	Date range	Newspapers (readership in 1000s)	Key word search used on the ProQuest database	Unique articles
Tasmania	Jan 2020 – Dec 2024	The Australian The Australian (Online) The Australian Financial Review Hobart Mercury (43) Hobart Mercury (Online) Launceston Examiner (32)	“offshore wind” AND (“Tasmania” OR “Bass Strait”)	246
New South Wales	Jan 2020 – Dec 2024	The Australian The Australian (Online) The Australian Financial Review Daily Telegraph (506) Daily Telegraph (Online) Sydney Morning Herald (390) Newcastle Herald (44) Illawarra Mercury (17) Port Stephens Examiner	“offshore wind” AND (“NSW” OR “Hunter” OR “Illawarra”)	1037

The full text of the identified newspaper articles was analysed using TDM Studio (ProQuest). To assess public sentiment toward offshore wind energy, a two-step process was applied using the GPT-4o-mini large language model (LLM) via the OpenAI Chat Completions API (<https://platform.openai.com/docs/api-reference/chat>). Each request included an instructional prompt as the system role and the article text as the user role. The prompts used for screening and sentiment scoring are shown in Table B.2.

Table B.2

Prompts used for relevance screening and sentiment scoring.

Step	System Prompt
Relevance	<i>You are a social scientist analysing whether a message is relevant to offshore wind energy. Answer strictly with 'yes' or 'no'. If the message is not about offshore wind energy or there is insufficient information, answer 'no'. Do not include any explanation or additional text.</i>
Sentiment	<i>You are a social scientist analysing sentiment toward offshore wind energy. Return a single numeric value between -1 and 1, where -1 is very negative, 0 is neutral, and 1 is very positive. Intermediate values reflect intensity (e.g., -0.5 moderately negative, 0.7 fairly positive). Reply with the numeric value only - no words or extra text.</i>

The first step screened each article for relevance to offshore wind energy. Article text was sent to the LLM with a prompt instructing it to respond strictly with “yes” or “no” to its relevance. Three replicate calls were performed for each article. If all three responses were “no”, the article was classified as irrelevant and excluded, whereas if any replicate returned “yes,” the article was classified as relevant and proceeded to the sentiment analysis step.

The second step scored the sentiment of each relevant article by requesting a numeric sentiment score between −1 (extremely negative) and 1 (extremely positive), with 0 representing neutral sentiment. Five replicate calls were made for each article, and the mean of the numeric responses was recorded as the sentiment score. If no numeric values could be parsed from the replicates, the article was reclassified as irrelevant and excluded from

the analysis. The entire process identified 246 unique articles related to Tasmanian offshore wind developments and 1037 unique articles related to NSW offshore wind developments.

To check the reliability of the GPT-4o-mini sentiment scores, 88 (36%) of the screened Tasmanian articles were randomly selected and independently classified into five discrete sentiment categories (*very negative*, *negative*, *neutral*, *positive*, *very positive*) by one of the authors (CC) using the *content analysis trustworthiness check list* (Elo and Kyngäs, 2008). These scores were compared article by article with the GPT-4o-mini results by translating the continuous LLM scores to discrete sentiment categories using five equal segments (−1.0: −0.6: −0.2 : 0.2: 0.6 : 1.0) and applying existing protocols (Condie et al., 2022c). Classifications from the human and AI approaches were identical for 77% of articles with 15% differing by 1 category, 7% by 2 categories, 1% by 3 categories, and none by 4 categories. Differences mainly occurred where offshore wind was incidental to the central focus of the article and expressed sentiments therefore related to other topics.

Distributions of sentiment generated by the human and AI approaches indicate first that the subsample of articles analysed is representative of the entire Tasmanian dataset (cf. B.1(a) and B.1(b)), and second that the AI sentiment results are consistent with the human assessment (cf. B.1(b) and B.1(c)). A Chi-square test of homogeneity indicated no evidence of a difference between the distributions generated by the AI sentiment analysis and the human sentiment analysis. These results support the use of modern LLMs such as GPT-4o-mini as an accurate and efficient means of estimating media sentiment.

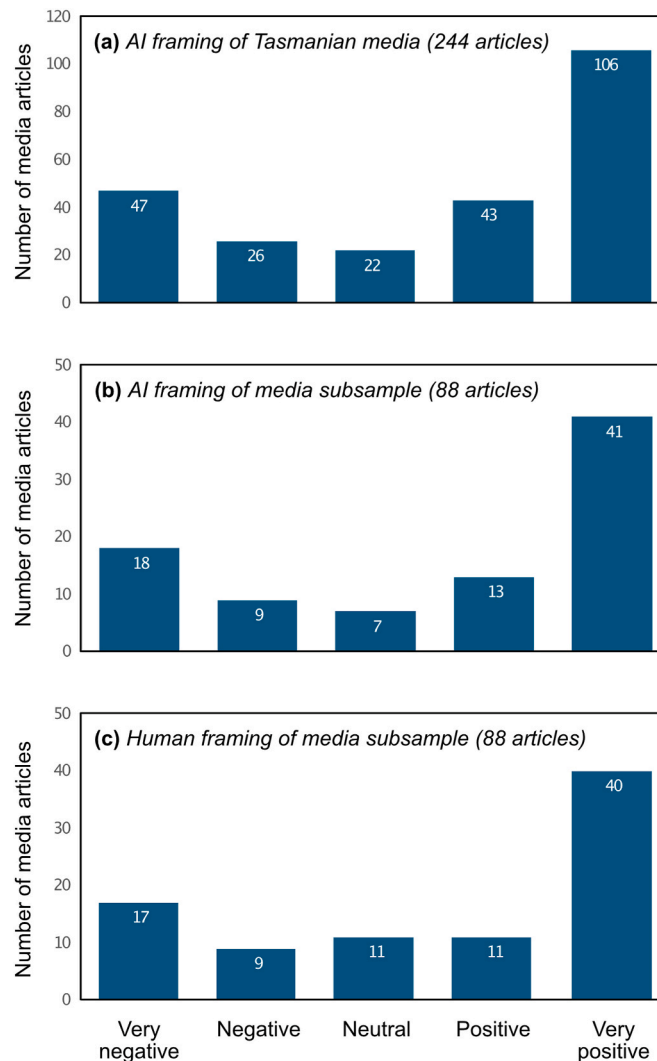


Fig. B.1. Histogram distributions of media article framing from the period 2020-2024. (a) AI framing of all screened Tasmanian media articles discovered. (b) AI framing of a random subsample (36%) of the Tasmanian media articles. (c) Human framing of the same subsample of Tasmanian media articles. Comparing (b) and (c) using a Chi-square test of homogeneity indicated no evidence of a difference between the two distributions ($\chi^2 = 1.097$, $df = 4$, $p = 0.895$) and a negligible effect size (Cramer's $V = 0.079$).

Data availability

Data will be made available on request.

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