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Quantum-Mechanical Modelling of Asymmetric Opinion Polarisation in Social Networks

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Abstract: We propose a quantum-mechanical model that represents a human system of beliefs as the quantised energy levels of a physical system. This model represents a novel perspective on opinion dynamics, recreating a broad range of experimental and real-world data that exhibit an asymmetry of opinion radicalisation. In particular, the model demonstrates the phenomena of pronounced conservatism versus mild liberalism when individuals are exposed to opposing views, mirroring recent findings on opinion polarisation via social media exposure. Advancing this model, we establish a robust framework that integrates elements from physics, psychology, behavioural science, decision-making theory, and philosophy. We also emphasise the inherent advantages of the quantum approach over traditional models, suggesting a number of new directions for future research work on quantum-mechanical models of human cognition and decision-making.

Keywords: backfire effect; confirmation bias; opinion polarisation; quantum mechanics; social media

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1. Introduction

The dynamics of human beliefs and radicalisation of opinions have emerged as defining factors in our society's trajectory, as witnessed across a myriad of political [1–6], educational [7], environmental [8–10], religious [6], moral [6,11–14], and racial divides [14,15]. Evidence of this pervasive polarisation is abundant. For instance, we see political polarisation in the United States, where Democrats and Republicans hold increasingly disparate views on topics such as gun control, climate change, and healthcare [3,16]. Racial divides are also starkly apparent [17], resulting in differing views on police brutality [18] and immigration policy [19]. In the context of religion, we observe polarisation in the form of divergent beliefs on topics such as abortion, LGBTQ+ rights, and the role of religion in public life [6,20]. Ethical polarisation is also evident in ongoing debates on euthanasia, capital punishment, and animal rights [21].

Yet polarisation is not confined to these broad social issues, since it extends into more specific realms such as differing views on vaccines, where pro-vaccine advocates and vaccine sceptics are at odds [11,13]. Opinions on technological issues involving artificial intelligence, genetic engineering, and data privacy are further examples [22,23]. We also observe polarisation in our responses to major global challenges, such as climate change [9,10,16], where supporters and sceptics hold divergent views. Polarisation further manifests itself in societal attitudes towards economic disparities, income inequality, and social safety nets [24].

These divisions have spawned numerous problems, ranging from unrest at the societal level to conflicts within smaller groups with opposing beliefs. People with conflicting beliefs are often regarded as adversaries, leading to divisive and destructive practices such as information warfare, cyberattacks, derogatory comments on social media, and the spreading of fake news [25]. While the damage inflicted to the information ecosystem by such actions is often unappreciated and underestimated, its impact on societal cohesion is profound and far-reaching.

This polarised landscape is significantly influenced by confirmation bias, a psychological phenomenon where individuals interpret or seek information that confirms their preexisting beliefs, while overlooking contradictory evidence [26]. Such a bias shapes the behaviour of social network users, leading them to select and propagate claims aligned with their beliefs, fuelling group polarisation and entrenchment of beliefs, as well as reinforcing and perpetuating societal divides. Of particular interest is the backfire effect—a manifestation of confirmation bias, referring to the tendency of people to give more credence to evidence that supports their preexisting beliefs [3].

Early research into the backfire effect highlighted that not only are fallacious beliefs stubbornly resistant to correction, but attempts to refute them can inadvertently cement them further [5,13,27–31]. This phenomenon extends to beliefs that align closely with an individual's worldview; for instance, challenging principles tied to Republican ideologies might only deepen a Republican's adherence to those principles. More recent studies have suggested that the backfire effect may not be as universally consistent as previously thought [32]. However, the current consensus in the field reaffirms that while refutations may temporarily sway beliefs toward accuracy, this impact is generally short-lived [4]. The impermanence of these corrections means that inaccuracies, as well as beliefs reinforced by personal ideologies, can continue to influence public opinion well after being discredited. The resilience of such beliefs and misconceptions likely stems from the corrective information not being conveyed in a manner that results in a long-lasting change in perspective [33]. This issue is compounded by the fact that individuals often navigate complex information through the lens of their preexisting worldviews and affiliations, which can override their interpretations and acceptance of new evidence [34].

To further understand the complex dynamics of the backfire effect, our work advances a model derived from the principles of quantum mechanics [35,36]. This approach provides a unique perspective for comprehending and quantifying opinion radicalisation, elucidating the evolution of individual beliefs when exposed to counter-attitudinal information and revealing its contribution to societal polarisation.

Examining societal opinion dynamics through the lens of this quantum-inspired model bears considerable implications. This model reproduces the asymmetric behaviour of opinion radicalisation commonly observed when individuals confront opposing views on social media. Such a radicalisation, augmented by the backfire effect, is prominently manifested in political domains. For instance, in the political arena of the United States, exposure to counter-attitudinal information typically results in an entrenchment of beliefs among both Democrats and Republicans. However, Republicans have been observed to be radicalised to a higher degree than Democrats in response to conflicting perspectives [3].

It is noteworthy that the applications of the model are not limited to politics, since the phenomenon of radicalisation applies to other societal issues such as climate change, gun control, and vaccinations, often leading to an intensification of individuals' initial beliefs when they are presented with contrasting evidence or viewpoints. Our model elucidates this counter-intuitive dynamics, thus offering a new perspective on the complex landscape of human beliefs and opinions.

Figure 1 provides empirical evidence of the 'double-sided' polarisation behaviour triggered by the backfire effect, observed in the domains of politics [3] and abortion [6]. Conversely, in Figure 1, the domains of climate change [9] and vaccination [13] are marked by a seemingly 'one-sided' view. This discrepancy arises due to missing data for these areas, as studies focusing on climate change and vaccinations typically present scientifically accurate information in experimental treatments, without offering opposing viewpoints.

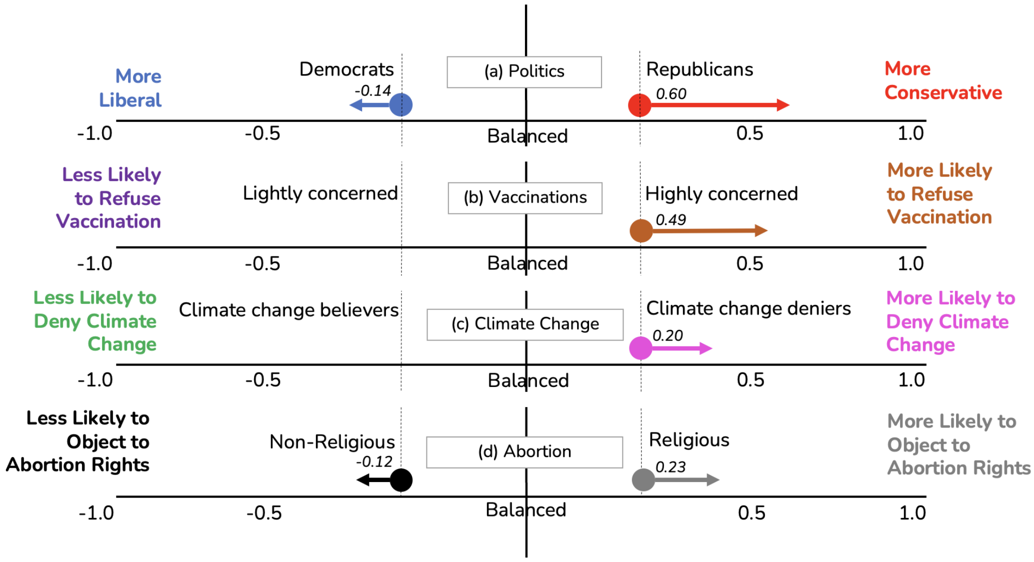

Figure 1. Notable examples of the backfire effect in the literature. The figure represents the backfire effect observed in four studies covering (**a**) politics [3]; (**b**) vaccinations [13]; (**c**) climate change [9]; and (**d**) abortion [6]. In each of these studies, groups exhibited the backfire effect after being subjected to an opposing view. Note: Each of the horizontal axes should be read independently. Results from the cited papers have been normalised to be presented on a scale from -1 to 1. The figure demonstrates the direction and magnitude of the backfire effect for one or more groups in each study, showcasing that Republicans, people highly concerned with vaccination side effects, climate change deniers, and religious people are more likely to become more conservative, more likely to refuse vaccination, more likely to deny climate change, and more likely to object to abortion rights, respectively, after being subjected to opposing views. At the same time, Democrats and non-religious people exhibit a much lower backfire effect in magnitude than their Republican and religious counterparts, respectively. Counterpart views are not available for all studies.

The apparent limitation of the available motivational data should not be perceived as a detriment to our investigation, since our model can predict radicalisation trends in contexts where data on opposing views are unavailable or scarce. Thus, by elucidating such trends, we aspire to contribute to an interdisciplinary understanding of opinion dynamics, with the potential of informing interventions that could mitigate polarisation and foster more productive and respectful societal dialogues.

Furthermore, the proposed model reveals the fundamental origin of these advantages over classical models in understanding the radicalisation of opinions, thereby providing a robust framework that can predict changes in opinion with superior accuracy and reliability.This model also contributes to the growing body of research exploring the plausibility of the 'quantum mind' hypothesis, which posits that the principles of quantum mechanics could underlie cognitive processes [36–38]. In particular, through its successful simulation of experimental data on opinion dynamics, the model provides further arguments supporting the potential of this hypothesis.

The examples of the backfire effect in Figure 1 provide evidence of the scale and gravity of polarisation across multiple dimensions of our society. Yet, understanding these dynamics is only the first step. The ultimate goal is to leverage these insights and devise strategies to alleviate the destructive effects of radicalisation and polarisation. By offering a comprehensive and robust framework to interpret these dynamics, the proposed quantum-mechanical model stands to make a contribution to these efforts.

2. Quantised Energy Level Model of the System of Human Beliefs

The application of the fundamental principles of quantum mechanics in the fields of behavioural science, economics, and decision-making has opened up novel opportunities for unifying and formalising previously heuristically formulated psychological, cognitive, and finance-related concepts and ideas [36,37]. In particular, an analogy between mental states and quantum states has been used to explain cognitive dissonance [39] and gender fluidity [20]. A similar approach has been adopted in models of confirmation bias [40,41], gambling [36,42], the prisoner's dilemma game [36,43], conjunction fallacy [36,41], and the Ellsberg paradox [36]. However, although there exist classical models of confirmation bias [40,41], opinion formation and polarisation [44–56], human morality [57], and backfire effect [15,58], the core principles of quantum mechanics exploited in this paper have not been previously applied to the aforementioned psychological phenomena.

We propose a quantum-mechanical model of the human system of beliefs (see the inset in Figure 2) and demonstrate its application to opinion radicalisation and the backfire effect in social networks. It is well known that a quantum-mechanical system can have only certain energy levels compared with the continuum of energy states of a classical system [35]. Therefore, drawing on the previous works in the domain of socio-physics [59,60], we represent the system of human beliefs as a set of discrete energy levels. Furthermore, in Figure 2, we draw a hypothetical parallel between the social network circles and atomic orbitals used in quantum mechanics to describe the location and wave properties of an electron in an atom [61]. The electrons occupy atomic orbitals that have discrete energy levels [61]. When atoms interact, their atomic orbitals overlap and energy levels hybridise [61]. Extending previous works that employed spin-like classical magnetic dipoles to understand and predict the social interaction between individuals [20,45,49,62,63], we rigorously adopt the quantum-mechanical processes of atomic orbital overlap and energy level hybridisation to model the influence of social network circles on the system of beliefs of an individual.

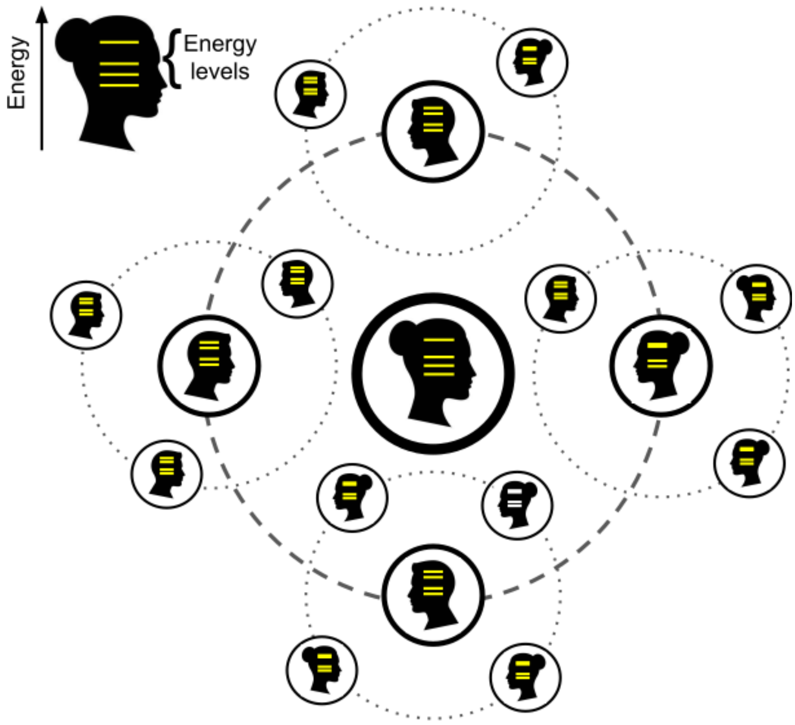

Figure 2. Sketch of a social network showing the social circles and human systems of beliefs represented by discrete energy levels (the horizontal lines superposed on the human head silhouettes). The physical analogy between overlaps of social circles and overlaps of atomic orbitals and concomitant energy level changes underpins the model proposed in this paper.

The proposed model stands on solid psychological, philosophical, mathematical, and physical ground. First, it is consistent with both the notion of discrete mental states [59,64–66] and the understanding of information as energy states of a physical system [67–69]. Second, the model captures the psychological [70] and mathematical [49,71] complexity of a system of human beliefs. Third, the model aligns with the famous philosophical maxim pronounced by Ortega y Gasset: 'Yo soy yo y mi circunstancia' ('I am me and my circumstance', see [72], p. 322; a link between Ortega and Gasset's circumstance and quantum aspects of cognition has also been established [73]). In the model, circumstance is represented by interactions between atoms and its influence results in a change in the energy level structure. Finally, the model relies on a rigorous solution of the fundamental Schrödinger equation [35], whose relevance to the domains of psychology and decision-making has been demonstrated [36,74].

To establish a physico-mathematical connection between the energy levels and a system of human beliefs, we employ a harmonic quantum oscillator model represented by an electron trapped in a one-dimensional rectangular well, where the energy states are quantised as $E_n \propto (n/L)^2$, with $n = 1, 2, \ldots$ being the number of the energy state and L the width of the well [35]. Noting that potential wells of different widths L have different allowable energy levels E_n, we arrange two or more potential wells into a chain to represent interactions of an individual with social neighbours (Figure 3). We also use the fact that electrons can change energy levels by emitting or absorbing a photon and note that crystalline solids can have energy bands that consist of many closely located discrete energy levels [61]. In the latter case, although electrons are restricted to the band energies, they can assume a continuum of energy values inside a band.

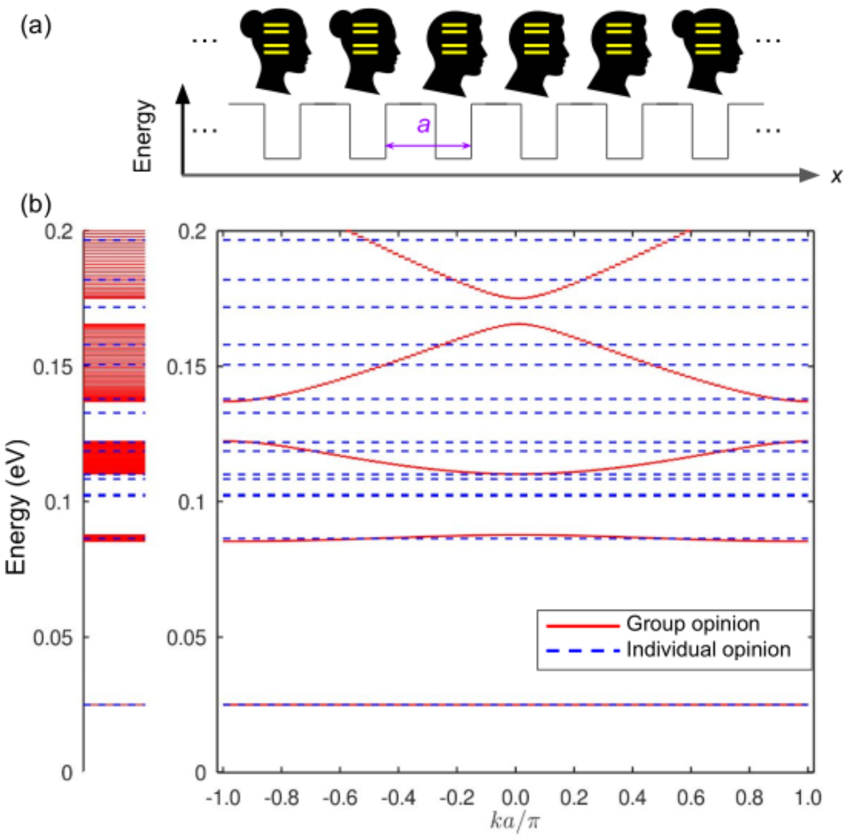

Figure 3. Quantised energy level model of opinion polarisation. (**a**) Social network of like-minded individuals represented as a one-dimensional lattice made of rectangular potential wells (parameter a denotes the period of repetition of the wells). (**b**) Energy dispersion diagram of the lattice of potential wells (the solid curves in the main panel) and the corresponding energy level structure (the solid lines in the inset). The dashed lines denote the energy levels of a standalone potential well corresponding to an isolated individual. Note that, in the group, the energy levels split and aggregate, forming bands of continuous energy states, compared with the purely discrete energy levels of the standalone individual. While transitions inside an energy band are readily possible, high energy is required to transition between the bands. This physical property is interpreted as opinion polarisation.

In exact sciences, theoretical models are often based on postulates, as famously exemplified by Einstein's postulates of special relativity [75] and the postulates that underpin Bohr's model of the atom [76]. In general, postulates are accepted to be true without proof, since they make a statement that is seen as truth within the framework of the model [77].

Using this approach, we postulate that, in our model, a rather regular and sparse energy level pattern corresponds to a polarised (biased) set of beliefs, but the beliefs of an idealised unbiased person or group of individuals are represented by a continuum of energy values. Other scenarios are also possible, including the case of several continuum state bands separated by large energy gaps that would correspond to the division of opinions into sub-groups [78]. An additional relevant discussion can be found in Appendix A.

We also choose a set of model parameters that have a strict physical meaning. If a person holds deeply polarised beliefs, a significant amount of information would be needed to ameliorate the situation [79]; for example, by means of metacognitive training [80]. Since information has been associated with energy [67–69,81,82], the quantum-mechanical model captures this scenario as the large energy needed for an electron to transition from one energy level to another. However, a set of densely packed energy levels would represent 'open-mindedness', because a continuous distribution of energy levels is characterised by a low transition energy, which means that the individual is receptive to new information, ideas, and opinions.

To implement the model as a computational code, we numerically solve the Schrödinger equation that defines eigenfunctions corresponding to eigenvalues E of the Hamiltonian operator $\hat{H}$ as [35]

$$\hat{H}\psi(\mathbf{r}) \equiv \left[-\frac{\hbar^2}{2m}\Delta + V(\mathbf{r})\right]\psi(\mathbf{r}) = E\psi(\mathbf{r})\,, \tag{1}$$

where $\hbar$ is Plank's constant, Δ is the Laplacian operator, m is the mass of the electron, and $V(\mathbf{r})$ is the scalar potential. We employ a one-dimensional finite-difference method, where Equation (1) is discretised along the coordinate x, so that $V(x)$ is represented as a vector of N equally spaced points with a step h_x [83]. Using a second-order central finite-difference scheme, we obtain

$$\psi''(x_i) \approx \frac{1}{h_x^2}[\psi(x_{i-1}) - 2\psi(x_i) + \psi(x_{i+1})]\,. \tag{2}$$

The substitution of Equation (2) into Equation (1) gives rise to a finite-difference version of the Schrödinger equation written in matrix form (see Ref. [83] and Ref. [84], Chapter 2 for additional numerical details):

$$-\frac{\hbar^2}{2mh_x^2}\begin{bmatrix} -2 & 1 & 0 & 0 & 0 \\ 1 & -2 & 1 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 \\ & & & \dots & \\ 0 & 0 & 0 & 1 & -2 \end{bmatrix}\begin{bmatrix} \psi(x_1) \\ \psi(x_2) \\ \psi(x_3) \\ \dots \\ \psi(x_N) \end{bmatrix} + \begin{bmatrix} V(x_1)\psi(x_1) \\ V(x_2)\psi(x_2) \\ V(x_3)\psi(x_3) \\ \dots \\ V(x_N)\psi(x_N) \end{bmatrix} = E\begin{bmatrix} \psi(x_1) \\ \psi(x_2) \\ \psi(x_3) \\ \dots \\ \psi(x_N) \end{bmatrix}, \tag{3}$$

where $m \approx 9.1093837 \times 10^{-31}$ kg and $\hbar \approx 1.054571817 \times 10^{-34}$ J·s. In all calculations, we set $h_x = 2 \times 10^{-10}$ m.

Using the virtual points x_0 and x_{N+1} that do not directly participate in the calculation but help compute the values of the neighbouring points, we employ Floquet periodic boundary conditions $\psi(x_0) = \psi(x_N)\exp(-jka)$ and $\psi(x_{N+1}) = \psi(x_1)\exp(jka)$ (see Ref. [85], p. 82), where j is the unit of the imaginary number, k denotes the wavevector, and a is the period of repetition of the profile of $V(x)$ (for an isolated potential well $\psi(x_0) = \psi(x_{N+1}) = 0$). The introduction of Floquet periodic boundary conditions changes the last element of the first row and the last element of the first column of the tridiagonal matrix in the left-hand side of Equation (3).

The numerical solution of Equation (3) using a standard procedure `eigs` of MATLAB/Octave software yields the eigenvalues E for each discrete value of the wavevector k corresponding to the first Brillouin zone. The energy level diagrams plotted alongside the dispersion diagrams are obtained by integrating the values of E for all values of k taken into account in the calculation. The computational code that implements the model can be accessed by following the link provided in the Data Availability Statement section.

3. Results

3.1. Opinion Polarisation in Social Networks

We first use our model to capture the phenomenon of opinion polarisation in a social network. Then, we explain the technical aspects of the model and demonstrate a relationship between the physics and dynamics of social networks, relaxing the need for the readers to understand physics-specific terms.

When two individuals do not interact and are not influenced by the news media, the systems of their beliefs, represented by the energy levels, remain unchanged because the corresponding wave functions—probability waves that govern the motion of the electron and are described by the Schrödinger equation [35]—do not overlap. However, as a result of information exchange between these individuals, the potential wells move closer to one another and the wave functions overlap, thereby forcing the energy levels to adjust and split, such that they remain unique [61].

Figure 3 shows the result of a simulation of the opinion polarisation in a social network, where we form a social network of like-minded individuals; i.e., individuals whose systems of beliefs are represented by the same discrete energy level systems. We take into account a large number of members of the social group and represent them as a periodically arranged sequence (one-dimensional lattice) of identical potential wells (Figure 3a).

The main panel of Figure 3b shows the calculated energy dispersion diagram (the solid curves) alongside the energy levels of a standalone single potential well (the dashed lines). The former depicts the group opinion formed in a social network of like-minded individuals, but the latter corresponds to the opinion of one individual considered separately from their social neighbours. The right inset to Figure 3b shows the discrete energy levels corresponding to the group (the solid lines) and the isolated individual (the dashed lines). In this calculation, the depth and width of the wells are 0.1 eV and 10 nm, respectively (the meaning of these parameters will be revealed below).

We can see that, by virtue of the laws of quantum mechanics [61], in our model of the social network, the original discrete energy levels corresponding to the individuals split and self-arrange, forming several allowed energy bands separated by band gaps (regions of forbidden energies [61]). According to the postulates of our model, the formation of energy bands corresponds to the polarisation of opinions: the opinions of the group participants are more likely to remain withing the energy bands, but changes in opinion are less likely because a high energy is required for an interband transition.

The presence of the fundamental effect of energy splitting differentiates our model from any previous physics-inspired models of social interaction (for a more detailed discussion see Appendix A). Indeed, in the Sznajd model [63] and its modifications [49], the interaction between two neighbours changes the opinions of their respective neighbours. However, the opinions of these two particular neighbours are assumed to be unchanged. A similar assumption is also made in the other models [44,86,87].

However, generally speaking, making this assumption contradicts the accepted philosophical vision of the dialogue as a means of change [88,89]. In fact, dialogue entails such quality relationships between individuals as mutuality, responsibility, engagement, and acceptance, inevitably resulting in the evolution of personal beliefs and views [90]. While such a change may materialise in a long-term perspective, thus making it possible to neglect it in certain social model situations such as the prediction of political election exit polls [91], it should be taken into account in a model of opinion polarisation in social media, where dialogue plays an important role [92].

In the calculation used to produce the data plotted in Figure 3b, we denoted the period of repetition of the potential wells as a and applied Floquet periodic boundary conditions, which are often employed in solid-state physics to approximate a large system using a small part called the unit cell [61]. We also used the concept of the reciprocal lattice, which represents the Fourier transform of the periodic lattice of potential wells in the physical space (the x-coordinate in Figure 3a) and that exists in the reciprocal space of the wavevector k. According to the convention adopted in the field of solid-state physics, we plotted the energy dispersion diagram as a function of the normalised wavevector ka/π in the range of values corresponding to the first Brillouin zone, which defines the unit cell in the reciprocal space [61].

Whereas the discussion above employs the terminology adopted in physics, we can establish a link between the physical concepts and those concepts used in data science and studies of social networks. Indeed, studies of social networks often exploit the notion of periodicity and rely on the Fourier transformation of data [93,94], highlighting the important role of the reciprocal space in analysis of big datasets [95,96]. Hence, readers who do not wish to use the physical language can also comprehend our model using the terminology adopted in the fields of graph signal processing [94], data science [93], or mathematical sociology [95]. Moreover, we present energy level plots alongside the dispersion diagrams, helping readers understand the mainstream discussion, without the need to use the concepts of wavevector and Brillouin zone. We also note that the depth and width of the wells used in our model can be made nondimensional, enabling the users of the model to employ the system of measure that is typical in their field of research. For example, the spacing between the discrete energy states can be related to the social distance [97] or opinion distance in social networks [98–100].

3.2. Opinion Radicalisation

Now, we showcase the ability of the model to capture the backfire effect and opinion radicalisation in social networks. As an example, we refer to a study demonstrating that exposure to opposing views on social media can radicalise political views [3]. In the cited paper, members of the Republican and Democratic parties received financial compensation for following officials and opinion leaders with opposing political views. As a result of the experiment, compared with the control group, both Republican and Democrat participants developed more radicalised views with respect to their respective traditional party positions [3]. Interestingly, the degree of opinion radicalisation was different among the two groups: the Republican participants showed substantially more conservative views but the Democrat participants only exhibited a slight but statistically significant increase in liberal attitudes (Figure 1, top panel).

The corresponding model situation is presented in Figure 4a, where persons with the same systems of beliefs, represented by regular potential wells, are exposed to an opposing opinion expressed by another person represented by an irregular potential well. Unlike the regular potential wells that are 0.1 eV deep and 10 nm wide, the irregular well is 0.07 eV deep and 20 nm wide (we remind that the parameters of the wells are chosen empirically and they are meaningful only in the framework of the postulates that underpin our model). Subsequently, the allowed energy levels of an individual irregular well taken alone were significantly shifted with respect to those of an individual regular well. To account for the presence of the irregular well in an otherwise periodic sequence of identical regular wells, we employed a super cell computational approach that is often used to model crystallographic defects, an interruption of the regular patterns of the arrangement of atoms in crystalline solids [61].

While the super cell approach appears to be unique to the domains of physics and mathematics, we show that it can easily be adopted in models of social networks. An infinitely large, idealised network consisting of identical individuals can be mathematically represented as one individual (the unit cell) that self-repeats an infinite number of times. A more realistic network will consist of different individuals. However, a careful analysis of such a network is likely to reveal the existence of sub-groups of similar individuals [101]. Considering such sub-groups as super cells, we can create a model of the network where the super cells repeat as many times as needed to reproduce the structure of the network.

We can further extend this idea by manipulating the opinions of individuals within a sub-group, i.e., within a super cell. For instance, we can require one individual within a sub-group to suddenly change their opinion for an opposite one. This action is equivalent to the introduction of a crystallographic defect, which is the reason why we adopt the physical term 'defect' in the discussion of our model.

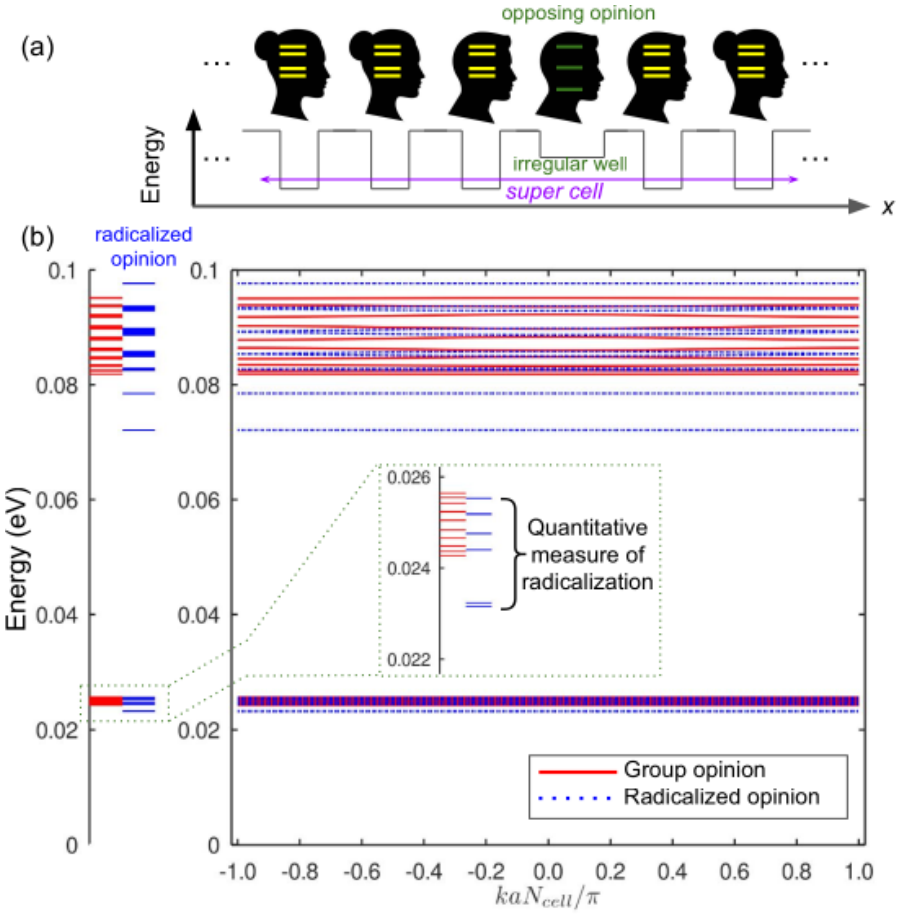

Figure 4. Example of opinion polarisation. (**a**) Like-minded individuals are exposed to an opposing opinion, represented by a one-dimensional lattice of identical potential wells with a 'defect' lattice node given by an irregular well. The super cell approach described in the main text is employed in the calculation. (**b**) Main panel: Energy dispersion diagram corresponding to the group opinion before the exposure to an opposing opinion (the solid curves) and after (the dotted curves). The respective energy level structures are shown in the left inset. Note that the exposure to the opposing opinion results in the addition of new discrete energy levels and splitting of the existing ones, which can be seen both in the right and central insets and which is interpreted as opinion polarisation. The degree of opinion polarisation can be estimated by computing the energy difference between the lowest and highest energy levels, as shown in the central inset.

In the main panel of Figure 4b, the solid lines denote the energy dispersion diagram corresponding to a polarised opinion in a group of like-minded individuals, which corresponds to the control group, where the irregular well was replaced by a regular one. The dotted lines plot the energy dispersion in the case of exposure to an opposing opinion. The corresponding energy bands are shown in the inset. For the sake of presentation, we limit the energy range of interest to $0 \ldots 0.1$ eV. For the readers interested in the physical and mathematical aspects of the model, we also note that the introduction of a super cell consisting of N_{cell} potential wells effectively folded the Brillouin zone, modifying the energy dispersion curves and requiring an adjustment of the wavevector normalisation as kaN_{cell}/π compared with Figure 3b.

We can see that the exposure to an opposing opinion changed the energy level structure, because a defect in an otherwise perfectly periodic lattice of potential wells produces a series of sparse energy levels. Since we stipulated that a sparse energy level pattern corresponds to a polarised set of beliefs, we can conclude that our model reproduces the backfire effect.

According to the data presented in Figure 1, radicalisation should also occur in a scenario that is the reverse of Figure 4a: the majority opinion becomes represented by the potential well considered in Figure 4a as irregular, but the formerly regular well serves as the 'defect'. We simulated this scenario using a super cell consisting of 0.07 eV deep and 20 nm wide potential wells containing a 0.1 eV deep and 10 nm wide irregular well (Figure 5a), which is a structure that is topologically opposite to that shown in Figure 4a.

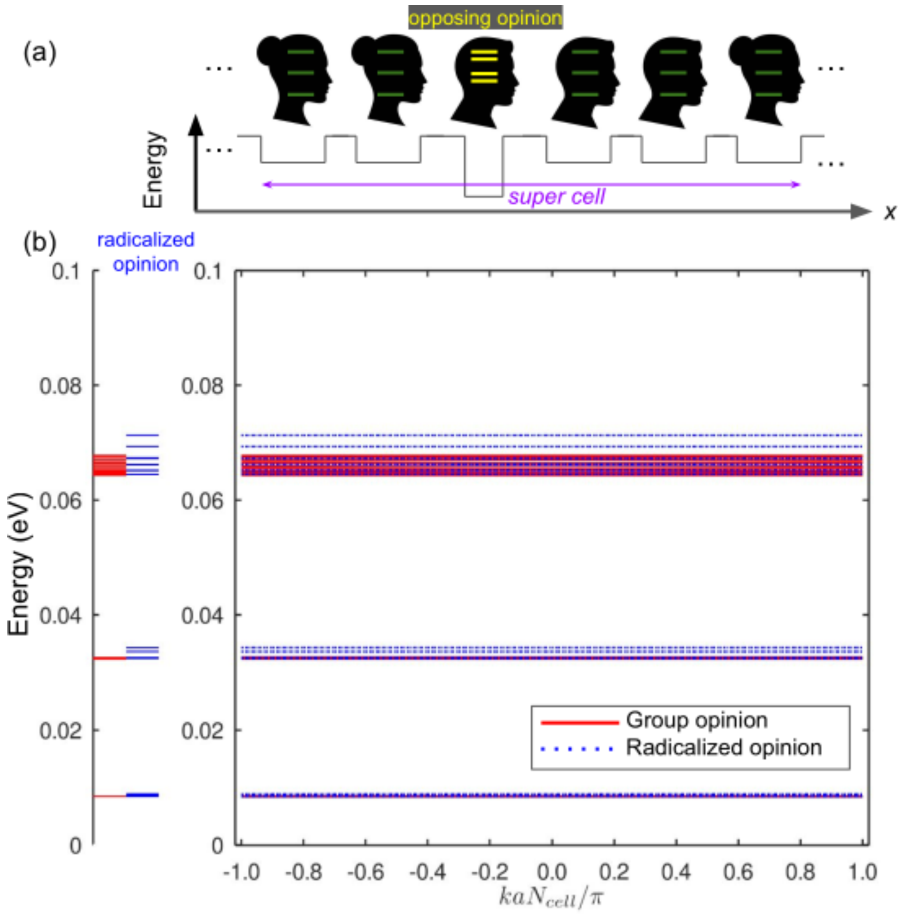

Figure 5. Example of opinion polarisation in the reverse scenario with respect to Figure 4a. (**a**) Like-minded individuals were exposed to an opposing opinion, represented by a one-dimensional lattice of identical potential wells with a 'defect' lattice node. Unlike in Figure 4a, the irregular well is deep and narrow but the majority opinion wells are shallow and wide. (**b**) Main panel: Energy dispersion diagram corresponding to the group opinion before the exposure to an opposing opinion (the solid curves) and after (the dotted curves). The respective energy level structures are shown in the left inset. Even though the exposure to the opposing opinion resulted in the addition of new discrete energy levels and splitting of the existing ones as in Figure 4b, these processes were less pronounced, thereby indicating a lower degree of opinion polarisation with respect to the scenario modelled in Figure 4.

The result of the corresponding calculation is presented in Figure 5b, where we observe that the exposure to an opposite view led to the formation of sparse discrete energy levels, i.e., to a radicalisation of the group opinion. We can see that the sparse energy levels in Figure 5b are quantitatively different from those in Figure 4b, which indicates that the levels of opinion radicalisation corresponding to the results presented in these figures were also different. Below, we will show that the difference between the results in Figures 5b and 4b correlates with the data presented in Figure 1.

In the work [3] that presents the asymmetric radicalisation data used in the top panel of Figure 1, the degree of radicalisation was studied using the Rubin casual model of potential outcomes [102], resulting in a quantitative liberal/conservative scale based on experimental data obtained from a mainstream social network. The energy states plotted in the insets to Figures 4b and 5b are analogous to the scale used in Ref. [3]. To provide a measure of radicalisation, in our model, we first calculate the difference between the highest and lowest 'group opinion' energy states and then compare the resulting values with the difference between the respective 'radicalised opinion' energy states. Applying this procedure to the energy bands at approximately 0.022 eV in Figure 4b and 0.008 eV in Figure 5b, we can establish that the opinion radicalisation in Figure 4 is a factor of 1.5 stronger than in Figure 5.

This result is close to the ratio of the experimental values for non-religious/religious (Figure 1, bottom panel) and consistent with the radicalisation ratio for Democrats/Republicans (Figure 1, top panel). Thus, although further model adjustments are required to obtain more accurate results, it is plausible that the model may predict at least approximate radicalisation data for pro-vaccine and pro-climate change groups (these data are not available, as explained in the caption to Figure 1) using the data available for anti-vaccine groups and climate change sceptics. In particular, the model confirms an intuitive conclusion that can be drawn from observing Figure 1: social groups that share more liberal views experience a milder radicalisation due to exposure to conservative views compared with the considerable radicalisation of conservative social groups exposed to liberal views.

4. Discussion

The model developed in this paper adopts a new approach that has not been used in the previous quantum models of decision-making and opinion formation. Since this work is a joint effort of a physicist working on the social aspects of AI and an expert in psychology, behavioural science, economics, and decision-making, it presents a integrative view of the quantum-mechanical models of opinion formation and polarisation compared with previous works written by experts in traditional fields of research. In particular, this paper combines the physical concept of the electronic band structure that represents energy levels with intricate psychological effects, elaborating on previous suggestions to describe mental states as discrete energy levels [59,60] and also bridging the gap between psychological studies and those interdisciplinary academic works that broadly contribute to the emergent research topics of quantum mind and socio-physics. Since this paper targets readers specialised in different research areas, ranging from psychology and decision-making to data science, mathematics, and physics, in this section, we use field-of-research-neutral language to summarise the main features of the proposed model, also demonstrating the place of the model in the taxonomy of socio-physical approaches to opinion formation in social networks.

4.1. The Origin of Quantum Advantage in Models of Social Media

Socio-physical models based on classical physical effects [44,45,49,63,71,103,104] have become an important topic of mainstream scientific research and have found practical applications outside academia [105,106]. Thus, one of the main questions of this paper is what, in general, makes a quantum-mechanical model attractive for the analysis of opinion polarisation in social networks.

To address this question, let us compare a classical digital computer with a quantum computer [107]. Similarly to an on-off light switch, a bit of a digital computer is always in one of two physical states corresponding to the binary values '0' and '1'. However, a quantum computer uses a quantum bit (qubit) that can be in the states $|0\rangle = \left[\begin{smallmatrix}1\\0\end{smallmatrix}\right]$ and $|1\rangle = \left[\begin{smallmatrix}0\\1\end{smallmatrix}\right]$. While these states are analogous to the '0' and '1' binary states of the digital computer, a qubit also exists in a superposition of the states $|0\rangle$ and $|1\rangle$, expressed as $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$ with $|\alpha|^2 + |\beta|^2 = 1$.

Computational algorithms based on measurements of a qubit are exponentially faster than any possible deterministic classical algorithm [107]. This advantage can be illustrated using the concept of the Bloch sphere (Figure 6) that depicts the multitude of qubit states that can be used to conduct a calculation. When a quantum measurement is performed [35,107], a closed qubit system interacts in a controlled way with an external system, revealing the state of the qubit under measurement. Using projective measurement operators $M_0 = |0\rangle\langle 0|$ and $M_1 = |1\rangle\langle 1|$ [107], the measurement probabilities for $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$ are $P_{|0\rangle} = |\alpha|^2$ and $P_{|1\rangle} = |\beta|^2$, which means that the qubit will be in one of its basis states. Visually, this measurement procedure means that the qubit can be projected on one of the coordinate axes of Figure 6.

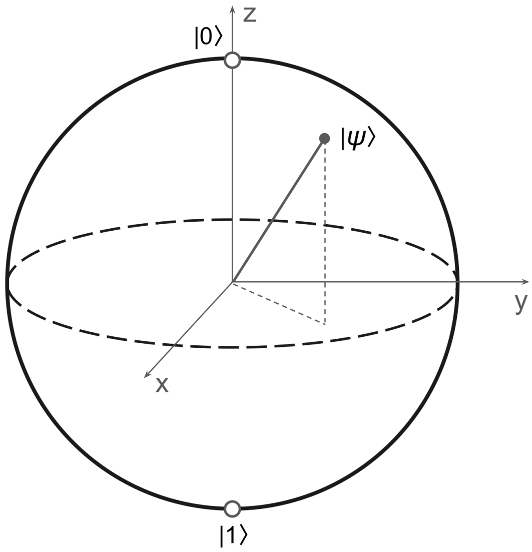

Figure 6. Illustration of a projective measurement of a qubit $|\psi\rangle$ using the Bloch sphere.

Thus, it has been demonstrated that quantum mechanics can model human mental states better than any existing classical model [36,108–110]. Indeed, referring to classical models where opinion states can be either '0' or '1' [49,63], in Figure 6, we can see that quantum mechanics enables us to describe human opinions using the multitude of possible qubit states. In particular, while in the classical models the two allowed states can be limited to 'agree' and 'disagree' [49,63], in a quantum-mechanical model, we can have a spectrum of opinions that gradually vary from 'agree' to 'disagree'. More intriguingly, a quantum-mechanical model of cognition is not constricted by any technical limitations of the hardware physical systems that realise qubits. This means that, in a model, we can unleash the full potential of the qubit states (as well as of more complex states, as discussed in Appendix A) to describe complex human mental states [36,37,111].

Further evidence of the superiority of quantum-mechanical models over the classical physical ones can be provided by considering the recent advances in the field of quantitative finance, where the methods of quantum physics play an increasingly important role [112,113]. Historically, the financial markets have been strongly influenced by the emotions of traders [114]. Therefore, it has been established that the processes that underpin the formation of the opinions of traders and the formation of opinion in social networks are essentially similar and intertwined [115,116] and that their analysis would benefit from the richness of the quantum states used in respective quantum quantitative finance models [112,113].

In fact, both financial markets [117] and the human brain [118,119] are dynamical systems. A dynamical system is a mathematical or physical system whose evolution can be described by differential equations that involve time derivatives. Subsequently, financial markets can be described by an appropriate differential equation that, for example, may correspond to a classical harmonic oscillator [120]. Yet, it was demonstrated that a quantum harmonic oscillator governed by the Schrödinger equation producing quantised eigenfunction solutions—essentially as in Equation (1) of our model—serves as a better model of financial markets [121]. Importantly, as with the model presented in this paper, the quantum oscillator financial model outperforms the classical oscillator financial models due to the quantum effects resulting in the formation of discrete energy levels. The same conclusion has been drawn in relevant quantum mind studies, where quantum oscillator models demonstrated significant advantages over the classical models [36,74].

Finally, the fundamental principles of quantum mechanics used in this paper have also been employed in a recent work [122] that demonstrated that quantum processes can help find conditions suitable for making conflict-free joint decisions between two individuals. Although the authors of the cited paper considered the quantum processes of photon entanglement and interference of orbital angular momentum, at the fundamental level, they reached similar conclusions. In particular, they revealed the importance of the symmetry of a quantum system for decision-making modelling. The relevance of symmetry to the model presented in this paper is discussed in Appendix A.

4.2. Quantum-Mechanical Model vs. Statistics-Based and Data Science-Driven Approaches

Now, we compare the quantum-mechanical model with the traditional statistics-based and data-science-driven approaches. As with the established classical physics-based models of opinion formation in social media [44,49,53,63], the present quantum-mechanical model differs conceptually from the statistics-based and data-science-driven methodologies adopted in the fields of psychology, econometrics, and decision-making [102]. Specifically, it provides a robust insight into the origin of the radicalisation effect, without relying on large datasets obtained in complex and time-consuming experiments involving large groups of the population.

Indeed, a typical single run of a computer program that implements the model presented in this paper requires about 10 s, which enables the user to gain an understanding of the processes underpinning the radicalisation in a very short period of time compared with the time needed to collect, process, and analyse experimental data (see the works cited in the caption to Figure 1). While the information about the time required to collect and process data is not readily available in the literature, in our own relevant work [123] we demonstrated that it takes approximately one hour of CPU time of a workstation computer for a quantum model to reproduce empirical psychological datasets obtained as a result of experiments conducted over several months.

As a next development stage, the agreement between the outcomes produced by our model and the experimental results can be increased using the fact that the potential well profiles capturing the intricate system of human beliefs can be arbitrarily complex. That is, the potential wells may not necessarily be rectangular but can assume a parabolic or a triangular shape or their combinations. To automatise the search for a suitable profile, one can use machine learning techniques, which have been employed to optimise the structure of photonic crystals, periodic dielectric structures that share some physical properties with the periodic array of potential wells [124].

4.3. Integration with Bot-Detection Systems and Decision-Making Software

Bot-detection is the process of identifying and distinguishing between automated bots and human users [125,126]. Bots can be detected using algorithms based on behavioural analysis, challenge–response authentication systems, and machine learning techniques [125]. Nevertheless, despite the constant progress in the domain of cybersecurity, bots remain a serious threat, since they can shape public opinion by spreading fake news and serving as an instrument for cyberbullying and harassment [125,126].

At present, many bot detection systems analyse user behaviour patterns, such as page navigation habits, to detect anomalies that may indicate bot activity. The model proposed in this paper offers the opportunity to extend the capability of bot detection systems by modelling the way humans think while they use social networks. Comparing such models with the decision-making patterns of users of social networks, a bot-detection system may differentiate a real user from a bot. This functionality should be especially useful, since the developers of bots employ artificial intelligence systems that learn to accurately reproduce certain behaviour patterns of social network users [126]. However, even the most sophisticated bot system cannot yet reproduce human thoughts, thereby revealing the synthetic nature of the bot when its behaviour is benchmarked against a quantum digital twin of a human.

A quantum digital twin can also be used in decision-making software to help business leaders make decisions based on a large number of factors, including their presence on social media and feedback received from them.According to a recent report [127], 41% of senior leaders in Australia make decisions on instinct alone, and 81% reported that their business suffered the consequences of such decisions. Similar decision-making distress also affects leaders in politics, police forces, secret intelligence, and the army, causing them to question or regret decisions they have made. The development of quantum models of human behaviour aligns with the vision expressed in the report in [127]: a judicious combination of artificial intelligence systems with advanced mathematical models should help extend the ability of a human mind to predict decision outcomes and de-risk operational transformation.

5. Conclusions

This paper demonstrates the potential of a quantum-mechanical model to illustrate, interpret, and explain the dynamics of opinion polarisation and radicalisation in social networks. We have shown that the structure of energy levels of a quantum system, specifically of a chain of potential wells, can effectively model social dynamics such as the interactions between individuals and groups.

Our results indicate that the phenomenon of opinion polarisation can be represented by the formation of continuous energy bands and interband gaps when like-minded individuals interact within a social network. These energy bands represent the polarised groups, with transitions between them requiring significant energy. The ability of this model to capture the experimental results obtained using the established social psychology methods is a promising indication of its predictive capacity.

Moreover, we extended this model to capture the effects of exposing like-minded groups to opposing views, demonstrating that this situation can lead to the creation of new, sparse energy levels, symbolising the radicalisation of the group's opinion. This was interpreted as the backfire effect, a behaviour observed in real-world scenarios and supported by empirical studies. We also showcased how variations in potential well profiles can influence the degree of opinion radicalisation, corroborating the observation that different groups might react differently to exposure to opposing views.

Utilising a novel approach of conceptualising social interactions, this model provides a theoretical basis for understanding and predicting social dynamics in intricate scenarios. Although this work primarily employs a one-dimensional model, it opens the door for future research extending the model to higher spatial dimensions and considering more complex potential well profiles. In conjunction with the ability of machine learning techniques to synthesise profiles that capture intricate systems of human beliefs, emotions, and brain activity, this property enables us to further refine the model and better represent and anticipate the multifaceted reality of social network interactions.

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Appendix A. Additional Discussion and Future Research Directions

Electron spin is a purely quantum-mechanical concept [35,61]. However, as discussed in more detail in [20,123], certain properties of the spin can be described using a classical magnetic dipole, making it possible to use the spin states $\uparrow$ and $\downarrow$ in classical socio-physical models [49,63]. At the conceptual level, these states may be compared with the basis $|0\rangle$ and $|1\rangle$ states shown in Figure 6.

In an idealised scenario, a classical physical magnetic dipole model of opinion formation may involve two interacting particles—individuals A and B—that can assume one of the two allowable states ξ' and ξ'' defined at any time by the position and momentum $\xi_A \equiv (\mathbf{r}_A, \mathbf{p}_A)$ and $\xi_B \equiv (\mathbf{r}_B, \mathbf{p}_B)$. The corresponding Hamiltonian function is $\hat{H}(\xi_A, \xi_B) = \mathbf{p}_A^2/(2m) + \mathbf{p}_B^2/(2m) + V(|\mathbf{r}_A - \mathbf{r}_B|)$, where m is the mass of the particles and $V(\mathbf{r})$ is the profile of potential [35]. Since $\hat{H}(\xi', \xi'') = \hat{H}(\xi'', \xi')$, we can conclude that, in the classical model, the common opinion state of a group consisting of two individuals is known to be within the permutation of the individuals.This ambiguity should not represent any difficulty in modelling the opinion dynamics. However, it does not enable one to differentiate the impact of the views of A based on the views of B and vice versa, which is disadvantageous for modelling the asymmetry of opinion radicalisation.

The treatment of a two-individual system using methods of quantum mechanics produces a more complex physical picture. Assuming that the states of A and B are $\psi'(\mathbf{r})$ and $\psi''(\mathbf{r})$, we can show that the observation of the interaction between A and B does not permit deciding whether the group opinion is in the state $\psi(\mathbf{r}_A, \mathbf{r}_B) \equiv \psi'(\mathbf{r}_A)\psi''(\mathbf{r}_B)$ or $\hat{\psi}(\mathbf{r}_A, \mathbf{r}_B) \equiv \psi''(\mathbf{r}_A)\psi'(\mathbf{r}_B)$. This situation is called exchange degeneracy and it originates from the fact that the functions ψ and $\hat{\psi}$ are both eigenfunctions corresponding to the set values produced by the measurement [35]. Subsequently, any linear combination $\alpha\psi + \beta\hat{\psi}$ with $|\alpha|^2 + |\beta|^2 = 1$ can represent the state of the system.

Quantum mechanics removes the exchange degeneracy, introducing a symmetrisation postulate that fixes the coefficients α and β of the linear combination of the states ψ and $\hat{\psi}$ [35]. Therefore, the states of the system consisting of individuals A and B are necessarily either all symmetric ($\alpha = 0$, $\beta = 1$) or all antisymmetric ($\alpha = 1$, $\beta = 0$) in the permutation of A and B. The symmetrisation applies to a system of N particles/individuals [35] and it can be used to capture the effect of asymmetric opinion polarisation.

In the proposed model, the corresponding states are antisymmetric and they are governed by the Pauli exclusion principle, according to which no two electrons can occupy the same quantum state [35]. Thus, in light of the illustration in Figure 2, by analogy with solid-state physical systems [61], each orbital labelled by the quantum number n can accommodate two individuals, one with the state $\uparrow$ and another one with the state $\downarrow$. Moreover, when the orbitals overlap, the Pauli principle prevents multiple-state occupancy, resulting in a change in the total energy of the system [61]. While this physical picture does not necessarily reflect the actual human mental states (in fact, models that emulate the actual mental states may suffer from fundamental drawbacks [128]), its integration into the model of social opinion dynamics adds novel degrees of freedom that enable a deeper understanding of complex human decision-making processes [36,59,60].

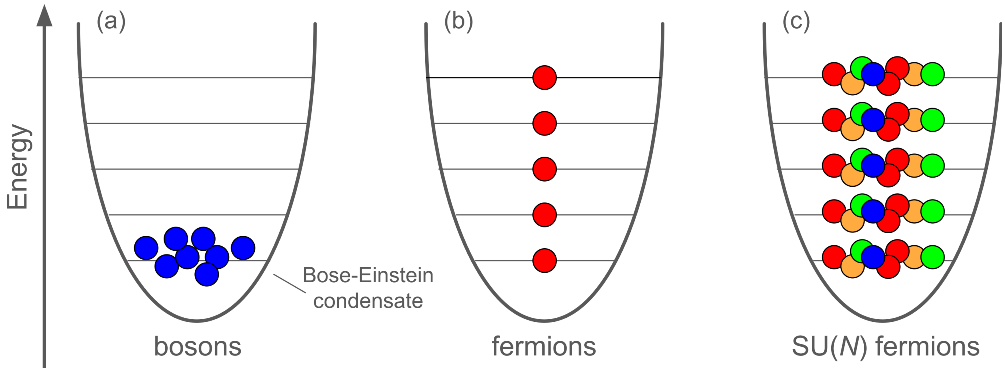

Figure A1. (**a**) Degenerate bosons, (**b**) fermions, and (**c**) SU(N) fermions. Unlike bosons, which can occupy the same energy level at low temperatures, fermions separate into different energy levels. However, SU(N) fermions can have N particles per energy level. In each level, each particle has $(N-1)$ distinct neighbours that strongly interact with one another.

The particles with antisymmetric states are called fermions [35]. Unlike fermions, bosons—particles with symmetric states—are not subject to the Pauli exclusion principle; i.e., two or more bosons can occupy the same quantum state (Figure A1). If we have two experimental setups, one containing a gas of bosons but another containing a gas of non-interacting fermions, as the temperature decreases to absolute zero, the gas of bosons collapses, forming a Bose–Einstein condensate (Figure A1a). However, fermions cannot reach this state, since they cannot occupy the same quantum state: they occupy discrete energy levels as depicted in Figure A1b, where the energy of the highest occupied quantum state is called the Fermi energy.

Thus, we anticipate that the incorporation of the quantum physical principles that underpin the properties of fermions and bosons into a model of opinion formation on social media will enables us to understand and predict even more complex social interactions. Interestingly, a similar idea was expressed in the field of the quantum modelling of financial markets [129], which additionally speaks in favour of the correctness of our discussion by establishing a link between the quantum models of social networks and the quantum models used in the finance sector. Yet, intriguingly, similar models have been shown to correctly describe the arrangement of people in a concert and cars in a parking lot [130]. Taken together, these applications demonstrate the significant potential of quantum models to capture complex human decision-making patterns.

Finally, utilising group theory—the mathematical framework for describing symmetry properties of quantum mechanical systems [131]—and drawing on recent advances in the field of quantum physics [132,133], we suggest a new research direction for further development of quantum-mechanical models of human cognition and decision-making. A recent work demonstrated that some real-life materials can have N distinct states, each of which have the same properties due to symmetry [134]. Such physical systems are called SU(N) symmetric [131,132]. In particular, SU(N) fermions can have N particles per energy level and, in each level, each particle has $(N-1)$ distinct neighbours that strongly interact with one another (Figure A1c). Taking this property into account in a model of social dynamics should dramatically increase the ability of the model presented in this paper, introducing additional degrees of freedom that can be used to represent the human mental states.

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