Using a Temporal-Causal Network Model for Computational Analysis of the Effect of Social Media Influencers on the Worldwide Interest in Veganism

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Using a Temporal-Causal Network Model for Computational Analysis of the Effect of Social Media Influencers on the Worldwide Interest in Veganism

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Abstract Over the years, a clear and steady rise can be seen in the interest in veganism. Although research has been conducted to determine the reasons why veganism has grown, ultimately there is still a necessity for further research on how social networks affect its growth. This paper aims to provide a possible explanation for the rise in interest, using computational analysis based on a temporal-causal network model focussing on social contagion. This model portrays a simulation of a sample size population on Instagram, showing how a social influencer can influence the opinions of people directly (influencers' followers) and indirectly (followers of the influencers' followers), and how this compares to a situation in which this influencer is not there.

Keywords Social contagion · Social media · Veganism · Network-oriental modelling approach · Temporal-causal network

1 Introduction

Over the last years, the number of vegans has noticeably increased. From 2014 to 2018, this number has quadrupled in the UK [13]. While there has been research studies towards the reasons why people became vegan, it has not yet been established how exactly this rise came to be. The main reasons why people become vegan are health and ethical reasons [11]. McDonald [9] attempted to research how people learn to become vegetarian or vegan, by conducting a qualitative study. According to this study, most participants already felt affection for nonhuman animals prior to

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Fig. 1 A Google search regarding the interest in vegan spread out over a period of six years, where 100% equals the highest number of searches for this term

becoming vegan, but they became vegan after experiencing one or more catalytic experiences. These experiences involved information about animal cruelty that was presented to the participant, which led to further action. After learning more about animal cruelty, participants eventually made the decision to give up animal products in their entirety. McDonald argued that openness and the willingness to learn were salient factors into the decision of becoming vegan. After becoming vegan, the participants in this study stated that their vegan lifestyle included the desire of educating others about animal cruelty [9]. Even though this research provides more insights into how people become vegan, ultimately it does not explain the substantial rise of interest in veganism in the last 10 years. As Fig. 1 shows, in 2018 the interest in 'vegan' shows a monotonically increasing trend: it has been strongly increasing since 2012. The assumption is that people are becoming more aware and learning more about veganism, which could contribute to the rise in interest of it entirely.

With the rise of the Internet and social media, people have obtained more access to all types of information compared to twenty years ago. Instagram, for example, has been a popular platform to show and sell products to people, proving to have an impact on buyers. Posting a picture next to a sales item appears to boost the sale conversions with a factor of seven [18]. This impact is not only true for sales but also appears to work for lifestyle changes. Nine out of ten experiments conducted by Maher et al. [8] showed significant improvements in health behaviour, and it is argued that behaviour changed because of social network sites. Vaterlaus [17] confirmed this, by showing that at least 38% of participants showed that their food choices were influenced by social media. This provided more support for the social ecological model, which indicates that several factors, including social media, appear to have an influence on health behaviours [5]. Social influencers especially appear to contribute to the fact that social media seem to have an impact on health behaviours. Social influencers are perceived as more appealing because they are arguably considered more popular than others. This perception of popularity even increased the perceived opinion leadership of some influencers [4]. This effect was also the case for pictures.

Pictures with more ‘likes’ were liked even more by participants than other pictures. This was also detectable within the neural responses in the brain, namely the nucleus accumbens, where popular pictures showed a greater response in this area [12]. This could possibly be explained by a persuasion principle of Cialdini; the number of ‘likes’ on a picture provides the opportunity of social proof, which means ‘when a lot of people are doing something, it is the right thing to do’ [2, 3].

2 The Temporal-Causal Network Model

According to the above-mentioned research, it appears that social media and social influencers can affect the lifestyle and buying behaviours of their followers. This can be categorized under social contagion, which can be explained as the spread of belief, affect or behaviour, where people influence on another, e.g. [1]. To simulate and analyse this computationally, the network-oriented modelling approach, presented in [15], was used; see also [16]. This approach can be considered as a branch in the causal modelling area which has a long tradition in AI; e.g., see [6, 7, 10]. It distinguishes itself by exerting a dynamic perspective on causal relations, according to which causal relations manifest effects over time. These causal relations themselves can also change over time. The type of network models that are used as a basis for this is called a *temporal-causal network model*. These network models are widely applicable, varying from biological and mental networks to social networks and beyond [16]. This also includes the social contagion principle.

To analyse the effect of an influencer on the spread of veganism computationally, an agent-based social contagion model was designed. The model consists of different nodes (agents) interacting with each other. The nodes only interact with the nodes that they are directly connected to. This connection can be bidirectional, which means that a node can express their opinion to a connected node, but also receive the opinion from that same node. On the other hand, it can be unidirectional, where an opinion will either be received or expressed. The nodes can still be influenced indirectly via some intermediate steps by other nodes that they are not connected to. The opinion that is communicated in this particular case will regard the nodes’ attitudes towards veganism. These opinions can differ in weight, where 0 is the lowest weight a node could have and 1 the highest. In this case, a value of 0 would mean no interest at all, whereas a value of 1 would mean high interest in veganism. Each node has an activation value, which varies over time. Based on the temporal-causal network that has been defined, this activation value depends on the interaction between the agents according to the following three elements: **connection weight** $\boldsymbol{\omega}_{X,Y}$, which represents the strength of the connection from state X to state Y, **speed factor** $\boldsymbol{\eta}_Y$, which represents how fast state Y is changing upon causal impact and **combination function** $\mathbf{c}_Y(..)$, which combines the causal impacts of other states on state Y. As there is not much specifically known about how specific agents are linked to an influencer, a scale-free network approach based on Tapan [14] was used to represent the population. This is a connected graph, where the majority

Fig. 2 Conceptual representation of the temporal-causal network model

of the nodes have one or two connections and only a few nodes have a plethora of connections. A sample size of 50 nodes has been chosen, where one node was chosen as the influencer (X_1). This influencer represents a popular person on social media who is actively posting about vegan. While looking at the real world, it is evident that not everyone is directly connected to each other. Therefore, this model divided all nodes into five subgroups, representing different clusters of the population. Subsequently, it is unlikely that all clusters in a population would be influenced by the same influencer(s). For this reason, the influencing node X_1 only impacts the first two clusters. This way, indirect effects are also presentable in the model. The conceptual representation of this model can be seen in Fig. 2, where the size of the nodes represents the number of outgoing nodes (influence) and the colours represent strongly connected nodes. The conceptual representation of a temporal-causal network model can be transformed into a numerical representation as shown in Table 1; see also [15, 16].

The following *difference* and *differential equation* for each state Y are obtained:

$$Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t)) - Y(t)]\Delta t$$
$$\mathbf{d}Y(t)/\mathbf{d}t = \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t)) - Y(t)] \tag{1}$$

The combination functions that are used to obtain a realistic simulation for the influence of a social media influencer on the overall interest in veganism are the *identity function* **id**(.) for states with a single impact and the *advanced logistic function* $\mathbf{alogistic}_{\sigma,\tau}(..)$ for states with multiple impacts, where σ is a parameter for steepness and τ a parameter for threshold.

$$\mathbf{id}(V) = V$$
$$\mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k) = \left[\frac{1}{1+\mathrm{e}^{-\sigma}(V_1+\cdots+V_{k-\tau})} - \frac{1}{1+\mathrm{e}^{\sigma\tau}}\right](1+\mathrm{e}^{-\sigma\tau}) \tag{2}$$

Table 1 From conceptual representation to numerical representation of a temporal-causal network model; adopted from Treur [16]

Concept	Representation	Explanation
State values over time t	$Y(t)$	At each time point t, each state Y in the model has a real number value in [0, 1]
Single causal impact	$\mathbf{impact}_{X,Y}(t)$ $= \boldsymbol{\omega}_{X,Y} X(t)$	At t state X with connection to state Y has an impact on Y, using connection weight $\boldsymbol{\omega}_{X,Y}$
Aggregating multiple impacts	$\mathbf{aggimpact}_Y(t)$ $= \mathbf{c}_Y(\mathbf{impact}_{X_1,Y}(t), \ldots, \mathbf{impact}_{X_k,Y}(t))$ $= \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y} X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y} X_k(t))$	The aggregated causal impact of multiple states X_i on Y at t is determined using combination function $\mathbf{c}_Y(..)$
Timing of the causal effect	$Y(t + \Delta t) = Y(t) + \boldsymbol{\eta}_Y\left[\mathbf{aggimpact}_Y(t) - Y(t)\right]\Delta t$ $= Y(t) + \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y} X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y} X_k(t)) - Y(t)]\Delta t$	The causal impact on Y is exerted over time gradually, using speed factor $\boldsymbol{\eta}_Y$; here, the X_i are all states with connections to state Y

An example of a numerical representation for agent state X_{14} in difference and differential equation format is, respectively:

$$X_{14}(t + \Delta t) = X_{14}(t) + \boldsymbol{\eta}_{X_{14}}[\mathbf{c}_{X_{14}}(\boldsymbol{\omega}_{X_1,X_{14}}X_1(t), \boldsymbol{\omega}_{X_{12},X_{14}}X_{12}(t)) - X_{14}(t)]\Delta t$$
$$\mathbf{d}X_{14}(t)/\mathbf{d}t = \boldsymbol{\eta}_{X_{14}}[\mathbf{c}_{X_{14}}(\boldsymbol{\omega}_{X_1,X_{14}}X_1(t), \boldsymbol{\omega}_{X_{12},X_{14}}X_{12}(t)) - X_{14}(t)] \quad (3)$$

with $\mathbf{c}_{X_{14}}(..) = \mathbf{alogistic}_{100,1}(..)$.

3 Simulation Results

The influence of a social media influencer on the overall interest in veganism of a population is analysed by using two scenarios. For each scenario, the timescale of the model is *time* 70 = 1 *year* with *time* 0 = 2012 and $\Delta t = 1$. Based on Google search data, we know that the interest in veganism in January 2012 was only 29% of the population compared to the interest six years later in 2018 (100%). Therefore, 15 people (14.5 rounded up) of the 50 people in this network are starting with an interest in veganism at *time* = 0 (2012) and are given an initial state value of $X_i(0) = 1$. The remaining people (35) are not interested in veganism at *time* = 0 and are given an initial value of $X_i(0) = 0$. The connection weights in this network are either 0 (state X is not influencing state Y directly), 1 (state X has a direct positive effect on state Y) or −1 (state X has a direct negative effect on state Y). The speed factor $\boldsymbol{\eta}_Y$ differs for each agent and varies between 0 and 0.1. For each agent Y with a single incoming connection, the *identity combination function* is used to estimate the activation value. For each agent Y with multiple incoming connections, given the activation values at time t, the *advanced logistic combination function* is used to calculate the activation value at time $t + \Delta t$ with *steepness* (σ) between 10 and 100, and *threshold* (τ) between 0 and 1.

Scenario 1 models the development when the influence of a social media influencer on the population is present. In this scenario, agent state X_1 with an *initial value* of 1 has 13 outgoing connections and 0 incoming connections and is called an 'influencer'. The rest of the states have a maximum of 6 outgoing influences. All states together have an average of 3.32 outgoing influences. The other settings are constructed according to the description above. The simulation results of the model can be found on the left side in Fig. 3. In the simulation of the first scenario, it is apparent that the interest in veganism grows over time. After 6 years (*time* = 420), every agent state is interested in veganism, but some agent states rise faster and sooner than others. This proves to be a realistic process due to personal differences and the strength of connections between agents.

To get a better view of the overall interest in veganism, the average is derived from the simulation and the result can be seen on the left side in Fig. 4. This shows that the average interest in veganism increases from 30 to almost 100% in 6 years. These results are in line with the expectations we had. If we compare this trend to

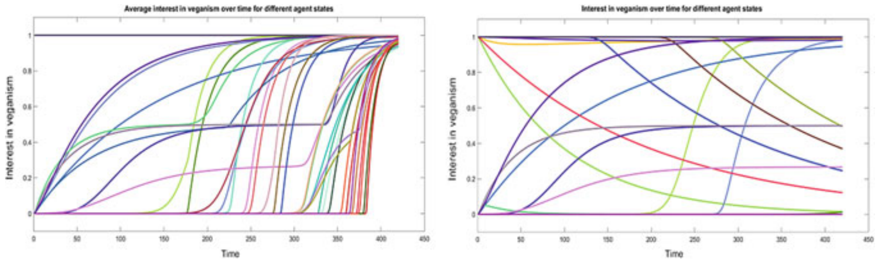

Fig. 3 Simulation of the temporal-causal network model for scenarios 1 (left, with influencer) and 2 (right, without influencer), where each line represents one agent state

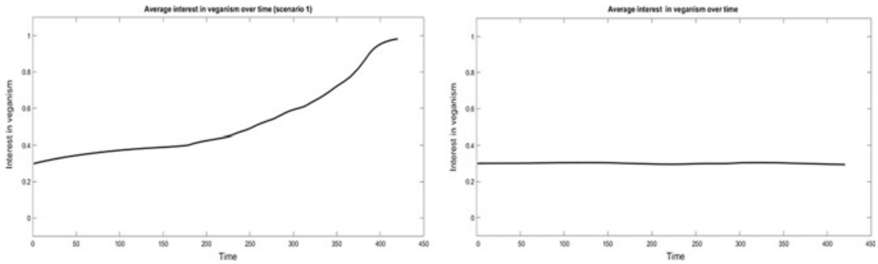

Fig. 4 Average interest in veganism of all agents combined over time for scenarios 1 (left, with influencer) and 2 (right, without influencer)

the worldwide interest in veganism derived from the Google search data and the literature, we can perceive approximately the same pattern.

Scenario 2 models the same process (with the same settings), but without the influencer X_1. This means that the outgoing connections of X_1 are 0 to each state Y. The simulation results of this adjusted model can be found in Fig. 3 on the right. Looking at the simulation results of the second scenario, we see that over six years, most of the people stay either interested in veganism or not interested in veganism. Only seven people that were initially uninterested in veganism became more interested over time. There were also seven people that became uninterested in veganism after previously harbouring interest. The reduced interest in veganism of some people arises since they are no longer influenced by the influencer, which leaves room for an increased influence of other (maybe) non-vegan people in their network. To obtain a better view of the overall interest in veganism, the average is derived from the simulation and the result can be seen on the right in Fig. 4. This shows that the interest in veganism is stationary over the time when the network is not influenced by the vegan influencer. If we compare this trend with the trend we have gathered in the first scenario, the influential power of a social influencer becomes visible. These findings are in accordance with our expectations since we expected the influencer to have a substantial influence on the overall interest due to social contagion and social proof.

4 Verification of the Network Model by Mathematical Analysis

In order to verify whether the implemented model does what is expected from the model specification, a mathematical analysis of stationary points was carried out. A state Y has a *stationary point* at some time point t if $\mathbf{d}Y(t)/\mathbf{d}t = 0$. For temporal-causal networks, there is a simple criterion to check whether there is a stationary point at t for state Y: a state Y in a temporal-causal network has a stationary point at time point t only if the speed factor of Y is 0 or $\mathbf{aggimpact}_Y(t) = Y(t)$, where $\mathbf{aggimpact}_Y(t) = \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t))$ (with $X_1, \ldots, X_k$, which are the states with outgoing connections to Y).

From scenario 1 shown in Sect. 3, eight stationary points with their time points t and their state values $X_i(t)$ were identified. To verify the model, these state values were compared to the values at the same time point t calculated using the right side of the equation $Y(t) = \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t))$ in the above criterion. To explain the mathematical analysis, the observed state value of agent state X_{22} at a stationary point at $t = 324$ is compared to the value $\mathbf{aggimpact}_Y(t)$ expressed in the equation above. The agent state X_{22} has incoming connections of X_{21}, X_{23} and X_{26}. The equation for the agent state X_{22} at $t = 324$ with combination function *advanced logistic function* with $\sigma = 20$ and $\tau = 0.5$ is as follows: $\mathbf{aggimpact}_Y(t) = \mathbf{alogistic}_{\sigma,\tau}(V_1, \ldots, V_k)$ with $V_i = \mathbf{impact}_{X,Y}(t) = \boldsymbol{\omega}_{X,Y}X(t)$. Here for the case of agent state X_{22} it holds

$$\begin{aligned}
V_1 &= \mathbf{impact}_{X_{21},X_{22}}(324) = 1 \times 1 = 1 \\
V_2 &= \mathbf{impact}_{X_{23},X_{22}}(324) = -1 \times 1 = -1 \\
V_3 &= \mathbf{impact}_{X_{26},X_{22}}(324) = 1 \times 0.5 = 0.5
\end{aligned}$$

Then

$$\begin{aligned}
\mathbf{aggimpact}_{X_{22}}(324) &= \mathbf{alogistic}_{20,0.5}(V_1, V_2, V_3) \\
&= \left[\frac{1}{1 + \mathrm{e}^{-20}((1 - 1 + 0.5) - 0.5)} - \frac{1}{1 + \mathrm{e}^{20*0.5}}\right](1 + \mathrm{e}^{-20*0.5}) \\
&= 0.500
\end{aligned} \tag{4}$$

The difference between the simulation value for state Y and the value $\mathbf{aggimpact}_Y(t)$ is called the *deviation*, and this portrays the accuracy of the model. If we compare this state value 0.500 for X_{22} at $t = 324$ with the value of $\mathbf{aggimpact}_Y(t)$ derived from the other state values at $t = 324$ in the simulation, which is 0.449, the deviation is $0.500 - 0.449 = 0.001$. The state values found in the simulation and the equations for $\mathbf{aggimpact}_Y(t)$ for X_{22} and other agent states with a stationary point can be found in Table 2. The stationary point equations all contain an accuracy <0.01, which contributes to confidence that the model was implemented in a correct manner.

Table 2 Stationary point equation outcomes

State Y_i	X_2	X_{16}	X_{20}	X_{22}	X_{24}	X_{26}	X_{28}	X_{42}
Time point t	406	401	152	324	283	192	397	411
State value $Y_i(t)$	1.000	0.996	0.495	0.499	0.262	0.496	0.996	0.999
$\mathbf{aggimpact}_{Y_i}(t)$	1.000	1.000	0.500	0.500	0.267	0.500	1.000	1.000
Deviation	0.000	0.004	0.005	0.001	0.005	0.004	0.004	0.001

5 Validation Using Empirical Data and Parameter Tuning

Lastly, comparing the model to the empirical data provided a validation of the model. This empirical data were retrieved from the Google search data mentioned in the beginning. To create an accurate model, time points were compared to the empirical data and the model was adjusted by tuning the parameters. This was achieved by comparing the average state of the agents in the model that was retrieved from the output created in MATLAB with the data provided by the Google search. The number of time points used in the proposed model was $n = 420$ (420 iterations with $\Delta t = 1$). Since the time point dimensions did not match yet with each other, the empirical data were converted into the same number of time points as the proposed model has. This provided a basis for a detailed and uniform way of comparison.

First, the empirical data were scaled to the dimensions of the simulation model (0–420). This means that the initial and final points from the empirical data, which were 2012-01 and 2018-01, were changed into 0 and 420, respectively. Each month that lies between 2012 and 2018 is converted to the scale of the simulation model by the formula: $\mathbf{timepoint}(t) = \mathbf{timepoint}(t - 1) + 5.83$, where t is a specific time point from the empirical data. The data for the time points that were not known yet were estimated by interpolation using a third-order polynomial trend line, which provided a formula to calculate the value for each time point of the model. This third-degree polynomial formula was as follows (with $\boldsymbol{t} = \mathbf{timepoint}$):

$$(0.000001\,\boldsymbol{t}^3 - 0.0002\,\boldsymbol{t}^2 + 0.0718\,\boldsymbol{t} + 27.048)/100 \tag{5}$$

Following this, the proposed model was compared to the empirical data, which was done in MATLAB. A sum of squares error SSR of 0.031953 was computed, which leads to root mean square, RMS = SQRT (0.031953/420) = 0.0087. These results indicate that the differences between the simulated data and the empirical data are quite small. However, there are still some differences, which can also be seen on the left in Fig. 5; in particular everywhere in the time interval the average of the simulation values is higher than the value of the empirical data, which indicates that there is room for improvement.

To improve the model and decrease the error, parameter tuning was used to find more optimal speed factor values. The speed factor of the average state X_{51} was 1.722 in the proposed model, which is based on the total speed factor values for all

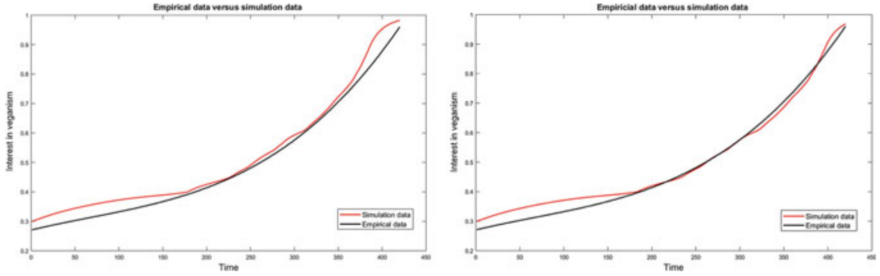

Fig. 5 Empirical data compared to the data of the proposed model before (left) and after (right) parameter tuning

Table 3 Results of parameter tuning by exhaustive search

$\eta_{X_{51}}$	1.722	1.700	1.682	1.665	1.648	1.631
SSR	0.0320	0.0279	0.0250	0.0240	0.0251	0.0282
RMS	0.0087	0.0082	0.0077	0.0076	0.0077	0.0081

states. An exhaustive search was used to find the speed factors that best represent the empirical data, which was executed by lowering the speed factor step by step for each state with 1% of its value at a time. The total speed factors $\eta_{X_{51}}$ and their SSR and RMS values for the different options in the search space can be found in Table 3. Table 3 shows that a total speed factor of 1.665 provides the lowest sum of squares error (0.0240) and root mean square (0.0076). This means that when the original value of each speed factor is multiplied by 0.97, this results in the best speed factor for the proposed model. The right side in Fig. 5 shows the proposed model after parameter tuning.

6 Discussion

In this paper, a temporal-causal network model concerning the influence of social media influencers on the overall interest in veganism is introduced. The model uses the network-oriented modelling approach described in [15, 16] and is based on the principle of social contagion and findings in the literature regarding social media and veganism. To verify the model, a mathematical analysis has been performed. To validate the model, parameter tuning has been performed by comparing it with empirical data.

The computational analysis presented in this paper provides more insights into possible reasons why people became vegan and proposed that this could be due to the rise of social media and vegan social media influencers. There are, however, some limitations that need to be taken into account while interpreting this model. The quantitative data that were found to validate the model is the amount of Google searches on the word 'vegan' over time, interpreted as the interest in veganism over time. There was no quantitative data available concerning the influence of social media influencers on their followers, or information on the composition of the network of an influencer. Therefore, this model represents a possible way of how the growing interest in veganism could have arisen, but it should be noted that this is one of many possible ways, maybe including ways where social media does not play an important role. Further research may be needed to determine in more detail the extent the influence social media influencers have on their followers, and particularly about the relationships among vegans on social media.

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