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Local approximation of path-dependent behavior:
the SHE-Model

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Associated Model: https://www.openabm.org/model/5194

Abstract

The *SHE-Model* (Model of Swarming and Herding agents affected by an Environment), which is presented in this paper, simulates opinion dynamics and collective movement dynamics in a group of ideal type path-dependent agents who perform swarming or herding behavior.

Let's assume there exists a path-dependent process that involves or affects agents, where a path-dependent process is a self-reinforcing process with the tendency towards a lock-in. What mathematics can be developed based on this definition and fundamental assumption? Corresponding to Coleman's Bathtub, the first step of disaggregation from path dependence theory to the ideal type path dependent has been deduced in a previous paper. This paper now focuses on the implementation of the ideal type path dependent agents in a simulation model, which is the second step. In the third step, the *SHE-Model* again aggregates the dynamics back to the macro level. Completing Coleman's Bathtub it can thus be said that if there is a path-dependent process affecting agents, social dynamics evolve that can be described by the *SHE-Model*.

Generally, on the macro level swarming and herding behavior occurs if there is a path-dependent process. Vice versa, simulations with the *SHE-Model* reveal that the simulated opinion dynamics are path-dependent processes. Thus, whenever there are opinion dynamics involved in a path-dependent process, these can be described by swarming and herding.

Accordingly, this proves that the ideal type path-dependent behavior implemented in the swarming and herding behavior in the *SHE-Model* is a basic element of path-dependent behavior. Therefore, the *SHE-Model* allows for a huge applicability to explain and describe social dynamics throughout society and the model can be used for the approximation of opinion dynamics and human behavior.

Keywords

path dependence, social simulation, agent-based modeling, path-dependent behavior, swarming, herding

1 Introduction

In times of social media, swarm intelligence, post-truth politics, and alternative facts opinion diffusion dynamics rule the world. Who takes the lead and who follows? In a group consisting entirely of swarming agents, all move in cycles. If cyclical movement is excluded and there is exactly one non-swarming agent, everybody directly or indirectly follows that one particular agent. Is this behavior realistic? Is this behavior stupid? Kominek (2012) explains that following behavior is not stupid but extremely optimized. Although it is not optimized with regard to the quality of the outcome, it is optimized by our brains with respect to the speed of decision-making. Using the least-effort-principle from social psychology, it is deduced that somebody who needs to take the same action decisions again and again rather uses a shortcut and just performs the actions instead of wasting time on lengthy decision-making processes again and again (Kominek 2012). This behavior seems very realistic at present, when everybody needs to make multiple decisions under time pressure. But what is the result? Path dependence.

In social sciences, a common understanding of path dependence is that "history matters": previous events shape subsequent ones. Path dependency theory has been coined by Arthur's research on increasing returns (1994) and David's case study on the QWERTY-keyboard (1997). Arthur discovered that in markets competing product shares stabilize over time. Seeking explanations for which technology wins in a market, Arthur introduced the theory of increasing returns "to show the process by which lock-in occurs and an outcome is selected" (Arthur 2013, p. 1186). While the final level of stabilization cannot be predicted at the time of the launch, the dynamics that lead to the stabilization can be described by an urn model or computer simulation of positive feedback. The economic argument behind these dynamics is the mechanism of increasing returns (Arthur 1994). David (1997) documented the consistency of the key placement from the early typewriters to modern computers. Even on smartphones the letters are placed in the same order on a "keyboard", if that wording is still appropriate, despite the fact that former reasons of optimization such as to prevent clashing or jamming of keys are not applicable anymore. Since the early days of path dependence theory many scientists have followed up on trying to extract or describe mechanisms that shape or stabilize a path-dependent process, discussing which cases can really be called path-dependent or whether they are just the outcome of utility optimized behavior and whether or not these are contradictions (Beyer 2015; Liebowitz & Margolis 2014). Similarly important is the debate on critical junctions, the beginning of paths or the very moment when the lock-in occurs (Collier & Collier 1991; Sydow, Schreyögg, Koch 2009), and path creation, which tackles the questions whether a path can deliberately be created or altered (Garud & Karnøe 2001). Nobel laureate Douglas North describes the effect of path dependence on decision-making in his book on institutions as follows: "At every step along the way there were choices— political and economic—that provided real alternatives. Path dependence is a way to narrow conceptually the choice set and link decision making through time. It is not a story of inevitability in which the past neatly predicts the future" (North 1990, pp. 98-99). Even though behavior cannot be predicted as long as agents have the freedom to choose differently, a good estimation may be possible by assessments of the manner in which path dependency narrows the choice set or even channels decisions or actions when asymptotically approaching a lock-in. Can path-dependent behavior be locally approximated close to a lock-in? This is the overarching research question that will be answered in this paper using the specifically designed *SHE-Model*.

The definition of path dependence used in this paper goes back to the early path dependence theory (Sydow, Schreyögg, Koch 2009):

A *path-dependent process*
is a *self-reinforcing* process
with the tendency towards
a *lock-in*.

Thus, taking a mathematical perspective: What conclusions can be logically developed from the assumption of existing path dependence following the above definition?

Can social behavior be locally aproximated with the *SHE-Model*?

In the next sections the *SHE-Model* is presented and applied to simulate and assess potential opinion dynamcis in a group of ideal type path-dependent agents. Although it is a basic swarming and herding model, the *SHE-Model* is designed to have hardly any cyclical movement in the networks of agents during the simulations. And, if available, the swarming agents follow somebody who has had the correct opinion in the previous time step, based on the feedback of the social environment.

The *SHE-Model* is used to reaggregate social dynamics from the micro to the macro level in a chain of reasoning from which follows that the *SHE-Model* can be used to approximate real life behavior.

The structural outline of the paper is that in the next section the important chain of reasoning is presented and explained. Afterwards, the *SHE-Model* is described in detail. In the subsequent section the model is used to answer the remaining questions from the chain of reasoning and to analyze how the simulated dynamics change when setup variables are altered. In a conclusion the core results are summarized and an outlook is briefly scetched.

2 The chain of reasoning

$\exists$ path-dependent process $p : A_i \to p(A_i)$ with A_i agents.

Does a path-dependent process necessarily lead to swarming and herding dynamics such as those simulated by the SHE-Model?

Vice versa, is all swarming and herding behavior embedded in a path-dependent process?

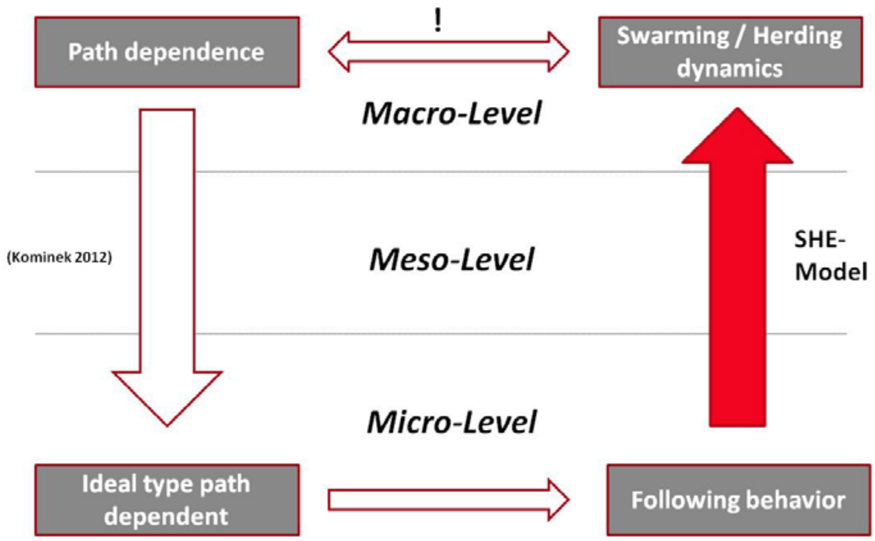

Figure 1: Chain of reasoning: As soon as the "!" is proven, the *SHE-Model* can be used as a local approximation of path-dependent behavior, so the social dynamics that are simulated with the *SHE-Model* approximate real life behavior.

2.1 From the macro level to the micro level

The first deduction is from the macro level, on which path dependence theory is usually discussed, to the micro level, seeking to explain how a path-dependent process affects the behavior of involved or affected agents.

How do people behave when they are affected by path dependence?

This question is chosen by Kominek (2012) as basis for the deduction of a theory of path dependence at the micro level: "Whatever it is that causes similar actions that can be understood as the following of a path, that way of acting becomes more and more of a habit" (Kominek 2012, p. 140). Applying the least-effort-principle (social psychology) a couple of times, which mainly states that the brain always takes the way of least effort to make decisions (e.g. Chaiken & Trope 1999), Kominek deduces that the permanent shortcut in decision-making results in a following behavior of the considered agents who are affected by path dependence. This means that the more an actor tends to decide and act path-dependently, the more his decision-making processes tend to resemble ideal type path-dependent behavior (Kominek 2012), which is to follow others such as neighbors or the masses, whatever is at stake in the given situation[1].

Thus, path dependency at the micro level can be described as a following behavior. The more an agent decides and acts path-dependently, the more his behavior resembles an ideal type path-dependent, which implies to follow others.

2.2 Conclusions at the micro level

In the second step, the theory of the ideal type path-dependent is implemented as the basis of the *SHE-Model*. What happens in a group of agents of ideal type path-dependent? To allow a wide applicability of the *SHE-Model*, the implementation of the ideal type path-dependent has to be as plausible as possible. In general, following behavior of agents can be either the following of individual agents, the majority of all agents, or the majority of agents within a certain subgroup, the average of all agents, or the average of agents within a certain subgroup, or even external institutions or norms, whichever seem accessible for the agents to follow. These kinds of following behavior can be divided into two types, one swarming type for agents who obtain the information they follow directly locally within their vision, and a herding type for agents who follow some globally aggregated information. In the *SHE-Model* the ideal type path-dependent agents are implemented as swarming or herding agents. While in each time step each swarming agent chooses one of its neighbors to follow for the opinion dynamics, a swarming agent moves in a flocking behavior such as aligning with others. Both are kinds of following behavior but over time the flocking behavior increases the likelihood of a swarming agent choosing to follow the same neighbor again and again, which supports the idea of path dependence. For the simulation of opinion dynamics herding agents are following the majority of all agents, i.e. the masses, while they move around in the average direction of all agents, which is herding. The idea behind this implementation is to start with a basic model but still allow for a certain variety and interaction of at least two types of agents. Does the chain of reasoning already hold true for this basic model?

[1] This theory of path dependence at the micro level (Kominek 2012) is deduced from the macro level definition of path dependence: A path-dependent process is a self-reinforcing process with the tendency for a lock-in (Sydow et al. 2009). This definition basically coincides with the more formalized definition by Vergne and Durand (2010) who "offer a narrow definition of path dependence as a property* of a stochastic* process which obtains under two conditions (contingency* and self-reinforcement*) and causes lock-in* in the absence of exogenous shock." (Vergne & Durand 2010, p. 737)

2.3 Back from the micro level to the macro level - the SHE-Model

Do the opinion or movement dynamics of a group of ideal type path-dependent agents always end up in a lock-in? Are multiple outcomes possible? During the simulations, the *SHE-Model* checks during each time step whether the group of agents already is in a lock-in and it stops as soon as the lock-in is reached. In the *SHE-Model* two types of lock-in are possible: an opinion-lock-in and a collective-movement-lock-in. It is even possible to have each type of lock-in separately or both reached at the same time step. Once the entire chain of reasoning holds true, this step becomes important because as soon as the "!" is proven, the *SHE-Model* can be used as a local approximation of path-dependent behavior so the social dynamics that are simulated with the *SHE-Model* approximate real life behavior.

2.4 Conclusions at the macro level

Does a path-dependent process necessarily lead to swarming or herding dynamics such as simulated by the *SHE-Model*? Or vice versa, is all swarming and herding behavior always embedded in a path-dependent process? Is all following behavior path-dependent? If the first, second, and third step of the chain of reasoning are all true, it follows that all path-dependent behavior can be described in swarming or herding dynamics as simulated by the *SHE-Model*. This chain of reasoning from the macro to the micro level and back to the macro level is also described by Coleman's Bathtub. For the other direction of conclusions, the results of the *SHE-Model* are important: if the opinion-dynamics are self-reinforcing with the tendency towards a lock-in they are path-dependent. If this holds true, then it can be concluded that for all following behavior that is simulated with the *SHE-Model* the opinion dynamics are path-dependent.

3 The *SHE-Model*

In the *SHE-Model* (Model of **S**warming and **H**erding agents affected by an **E**nvironment) a group of agents of the ideal type path-dependent is simulated. Agents of the ideal type path-dependent are following others, e.g. their neighbors or the masses, with regard to opinion dynamics and movement. Thus, in the model, which is coded in NetLogo (Wilensky 1999), there are two different types of agents in a given environment:

Swarming agents: A swarming agent copies the opinion of a neighbor, which is another agent within his vision. He prefers to choose an agent who has had a correct opinion in the previous time step. The swarming movement resembles flocking behavior.

```
to opinion-swarming
  find-swarm-neighbors
  ifelse any? swarm-neighbors with [size? = true]
    [ find-big-neighbor
      create-link-to nearest-neighbor
      set new-color [color] of nearest-neighbor]
    [ if any? swarm-neighbors with [size? != false] [
      find-random-neighbor
      create-link-to nearest-neighbor
      set new-color [color] of nearest-neighbor]
    ]
end

to swarming  ;; turtle procedure
  find-swarm-neighbors
```

```
  if any? swarm-neighbors [
    find-nearest-neighbor
    ifelse distance nearest-neighbor < minimum-separation
      [ separate ]
      [ align ]
  ]
end
```

Herding agents: A herding agent follows the masses. Thus, his opinion corresponds to the majority opinion of all other agents. The herding agent copies the average heading of the entire group for his movement.

```
to opinion-herding
  if count (turtles with [color = blue ]) > count ( turtles with [color = yellow] ) [
    ask cows [ set color blue ]
  ]
  if count (turtles with [color = blue ]) < count ( turtles with [color = yellow] ) [
    ask cows [ set color yellow ]
  ]
  if count (turtles with [color = blue ]) = count ( turtles with [color = yellow] ) [
    ask cows [ ifelse random 2 = 0 [ set color yellow ] [ set color blue ]]
  ]
end

to herding  ;; turtle procedure
  find-swarm-neighbors
  if any? swarm-neighbors [
    find-nearest-neighbor
    ifelse distance nearest-neighbor < minimum-separation
      [ separate ]
      [ align-group ]
  ]
end
```

Environment: The environment gives feedback on which opinion is correct and can be changed randomly or manually.

```
to check-environment
  if environment = "Yellow is good" [
    set environmental 0  ; true means, yellow is good, yellow turtles will grow
  ]
  if environment = "Blue is good" [
    set environmental 1  ; false means, blue is good, blue turtles will grow
  ]
  if environment = "Avoid a lock-in" [
    if count turtles with [color = blue] >  (number-of-agents * 0.9 ) [set environmental 0]
    if count turtles with [color = yellow] > (number-of-agents * 0.9) [set environmental 1]
  ]
end
```

In the model setup the user can determine the total number of agents (population) and choose how many of the agents (percentage of the population) are herding agents and how many agents (percentage of the population) are of a particular color, e.g. yellow, which represents the opinion of those agents. Conversely, all non-herding agents are swarming agents and all non-yellow agents have a different color, e.g. blue.

3.1 Swarming

In the model setup the swarming agents are assigned the default shape (as birds) and randomly spread. When it is their turn to take action during the model simulation, each of them performs the following steps: The swarming agent looks for neighbors (other swarming or herding agents) within its vision. From these neighbors it selects one to point to and prefers a big one, which implies that this neighbor has been correct (feedback from the environment) during the previous time step. Then the swarming agent follows the one pointed to by copying the color of the selected neighbor. If there is no other agent within its vision, it maintains its previous color. When it receives feedback from the environment it grows if it has the correct color and it shrinks if it has the wrong color. When the movement button is switched on, the swarming agent moves according to the swarming dynamics, which are based on the flocking model from the NetLogo model library (Wilensky 1998).

Why do swarming agents prefer to select a big neighbor?

Every agent points to exactly one of the other agent whom he follows during a given time step or if nobody is in his vision he follows himself and maintains the color of the previous time step. When in a group only consisting of swarming agents each points to one of its neighbors they create at least one cycle in the network, which can be proven by complete induction.[2] So it is not generally possible to rule out cycles in the *SHE-Model*. But to reduce the likelihood of local occurrences of cycles, in the simulations all swarming agents have a simple preference to locally choose a particular agent, if available. And this particular agent is coded to be a big one, an agent who had the correct opinion in the previous time step. This implementation increases the likelihood of an adaptive behavior in the simulations.

3.2 Herding

In the model setup herding agents are shaped as cows and randomly distributed in the NetLogo world. During the model run, when it is their turn to take action each of them performs the following steps: The herding agent evaluates which color is predominant among all other agents (all herding and swarming agents). Then the herding agent follows the masses by taking on that dominant color. When the feedback from the environment is received, the herding agent grows if he has the correct color and shrinks if he has the wrong color. When the movement button is switched on, the herding agent turns towards the average heading of all other agents (swarming and herding ones) and moves in that direction.

3.3 Environment

The environment is determined by the user through a button. The user can choose between three alternatives: either yellow or blue is set to be “good”, i.e. the correct opinion, or the feedback is generated to "avoid a lock-in", trying to avoid an opinion-lock-in at each time step. The setup allows for a manual change by the user through the interface between time steps. Also, the feedback can be evoked after changing the environment option on the interface. The environment provides feedback on the decisions the agents have taken so the agents with the correct opinion grow and the others shrink. The environment itself is not visualized in the *SHE-Model* simulations. The environment only feeds back on the opinions (colors) the agents have, so they either have the right opinion – then they grow – or they have the wrong opinion – then they shrink in size.

[2] If there is at least one non-swarming agent in the *SHE-Model* that consequently is a herding agent and cycles are excluded, all swarming agents follow that one non-swarming agent, which can be proven by complete induction, too.

Why "avoid a lock-in"?

When movement is switched on and herding is less than 50%, the swarming dynamics are so efficient in spreading the opinion favored by the environment that a collective-movement-lock-in is very rare. It only occurs in 2.5% of the runs and only 0.03% of the runs with vision 5. Therefore, I have created the chance of switching the environment to "avoid a lock-in", which implements the idea of trying to avoid an opinion-lock-in to allow in the simulations to reach a collective-movement-lock-in to analyze the swarming/herding dynamics more thoroughly. Consequently, when the "avoid a lock-in" option is selected for the environment on the interface, in the simulation the environment "switches" from "yellow is good" to "blue is good" when there are less than 10% of the population of agents left whose color is blue. That way a new round of opinion adaptation starts, trying to avoid the opinion-lock-in. The limit of 10% is arbitrary but set up as a constant in the code[3].

4 Simulations and Results

A few questions from the previous section still need to be answered:

- Do the actions of a group of ideal type path-dependent agents always end up in a lock-in? Are multiple outcomes possible (when aggregating from the micro level to the macro level)?
- Are the opinion-dynamics self-reinforcing with the tendency towards a lock-in, thus, path-dependent (for the final conclusion on the macro level)?
- Finally if the chain of conclusion is proven: On which model variables do the social dynamics simulated with the *SHE-Model* depend in which way (to obtain information on potential real life behavior)?

To assess whether the actions of a group of ideal type path-dependent agents always ends up in a lock-in in the simulations, all combinations of relevant variables need to be simulated in the NetLogo BehaviorSpace and it has to be noted if a lock-in occurs and which kind it is or if both lock-ins are reached at the same time step. An interesting feature of path dependence that is mentioned in the literature is that in the beginning of a process the final level of the lock-in cannot be predicted, i.e. multiple outcomes are possible and the process is not entirely deterministic (Arthur 1994, Verne & Durand 2010). To measure this chance for multiple outcomes in the model simulations at the state of the lock-in at the end of the simulation the final number of yellow agents is counted. The standard deviation can then show how strongly this final number of yellow agents then depends on the random spread of the agents at the beginning of the simulation.

To assess whether or not the simulated opinion dynamics are path-dependent, in addition to monitoring the lock-ins, the dynamics along the way of reaching the lock-in need to be measured. Therefore, the number of steps until lock-in is counted and analyzed. The simulations are started with only one yellow agent, so then the opinion diffusion can be assessed by counting the number of steps until lock-in and noting the final number of yellow agents. If even in a changing environment always the correct opinion diffuses it can be concluded that the dynamics are self-reinforcing.

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[3] When analyzing the simulation results it can be concluded that for some visions the level of 10% is sufficient, for some it is too large and for others too small. E.g., for vision 5 it still happens very often that because of the larger radius of agents within vision an agent of the preferred color can be spotted by a larger group of agents who then all adapt to that opinion in the same time step. Thus, they can be more than 10% of the population and still produce an opinion-lock-in, exceeding the limit for an environmental change in the setting of "avoid a lock-in".

Finally, for real life applications it is interesting to obtain more information about the interdependencies of variables used for designing the simulated dynamics in the *SHE-Model*.

Which variables affect the social dynamics in which way?

4.1 What happens when a group of ideal type path-dependent agents interacts?

This is the fundamental question of the *SHE-Model*. Following each other or the masses, the agents of the ideal type path-dependent can move around in a swarming or herding behavior and adapt to opinions from others. There are two basic dynamics that can occur in the simulations of the *SHE-Model*: Opinion dynamics that are marked by the colors and movements. While movements affect opinion dynamics, opinion dynamics do not affect movements (Tab. 1). And while the environment only affects the opinion dynamics, e.g. the vision affects both opinion dynamics and movements.

When running the *SHE-Model*, first the setup creates the number of agents according to the pre-defined ratio of swarming and herding agents and spreads them randomly in the world. Also the initial heading of the agents is random. The agents are colored based on the pre-defined percentage of yellow agents. Then the ideal type path-dependent agents are ready for the go-procedure.

variables on the user interface	**opinion dynamics**	**movements**	**in the simulations**
number-of-agents	has an effect	has an effect	100
percentage of herding agents	has an effect	has an effect	0-100
percentage of yellow agents	has an effect	no effect	1
environment	has an effect	no effect	yellow is good, avoid a lock-in
vision	has an effect	no effect	3-5
movement	has an effect	has an effect	none, swarming and herding
show-links	no effect	no effect	off
minimum-separation	has an effect	has an effect	1
max-align-turn	has an effect	has an effect	13.75
max-cohere-turn	has an effect	has an effect	5.5
max-separate-turn	has an effect	has an effect	1.5

Table 1: Variables in the user interface, their effect on the opinion dynamics or movements and how they are set or changed throughout the simulations in the BehaviorSpace of NetLogo.

To assess the movement and opinion dynamics that can evolve in a group of path-dependent agents from a social simulation perspective, it is particularly interesting to vary the combination of agents and thus the percentage of herding versus swarming agents (Tab. 2) as well as the percentage of yellow versus blue agents. At which constellation do significant effects occur?

Furthermore, to analyze the number of steps it takes until the population reaches a lock-in it is important to know how quickly a preferred opinion spreads throughout the population. Therefore, the agent's vision (Tab. 2) is an important variable to vary in order to check the dependence on single agent's characteristics versus the effects of initial group constellations such as the percentage of herding agents.

Especially when analyzing the dynamics that lead to a collective-movement-lock-in, it helps to be able to change the environment variable during the run of a simulation to avoid an opinion-lock-in prior to the collective-movement-lock-in.

To focus on these variables in the assessment of path-dependent processes, the other four variables shaping the movement, which are minimum-separation, max-align-turn, max-cohere-turn, and max-separate-turn, are held constant. Therefore, simulations are performed for the following combinations of variables:

		no movement					with movement					with movement "avoid a lock-in"			
		vision					vision					vision			
		3	3.5	...	5		3	3.5	...	5		3	3.5	...	5
percentage of herding agents	0														
	1														
	...														
	100														

Table 2: The *SHE-Model* is run using the BehaviorSpace of NetLogo with 1,000 runs for each of the combinations denominated in this table.

1,000 individual simulation runs are performed for each combination, so there are 1,515,000 runs in total (Tab. 2). During the runs the number of steps until the lock-in is recorded as well as the type of the lock-in, and the final number of yellow agents at the moment when the lock-in is reached (results can be found in Fig. 2, Fig. 3, and Figs. 5-7). Afterwards the standard deviations of the number of steps until lock-in and of the final number of yellow agents are also calculated. The standard deviation is used for inferences on the relevance of the random spread at the beginning of each run and thus of the relative starting positions of the agents.

4.2 What are the key findings?

In the situation of the opinion-lock-in either all agents have the same color or there are agents who cannot reach out to adapt to the environment anymore. Therefore, there are a number of agents of one color left that cannot change anymore (cf. e.g. Fig. 4). In the situation of a collective-movement-lock-in all agents have the same heading so they move collectively in the same direction and their positions relative to each other do not change anymore. If a collective-movement-lock-in occurs there could also be an opinion-lock-in in the cases, when the number of agents of one color does not change anymore. But a collective-movement-lock-in can also happen without an opinion-lock-in if the number of agents of one color changes periodically within a frequently changing environment.

Without movement in the simulations there is always an opinion-lock-in and no collective-movement-lock-in (Fig. 2). The latter is very improbable because the headings of the agents do not change and a collective-movement-lock-in in the case of no movement implies that all agents have the same heading from the very beginning, which is extremely unlikely for 100 agents with randomly set up headings. With movement, the collective-movement-lock-in still occurs rather seldom (Fig. 3, left): for shares of herding agents below 40% there is hardly ever a collective-movement-lock-in. For larger shares of herding agents the collective-movement-lock-in occurs more often, with a maximum for 50% herding agents, when almost always a collective-movement-lock-in occurs (Fig. 3, middle left). For even larger shares of herding agents a collective-movement-lock-in occurs with a decreasing tendency. The reason is that the very step when in a simulation with a share of 50% herding agents the masses change their mind, the group already reaches an opinion-lock-in. With movement switched on and the herding agents set up randomly in the world, the swarming agents are likely to follow herding agents. Partly clustered in swarms the swarming agents locally approach the heading of the herding agents while the herding agents only change their headings in tiny nuances as long as the swarming agents differ. For shares of herding agents that are larger than 50% the herding agents never change their opinion but with the masses heading in one direction anyway a collective-movement-lock-in can be approached sometimes even more quickly than an opinion-lock-in (Fig. 3, left). Only for shares of herding agents between 60% and 90%, there is a chance for a collective-movement-lock-in without an opinion-lock-in, which occurs up to about 20 times in 1,000 simulations (Fig. 3, top left).

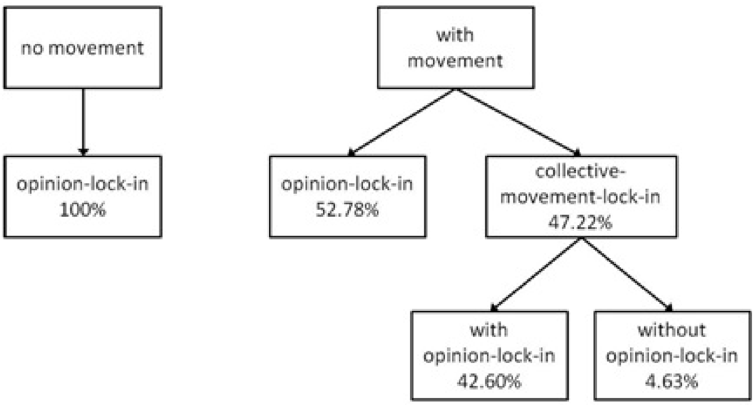

Figure 2: Overview of potential lock-ins in situations of no movement or with movement including the case with movement and the environmental setting of "avoid-a-lock-in".

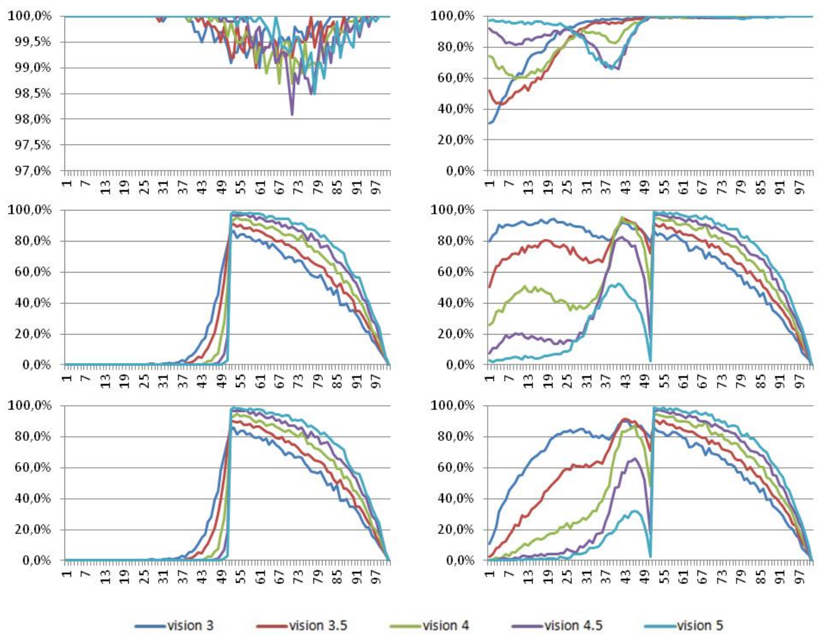

Figure 3: Percentage of the number of runs of the *SHE-Model* with movement that result in an opinion-lock-in (top), in a collective-movement-lock-in (middle), or in both at the same time (bottom) plotted in dependence on the share of herding agents (x-axis). On the left, the *SHE-Model* is run without avoiding a lock-in; on the right, the environmental setting is „avoid a lock-in“.

4.2.1 No movement

When running the *SHE-Model* in a set environment an opinion-lock-in occurs quickly if there is no movement (Fig. 5, left). In the situation of the lock-in either all agents have the same color or there are agents who cannot reach out to adapt to the environment anymore. Consequently, the number of agents of one color can no longer change (Fig. 4).

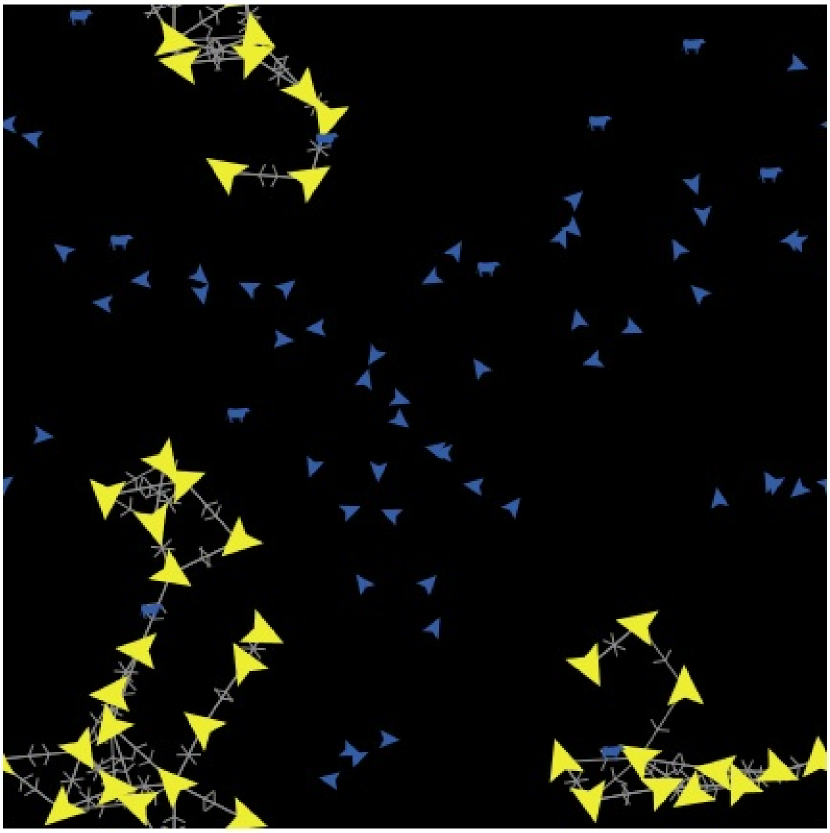

Figure 4: Example of an opinion-lock-in without all agents having the same color. Screenshot of the model world after 11 ticks when the opinion-lock-in is reached with a final number of 38 yellow agents and without a collective-movement-lock-in. The starting variables have been: Number of agents: 100, percentage herding: 10%, percentage yellow: 1%, environment: "yellow is good", vision: 3.5, movement: none, show-links: on, minimum separation: 1, max. align turn: 13.75, max-cohere-turn: 5.5, max-separate-turn: 1.5.

A clear trend can be observed: the higher the percentage of herding agents, the lower the average number of steps until lock-in. However, for visions of 4.5 and 5 at first a slight increase in steps until lock-in occurs up to about a share of 35% or 45% herding agents (Fig. 5, top left).

The reason is that for visions of 4.5 and 5 nearly all agents are reached if the percentages of herding agents are low because swarming is very efficient for large visions. Thus, for low percentages of herding agents they rather obstruct the swarming agents (especially locally) because they do not adapt to changes in the environment like the swarming agents. When the average of the final number of agents with a correct opinion decreases (significantly) (Fig. 5, top right), the average number of steps until lock-in also decreases (with increasing percentage of herding) (Fig. 5, top left) because on average fewer steps are needed to reach fewer agents.

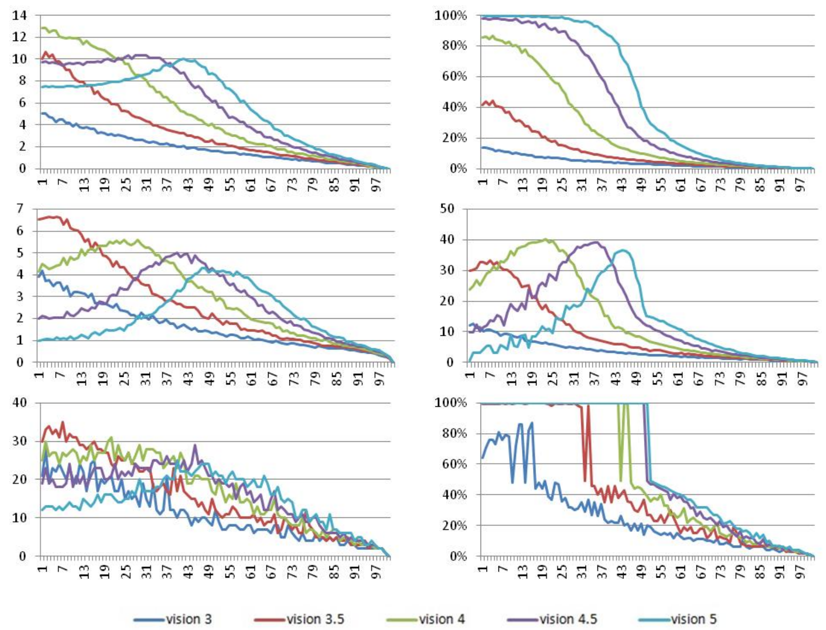

Figure 5: Results of the runs of the *SHE-Model* without movement plotted in dependence on the share of herding agents (x-axis), averaged over 1000 runs for each combination. On the left: average steps till lock-in (top), average standard deviation for steps till lock-in (middle), maximum steps till lock-in (bottom); on the right: average percentage of final yellow agents among the entire population (top), average standard deviation of the number of final yellow agents (middle), maximum percentage of final yellow agents among the entire population (bottom).

The number of steps until lock-in significantly depends upon the spread of agents in the world (Fig. 5, middle left). For visions 3 and 3.5 the standard deviation for the average number of steps until lock-in is largest for small shares of herding agents. In that case the herding agents even have a positive effect on the number of steps because for small visions herding agents can help to reach remote regions and a larger spread more promptly (Fig. 5, top left). If not all agents are reached despite larger numbers of herding agents (Fig. 5, top right) it is likely that either single agents are too distinct and far away, which depends on the spread of agents in the setup and is documented by the standard deviation (Fig. 5, middle right), or not even all herding agents are reached, which implies that less than half of the agents are finally reached (yellow) (Fig. 5, top and bottom right). In the latter case the herding agents can practically block swarming agents and prevent their contact with other yellow agents, diminishing their ability to adapt. Especially if the share of herding agents is close to but still below 50%, the herding agents can block the swarming agents or significantly increase the distance they have to cover before getting in touch with other swarming agents because they have to find their way around the herding agents. If the share of herding agents is larger than 50% they definitely do not adapt to a changing environment themselves in any case (Fig. 5, bottom left). And a large share of herding agents can effectively disconnect and thereby prevent some of the swarming agents from adapting. Thus, the total number of agents that is potentially able to adapt is smaller than the initial group size. Furthermore, they reach a lock-in more quickly, which is particularly the case for large shares of herding agents (Fig. 5, bottom right).

The maximum number of steps until lock-in depends significantly on the spread of agents in the world (Fig. 5, middle left). The maximum number of agents reached significantly depends on the percentage of herding agents and the extent of vision of each agent (Fig. 5, bottom right).

4.2.2 With movement – swarming and herding in a "yellow is good" environment

If movement is switched on in simulations that are comparable to the experiments without movement, the opinion-lock-in is more likely to reach all agents (cf. Figs. 5 and 6, top and bottom right), and in cases of a share of herding agents larger than 50% at least all swarming agents. However, this does not have to be quicker (cf. Figs. 5 and 6, top and bottom left) because more agents need to be reached and the movement clustered in swarms could prevent groups of agents to actually meet the agents of the environmentally preferred opinion. Theoretically, even with movement in a fixed environment there are cases possible with a low density and a relatively small vision that leads to an opinion-lock-in without all agents having the same color or where it takes very long until the color is finally spread completely: For example, let there be a population of two swarming agents of different colors with different headings (if they had the same heading, they would be in a collective-movement-lock-in, which is considered later on). Then depending on the starting distance between the agents, their velocity, and the angle between the lines of their movement, it might take very long until they meet. There may also be cases, in which they never meet because they move periodically. If they meet they adapt to the preferred color resulting in an opinion-lock-in of all having the same color. If they never meet, the result is an opinion-lock-in with different colors.

But if the population is large enough and the density is sufficient for the swarming and herding mechanisms to be effective, the movement leads to quicker lock-ins and in the state of the lock-in all agents have the same color.

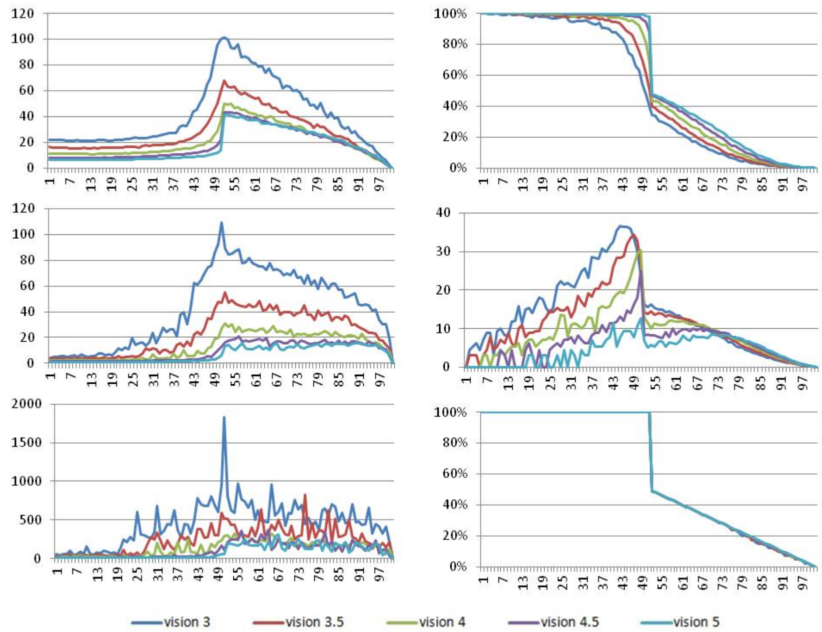

Figure 6: Results of the runs of the *SHE-Model* with movement but without avoiding a lock-in plotted in dependence on the share of herding agents (x-axis), averaged over 1000 runs for each combination. On the left: average steps till lock-in (top), average standard deviation for steps till lock-in (middle), maximum steps till lock-in (bottom); on the right: average percentage of final yellow agents among the entire population (top), average standard deviation of the number of final yellow agents (middle), maximum percentage of final yellow agents among the entire population (bottom).

4.2.3 Movement without avoiding a lock-in

Both the average number of steps (Fig. 6, top left) and the average number of finally reached (yellow) agents (Fig. 6, top right) significantly depend upon the percentage of herding agents. Especially, the maximum number of finally reached (yellow) agents does not depend on the vision anymore at all but only on the share of herding agents (Fig. 6, top right). The standard deviation of the average number of finally reached (yellow) agents (Fig. 6, middle right) depends upon the vision but only if the share of herding agents is lower than 50%. Considering the average or maximum number of steps until lock-in (Fig. 6, middle and bottom left), these are clearly affected by the vision: more steps are needed for smaller visions and fewer steps for larger visions, showing a higher level for shares of herding agents that are larger than 50%.

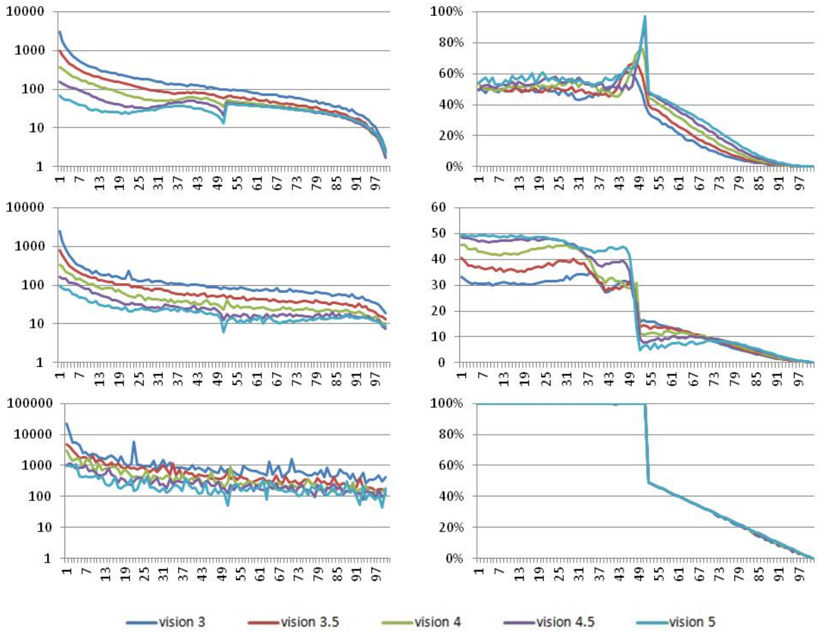

Figure 7: Results of the runs of the *SHE-Model* with movement and in the „avoid a lock-in“ environment plotted in dependence on the share of herding agents (x-axis), averaged over 1000 runs for each combination. On the left in a logarithmic scale: average steps till lock-in (top), average standard deviation for steps till lock-in (middle), maximum steps till lock-in (bottom); on the right: average percentage of final yellow agents among the entire population (top), average standard deviation of the number of final yellow agents (middle), maximum percentage of final yellow agents among the entire population (bottom).

4.2.4 Movement, swarming and herding while avoiding a lock-in

In case of swarming and herding in an "avoid a lock-in" environment the vision hardly matters (Fig. 7) despite the fact that for a vision larger or equal to 4 the logarithm of the average number of steps shows a significant change in behavior at a share of herding agents of 50% (Fig. 7, top left). For a percentage of herding agents smaller than 50%, the average share of finally yellow agents is around 50% for all visions, which is half of the total population size (Fig. 7, top right). This is not a surprise because throughout the simulation the environment can change and it is random which color finally is environmentally preferred when the lock-in occurs. But there is a clear maximum for the average final number of yellow agents for each vision. This maximum is higher and more pronounced the larger the vision is. Furthermore, to reach that maximum a larger share of herding agents is necessary for larger visions, approaching 50% from below. This is due to the fact that the closer the share of herding agents gets to 50% the more likely it is that the entire population enters the lock-in during the very step, in which the herding agents change their mind. And because of the setup rule for the environment to switch to the other color as preferred one whenever there are less than 10% of the agents of that color left, the environment does not change but the population rather locks-in with the preset environment, which is "yellow is good", for a share of herding agents that is close to 50%. The same argument about the environment holds for shares of herding agents that are larger than 50%. Therefore, the graphs for those cases do not differ from the ones with movement without avoiding a lock-in (cf. Figs. 6 and 7).

The standard deviation for the average number of final yellow agents is larger for shares of herding agents that are smaller than 50% than for shares that are larger than 50% (Fig. 7, middle right). And it increases the larger the vision becomes. The latter is especially interesting because for movement without avoiding a lock-in this correlation is the opposite way: it increases the smaller the vision becomes (Fig. 6, middle right). The explanation is that in the setting of "avoid a lock-in" the environmental preference for yellow or blue changes. And for shares of herding agents that are smaller than 50% the environment changes frequently from "yellow is good" to "blue is good" and back. It is more likely that not all agents are finally reached in the final environment right before the lock-in for a smaller vision than for a larger vision, comparable to the other simulations with movement and without a changing environment. But "all agents reached" can differ between zero, which corresponds to the case that all agents are finally yellow in a "blue is good" environment, and 100, which represents the case that all agents are finally yellow in a "yellow is good" environment. Therefore, the spread of results and thus their associated standard deviation is larger for larger visions and smaller for smaller visions (Fig. 7, middle right).

4.3 Implications for the chain of reasoning

4.3.1 Is a lock-in always reached? Are multiple outcomes possible with regard to the final share of colors?

In the *SHE-Model* there are two components that can cause a global lock-in: The opinion dynamics (colors) and the structure (spatial network or collective movement). The lock-in is defined as the inability to adapt to a changing environment. Considering the opinion dynamics, in the *SHE-Model* simulations the ideal type path-dependent agents reach a lock-in when all agents have the same opinion. Or a lock-in can already be reached through structural effects in spatial networks or collective movement if in all discrete parts of the model world all agents locally share the same opinion. In the model simulations run with the *SHE-Model* and analyzed in the previous section a lock-in has always occurred (Figs. 2 and 3).

A non-moving spatial network is structurally inflexible. Depending on the distance of swarming agents and their vision it can happen that there are parts of the network that are blue and others are yellow and there is no way that each of the parts can adapt to the other (Fig. 4). In a moving network this particular situation seems less likely but still there are simulations of the *SHE-Model*, in which opinion dynamics are limited because all agents move in the same direction in one collective movement and the distances between them remain constant (Fig. 3, middle). So there are even cases of collective movement, in which colors may be locally different from the rest of the world but they are unable to spread out when the collective-movement-lock-in is reached (Fig. 3, bottom). Therefore, they cannot adapt to a changing environment anymore and also an opinion-lock-in is reached concurrently.

In the setup of the *SHE-Model* all agents are distributed randomly. And also their heading is initially random. Consequently, just based on the ratio of herding to swarming agents or the initial number of yellow or blue agents it cannot be predicted at which ratio of blue to yellow the agents will lock-in or in which direction the population is finally heading when the lock-in is reached via the collective movement. This guarantees the possibility of multiple outcomes.

4.3.2 Are the opinion dynamics simulated with the SHE-Model path-dependent?

To answer this question, in addition to the previously analyzed tendency towards a lock-in it needs to be assessed whether or not the opinion dynamics are self-reinforcing. Well, they are: If there are more than 50% herding agents in the population, the masses consisting of the herding agents reinforces the predominant color. If there are less than 50% herding agents in the population, the environment enforces the correct color. Swarming agents spread the correct color within their reach and thus reinforce the color via the hierarchical structure of the bottom-up network. The spatial hierarchical structure has the effect that the larger the group of agents of the correct color is, the higher the probability becomes for the rest of the agents to adapt to that color. The lock-in can occur before all agents are reached as described above. But nevertheless, before the lock-in the opinion dynamics are self-reinforcing.

Therefore, the path dependence experiment using the *SHE-Model* is comparable to the path dependence experiments by Arthur (1994). This is important because this proves that the definition of path dependence at the micro level is a coherent extension of the concept of path dependence at the macro level (concept by e.g. Arthur 1994; David 2001).

5 Conclusion

The *SHE-Model* presented in this paper can be used as a local approximation of path-dependent behavior, so the social dynamics that are simulated with the *SHE-Model* approximate real life behavior. This is deduced in a chain of reasoning for opinion dynamics simulated with the *SHE-Model*. Starting with a definition of a path-dependent process, in this paper it is assumed that path-dependent processes exist. On this basis a former deduction (Kominek 2012) is used to deduce an ideal type path-dependent who basically performs following behavior. Therefore, where people in real life are affected by a path-dependent process, their behavior is shaped in a way that they tend to follow others. This following behavior is implemented in the *SHE-Model* to assess what dynamics can evolve from this kind of behavior to address the question: What is the implication of path-dependent processes on opinion dynamics in real life?

For opinion dynamics the chain of reasoning can be completed from the macro to the micro level and back to the macro level including the *SHE-Model* for aggregation. And for opinion dynamics even the opposite direction of conclusion holds true, which implies that the dynamics simulated with the *SHE-Model* can be used as local approximation for path-dependent processes that are in or close to a lock-in. This reveals great chances for real life application even though the *SHE-Model* presented in this paper is only a basic model: Swarming and herding behavior consist of very simple rules. But this is also the strength of the model that even these basic rules lead to a model that fulfills the chain of reasoning that allows the use of the model as an approximation.

In the future the *SHE-Model* can be fine tuned to improve the approximation of real life behavior while at each step of changing the model one needs to check whether the chain of reasoning still holds true to prove its real life applicability. And in case studies applications of the *SHE-Model* can assess how precise an approximation of real life behavior already is using this basic model. This may reveal in which direction further fine tuning is necessary.

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