CHAPTER 5

THE DIFFUSION OF BINARY VERSUS CONTINUOUS BEHAVIOR ON SOCIAL NETWORKS

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ABSTRACT

Diffusion studies investigate the propagation of behavior, attitudes, or beliefs across a networked population. Some behavior is binary, e.g., whether or not to install solar panels, while other behavior is continuous, e.g., wastefulness with plastic. Similarly, attitudes and beliefs often allow nuance, but can become practically binary in polarized environments. We argue that this property of behavior and attitudes – whether they are binary or continuous – should critically affect whether a population becomes homogenous in its adoption of that behavior. Extant models show that only continuous behavior converges across a network. Specifically, binary behavior allows local convergence, as multiple states can be local majorities. Continuous behavior becomes uniform across the network through a logic of communicating vessels. We present a model comparing the diffusion of both types of behavior and report on a laboratory experiment that tests it. In the model, actors have to distribute an investment over two options, while a majority receives information that points to the optimal option and a minority receives misguided information that points toward the other option. We show that when adjacent persons receive misguided information this can hinder convergence toward optimal investment behavior in small networked groups, especially when subjects cannot split their investment, i.e., binary choice. Results falsify our theoretical predictions: Although investment decisions are significantly negatively affected by local majorities only in the binary condition, this difference with the continuous condition is not itself significant. Binary and continuous

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behavior therefore achieve comparable incidences of optimal investment in the experiment. The failure of the theoretical predictions appears due to a substantial level of error in decision-making, which prevents local majorities from locking in on a suboptimal behavior.

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Keywords: Diffusion; continuous; binary; innovations; social networks

INTRODUCTION

Diffusion studies on the propagation of behavior across social networks can be instrumental to understanding and potentially addressing key social problems of our time, such as the demand for large scale adoption of pro-environmental behavior (Flache et al., 2017). Research utilizing social influence approaches (Abrahamse & Steg, 2013) addresses the question of how existing social networks can be used to deliberately initiate and catalyze such transitions. For these approaches to be successful, it is vital to understand the social processes underlying the diffusion of behavior, attitudes or beliefs across a networked population. Social influence can be described as a force that guides individuals' opinions, attitudes, beliefs and behaviors towards those of others (Flache et al., 2017). This process is especially prominent in situations with uncertainty where people can infer their choice from others' prior decisions (Bikhchandandi et al., 1992).

Research on social networks has addressed how different network structures affect information diffusion in social networks (Flache et al., 2017; Friedkin, 2001; Granovetter, 1973, 1978; Uzzi et al., 1993). Most research within the opinion dynamics and social influence literature has considered beliefs or opinions as either binary or continuous without paying much attention to the impact of this difference. It is a largely unresearched question whether social influence processes are fundamentally different when individuals influence each other through binary either-or decisions or when their choices provide more gradual information on the support for one or the other opinion. Yet, as we will show, a comparison of extant models suggests that continuous processes tend to converge on a network-wide behavior while binary processes often get trapped in dense subnetworks. If true, this would suggest the importance of having more continuous ways to communicate information and beliefs on efficient options between people in a network, rather than that people only have binary information on their neighbors beliefs or investment behavior. Potentially, simply asking if someone contributes is less effective for the spread of a decision within a networked group than asking how much they contribute. This can lead to insight for policy makers or designers of diffusion strategies on the importance of making sure that more nuanced information can be exchanged.

Previous research has come to the general conclusion that one can average with continuous opinions, yet binary opinions only allow for adoption of the most common opinions among neighbors (Flache et al., 2017). Much of this argumentation has been based on the famous model of the dissemination of culture by Axelrod (1997) who illustrated how local convergence can generate global polarization. We share this interest for the problem of small groups converging on a minority behavior forming a local majority of persistent diversity. A local majority is a group that is small in comparison to the larger group they belong to, but clustered together in such a way that their views can form a majority in their direct surrounding. We want to investigate if these local majorities of clustered information are more problematic in a binary investment process. More specifically, we argue that adopt-or-not-adopt threshold models (Granovetter, 1978) generate clusters receiving misguided information to form a stable local majority, whereas models of opinion updating (Friedkin, 2001) do not, as they allow a more nuanced form of information spreading. To theoretically isolate the effect of binary behavior we bring together these two modeling approaches in a simple model in which we vary binary and continuous investment processes but keep everything else constant.

We test our prediction with a novel experiment that closely matches our theoretical model. Participants can invest in an uncertain investment opportunity about which they receive some information, while they are connected in a network. Depending on the experimental condition they must either invest all or nothing or they can split their investment. Their investments are then observed by network neighbors. These observations influence investment behavior in a next investment round. In this way we experimentally test and compare the social influence process through binary decision behavior with a social influence process allowing continuous decision behavior. Following Axelrod (1997) and Flache et al. (2017), we predict that, on the one hand, binary investment behavior can stabilize in locally converged subgroups that adopt different types of investment behavior, while some of the subgroups get "stuck" in investment behavior that is inefficient, because they cannot access all the information available in the network. On the other hand, continuous investment behavior is expected to become uniform across the network through a logic of communicating vessels, meaning that continuous investment behaviors are able to display more nuanced information with regards to how confident a decision is.

Summarizing, we address the following research question: To what extent does the continuity of investment behavior increase the chance of convergence to investment behavior that is efficient compared to binary investment behavior in a network where everyone starts with an ambiguous signal about what the efficient investment behavior is?

Continuous Versus Binary Models

We see two types of models in the literature, those based on continuous opinions and those based on the spread of discrete behaviors, with these properties producing different outcomes. The existing social influence literature focusing on situations where over the course of several rounds people update their continuous scale attitudes (Becker et al., 2017; Degroot, 1974; Friedkin, 2001; Lorenz et al., 2011), predicting network-wide convergence on a universal opinion. The spread of discrete behaviors is instead studied in threshold models or models of behavioral contagion (Centola & Macy, 2007; Granovetter, 1978; Rogers, 1983). These models generally predict convergence only in local pockets, with different behaviors remaining present in the network. When comparing them thoroughly it becomes more apparent that the basic property of behaviors and attitudes being binary or continuous is indeed fundamental in determining global versus local convergence.

In the first strand of models, individuals' opinions are formed in a multifaceted process where opinions of other persons enter into the process of opinion formation (Friedkin & Johnsen, 1990). Dynamic opinion models such as the Hegselmann-Krause model argue that reaching opinion consensus due to repeated averaging of opinions among agents is not straightforward as agents normally neither fully adopt nor strictly disregard opinions of other agents but take into account others opinions with different weights given the more complex process of opinion formation (Hegselmann & Krause, 2002). These opinion dynamic models are based on the social learning process of the DeGroot model (Degroot, 1974), that has inspired influence models such as Friedkin's (2001) model of norms, that let individuals opinions and behaviors converge by a process of continuous averaging. In such models, everyone's final opinion is a weighted average of the starting opinions in the network. Hegselmann-Krause agree that in the classical case of equal confidence in others and constant weights put on the opinions of others the reaching of a consensus is typical in the continuous decision process (Hegselmann & Krause, 2002). These models focusing on opinions and attitudes therefore argue that individual's opinions stabilize and converge by a process of continuous averaging and adaptation. Note that, e.g., Hegselmann and Krause (2002) also specify variants of these models on more contested opinions that do not predict convergence (see Flache et al., 2017 for an overview). We think these extensions apply less to our context, because they study explicitly contested issues in which individuals adapt their opinion away from others who think very different, while in our experiment there is clearly one best and one worst situation.

The second strand of models address situations where individuals are deciding between two alternatives, such as adopting or not adopting an innovation (Rogers, 1983), based on some threshold number of other people moving first before people are convinced to behave or invest in a certain way (Granovetter, 1978). Such models study the existence of a critical mass and how collective action can be coordinated (Macy, 1990), and explain how diffusion of binary behavior might depend on external factors. In these discrete models actors are not aware to what degree a person is in favor or against a certain option. All people who are in favor of some option communicate just that one option, even if there are much more nuanced differences in the degree to which they favor that option over another. The model of the dissemination of culture by Axelrod (1997) generates local convergence, with some neighborhoods settling on a different behavior than others. In the model, small connected groups can form a majority locally and become resistant to change.

The above review suggests that previous models of continuous behaviors tend to generate behavioral convergence and those of binary behaviors tend to generate behavioral differentiation: Continuous opinions allow for a form of averaging, compared to binary opinions which only allow for adoption of the most common opinions among neighbors (Flache et al., 2017). However, the models we reviewed also differ in various kinds of other ways. In order to theoretically isolate the effect of binary versus continuous choice on behavioral convergence we now introduce a simple unified model.

THEORETICAL MODEL

We create an influence model in which actors are organized in a network and have to decide what the best choice out of two investment options is, while having ambiguous information about what the best option is. If all actors would pool all information, they would know what the best option is. However, as they can only observe investment behaviors of their neighbors and therefore only have local information, misdirected information can be concentrated locally. Actors in that part of the network might then get stuck in suboptimal behavior. By allowing diffusion of either binary or continuous investment information, we can theoretically test whether such suboptimal outcomes are more likely in parts of the network when social influence is based on binary behavior.

We use four networks (see Fig. 5.1). The networks vary by both clustering – the prevalence of closed triads – and density – the average number of ties. Clustering impacts the possibility for information to remain closed off in a corner of a network. Network density affects the speed of information spread (Buskens & Yamaguchi, 1999; Granovetter, 1973; Uzzi et al., 1993). In all networks, actors have either two or three connections with others (i.e. degree 2 or 3). Density is lowest in network 1 (average degree is 2), intermediate in networks 2 and 3 (average degree is 7/3) and highest in network 4 (average degree is 3). Networks 2 and 3 vary in clustering while having the same degree distribution.

We develop a decision model that we can simulate over these four networks. Within a network, each actor has to decide how to distribute 10 points over two options. In the binary condition they must invest either 0 or 10 points, while they can freely distribute the 10 points in the continuous condition. The two options

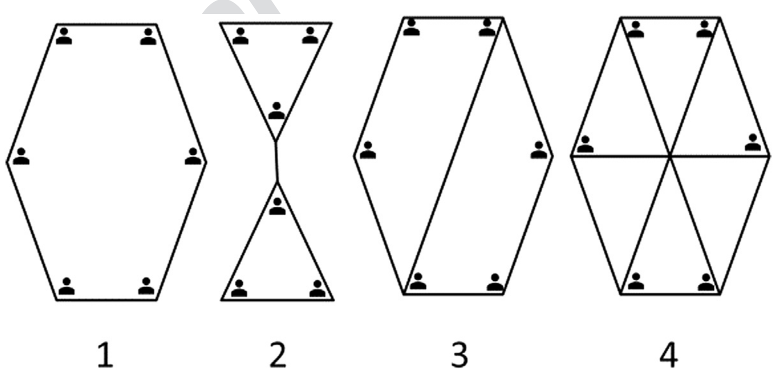

Fig. 5.1. Network 1 Through 4.

are represented by two possible vases that are filled with black and white balls. The vases can be seen in Fig. 5.2 below. One of the two vases is the actual vase that is selected by the computer. We call this vase the "correct" vase. One of the two possible vases has two black balls and four white balls; the other vase has four black balls and two white balls. The balls from one of the two vases are distributed among the actors in the network, without replacement. Actors who receive a black ball can infer that the likelihood they received this ball from the vase with a majority of black balls is 2/3.

From this starting point our model proceeds as follows:[1]

(1) Each actor receives a ball with a color that provides their initial private information as explained above.
(2) Each actor makes an investment decision, either investing 10 points in one vase or 10 points in the other vase in the binary condition or freely allocating the points among the vases in the continuous condition.
(3) Each actor sees the initial investment decisions of all network neighbors and makes a second investment decision.
(4) Each actor sees the second investment decisions of all network neighbors and makes a third investment decision.
(5) Each actor sees the third investment decisions of all network neighbors and makes a fourth and final investment decision.

Each actor gets to keep the points invested in the correct vase while points invested in the other vase are lost. For the binary decision condition, the model assumes that each actor starts with investing in the vase that has a majority of balls that is the same as the color of the ball the actor received. After observing the investments of their neighbors, actors invest in the vase that is most often invested in by themselves and their neighbors together. So if someone with two neighbors invests in the vase with a majority of black balls, but both neighbors invest in the other vase, this actor will start to invest also in the other vase. If a person has three neighbors and there is a tie in terms of investments, so two neighbors invest in one vase and this focal actor and the last neighbor invest in

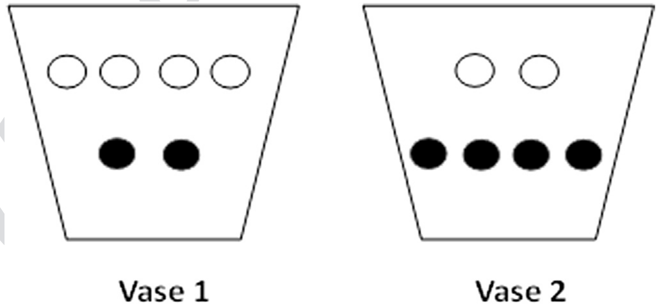

Fig. 5.2. Example of the Vases 1 and 2.

the other vase, this actor will invest in the vase in accordance with their previous investment. This decision process continuous until the fourth and final investment has been made by every actor.

For the continuous condition, we assume that the actors start investing in each of the vases with a proportion of the investment that is equal to the likelihood that this is the actual vase from which the balls are drawn. Given the two vases the balls can be drawn from, this implies that actors invest 2/3 of the total possible investment in the vase that has the majority of balls in the color of the ball the actor received and 1/3 of the investment in the other vase. For the second investment, actors average the proportions of their own investment and that of their neighbors, for each of the vases, which will be their new proportions to invest. From the third investment onward, we assume that actors start to make more decisive investment decisions toward the extremes. The motivation for this decision is that because the average increasingly includes global information, actors should be increasingly confident what the majority ball in the vase was and will thus predominantly invest in that vase. This is done according to the following formula, where "average" is the average over own and neighbors' investments in the previous round and c is the parameter used for capturing the confidence of the actors:

$$\text{investment(round)} = \frac{\text{average}^{1+(\text{round}-2)c}}{\text{average}^{1+(\text{round}-2)c} + (1-\text{average})^{1+(\text{round}-2)c}}.$$

In the main simulations, we use a parameter $c = 2$. In round 2, this leads to an investment decision that equals the average. For example, an average of 0.67 observed in round 1 produces an investment of $0.67^1/(0.67^1 + 0.33^1) = 0.67$ in round 2. In round 3, where the average is more likely to indicate the correct vase, confidence in making the right decision is greater: an average of 0.67 in round 2 is in round 3 transformed into an investment decision of $0.67^3/(0.67^3 + 0.33^3) = 0.89$, while 0.33 produces an investment of 0.11 such that the sum remains 1. Note that if the average = 0.5, the value remains 0.5, which is in accordance with that people who find it equally likely that one or the other ball is the majority ball will not adapt their conviction in either direction.

In Fig. 5.3 we illustrate the simulations, to show that the binary and continuous decision conditions can lead to different outcomes. Two neighboring actors in network 1 with the minority information that are in the binary decision condition will keep investing in the same vase. They will do so as they form a local majority of minority information, whereas the remaining four individuals make a different choice and invest in the correct vase. By contrast, in the same situation of network 1 with clustered minority information of two neighboring actors the continuous decision process provides more nuanced information to the actors and allows a convergence towards the correct investment decision. The continuous decision process communicates to connected actors not only if an actor is investing but also to what degree they are investing. Resulting in all actors in the network to eventually invest into the correct vase.

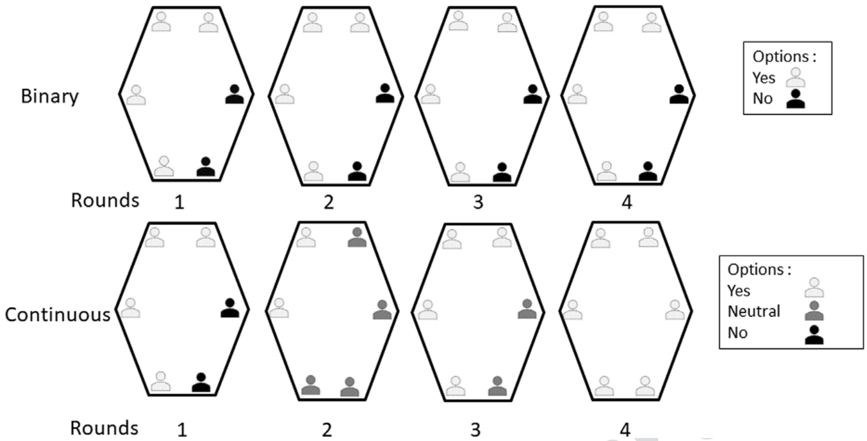

Fig. 5.3. Local Majorities and the Diffusion Process.

Using this theoretical model, we conducted simulations to reproduce the diffusion process in our four networks distinguishing between the binary and the continuous scenario. We run this process by randomly distributing the six balls in the network for 10,000 times and recording the proportion correct final investment by all actors, i.e., the proportion of points that were invested by the group into the vase that was indeed the vase from which the balls were drawn in the last round of the simulation. We split the simulation results by our four networks, by whether the decision was continuous or binary and by whether there was a local majority of minority balls. As explained earlier, a local majority refers to two neighboring nodes receiving the two minority balls. Table 5.1 shows that in case of no local majority in all conditions, actors quickly converge on investing in the correct vase. However, if there is a local majority, this does not happen, especially in the binary condition. Looking in more detail at the simulation, the local majorities insist on choosing the wrong vase even if one would go beyond four rounds of investments. In the continuous condition, there is still convergence in networks 1, 3 and 4 and only in network 2, the clustered actors also stick to the wrong vase if indeed the minority balls are given to two nodes in the same group

Table 5.1. Simulated Average Proportion Correct Final Investment Per Network, Per Condition and Depending on Whether the Initial Balls With the Minority Color Where Given to Two Connected Actors (Local Majority).

Network	Binary		Continuous	
	Local majority	No local majority	Local majority	No local majority
1	0.67	1	0.84	0.94
2	0.57	1	0.69	0.96
3	0.67	1	0.90	0.95
4	0.67	1	0.97	0.96

of three. Following the literature indicating that density should speed up the process of information (Granovetter, 1973), or behaviors (Buskens & Yamaguchi, 1999; Uzzi et al., 1993) spreading among a networked group, we control and check for such an effect in the analyses. Our simulations, however, do not indicate a clear density effect. Therefore we do not formulate hypotheses about density. We check for density effects in the experiment by including dummy variables per network in the analyses. Below is an overview of our simulations used to derive our hypotheses.

Table 5.1 shows that local majorities hinder the social influence process and predominantly in the binary condition. While local majorities also slow down consensus formation in the continuous scenario, only in the clustered network 2 disagreement is persistent under our assumptions even in the continuous scenario. This brings us to the following hypotheses:

H1. In networks in which a local majority receives the minority ball, fewer people will invest in the correct vase than in networks without a local majority receiving the minority ball.

H2. The difference between a local majority and no local majority is larger in the binary condition than in the continuous condition.

H3. In the more clustered network 2, a local majority receiving the minority ball leads to fewer people investing in the correct vase than when the same scenario occurs in another network.

METHODS

Design

Experiment

We compare the diffusion of a binary and a continuous behavior in a computerized experiment in the Experimental Laboratory for Sociology and Economics (ELSE) at Utrecht University. We assigned 222 participants to groups of 6. Each group played 8 "investment games" following our theoretical model. The composition of the groups did not change over the 8 games, but group members could not identify who was who in a subsequent game. 114 participants started playing the investment games in each of the four different networks making continuous investment decisions. This is followed by the playing of another four investment games in each of the networks, this time making binary decisions. 108 participants started with making binary decisions and then made continuous investment decisions.

Setup

Participants were embedded in a social network of six participants but had to make an individual investment decision with an uncertain outcome. Participants were informed that they had to choose how they would like to invest their points in one of two vases, with one being the correct one and the other option being wrong, closely following our theoretical model. Every point invested in the right vase was added to the payoff of the participant. Every point not invested in the right vase was lost for the participant. 10 points earned by the participant had a value of 50 euro cents. Since each participant played eight games with four investment rounds each, they could earn up to 320 points, which would equal to 16.00 euros. Each participant received a minimum of 5 euros for participating even if they earned less than 100 points.

The vases, which can be seen in Fig. 5.2 above, are essential to the game and show a distributions of black and white balls, and they are the information available to each participant in each group. The white and black balls represent the possible distributions of balls. Each participant of a group of six received one of the six balls from either vase 1 or vase 2 at the beginning of the game, and knew that all participants received one ball from one vase without replacement. This ball provided all participants with some information about which of the two vases is applicable to their group. Each participant knew that the six balls from the vase applicable to them had been distributed to their group randomly without replacement. The participants' task was to speculate what vase applies to their group. Each participant was informed that they could not see all participants' decisions but only their own decisions and the ones of the participants they were connected to, their network neighbors. Given our four network structures (see Fig. 5.1), a participant saw the investment decisions of either two or three other participants they were connected to in their group. The participants were not informed about the specific network structure they found themselves in, only that they were playing in a group consisting of six participants.

The color of the ball that a participant received provided them with the initial predisposition as to which of the two vases was likely to be the correct one, as in each vase there was a clear majority of white or black balls. Given that the ball color was the only initial information a participant had, we would expect a participant receiving a white ball to invest into vase 1 and a participant receiving a black ball to first investment into vase 2. Participants were then told that each game consisted of four rounds. In the binary condition, the participant could then decide to invest 10 points into vase 1 or 10 points into vase 2. After participants saw the decisions of the participants they were connected to, they again had to decide where they wanted to invest 10 points. The participants repeated this procedure for another three rounds until the first game was finished. The same procedure was followed in the continuous condition, with the difference being that participants were able to choose any number from 0 up to and including 10 to invest in either vase. The remaining amount was automatically invested in the other vase. All participant groups played all four networks in a randomized order. In order to test the importance of the difference between the continuous and the binary diffusion processes within networked groups especially for groups with local majorities receiving the minority ball, we ensured that there was a sufficient number of cases where two adjacent persons received the minority balls. We accomplished this by not drawing individual balls uniformly randomly from
Q2 the vase (which would lead to a large majority of cases without a local majority, but instead weighting the probability of each draw such that distributions with and without local majorities occurred about equally often.

VARIABLES

The dependent variable is *proportion correct final investment:* the proportion of points invested by a group in the correct vase at the end of each of the four rounds of the game.

Independent variables: *local majority:* dummy variable indicating whether two connected actors received the two minority balls (1) or not (0); *continuous:* dummy variable whether the decision process was continuous (1) or binary (0); *network X*: dummy variables for the network in which the decision process took place with $X = 1, 2, 3, 4$.

RESULTS

Local Majorities

Given that 222 participants played the investment game eight times, we have 1776/6 = 296 group level observations. The participants were equally spread among local and no local majorities with 140 group level observations (47.3%) where there was no local majority and 156 observations (52.7%) where adjacent persons received the minority balls. Fig. 5.4 shows *Proportion correct final investment* for these two situations. Participants were significantly less successful in investing in the correct vase if a local majority received the minority balls initially ($N = 296$, Mann-Whitney ranksum test, $z = 2.51$, $p = 0.012$). Thus, the

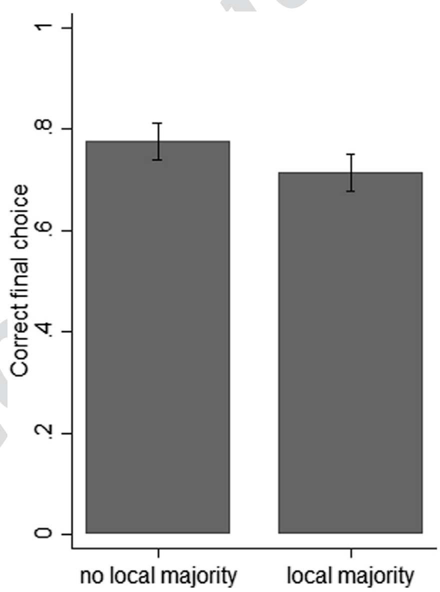

Fig. 5.4. Average Proportion Correct Final Investment With and Without a Local Majority in a Network of Six Participants.

proportion of correctly invested points in a networked group is significantly less when there is a local majority situation in their networked group than when they play the game without adjacent participants receiving the minority information at the beginning of the game. This supports hypothesis one.

Binary Versus Continuous Diffusion

When comparing the binary and continuous decision process for local majority and no local majority situations, we observe the difference in the success rate for investing in the final round for the binary decision process ($N = 148$, Mann-Whitney ranksum test, $z = 2.54$, $p = 0.011$), but not for the continuous decision process ($N = 148$, Mann-Whitney ranksum test, $z = 0.84$, $p = 0.402$) as can be seen in Fig. 5.5 below.

This suggests that diffusion for the continuous decision process is more resilient to local majorities than the binary decision process. To make these observations more precise we do a multivariate analyses and have a closer look at the specific differences for each network, between the conditions and ball distributions with and without a local majority. Fig. 5.6 illustrates the proportion correct final investment, when separating the local and no local majority situation and comparing the continuous and the binary decision process for each network. Here we are especially interested in network 2 as it is the network with clustering.

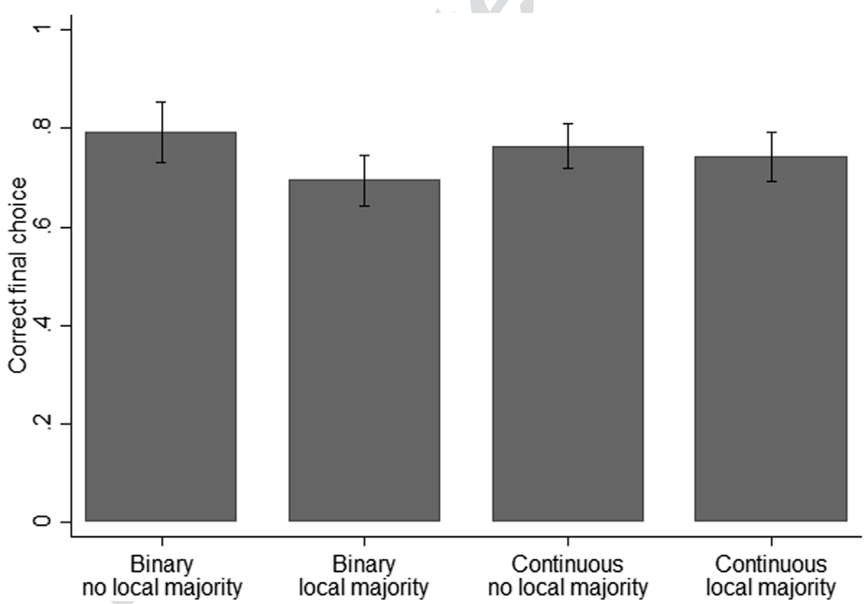

Fig. 5.5. Comparing the Average Proportion of Correct Final Investment of Participants Making Binary or Continuous Choices for Groups Starting With and Without a Local Majority.

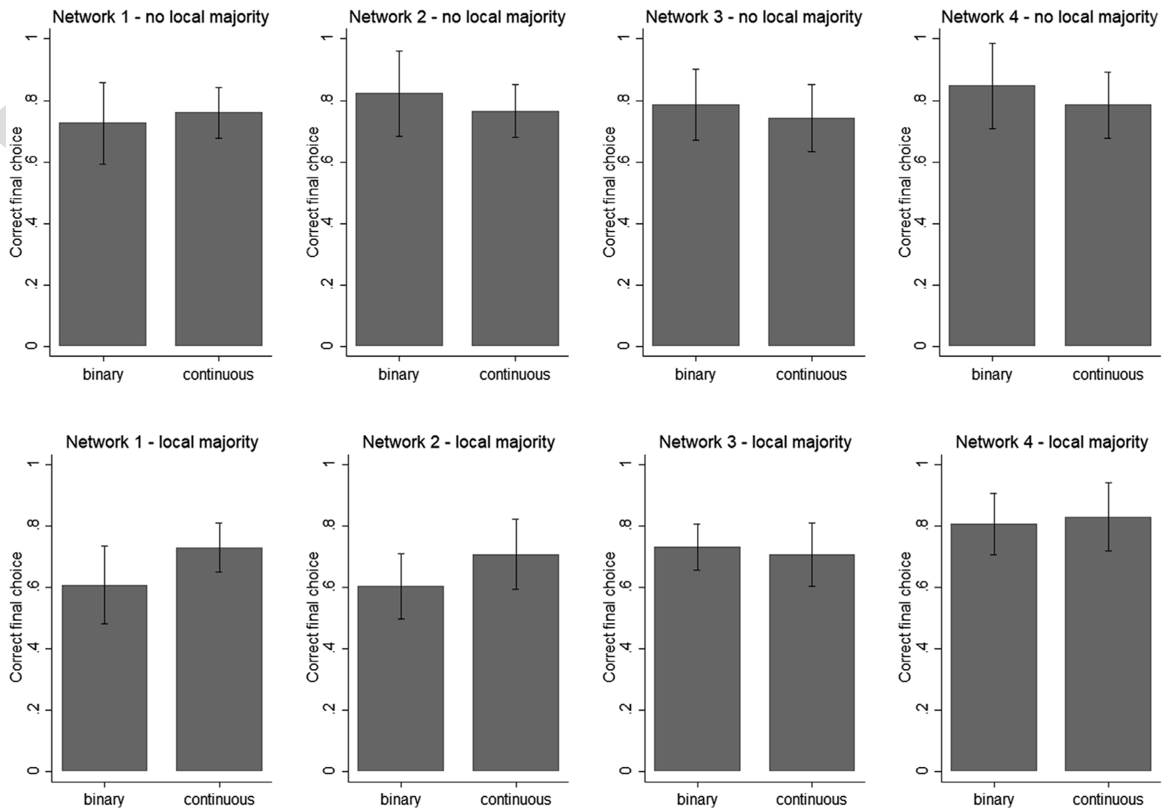

Fig. 5.6. Comparing the Average Proportion Correct Final Investment Among All Networks With Binary and Continuous Investments and With and Without a Local Majority.

We do not find a difference in proportion correct final investment, when separating by the local majority situation and comparing the continuous and the binary decision process by each network. We do not find such a difference when comparing the binary versus the continuous decision process for groups of participants playing in a local majority in network 2 ($N = 39$, Mann-Whitney ranksum test, $z = -0.97$, $p = 0.334$). This test however only indicated that there is no significant difference if participants played in the continuous or binary condition for when there are situations of local majority, however when we look at the conditions separately we do find a difference. Looking at the binary decision process specifically, we do see that there is a significant difference between the local and no local majority situation in network 2 ($N = 37$, Mann-Whitney ranksum test, $z = 2.46$, $p = 0.014$). Though when we look at the at the continuous decision process specifically, we do not see a difference between the local and no local majority situation in network 2 ($N = 37$, Mann-Whitney ranksum test, $z = 0.96$, $p = 0.337$).

A linear regression analysis is done to further test if the effect of local majorities holds and to see if there is a significant difference between the binary and the continuous decision process when there is a local majority. Because the same group of participants played eight games, we need to correct for clustering of observations over these groups. We do not correct for the session level, because the different groups within sessions do not interact with each other. As it can be seen in Table 5.2, Model 1 is testing the main effect of a local majority and the continuous decision process. There is a significant effect of local majorities, which supports our first hypothesis (*H1*) that local majorities cause about 6% less points invested in the final round into the right vase ($B = -0.063$, $p = 0.015$). There

Table 5.2. Regression of the Proportion Correct Final Investment Per Group by Local Majority, Continuous Versus Binary Decision Process and the Network (Standard Errors Are Corrected for Clustering Over Observations, 8 Observations Per Group).

	Model 1	Model 2	Model 3
Local majorities	−0.063* (0.024)	−0.105** (0.038)	−0.056 (0.041)
Continuous	0.011 (0.026)	−0.033 (0.044)	−0.030 (0.044)
Continuous × local majority		0.084 (0.061)	0.083 (0.060)
Network 1	(Ref)	(Ref)	(Ref)
Network 2	0.016 (0.036)	0.015 (0.036)	0.018 (0.036)
Network 3	0.039 (0.029)	0.039 (0.029)	−0.010 (0.038)
Network 4	0.112*** (0.032)	0.114** (0.032)	0.065 (0.040)
Network 2 × local majority			−0.096 (0.053)
Intercept	0.729*** (0.037)	0.754*** (0.041)	0.775*** (0.045)
R^2	0.055	0.063	0.075

Note: $N = 296$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$ (two-sided).

does not seem to be a significant difference between the continuous and the binary decision process in general ($B = 0.011$, $p = 0.658$). Model 2 adds the interaction between being in a local majority situation and whether people are in the continuous or binary condition to test hypothesis 2. Although the proportion investment in the correct vase is 8% higher with a local majority for the continuous process compared to the binary process (*H2*), the difference is not significant ($B = 0.084$, $p = 0.174$). When checking for a density effect we do observe that the proportion of points invested into the correct vase in the last decision round is significantly higher in the denser network 4 when compared to the less dense network 1 ($B = 0.11$, $p = 0.001$). Note that networks 2 and 3, which have average densities are as expected also between networks 1 and 4. Model 3 tested whether the effect of local majority is different for the clustered network 2. The negative effect of local majority is only marginally significantly stronger in network 2 compared to the other networks jointly although it tends in the right direction ($B = -0.096$, $p = 0.075$). Also if we include interactions of local majority with all networks separately, no significant differences are found (analysis not reported). We therefore do not find support for our third hypothesis (*H3*).

Table 5.3 shows the actual average proportion correct final investment, per network, per condition and depending on whether the initial balls with the minority color where given to two connected actors (local majority). This table can be compared to the simulated data of Table 5.1. For completeness, Fig. 5.B1 in the Appendix B shows an overview of how points invested into the correct vase develop over rounds, illustrating that convergence on the correct vase is hindered mostly with a local majority for the binary decisions in networks 1 and 2. Table 5.3 also illustrates that the largest deviations from the simulation can be found for the cases within a local majority in which the proportions invested in the correct vase are considerably lower than predicted. This reduces the differences between the networks with and without local majority, which might help understand the weak effects found in our analyses. We return to this point in the discussion.

Table 5.3. (Actual) Average Proportion Correct Final Investment Per Network, Per Condition and Depending on Local Majority.

Network	Binary		Continuous	
	Local majority	No local majority	Local majority	No local majority
1	0.61 (0.062)	0.73 (0.063)	0.73 (0.038)	0.76 (0.041)
2	0.60 (0.052)	0.82 (0.066)	0.71 (0.054)	0.77 (0.041)
3	0.73 (0.037)	0.79 (0.054)	0.71 (0.049)	0.74 (0.052)
4	0.81 (0.050)	0.85 (0.063)	0.83 (0.052)	0.78 (0.053)

DISCUSSION

Small groups sometimes fail to converge on optimal behavior forming a local majority of persistent suboptimal behavior. To our knowledge, we are the first to directly investigate in a systematic laboratory experiment if these local majorities are more problematic in a binary influence process than in a continuous influence process. More specifically, we compare two well-known families of models, namely binary diffusion models (Granovetter, 1978) which permit clusters of failed adoption, with models of opinion updating (Friedkin, 2001) in which convergence to consensus is practically inevitable in connected networks. We created a simple model in which we compare binary and continuous investment processes. Based on our simulations of this model, it was predicted that the phenomenon of local majorities where adjacent persons receive misguided information indeed hinder the diffusion toward optimal investments in a networked group predominantly in binary diffusion processes. Our results are in line with the prediction that local majorities hinder investments in the best option. Our results however are not in line with our other theoretical predictions: the binary process does not exhibit significantly less optimal investments with local majorities than the continuous.

When comparing the decision process among the clustered network 2 and the other three networks the negative effect of local majority is not significantly stronger in network 2 compared to the other networks jointly. When checking for a density effect we do observe that the proportion of points invested into the correct vase in the last decision round is significantly higher in the denser network 4 when compared to the less dense network 1. For policy makers it can be noted that it does not seem critical whether a decision process is binary or continuous. However, local majorities are problematic and we provide evidence that they hamper the spread of a correct investment.

The failure of our theoretical predictions might be related to the empirical decision process of human participants being more noisy than the simulated agents. The substantial level of deviations of the participants compared to was modeled prevents local majorities from locking in on a suboptimal behavior. On the other hand, it also slows down the diffusion to the optimal situation when no local majorities are present. Our macro level behavioral assumptions do not take into consideration that an initial bias favoring one of two options can survive over an extended period of further sampling (Harris et al., 2020). Similarly, it has been shown that there is a form of noise in social networks that prevents populations reaching consensus, due to an endogenous noise where agents desire to maintain some uniqueness in their opinions and actions (Stern & Livan, 2021). Our experiment is sensitive to such forms of noise. Our simulations did not include any noise, but when we update our simulations to incorporate noise our new predictions fit better with the empirical observations and reflect the average proportion of points invested in the correct option per network, per condition and depending on local majority. Table 5.B1 in Appendix B shows results for an updated simulation that includes decision noise. This table also illustrates that differences between conditions attenuate with noise, which might be an explanation that most predicted differences are not significant in the experiment.

A limitation to our research is that our data collection had months between experiments due to the corona epidemic forcing us to close the ELSE lab for several months in 2020 and 2021. Data collection started in October 2020 and took until October 2021. The experiment could not be too extensive and that was one of the reasons that we limited the number of decision rounds per game to four, while due to the noise in the process a longer period to reach consensus might have been illustrative. Future research should investigate if more power in the form of more participants playing and more rounds of investing within each decision game, could provide the continuous decision process more time for achieving homogenous adoption. Additionally, it would be interesting to observe which diffusion process is quicker in achieving homogenous adoption. Is binary quicker when people are well connected as it leaves no availability for ambiguous answers?

BIOGRAPHICAL NOTES

Philipp Schneider is PhD student at the Department of Sociology/ICS, Utrecht University. He is part of the SCOOP research program and his current research focuses on understanding the conditions under which residents can be successfully mobilized to partake in the energy transition.

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DISCLOSURE STATEMENT

The authors declare no competing interests. There are no financial or non-financial interest that have arisen from the direct applications of our research.

DATA AVAILABILITY STATEMENT

The data are available upon request.

CODE AVAILABILITY STATEMENT

The code are available upon request.

ETHICAL APPROVAL STATEMENT

We obtained approval and a waiver of informed consent by the Ethics Committee of the Faculty of Social and Behavioral Sciences of Utrecht University. The approval is filed under number 20-477.

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NOTE

1. This is a simplified version of a decision situation which can be found in other experiments such as the multi-armed bandit problem (Hofstra et al., 2015), for which Vriens and Corten (2018) explained that the typical individual learning strategies of exploration and exploitation are not always possible under certain conditions resulting in individuals to rely on social learning.

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APPENDIX A. EXPERIMENT INSTRUCTIONS

EXPERIMENTAL LABORATORY FOR SOCIOLOGY AND ECONOMICS

Universiteit Utrecht

INSTRUCTIONS

Welcome! These instructions are the same for all participants. Please read them carefully. If you have any questions, please raise your hand. One of the experimenters will approach you and answer your question. You can earn money by means of earning points during the experiment. The number of points that you earn depends on your own choices. At the end of the experiment, the total number of points that you earn during the experiment will be exchanged at an exchange rate of: *20 points = 1€*. The money you earn will be rounded up to the next 50 euro cents and paid out in cash at the end of the experiment. There is a minimum payment of 5 euros. Other participants will not see how much you have earned. During the experiment you are not allowed to communicate with other participants. Please turn off your mobile phone and put it in your pocket or bag. You may only use the functions on the computer screen that are necessary to carry out the experiment.

OVERVIEW OF THE EXPERIMENT

In this experiment, you will play investment games that involve you and 5 other participants. You play in networks that have been programmed to connect groups of 6 computers in the lab. There are 4 different ways the computers will be connected to each other, which are the 4 networks of this experiment. All participants will be randomly assigned to a position in the network. You will only be able to see the decisions of 2 or 3 other participants in your network. You will therefore at no point during this experiment see the investment decisions of all 6 participants of your network. You have to make your investment decisions based on the information that you receive at the beginning and the investment decisions of the 2 or 3 other participants that you will see. The aim of each game is to find out which of the two vases represented by Fig. 5.A1 is the vase your group of 6 participants has been assigned to. You earn points by choosing the correct vase.

As you can see, the vases show distributions of black and white balls and they are the information available to your group. You do not know which of the two vases has been selected for your network. Each participant in your network receives one of the balls randomly drawn from the selected vase, without replacement. Your task is to make investment decisions based on what vase you think was selected for your group. The color of your ball as well as the investment decisions of the 2 or 3 other participants in your network may lead you to think a particular vase was selected. In total you will play 8 games with each vase having a 50% chance to be drawn and every game consisting of four rounds of investment decisions each worth 10 points.

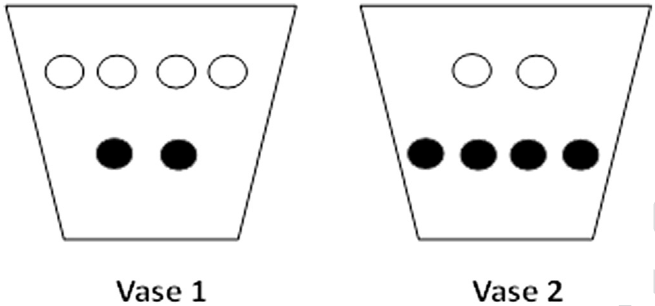

Fig. 5.A1. The Vases of the Game.

Each game is therefore worth 40 points which are divided equally over the 4 rounds of the game. In the first round of each game, you will receive a ball from the selected vase, either white or black, after which you have to make a decision whether to invest points in Vase 1 or in Vase 2. After this first round, you will see the first round decisions of the 2 or 3 other participants that you can see in your network, and they will see your decision. You then make your second investment decision, deciding to invest in Vase 1 or in Vase 2. The same procedure is repeated in the third and then in the fourth the final round of each game. Every point you invested in the correct vase you get to keep and will earn you real money, every point invested in the wrong vase will be gone.

EARNINGS

For every correct investment decision you make you will get to keep the invested points, since you will play 8 games with 4 investment rounds each you can earn Q3 up to 320 points in total. You can therefore earn up to 16,00 Euros in this experiment, and at least you will always get 5 Euros for participating.

END OF EXPERIMENT

You must fill out a questionnaire at the end of the experiment. You will then be asked to collect your payment one participant after each other at the front of the lab. If you have any questions, please raise your hand and the experimenter will come to you. Thank you very much for participating in this experiment.

OVERVIEW OF THE SESSION

The experiment lasts about *1 hour*. The 8 games are played in 2 stages, each stage consisting of 4 games all in different networks. Before you play the first 4 games, we will first ask you to answer some quiz questions about the game.

The investment decision questions will appear multiple times throughout the experiment, to be precise for every of the 8 games you will be asked to make 4 investment decisions. You do not have to be consistent with your answers to these questions, as each of the four games is played in a different network.

After this first stage of 4 games, you will receive new instructions on your computer screen for the second stage of the experiment. The second stage of the experiment is very similar to the first stage, both in length and in what is required of you as a participant.

Because you play together with other persons, you will sometimes have to wait until the other persons have made their decision. These waiting times are incorporated in the total expected duration of 1 hour for the experiment.

Please go back to the computer screen if you have finished reading these instructions and click Continue.

APPENDIX B. SIMULATIONS ADAPTED WITH DECISION NOISE

Table 5.B1. Simulations – Proportion Correct Final Investment in the Network in the Correct Vase Including Noise.

Network	Binary		Continuous	
	Local majority	No local majority	Local majority	No local majority
1	0.62	0.69	0.63	0.65
2	0.59	0.70	0.61	0.66
3	0.61	0.72	0.64	0.67
4	0.63	0.7	0.67	0.67

Fig. 5.B1 shows an overview of how many points were invested on average in the correct vase, for each round. The line of short black dashes and the line of long gray dashes show how the local majority conditions generally lead to less correct points invested. With the line of short black dashes representing the binary local majority condition which clearly obstructed the spread of the correct investment decision in Networks 1 and 2.

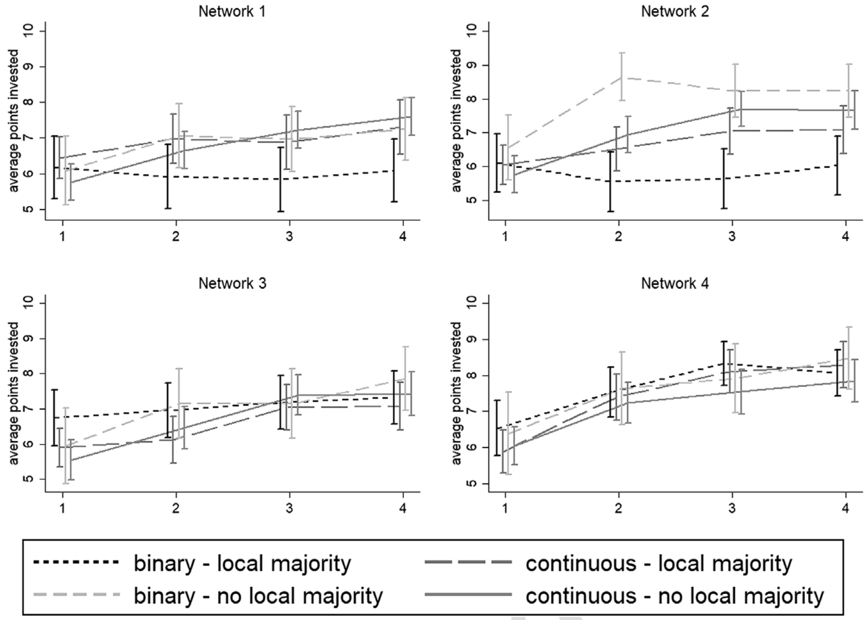

Fig. 5.B1. Comparing the Average Points Correctly Invested for All Four Networks for Binary and Continuous Investments and With and Without a Local Majority.

Author Query Form

Queries and/or remarks

[Q1]	As per style, there should be a minimum of 6 and a maximum of 10 keywords. Please provide remaining keyword(s).
[Q2]	Please provide closing parenthesis for this opening parenthesis.
[Q3]	Please check the numeral value 16,00.

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