Releasing the brake: How disinhibition frees people and facilitates innovation diffusion

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Abstract: In this paper, we focus on a new aspect of the diffusion process that can help explain the virality of online new product campaigns. We propose that the sense of anonymity associated with being online liberates people from impression management concerns. This facilitates individuals to express themselves more freely at the individual level, in turn having a major accelerating on diffusion at the group level. We tested our hypothesis with a novel experimental paradigm as well as via an agent-based model (ABM). Participants in the experiment were tasked with coordinating on a product selection and confederates acted as a minority trying to spread the innovative product. The ABM mirrored the experimental game using an agent-level social payoff function. Across both empirical settings, we found that individuals are more likely to explore novelties in anonymous settings, which allows societies to reach the tipping points that are required for innovations to diffuse more easily.

Keywords: diffusion, impression management, agent-based model

Track: Consumer Behaviour

1. Introduction

Inspired by the research on how viruses spread across networks of individuals, scholars have first tried to understand and predict social diffusion of innovations (e.g. new products) via factors that play out on the aggregate level (Bass, 1969). Examples of studied include (1) the relative benefit of an innovation over its predecessors and (2) the role of network structure (Rogers, 2010). While later research incorporated certain individual level factors that are unique to humans, including social influence (see Peres, Muller, & Mahajan, 2010), the literature stream is still mostly void of examining the role that impression management concerns (Leary & Kowalski, 1990) play in an innovation diffusion process. The awareness that others can witness one's adoption choices can have an important impact on the individual's decision to adopt or not. For example, individuals may strategically refuse an innovation that they privately like in order to appear to others as consistent and cooperative. In order to address this gap, we examine how the diffusion process differs between environments where these impression concerns are more or less pronounced, viz. between online and offline environments.

When individuals interact offline—i.e. when they are identifiable and feel exposed—they are in a behaviourally inhibited state. In this state, adopting an innovation is risky for the individual since it breaks the consistency of one's behaviour and contradicts the current majority, both actions can thus create an unfavourable impression (Leary & Kowalski, 1990) and are perceived to lead to social exclusion—a consequence people fear deeply (Cialdini & Goldstein, 2004). Therefore, when inhibited, individuals tend to avoid breaking away from an established consensus until they consider it socially safe to do so. On the other hand, when people interact online—i.e. when they feel anonymous and socially disconnected—they become more disinhibited (Hirsh, Galinsky, & Zhong, 2011). Disinhibition frees individuals from social considerations such as consistency and, consequentially, removes the perception of the threat of exclusion (Kiesler, Siegel, & McGuire, 1984). Thus, disinhibition, arising in online environments, increases the likelihood of individuals adopting innovations early, when, offline, it would have not yet been socially safe to do so.

These individual-level findings are quite established in psychological literature (Hirsh et al., 2011), but we take a step further and consider the macro implications of disinhibition—i.e. how disinhibition may impact the diffusion speed across a social network over an extended period of time. In any diffusion process, people can typically take up one of three social roles, namely of innovators, of early adopters (hereafter referred to as explorers) or of late adopters (hereafter referred to as followers) (Rogers, 2010). Innovators are individuals who are the first to notice the upsides of an innovation and actively push for its enactment, while the explorers and followers adopt the innovation at later stages of the diffusion process, often as a direct result of the pressure from the innovators. However, there is an important psychological difference between explorers and followers. On the one hand, explorers are individuals who, regardless of the current degree of innovation adoption, are willing to take risk and try out new alternatives. On the other hand, followers are individuals who only adopt an innovation when it is socially safe to do so, i.e. when it is evident that everyone else is also adopting it. Disinhibition, we hypothesise, may thus have a substantial implication for diffusion dynamics—i.e. when disinhibited, individuals are more likely to take on the role of explorers and try out innovations early. Additionally, since any increase in the proportion of explorers within a social network can lead to sizable changes in the speed of diffusion, we further hypothesise that groups in disinhibited environments adopt innovations faster.

2. Methodology

2.1. The experimental study

To empirically examine our hypothesis, we required an experimental game that fulfils multiple criteria. Since no experimental paradigm exists yet that would fulfil criteria we set, we developed a novel experimental paradigm called the New Product Game (NPG) that aims to closely simulate a real-life diffusion processes. In the coming paragraphs, we will explain the unique design choices we implemented to address our requirements.

First, in order to capture a diffusion process that occurs over time, NPG is structured as a multi-round group game. Here, experimental groups consist of 8-16 participants that play the game seated together in a room. In each group, the participants' task is to enact that they are a part of a board of directors and decide which of two new products, named Tao and Eta, to launch. Having only two choices allows for a clear status quo and innovation alternative to be defined within the group. The specific way in which participants are asked to coordinate to reach a consensus is as follows. In each round, each participant first independently chooses one of the two products. Then, she observes the proportion and nicknames (which each person chooses before the game) of people that chose each of the two products in that round. The round then ends. The game continues until the round in which all participants choose the same product—i.e. until the group reaches a full consensus on which new product to launch (or until round 24 in the case that no consensus is reached).

Second, within the given setting, we manipulated anonymity (vs identifiability) to be able to discern the effects of disinhibition on diffusion. We did so by seating all participants together in a room arranged in a circle facing inwards. In both conditions, every participant could see every other participant during the game and was explicitly told not to physically communicate with each other in any way. The manipulation was induced on a group level by, in the *identifiable groups*, giving participants nickname tags that were physically in front of the person, making it possible to know which person chose which product in a specific round of the game. In the *anonymous groups*, on the other hand, participants did not receive physical nametags and could thus not have their decisions linked back to them. A manipulation check shows that we successfully manipulated anonymity as the individuals in the identifiable groups were aware that others can see their choices and felt exposed to a greater extent (Anonymous, $M = 5.37$, $SD = 1.99$; Identifiable, $M = 7.56$, $SD = 1.65$; $t\ (81.3) = 5.55$; $p < .001$; $d = 1.20$).

Third, to be able to observe a natural diffusion process, we first include an organic establishment of a status quo in the game and then introduce a group of innovators (i.e. confederates) trying to overthrow it. In each group, 25%-34% of participants are confederates whose decisions were pre-programmed (following Centola, Becker, Brackbill, & Baronchelli, 2018). However, the confederates are still physically placed in the same room as players and given a separate task during the game so as not to evoke any suspicion in regular participants. The algorithm that determines the confederates' choices operates in two separate stages. At the beginning of the game, all but one confederate choose the majority-supported product and thus help establish an initial consensus among the participants. Then, after all regular participants (i.e. non-confederates) choose the same product for the first time (i.e. initial consensus round), all confederates start choosing the opposite product and continue to do so until the end of the game. This way, in the second part, confederates provide a minority of innovators that contradicts the status quo (i.e. initial consensus) by adopting the innovation.

Fourth, social stakes in an experimental situation are usually low. Therefore, to amplify the naturally occurring social considerations and incentivise regular participants for exhibiting change-related behaviours, we used monetary bonuses. The size of the bonus they received in the NPG is dependent on two factors. On the one hand, a pool of money is available for group payoff and decreases with each new round of the game played, which motivates individuals to coordinate and reach a consensus quickly. On the other hand, at the end of the game, each participant receives a fraction of the group payoff that is proportional to the number of rounds in which she chose the innovation compared to the number of times everyone in the group chose it. This aspect motivates individuals to remain consistent in their choices throughout the game and to predict which product choice will become the final consensus. In sum, these two aspects of the incentive system induce participants with conflicting change-inducing and change-inhibiting motivations, while at the same time producing a situation with no ex-ante dominant strategy, forcing participants to pay attention to the induced social considerations.

We ran the experimental study in the research lab at our faculty in September and November 2019. One hundred and twenty-three students participated in our study, 88 in the role of a regular participant and 35 in the role of a confederate. Note that only the choices of regular participants are used in our analyses. The final study sample thus consisted of 48 (54.5%) female and 39 (44.3%) male participants. Their average age was 22, ranging from 18 to 32. A majority of participants held a secondary educational degree (n = 49), while there were also some participants with a post-secondary (n = 4) and a university (n = 34) education level. One participant refused to share their demographics. The participants were distributed among 10 experimental groups, with 5 groups playing the game in each of the two conditions.

2.2. The agent-based model

Basing on the NPG, we further defined an agent-based model (ABM), which is a popular approach to study diffusion. In our model, each agent will interact with many other agents and then update her decision (from two possible choices, e.g. Eta or Tao) in a repeated process. With high probability, the agent will choose the decision to maximise her social payoff defined by a function below, but has a nonzero probability of selecting the other decision (due to e.g. mistakes, or random behaviour). This is a standard noisy best-response dynamic in evolutionary game theory (Blume, 1993).

The strength of ABMs lies in the fact that at the agent (individual) level, the model can be simple, but via interactions, the group of agents can display complex collective behaviour, such as fast diffusion. In our work, the first objective of the ABM was to first replicate the experimental findings, including the difference between the anonymous and identifiable conditions at an agent level and small group level. Second, we use the ABM to simulate much larger groups over a substantially longer period of time; this provides a feasible approach for applying the insights obtained from the small group experimental setting to predict what might occur at a societal level.

We assume that there are $n \geq 2$ players (agents), indexed from $1, 2, \ldots, n$, who play in a game at discrete time instants (rounds) $t = 0, 1, \ldots$. In the experimental setup, n is the number of confederates plus regular participants. The decision of player i at time t is represented by $x_i(t) = 1$ or $x_i(t) = 0$ if the player chooses Eta or Tao, respectively. Letting $x_{-i}(t)$ denote the decisions of all players other than player i at time t, the social payoff function for player i to choose decision $x_i = 0$ or $x_i = 1$ at time $t + 1$ is given by

$$\pi_i\big(x_i \mid x_{-i}(t-1), x_{-i}(t), x_i(t)\big) = \frac{b_i}{n} \sum_{j=1, j \neq i}^{n} X_i^{\top} X_j(t) + k_i X_i^{\top} \begin{bmatrix} x_i(t) \\ 1 - x_i(t) \end{bmatrix} + k_i X_i^{\top} \begin{bmatrix} \hat{x}_i(t) \\ 1 - \hat{x}_i(t) \end{bmatrix}, \quad (1)$$

where for all $i = 1, \ldots, n$, the positive constant parameters b_i, k_i, r_i satisfy $b_i + k_i + r_i = 1$, and $X_i = [x_i, 1 - x_i]^{\top}$. The quantity $\hat{x}_i(t) = \big(1 + \big(\sum_{j \neq i} x_j(t) - \sum_{j \neq i} x_j(t-1)\big)\big)/2n$ measures the temporal trend of Eta players in the group. Confederates are given parameters which ensures Eta is always selected.

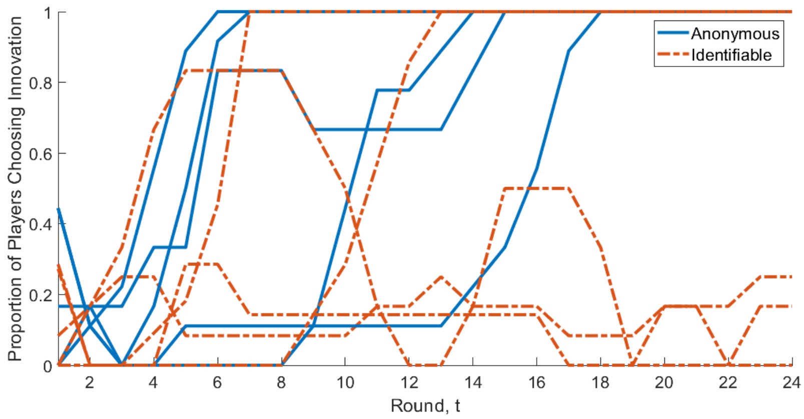
We now give some intuitive explanation of the model. The first term on the right hand side of Eq. (1) represents a coordination game, which is a classical diffusion model for social innovation (Peyton Young, 2011). This term drives player i to select the same decision as the majority of the other players, reflecting *conformity*. However, we introduce two simple additional mechanisms missing in existing models to fully capture the different social context between the inhibited and disinhibited state. The second term on the right of Eq. (1) reflects *consistency*, by offering the player a bonus payoff for playing the same strategy at time $t + 1$ as at time t. The third term captures a player's tendency to *explore when it detects social change is occurring*, and can be related to *dynamic norms* (Sparkman & Walton, 2017). The values b_i, k_i, r_i are the weights player i puts on each of the three factors when making her decision.

We designed a statistically-principled procedure to estimate the model parameters b_i, k_i, r_i, with precise details omitted. We give explorer agents and follower agents different parameters b_i, k_i, r_i; for example, explorer agents have a smaller k_i and larger r_i compared to follower agents, to reflect their propensity to try out new alternatives. By varying the ratio of explorer agents to follower agents, the ABM is able to capture the disinhibited and inhibited social contexts of the experiments.

3. Results

As it is shown in *Figure 1*, we observed a substantial difference in innovation diffusion between the *anonymous* and the *identifiable* groups in our experimental game. In the given timeframe, full diffusion (i.e. a consensus) occurred in only two identifiable groups, while all five anonymous groups display a pattern of full diffusion. We tested whether this difference between anonymous and identifiable groups, as hypothesised, can be attributed to individuals in the anonymous groups changing their product choices (i.e. exploring) more often. Using OLS estimations, we regressed the proportion of rounds in which an individual chose the innovation after the initial consensus—i.e. the probability of adopting the innovation—on anonymity while controlling for a multitude of relevant demographic and personality characteristics of the individual (which we included to account for small imperfections in randomisation procedure). The results show a strong effect of anonymity on the probability of adopting the innovation (β = 27.05, *SD* = 7.15; $p < .001$), meaning that being in an anonymous group (compared to identifiable) increases one's likelihood of adopting the innovation by 27 percentage points. Furthermore, by moderating this effect using different self-reported personality measures, we obtained preliminary evidence indicating that consistency considerations play an important role in the diffusion process. Specifically, the effect of anonymity on the likelihood of adoption is more pronounced for individuals who are low in need for consistency. The full regression tables are omitted due to spatial limitations.

Figure 1. The proportion of regular participants choosing the anti-initial consensus product (i.e. innovation) across rounds in each experimental group.



Based on the experimental data, we defined parameters for the ABM (i.e. b_i, k_i, r_i), ratio of which determined whether an individual agent in a group is an explorer or a follower. To assess whether the chosen parameters indeed fit experimental data sufficiently, we first used the ABM to replicate the experimental data. The diffusion patterns that the ABM exhibited within the 10 groups (with the same group size and innovator proportion as the groups in the experimental study) were similar to the outcomes of the actual experimental sessions. This leads us to believe that the model captures the data well. A notable side observation is that the biggest difference between explorers and followers in the model was in the consistency parameter (k_i), further indicating its central role in the diffusion process.

Figure 2. The time steps T* it takes for a full diffusion to occur as a function of different explorer-follower ratios and sample sizes.

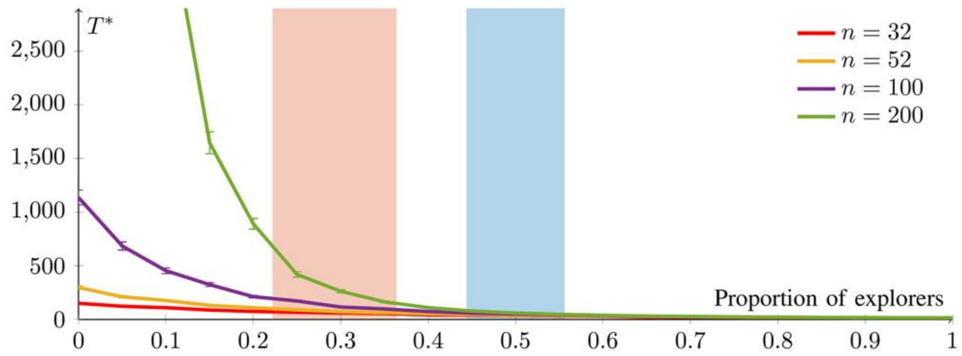
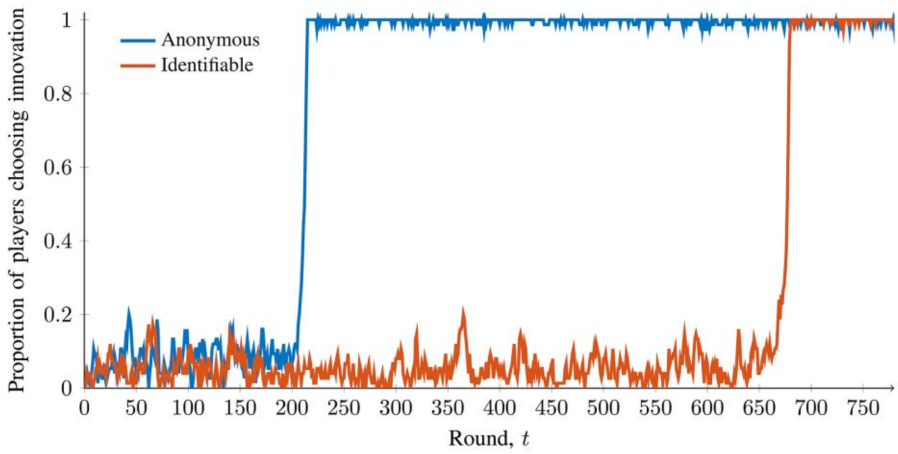


Figure 3. The proportion of agents choosing the innovation across time steps in each condition in a sample size of 200 (50 confederates)



Furthermore, using the parameters obtained from the data and running large-sample simulations, the ABM shows that, on a societal level, there is an important difference in diffusion between anonymous and identifiable groups. This difference is displayed in *Figure 2*, which plots the time steps it takes for a full diffusion to occur at different sample sizes as a function of the distribution of explorers and followers within a group. The left shaded area marks the most likely explorer-follower ratio interval for the identifiable groups and the right shaded area marks the most likely explorer-follower ratio interval for the anonymous groups. Comparing the two, it can be seen that, in the anonymous groups, the time needed for full diffusion grows less linearly with respect to increasing sample size, while in the identifiable groups, the change in time needed for a full diffusion to occur increases exponentially with respect to increasing sample size. In other words, moving from an identifiable to an anonymous setting seems to cross the threshold of explorers needed for a tipping point to be reached under any sample size within a realistic time frame (given that the proportion of innovators in the group is kept at a constant rate of 25%). The striking difference in diffusion speed between the anonymous and identifiable condition for bigger samples is also clearly illustrated in *Figure 3*, which displays the detailed diffusion simulation behaviour for a single group of 200 people. Notice that in both conditions, that once the tipping point is reached, diffusion is explosive, reflective of real-world viral processes.

4. Discussion

Our experimental data clearly suggests that diffusion occurs faster in an *anonymous* setting due to the increased likelihood of groups containing more explorers. This finding was additionally replicated by the defined ABM. Furthermore, using the parameters obtained from the data and running large-sample simulations, the ABM showed that the slightly different ratios of explorers/followers between the anonymous and identifiable groups can produce a noticeable difference at the societal level—i.e. whether a large society will reach a tipping point or not.

The main theoretical contribution of our study lies in its demonstration of the wide-scale implications of established psychological individual-level processes (i.e. macro implications of micro processes). In other words, it shows how minor differences in individual behaviour produced by the social context—i.e. whether or not one perceives his impression to be on the line—can result in wildly different societal diffusion outcomes. Given that individual impression concerns have mostly been disregarded by diffusion scholars, this finding illuminates the importance of considering its effects in the future models.

Beyond theory, our research can also provide relevant managerial implications. As mentioned in the introduction, the same diffusion process as we studied underlies the spread of a new product following its launch. Therefore, our central finding of the effect of anonymity on the likelihood of adoption also sheds some light on the need to consider psychological outcomes of a communication channel when making predictions about product adoptions.

Also beyond marketing, there are certain diffusion contexts where a contextual factor such as anonymity can render reputational concerns obsolete. One of the most salient phenomena that fits this description are online social movements. Given the prevalence of online platform usage among people nowadays, the finding of faster diffusion online can help us explain some of the rapid online social movements that appeared in the past years and why they spread so swiftly. Examples of such movements include #BlackLivesMatter, #MeToo, the Arab Spring, and the rise of the alt-right.

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