

SURFING YOUTUBE: LOOKING FOR ALGORITHMIC OVERDEPENDENCE USING  
SIMULATED DIGITAL CONTENT PLATFORM RECOMMENDERS

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## **ABSTRACT**

With the emergence of algorithmic recommender systems that are designed to filter the massive amounts of information and choices presented to use in an online environment, there have also arisen concerns that consumers can rely too much on these recommenders, making them worse off than if they had relied on their own judgment. My contribution to the literature of ‘algorithmic overdependence’ is threefold; first, I extend the literature to treat online media content marketplaces such as YouTube and Netflix that serve video content to consumers. Second, I adopt an experimental approach using agent-based modeling to simulate the target environment. Third, I treat the situation as a Weitzman-type “Pandora’s Box” optimal search problem.

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# **I Introduction**

Media consumption has expanded greatly in variety and amount over the past two decades – notably, much of present media consumption is now carried out on digital platforms which operate through enabling and generating revenue from interactions between users (Towse and Hernández 2020). With the scale of media output available on these platforms, both the platforms themselves and consumers must deal with information asymmetry and matching problems of significant scale. Platforms such as YouTube, for instance, host such massive amounts of media that its consumers face severe difficulties in evaluating all alternatives. In response, many of these platforms have introduced recommendation systems that are designed to address this problem by using data collected from the platform’s users to automatically evaluate alternatives and generate recommendations for which media alternatives to consume. However, there is a surprising scarcity in empirical evidence on the effect of these recommendation systems on user decision making, and what kinds of recommendation systems that these platforms may be incentivized to create.

I aim to address this gap by constructing a simulation of a video media platform environment as an agent-based model (ABM) that consists of simulated platform users that watch videos offered by the platform, and a recommendation system that recommends videos in the users’ neighborhood as they navigate the platform. The simulation is set up similar to a randomized trial: I have a control group of virtual users that navigate the platform and try to optimize their search for the best videos possible, and two treatments where a recommendation system is present; one treatment where the system randomly recommends videos, and another treatment that recommends the highest-value videos in users’ search area.

This extends earlier work done that studies the effects of recommendation systems on users’ decisions, and how they could improve these decisions by lowering search effort (Haubl & Trifts 2000; Adomavicius and Tuzhilin 2005), by testing the effects of recommendation systems in media consumption platforms where strict technical dominance between products is more difficult to establish. It also specifically extends the work of Banker & Khetani (2019) which found evidence for *algorithmic overdependence* where users’ decision quality can actually decline by trusting the recommendation systems too much. The main aim of our paper is to try to

replicate findings for algorithmic overdependence in media consumption platforms such as YouTube.

## II Literature Review

The body of literature on recommendation systems has mixed findings on the effect of these systems on consumer decision-making. Haubl & Trifts (2000), for instance, find positive effects of recommendation systems on user decision quality by allowing consumers to “...more efficiently screen the (potentially very large) set of alternatives available in an online shopping environment.” In a controlled experiment using a simulated online store, they find that use of the recommendation system improves quality of consideration sets, improves quality of purchasing decisions, and reduces consumers’ search efforts. Xiao and Benbasat (2007) also provide a literature overview that show a number of papers finding evidence for recommendation systems improving the decision quality of consumers in preference matching scores, confidence in decision, choice of non-dominated alternatives, and product switching.

However, there is also a set of literature that finds evidence for potential negative effects of recommendation systems on consumer decision-making; most notably, Banker and Khetani (2019) find that consumers are susceptible to *algorithmic overdependence*, which they characterize as a Type I error where consumers adopt recommendations even when they are inferior and the consumer would have been better off following their own original decision. The effects of algorithmic overdependence is exacerbated by situations of imbalance in perceived expertise where the consumer feels that the recommendation system is highly complex and effective. Attempts to control for confounding factors such as attention limits, cognitive effort and capacity limits, and understanding limits still result in finding evidence for algorithmic overdependence.

Methodologically, the specific application of agent-based modeling to modeling the effects of recommendation systems is relatively novel; however, experimental approaches to studying these systems commonly simulate the platform environment, as in Haubl & Trifts (2000) which conducted an experiment using a simulated shopping environment, and Banker & Khetani (2019). Moreover, Rand and Rust (2011) argue that ABMs are useful for modeling marketing phenomena that are “...too complex for conventional analytical or empirical approaches.”

I argue that such complexity is the case here, as the value of visual media consumption is highly influenced by the state of mind of the consumer, the number of alternatives is extremely large, and there is uncertainty as to the details of how YouTube’s algorithm is trained. Covington et al. (2016) cover YouTube’s recommendation system at a high level, but note that recommending YouTube videos is extremely challenging from the point of view of *scale*, *freshness* (the amount of new content being continually uploaded), and *noise* (difficulty of predicting user behavior) (p. 1). Given this, I argue that an ABM approach allows to study the platform and the effects of its recommendation systems on users by reducing the complexity of the environment to simulated users and algorithms that I have complete control over, and where I can reduce and control the problems posed by scale, freshness, and noise.

Finally, I adopt a Weitzman (1979)-type optimal search problem approach to characterize the environment faced by virtual users in the ABM. The use of Weitzman (1979) has precedent in the marketing literature on studying user behavior on online platforms, such as Kim et al. (2010) that build on Weitzman’s model to estimate demand and search primitives; Honka and Chintagunta (2016) use it to analyze consumer consideration sets in the auto industry; finally, Ursu (2018) uses the model to analyze data generated from a field experiment at Expedia to identify the causal effect of rankings. However, our use of Weitzman in examining the effect of recommendation systems is a novel application. Specifically, I draw on Weitzman’s “Pandora’s Box” model where an agent opens boxes sequentially in any order, with the aim of maximizing expected value of the greatest discovered prize, minus costs of opening the boxes.

### III Theory

To approach this problem, I conceptualize the situation of choosing between different video options as an optimal search problem ala Weitzman (1979). As a “Pandora’s Box” problem, videos can be thought of simply as a set of boxes  $B = \{1, 2, \dots, n\}$  with prizes and costs of opening generated from a known cumulative distribution function  $F_i$ . The search problem for an agent, then, is to maximize the expected total value of the prizes minus the cost of opening the boxes, as the following:

$$R = \max_{i \in S} x_i - \sum_{i \in S}^{i=1} c_i \quad (1)$$

Weitzman's problem has wide applications: house-hunting, house-selling, job search, and looking for research ideas. It's particularly well-suited to thinking about problems involving numbers of alternatives presented to a consumer; Varian (1999) used the example of an airport book store where people are in a hurry, there's mental effort involved with examining books, they'll only take one book with them, and you have some idea of how likely the person is to like a book. Then the problem is what order to show consumers the books. The importance of being able to solve this problem becomes more important the more alternatives you have for consumers to choose from.

To solve the Pandora's Box problem, define an index  $I_i$  for each box  $i$  as follows:

$$E(V_i) - C_i \quad (2)$$

where  $E(V_i)$  is the expected value of the prize in box  $i$ . While there are boxes remaining in  $B$ , do the following:

1. Find the box  $i^*$  with the maximum index:

$$i^* = \max_{i \in B} I_i \quad (3)$$

2. If  $I_{i^*} > 0$ , open box  $i^*$ , add the prize  $V_{i^*}$  to the total prize, add the cost  $C_{i^*}$  to the total cost, and remove box  $i^*$  from  $B$ .

3. If  $I_{i^*} \leq 0$ , stop and do not open any more boxes.

In our example of applying this to YouTube, there are billions of videos available to the consumer to choose from, and there's mental effort involved with examining whatever videos show up on the home page. The recommendation system is essentially a technology for

attempting to solve this problem of figuring out in what order to show users the videos available on the platform. And since Weitzman’s problem has a well-defined index policy solution for calculating the optimal stopping point in the search problem, if you generate your alternatives from a known distribution, you can always calculate this solution no matter how many alternatives you create, making it ideal for simulation purposes and benchmarking decision quality on the part of users.

## **IV Experimental Model**

YouTube’s approach to solving this problem through their recommendation system is unknown in the fine details. Their paper outlining the deep learning algorithmic approach to recommendations covers the high-level structure of the system, but doesn’t provide details on what the algorithm is actually trained on – only that the system uses the “...implicit feedback of watches to train the model, where a user completing a video is a positive example,” and that this feedback extends far into very implicit aspects of a user’s history. I also know that some effort is made to weight this feedback to account for the preference of users for fresh content (Covington et al. 2016).

Given the lack of fine details of how the model is trained, the infeasibility of replicating the model at scale even with those details, and other noise factors that also increase complexity, I opt for an agent-based modeling approach to simulate the consumption of YouTube videos, and video-based digital content platforms more generally. Agent-based modeling is useful when dealing with “black box” type problems where I don’t have good data on what is going on inside the black box. Instead, agent-based modeling allows trial-and-error experimentation using different assumptions and designs until you find a set of assumptions that appear to robustly replicate the stylized facts about the phenomena I do observe.

ABMs do suffer a drawback in terms of external validity problems – while within the context of the simulated environment, explanatory variables are causal by default as I know the entire population and control all its characteristics, there is no definitive means of generalizing outside of this environment to confirming that these same variables are causal in the real world.

Validation can be used to try to address these issues by matching data generated by the ABM against stylized facts that I know about the real world.

Finally, ABMs do have an advantage over in-person experiments, as they also allow for scaling up to match the real scale of the subject of interest, something that is often not feasible with other methods such as consumer behavior experiments (Rand & Rust 2011). However, given the earlier issues mentioned concerning external validity, a hybrid approach can also be adopted where human subject experiments are adopted to provide “...a ready-made source of empirical regularities that can be used to calibrate or test ACE (Agent-based Computational Economics) of individual decision-making and belief or expectation formation” (Duffy 2006). In this paper, I focus on results from the ABM, but given the complexity of human behavior in this setting, I intend to extend this work by pairing with a human subject experiment.

I also feel that an agent-based approach has natural synergy with our decision to approach the problem as a Weitzman Pandora’s Box-type setup, which allows direct simulation of the problem facing agents by generating “videos” as boxes with prize values and costs drawn from a known cumulative distribution function, allowing scaling up to a number of alternatives approaching the actual target environment of YouTube’s digital platform.

## IV.1 Setup

Our agent-based model consists of a 20x20 grid with two types of “agents”: watchers and videos. Each cell on the grid is initialized with a video with prize values and costs drawn from a known prize distribution  $\sim N(100, 20)$ , and cost distribution  $\sim N(10, 2)$ . All code for the model can be found at [this GitHub repository](#).

In addition to the two agents, the model also has a recommendation system that solves the Pandora’s Box problem for the distribution of videos across the grid using the max index calculation detailed in the previous section. The recommender calculates the total prize and total cost, and the difference between the total prize and total cost represents the net gain possible from an optimal searcher.

In this model, watchers move about the grid and try to maximize their payoffs from opening the videos located on the grid cells. The recommendation system observes the videos in the Moore neighborhood of the watcher and is able to calculate which video has the highest payoff.



There are three versions of the model: a control model and two treatment models, “random,” and “high-value”. In the random treatment model, the recommendation system recommends a random video in the watcher’s neighborhood. In the high-value treatment model, the system instead recommends the highest value video in the watcher’s neighborhood.

Each model consists of a number of sessions, where each session will last for 20 rounds or “steps”. Each session will consist of one watcher placed on the grid at random that will then attempt to solve their search problem and maximize gains from opening videos. As an example, if in the experiment total, each model runs 50 sessions, then I will have 50 watchers run up to 20 rounds for each session, for the control, random, and high-value treatments, for a maximum of  $50 * 20 * 3$  rounds. The data collected from the model consists of the final net payoff and to the watcher along with the watcher’s characteristics, so in the example just given, a total of 150 observations would be generated (50 final payoffs per model).

#### IV.II Watchers

For each session of the model, one watcher agent is placed on the grid at random. Each watcher is initialized with the following characteristics:

1. A **memory of past locations** representing videos that they’ve already opened.
2. A **memory of past payoffs**.
3. A **running average payoff** measure.
4. A “**payoff direction**” holding the sign of their payoffs so far.
5. The **number of rounds** they have already been through.
6. An “**acuity**” parameter representing their ability to calculate the expected value of a given neighborhood of videos according to a soft-max calculation, instead of just pure random selection.
7. A “**recommender trust**” parameter determining the percent chance a watcher has of overriding their own decision with the decision of the recommender.

8. A “**patience**” parameter determining the magnitude of the payoff direction measure they will wait until they end the round. For instance, if this is 3, then if a watcher’s average payoff declines for three rounds in a row, or increases for three rounds in a row, the watcher will end the session.

During each round of the model, watchers will perform the following sequence of actions:

1. **Calculate whether they should stop searching.** This occurs if they either hit the specified magnitude of their patience parameter, or they run out of videos to search.
2. **Move to a new cell in their neighborhood.** This is done through probabilistic selection of a cell in their neighborhood, depending on their acuity measure. If their acuity is 0, they will pick a cell completely at random. If their acuity is  $> 0$ , then they will perform a soft-max calculation, where a max acuity value of 100 will result in the highest possible weights being assigned proportional to the value of the potential options.
3. **Open the video box** and record the resulting payoff in their memory.
4. **Calculate average payoff** according to their current payoff memory.
5. **Calculate payoff direction** according to whether this payoff is greater or lesser than the next most recent payoff.

## V Empirical Results

At the end of each session in the experimental model, the model will report the following data:

- Final payoff of that session’s watcher.
- The search quality of the watcher as a ratio between the watcher’s final payoff and the optimal payoff determined by the model for that distribution of videos.
- The watcher’s characteristics of acuity, patience and recommender trust.
- The number of rounds completed by the watcher.
- A dummy variable for whether the random recommendation treatment was in effect.
- A dummy variable for whether the high-value recommendation treatment was in effect.

I estimate average treatment effects via a set of three regressions, one bivariate and two multivariate. The bivariate model is as follows:

$$Y_i = \beta_1 acuity_i + \epsilon_i \quad (4)$$

Where  $Y_i$  is the percentage of optimal search value realized by the agent as the result of their individual search history and  $acuity_i$  is the acuity parameter of the agent determining how much they calculate probabilities via the soft-max algorithm.

I also run two additional multivariate models that include parameters for trust in the recommendation system, and dummy variables indicating assignment to high-valuation of random recommender treatment:

$$Y_i = \beta_1 acuity_i + \beta_2 trust_i + \beta_3 recommender\_random_i + \epsilon_i \quad (5)$$

$$Y_i = \beta_1 acuity_i + \beta_2 trust_i + \beta_3 recommender\_hv_i + \epsilon_i \quad (6)$$

In these models,  $trust_i$  is the recommender trust parameter of the agent determining the probability that they will choose the video recommended by the algorithm regardless of what their own choice might be.  $Recommender\_random$  and  $recommender\_hv$  are dummy variables indicating assignment to the random recommendation or high-value recommendation treatments respectively. Running these models yielded the following results:

Figure 1: Effects of Recommender Type and Consumer Trust on Search Quality

	(1)	(2)	(3)
	<i>search_quality</i>	<i>search_quality</i>	<i>search_quality</i>
<i>acuity</i>	0.00000610 (0.59)	0.00000609 (0.59)	0.00000723 (0.70)
<i>recommender_trust</i>		0.00000993 (0.95)	0.0000100 (0.96)
<i>recommender_random</i>		-0.00151* (-2.35)	
<i>recommender_hv</i>			0.00192** (3.00)
<i>_cons</i>	0.0177*** (29.26)	0.0177*** (21.19)	0.0165*** (19.86)
<i>N</i>	1500	1500	1500

*t* statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

From this figure, we can see that the two recommender treatments are both statistically significant, with the high-valuation recommender being more significant. Both have the expected signs: the random recommendations will, on average, lead the agent to make worse decisions, and the high-valuation recommendations will, on average, lead the agent to make better ones. However, while the magnitude of their effects are quite large compared to *acuity* and *recommender\_trust*, these still appear to be relatively marginal effects, constituting only a tenth of a percentage point average difference in mean search quality. It's also interesting to note that *recommender\_trust* itself fails to obtain statistical significance, even though the two treatment effects are significant.

Finally, in comparison to the treatment effects themselves, the constant is both significant and is larger by a full order of magnitude. Repeated runs of the ABM reveal inconsistency in finding significance in the recommender treatments; however, the constant is consistently significant. This led me to suspect that a variable perhaps had been omitted that has more explanatory power than the first model included. I reran the model, this time changing it so that the *patience* parameter for agents is also randomly chosen from a range between 1 and 6, instead of fixing it to a static value of 3 like I had earlier. Rerunning the econometric models now as multivariate

regressions with patience included as an explanatory variable yielded the following results:

Figure 2: Effects of Patience on Search Quality

	(1) <i>search quality</i>	(2) <i>search quality</i>	(3) <i>search quality</i>
<i>acuity</i>	-0.000119 (-1.61)	-0.0000867 (-1.18)	-0.0000943 (-1.28)
<i>patience</i>	0.0215*** (14.72)	0.0214*** (14.79)	0.0212*** (14.58)
<i>recommender_trust</i>		-0.000178* (-2.44)	-0.000183* (-2.49)
<i>recommender_random</i>		-0.00960* (-2.19)	
<i>recommender_hv</i>			-0.000336 (-0.08)
Constant	-0.0256*** (-4.26)	-0.0146* (-2.09)	-0.0166* (-2.32)
Observations	300	300	300

*t* statistics in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Compared with the previous bivariate and multivariate regressions, *patience* has more statistical significance at the 1% instead of 5 and 10% levels than the other explanatory variables besides the constant in the first model. It also has more economic significance, with coefficient values larger than the other explanatory variables by at least an order of magnitude. Also note that *recommender\_trust* has picked up significance with a negative sign, indicating that controlling for patience, recommender trust is associated with lower decision quality, in *both* the random and high-value recommender treatments. *Recommender\_hv* also loses significance compared to the first results.

Interpreting these results, it appears that how long an agent is willing to search has a much stronger association with greater final payoffs than the accuracy of their judgment of the alternatives as represented by *acuity*, or the type of recommendation system in place; in fact, any type of recommendation system may make them worse off on average.

Comparing this to Banker and Khetani (2019), the first set of regressions contains some limited evidence for algorithmic overdependence as represented by a positive and statistically significant

coefficient on the high-value recommender treatment, compared to a negative coefficient on the random recommender treatment. However, no evidence is found for the causal effect of trust in the recommender itself, which is inconsistent with the findings of Banker and Khetani’s treatments that prime human subjects to have different judgments of the expertise level of the recommender compared to their own expertise.

The second set of regressions also finds limited evidence for algorithmic overdependence in the negatively-signed and significant random recommendation treatment, and this time with accompanying statistical significance of recommender trust. However, a high-valuation recommendation system appears to have no effect. And compared to both treatments and recommender trust, the patience of the watcher appears to have much greater impact.

I believe that the difference between these two sets of regressions can potentially be explained by the setup of the ABM, which is spatialized and involves the agents being only able to search and explore boxes in the immediate cells surrounding their cell, their Moore neighborhood. This means that search of all options is limited by their location, which is a departure from the original Pandora’s Box problem posed by Weitzman, where the solution assumes that agents are able to evaluate all alternatives freely without restriction. By imposing spatial limitations, I may have inadvertently reduced the ability of recommendation systems to provide useful or detrimental advice. Instead, the payoffs are heavily dependent on whether the patience factor of agents is great enough to overcome the probability of going on a losing streak due to the requirement that they only evaluate alternatives in their immediate neighborhood.

## **VI Conclusion**

In this paper, I used an agent-based modeling approach combined with a Weitzman-type Pandora’s Box model to simulate viewer consumption of media on YouTube and other digital media content platforms as an optimal search problem. The results show some limited evidence for algorithmic overdependence ala Banker and Khetani (2019), but differences between the sets of regressions after including patience as a factor revealed concerns over the appropriateness of the spatialized setup of the ABM as an environment for a Pandora’s Box optimal search problem for exploring these questions.

Further steps would include revising the ABM to allow watchers to move anywhere on the grid at will, allowing evaluation of all alternatives and widening the consideration set of each watcher. Additionally, in this revised version of the ABM, I would engage in more thorough hyper-parameter space search to test models for each possible value of each parameter of the watchers. Finally, a human subject version of this experiment may be warranted to generate real-world empirical data that may help revise the assumptions in exploring these problems.

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