Using Agent-Based Modeling to Predict the Diffusion of Safe Teenage Driving Behavior Through an Online Social Network

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Objective: To use agent-based modeling to examine how peer influence in a social network affects behavior change among teenage drivers. **Background:** Teenagers are involved in more fatal driving crashes than any other age group. A solution to the problem is to utilize both feedback systems and online social networks to promote safe driving behavior. **Methods:** Using a combination of intention (from the Theory of Planned Behavior) and habit, agent-based modeling was used to predict the spread of safe driving behavior through an online social network after the implementation of a feedback system **Results:** The initial conditions of the social network (e.g., the number of agents to initially engage in safe driving behavior and the number of opinion leaders who use the feedback system), as well as the threshold used to determine intention drive safely had a significant effect on the final number of agents to engage in safe driving behavior. **Conclusion:** Agent-based modeling suggests that leveraging the power of feedback systems and social networks can lead to a positive change in teenage driving behavior. **Application:** Agent-based modeling can be a viable tool in predicting teenage driver behavior given the correct choice of parameters.

INTRODUCTION

Although programs such as graduated drivers licensing have proven beneficial (Shope & Molnar, 2003), teenagers are still involved in more fatal crashes than any other age group (Compton & Ellison-Potter, 2008), suggesting the need for other approaches. One solution to the problem of fatal teenage crashes is to give them feedback regarding driving performance (Carney, McGehee, Lee, Reyes, & Raby, 2010), which has proven beneficial in improving adult driving behavior (Donmez, Boyle, & Lee, 2007, 2008; Malenfant, Wells, Van Houten, & Williams, 1996; Shinar & Schechtman, 2002; Van Houten & Nau, 1983). Feedback to improve driving performance has primarily focused on individual drivers, but greater benefits might be achieved by considering drivers' social network. Social networks have proven to be influential in decision-making and lifestyle choices, especially among teenagers (Brown, Clasen, & Eicher, 1986).

Compared to other life stages, peer influence is particularly strong and apparent during adolescence (Allison, 2001) as peers serve as role models for social comparison (Maxwell, 2002). Among adolescents, peers are the strongest predictor of behavior when promoting delinquency, drug use, and sexual activity (Brown, Bakken, Ameringer, & Mahon, 2008). However, peer influence can also inhibit risky behavior (Romer & Hornik, 1992) and encourage positive behavior, such as academic achievement (Brown, et al., 1986). If a similar phenomenon occurs with teenage drivers, it may be possible to use social networks to spread safe driving behavior.

To achieve this behavior change, safe driving behavior needs to diffuse through the teenage social network. The diffusion of innovations involves the spreading of new ideas and social practices within a society. For this to occur, individuals must observe another engaging in a behavior and then do something similar. In particular, individuals tend to follow those who are opinion leaders within the society. Typically, the cumulative adoption of an innovation follows an S-shaped curve when plotted over time (Bandura, 1977; Rogers, 2003).

One method that capitalizes on both the advantages of feedback systems and social networks is to allow opinion leaders to view feedback of their driving performance compared to peers on a social networking website. Targeting opinion leaders for diffusion tends to increase the speed of information spread and the overall adoption percentage (van Eck, Jager, & Leeflang, 2011). In addition, the internet makes the behavior of opinion leaders more visible to a larger social group. What differentiates this feedback from past studies is the simplicity of information (e.g., viewing number of texts sent per drive), comparing their performance to peers to enforce social norm conformance, and using a social networking website to reach a larger audience. Giving individuals information in relation to their peers and enforcing social norms has proven beneficial in increasing safety habits among delivery drivers (Ludwig, Biggs, Wagner, & Geller, 2002) and in preventing binge drinking (Neighbors, Larimer, & Lewis, 2004). Once opinion leaders become more aware of their driving performance and begin to drive safely, the behavior may spread through the social network, encouraging others to drive safely.

The diffusion of information and subsequent behavior change has successfully been modeled using agent-based techniques (Bonabeau, 2002; Macy & Willer, 2002; Schwarz & Ernst, 2009; van Eck, et al., 2011). Agent-based modeling (ABM) is a process where a system is modeled as a collection of decision-making agents. Each agent makes decisions based on rules and interacts with other agents. ABM allows for analysis of relationships between agents and how they evolve and learn over time (Bonabeau, 2002; Macal & North, 2010). ABM also makes it possible to explore peer influence in a way that is more resource efficient than other means, such as large scale driving experiments.

The purpose of this research is to use ABM to examine behavior change (e.g., whether or not to text and drive) among teenage drivers. The model describes how agents interact and influence via social norms, i.e., if an agent's connections

 DOI 10.1177/1071181312561478

engage in a behavior, s/he is very likely to engage in that same behavior. When analyzing the diffusion of behavior using ABM, agents' behavior was modeled as an interaction between intention from the Theory of Planned Behavior (Ajzen, 1991) and habit (Aarts, Verplanken, & van Knippenberg, 1998). As these concepts have never been jointly applied to modeling driving behavior, this research is exploratory, but it is expected that the greatest behavior change will be a result of low behavior change (i.e., intention) thresholds and many initial agents who engage in safe driving behavior. The insights gained should help identify the need to consider driving behavior as a collective phenomenon rather than purely limited to individual drivers.

METHODS

Teenager's driving behavior was modeled using NetLogo 4.1.3 (Wilensky, 1999) and was based on the Preferential Attachment (Wilensky, 2005a), Small World (Wilensky, 2005b), and Virus on a Network (Stonedahl & Wilensky, 2008) models.

Model Characteristics

The agent-based model for the diffusion of safe driving behavior starts from individual decision-making of teenage drivers. A social network connects the drivers and leads the behavior of one driver to influence that of another. To model behavior, the following protocol for describing agents based models was used (Grimm et al., 2006).

Individual agents. The agents are newly licensed teenage drivers who have not formed strong driving habits. The agents are connected within a small-world, scale free network, typical of online social networks (Mislove, Marcon, Gummadi, Druschel, & Bhattacharjee, 2007; Panzarasa, Opsahl, & Carley, 2009). The nodes of the network are agents (teenage drivers) and the connections between nodes represent a relation between agents where they communicate online. Each agent was characterized as either engaging in safe driving behavior (e.g., not texting while driving) or engaging in unsafe driving behavior (e.g., texting while driving).

Model overview. Intention, from the Theory of Planned Behavior, captures the motivational aspects that influence behavior, such as how hard one is willing to try. More specifically, intention is a linear combination of attitude—a favorable evaluation of safe driving behavior, behavioral control—resources available for behavioral achievement, and subjective norm—social pressure to perform safe driving behavior (Ajzen, 1991). In this model, intention only relates to safe driving behavior as it is assumed that no drivers would purposefully intend to engage in unsafe driving behavior. With intention, attitude is increased by the usage of the feedback system, behavioral control is randomly determined, and the subjective norm is based on the (safe driving) behavior of the agent's connections. Given that intention only determines behavior under volitional control, it follows that habit moderates or interacts with intention in determining behavior (Verplanken, Aarts, Knippenberg, & Moonen, 1998). As such, each agent had its own attitude, behavioral control, subjective norm, and habit. Intention determines behavior when habit is weak, while habit determines behavior when habit is strong.

Process initialization. There were 215 agents, the average size of a high school cohort (Chen, 2011). To begin, 25-75% of agents engaged in unsafe driving behavior, similar to teenage engagement in other dangerous activities (e.g., talking, texting; Madden & Lenhart, 2009). For agents with safe driving behavior, attitude towards engaging in safe driving behavior was initially set to a random value between zero and one. For agents with unsafe behavior, they had an attitude towards engaging in safe driving behavior of zero. Behavioral control was randomly drawn from a uniform distribution ranging from zero to one, to reflect the distribution of the capacity of agents to achieve the desired behavioral outcome—safe driving behavior. Subjective norm was social influence (randomly drawn from a uniform distribution ranging from zero to one) multiplied by the proportion of the agent's connection that adopted safe driving behavior, similar to other diffusion equations (Bass, 1969; Delre, Jager, Bijmolt, & Janssen, 2007). Habit was randomly drawn from a uniform distribution ranging from zero to one. If agents engaged in unsafe driving behavior, they had an unsafe driving habit and likewise for safe driving behavior. It is important to note that habit was initially set to a low value to allow for agents to be susceptible to behavior change. This is realistic given that teenagers are just learning to drive and as such, have not formed concrete habits.

Next, opinion leaders began to use the feedback system. Agents were considered opinion leaders if, when ranked in descending order by number of connections, they were at the top. If agents used the feedback system, their attitude towards safe driving behavior increased by 0.01. In addition, a change in attitude was subject to a lag of ten time steps, or three days. Once opinion leaders began using the feedback system, the model proceeded in time steps with one time step corresponding to one thought about driving behavior. Assuming that agents think about driving three times a day, three time steps is one day. The maximum number of time steps was 300 (100 days) to allow the system to reach equilibrium.

Input. At each time step, each agent evaluated his/her own individual characteristics (i.e., attitude, behavioral control, subjective norm, and habit) and then decided whether s/he wanted to adopt safe driving behavior. Attitude and behavioral control were not dynamic—they remained constant throughout the simulation. Subjective norm changed dynamically according to the number of safe or unsafe agents. Habit increased by 0.01 with each time step, e.g., the habit of a safe driving agent was strengthened as they continued to drive safely. Given that habits form, on average, in 66 days (Lally, van Jaarsveld, Potts, & Wardle, 2010), if habit was less than 2, it was considered weak and an agent's behavior was determined by intention. If habit was greater than two, behavior was determined by habit.

Experimental Design

The intention threshold that leads to safe driving, the percentage of opinion leaders to initially use the feedback system, and the percentage of agents to initially engage in safe driving behavior was varied to examine their impact on agents driving behavior. Intention threshold ranged from 1 to 3 in

0.25 intervals. This range of intervals was chosen to correspond to a low and high threshold, respectively, given the initial values for attitude, behavioral control, and subjective norm. Percentage of opinion leaders to use the feedback system was 10, 20, or 30%. Percentage of agents to initially engage in safe driving behavior was 25, 50, or 75%. One intention threshold, one value for percentage of opinion leaders, and one value for percentage of agents to initially engage in safe driving behavior was chosen for each simulation run. Therefore, a 9 (intention threshold) x 3 (percentage of opinion leaders) x 3 (percentage of initial safe agents) between-subjects design was implemented. Twenty simulation runs were completed for each combination of the independent variables, similar to previous studies (Delre, et al., 2007), yielding 1620 simulation runs. The primary dependent variable was the number of agents who engaged in safe driving behavior.

RESULTS

The data were analyzed using the, ‘lmSupport’ (Curtin, 2011), ‘ggplot2’ (Wickham, 2009), and ‘RNetLogo’ (Thiele, Kurth, & Grimm, 2012) packages in R 2.13.1 (R Development Core Team, 2011).

The final number of agents to engage in safe driving behavior was sensitive to intention threshold (b = -8.45, *t* (1612) = -12.30, $p < 0.001$) indicating that as the intention threshold increased by 0.25, the number of agents engaged in safe driving behavior decreased by 8.45 (Figure 1). The lowest intention threshold resulted in the most safe agents (M = 176.39, SD = 11.36) and the highest threshold resulted in the least safe agents (M = 133.52, SD = 22.12). With low thresholds, many agents immediately transitioned to safe driving behavior as the subjective norm and behavioral control components were likely to exceed the low threshold. On the other hand, at high thresholds (above two), there is little differentiation between thresholds and behavior change is gradual.

The percentage of opinion leaders who used the feedback system had a significant effect on the final number of safe agents (b = 9.21, *t* (1612) = 5.15, $p < 0.001$), such that as the number of opinion leaders increased by 10%, the final number of sage agents increased by 9.21. When 10% of opinion leaders used the feedback system, less agents engaged in safe driving behavior after 100 days (M = 139.79, SD = 24.67), but when 30% of opinion leaders used the feedback system, more agents engaged in safe driving behavior after 100 days (M = 152.53, SD = 20.03).

The percentage of agents who initially engaged in safe

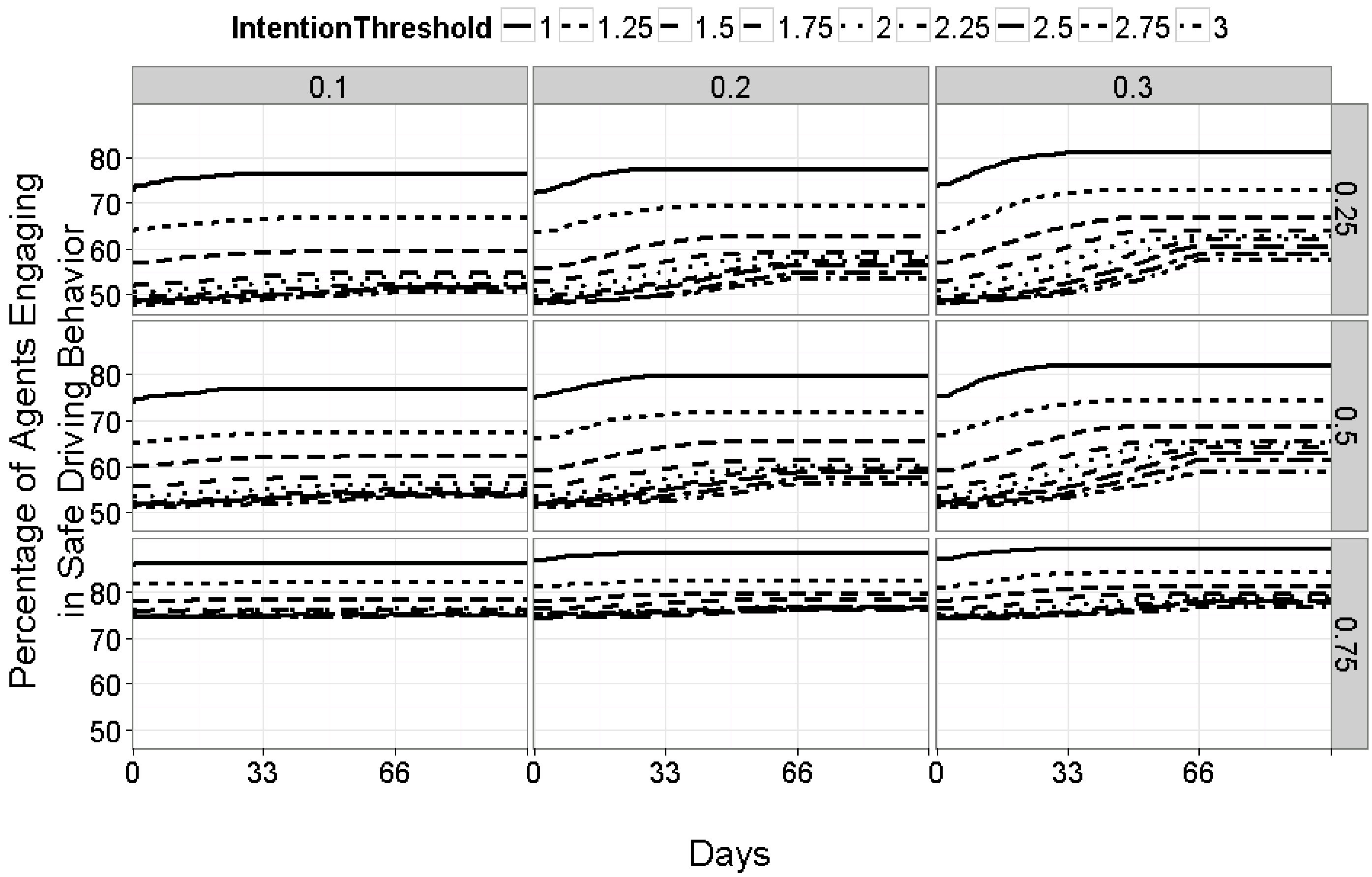

Figure 1: Diffusion curves showing the mean percentage of agents engaging in safe driving behavior over time; from left to right, the graphs show an increase in the percentage of opinion leaders who used the feedback system, and from top to bottom, the graphs show an increase in the percentage of agents who initially engage in safe driving behavior.

driving behavior significantly predicted the final number of safe agents (b = 15.50, t (1612) = 8.66, p < 0.001), such that as the percentage of agents increased by 25%, the final number of safe agents increased by 15.50. When the initial number of agents who engaged in safe behavior was at 25%, the mean number of final safe agents was 131.77 (*SD* = 17.98), while when the initial number of safe agents was 75%, the mean number of final safe agents was 170.22 (*SD* = 9.38). Given that the model began with 75% safe agents (approximately 160 agents), 170 safe agents after 100 days is not a substantial increase. This indicates that if the network is already relatively safe, the feedback system and subsequent diffusion through the network will not result in a significant behavior change.

Intention threshold and percentage of initial safe agents interacted (b = 1.80, t (1612) = 5.67, p = 0.004), such that the difference between intention thresholds was greater when the percentage of initial safe agents was small (i.e., 25%). The percentage of opinion leaders and the initial percentage of safe agents also interacted (b = -1.76, t (1612) = -2.12, p = 0.03), such that the difference between percentage of opinion leaders was greater when the percentage of initial agents was small (i.e., 25%).

DISCUSSION

ABM was used to predict teenagers' driving behavior. The model was created based on documented features of social networks and agents behaved according to simple rules, which led the behavior of one agent to influence another. Results indicate that the threshold used to determine when intention changes behavior has a substantial result on how safe driving behavior spreads throughout the network. Low threshold values led to more agents engaging in safe behavior while high thresholds had the opposite effect. In addition, the percentage of agents who initially engaged in safe behavior and the percentage of agents to initially use the feedback system had an effect on behavior change, such that as more agents were initially engaged (either by engaging in safe driving behavior or using the feedback system), more agents engaged in safe driving behavior after 100 days. However, a network where the majority of the agents are initially safe results in only a small number of agents reverting to safe driving behavior. It is important to note that none of the model settings led to 100% adoption of safe driving behavior, indicating that there will always be some teenage drivers who are unreachable (i.e., not connected) and unaffected by the influence of social norms. This exploratory research suggests agent-based models might be useful in identifying how powerful some strategies such as utilizing opinion leaders, might be in changing teenage driving behavior.

Future Work

The model presented here represents a minimal description of teenage driving behavior, and it can be refined to present a more accurate picture of how social networking techniques influence driver behavior. In subsequent extensions of this work, agents will be modeled as more complex individuals that have characteristics, such as age, gender, self-efficacy (Ajzen, 2002), locus of control (Ajzen, 2002), and riskiness (Reason, Manstead, Stradling, Baxter, & Campbell, 1990). Each of these factors has been shown to predict driving behavior (Shope & Bingham, 2008). In addition, given that the distinction between habit and intention is not discrete, future work will predict behavior based on a continuum to allow for each process to simultaneously predict behavior. Future models will also consider the full range of influences that complement online social connections. For example, a teenager will engage in safe driving behavior based on the effectiveness of mass media campaigns (Rogers, 2003), word of mouth (van Eck, et al., 2011), and online social influence. Another point of exploration would be to use a time step that is more related to actual behavior. While each time step corresponds to an agent's reassessment of the situation, how often people think about behavior and how often they contact others is a subject of research. In any case, to capitalize on the value of ABM in the driving domain, the model should be validated with real-world data. However, the difficulty of conducting such an experiment on the scale needed of a social network represents a formidable challenge.

Conclusion

Using ABM to simulate how online social networks might influence the spread of safe driving behavior is a novel approach to assess strategies to curb the number of teenage driver fatalities. Importantly, this approach moves beyond a focus on the individual to consider collective behavior as it affects driver distraction. The model considers the value of interacting agents and does more than just consider behavior on the individual level, like past models (Cooper, Vladisavljevic, Medeiros-Ward, Martin, & Strayer, 2009). In addition, it also allows researchers to examine the effect of an intervention without running costly driving simulator studies. Preliminary results suggest that the threshold used to determine intention and the initial conditions of the network (e.g., how many agents initially engage in safe driving behavior and how many opinion leaders use the feedback system) have a significant effect on how safe driving behavior spreads. Overall, this research provided first steps in identifying how safe driving behavior would spread through a network of teenage drivers.

ACKNOWLEDGEMENTS

The authors thank the anonymous reviewers and members of the Cognitive Systems Laboratory for their comments and suggestions. This work was supported by the National Science Foundation by a Graduate Student Fellowship to Shannon C. Roberts.

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