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Development and Use of an Agent-based Model to Assess the Effect of Forecast Credibility on Urban Traffic During Snow Events

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DEVELOPMENT AND USE OF AN AGENT-BASED MODEL TO ASSESS THE EFFECT OF FORECAST CREDIBILITY ON URBAN TRAFFIC DURING SNOW EVENTS

by

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ABSTRACT

DEVELOPMENT AND USE OF AN AGENT-BASED MODEL TO ASSESS THE EFFECT OF FORECAST CREDIBILITY ON URBAN TRAFFIC DURING SNOW EVENTS

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With the difficulties in snow accumulation prediction, the potential for false alarms and forecast misses arise. These forecast errors can lead to a lack of public trust and poor decisions in responding to future weather hazards. There has been little research on how individuals respond in the future to false alarms and forecast inconsistencies. We developed an agent-based traffic model to demonstrate how snow forecasts and public response interplay. This model factors receptiveness to expertise, forecast severity, and forecast credibility into the agents' work-related travel decisions. Agents are grouped into three categories: firm workers, service workers, and household workers, where firm workers can work from home, service workers must go into work, and household workers always work from home. It was found that forecast severity has the most effect on the number of agents traveling, while credibility factors into agents' decisions if they have the option to work from home. Owing to uncertainties in actual accident rates during snowfall, no firm conclusions were made in terms of how such events might interact with forecast severity and credibility, although there does appear to be potential for significant regional differences in these effects. This model is a first attempt at simulating the role that these factors play in work-related travel decisions and outcomes, but it is deliberately simple. Recommendations are made regarding useful enhancements to the model framework.

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LIST OF ABBREVIATIONS

IDSS	Impact-Based Decision Support Services
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service

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1. Introduction

Snow accumulation is difficult to predict. While forecasts have been improving (Alley et al. 2019) there are still inaccuracies and forecast failures (Duell 2019). Less successful forecasts have an impact on how the public interprets the risks of weather hazards (Burgeno and Joslyn 2020). If there is a snow event that is more impactful than predicted, people may be traveling in a dangerous situation. If a snow event is less impactful than forecast (i.e., false alarms), events may be unnecessarily canceled, causing economic loss.

The problem that arises with false alarms is that they have the potential to lead individuals to make poor decisions during future weather hazards. If forecasts are seen to be inaccurate, the public will have less trust in those providing them (Burgeno and Joslyn 2020). A well-known principle of forecasting is that a perfect forecast has no value if nobody pays any attention to it. The National Weather Service (NWS) shifted to the Impact-Based Decision Support Services (IDSS) approach in 2018 to help core partners (i.e., emergency personnel and public safety officials) make decisions when lives and properties are at risk due to weather, water, or climate impacts [National Oceanic and Atmospheric Administration (NOAA), 2018].

There has been little research done on how individuals respond in the future to false alarms or poor forecasts (Ripberger et al. 2015), especially when it comes to snow events. Understanding how people react to snow forecast accuracies and inaccuracies will lead to better communication of potential impacts so they can make informed decisions and stay safe, consistent with the NWS shift to decision support services in the furtherance of public safety. There is a complex interplay between the quality of the forecast and the public response to it, and especially the time-dependent nature of this interaction.

Three experiments were conducted at the University of Washington to test how accuracy and consistency of snow forecasts would affect school closing decisions (Burgeno and Joslyn 2020). Students were given snow accumulation forecasts and a threshold of when to close school. The number of forecasts leading up to the event they were provided and the threshold to close school was different for the first two experiments. The third experiment was conducted to see if the results from the previous experiments would hold. This study found that inaccuracy decreased trust and more cautious decisions were made when forecasts were inconsistent.

After a major Colorado winter storm in 2006, an internet survey was sent out asking how residents received their weather information for that storm, if they decided to stay home that day, how they made that decision, and their perceptions of forecast accuracy (Drobot 2008). Based on this survey, most people received their information from local television stations and 48% of respondents went to work or school that morning. Of those who stayed home, 65% made that decision based on the forecast. Of those who did not stay home that day, 76% went home early, most having a longer commute due to weather conditions. Most people felt that the forecasts underpredicted the actual accumulated snow, though this was difficult to verify. 56% of respondents felt that the snow began falling at the time forecast, and 78% of those people also believed the snowfall amount was predicted correctly. Responses to accuracy appeared to depend on the decision to stay home or not. Of those who stayed home, 7% stated that less snow than predicted fell compared to 3% of those who did not stay home. 60% of those who did not stay home said more snow than forecast fell compared to the 52% of people who stayed home. 70% of participants that were stuck on the road thought more snow fell than was forecast.

Another internet survey was sent to residents of tornado prone areas of the United States to see how false alarms impact people's trust in the tornado warning system (Ripberger et al.

2015). 144 questions about weather, tornadoes and warnings were asked to help gauge participants' perceptions on these topics. These answers were then compared to NWS warning and event archives. This study found that false alarm events do have an impact on credibility of the warning system and how people respond to those warnings.

The goal of this research will be a conceptual exploration of the influence of successive snowfall forecast successes or failures on subsequent public response using a simple agent-based model. This thesis is organized as follows. Section 2 will provide a description of the agent-based modeling approach. Section 3 will summarize the experiments conducted using this model and results. Section 4 will provide a concluding discussion, with a view towards future research.

2. Methods

We built an agent-based traffic model to explore the interplay between snow forecasts and public response. This model has a geographic region of 50 km x 50 km with 500 x 500 grid points (i.e., each grid cell represents a 100 m x 100 m block; Fig. 1). This region includes a city region, a suburban region, and a rural region. These are structured (in geography, population, and work activity) with relative proportions consistent with a typical metropolitan area in the United States (Parker et al. 2018). Each region has an assigned road network (Fig. 2). The city has 10 roads per grid cell, the suburban region has 5 roads per grid cell, and the rural region has two roads per grid cell. There are also some areas on the map where there are no roads. These areas are built to account for greenery, bodies of water, and agriculture.

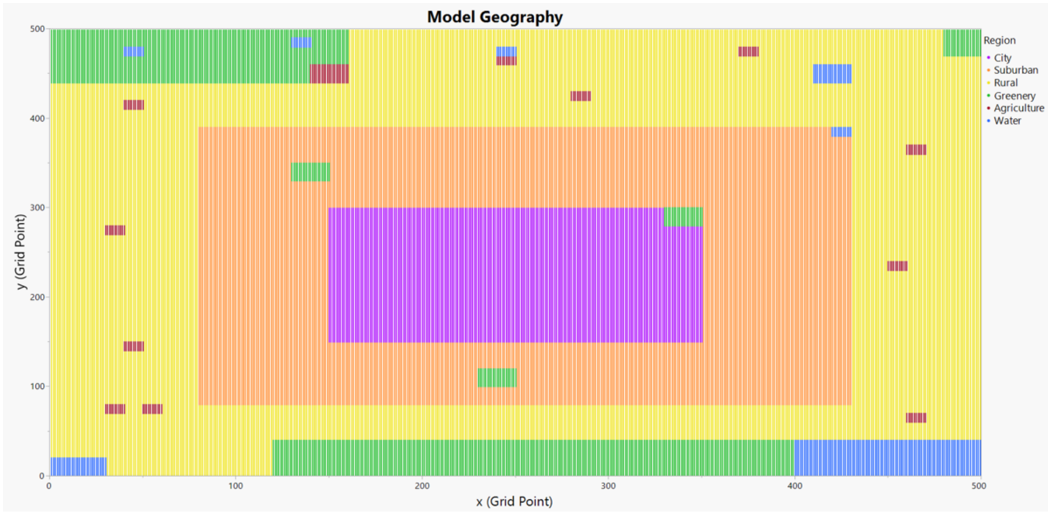

Figure 1. A map of the geography used in this model. This region is 50 km x 50 km, shown as 500 x 500 grid points. Each grid represents a 100 m block. The city area is indicated in purple, the suburban area is indicated in orange, the rural area is indicated in yellow, greenery is indicated in green, agriculture is indicated in red, and water is indicated in blue.

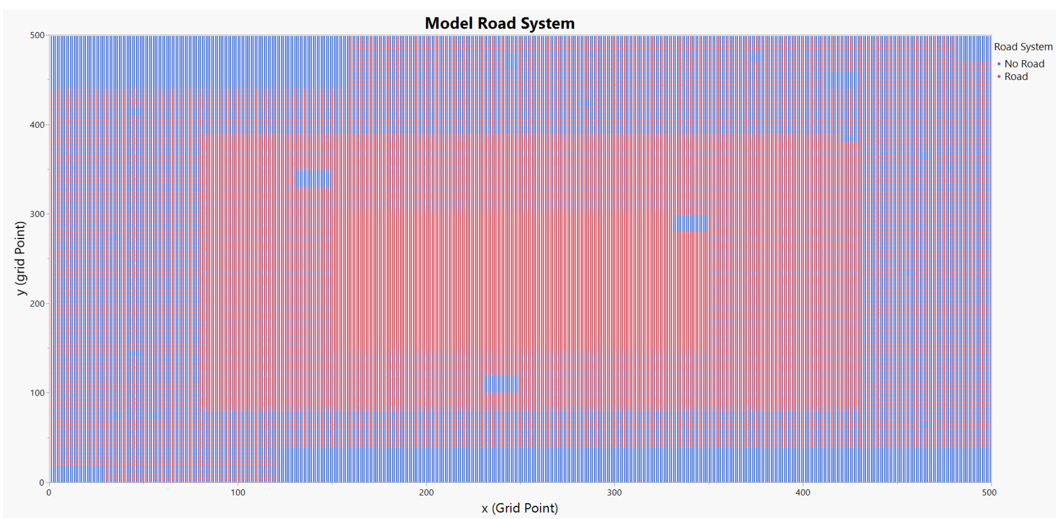

Figure 2. A map of the road system used in this model. Roads are represented in red, while areas without roads are represented in blue.

There are a total of 578,473 agents that populate this map, broken into three groups of workers: firm workers, service workers, and household workers. Firm workers live in the city and suburban regions, but all travel into the city to work. Service workers live in all three regions but travel into the city and suburban regions to work, with most working in the city. Household workers live in all three regions but work at home, so no travel is needed for them. 22% of the total population are firm workers, 67% work in service, and the remaining 11% are household workers.

The model runs over 24-hour periods. During these time periods, there are different 8-hour shifts for each type of worker. Firm workers have one shift from 9 am to 5 pm. Service workers are assigned to one of two shifts (4 am to 12 pm or 12-8 pm). Since household workers do not have to travel to their job, there is no shift time assigned to them (i.e. they are not modeled). The agents leave for work at the beginning of their shift and return home at the end, where the timing of these trips is governed by the road system, traffic patterns, and weather (i.e., it is dynamic).

To test agent sequential responses, the model loops over one non-weather base event and 5 snow events, each consisting of a 24-hour period as described above. These events include information on snowstorm magnitude and forecast error characteristics. Agents use this information to decide whether they will commute to work or stay at home. The results of their decision and the storm information will be remembered for future snow events, and that will play a role in the agents' probability of staying home during the next event.

To implement these weather conditions, we start with three variables: F1, F2, and F3.

Table 1. A description of the three variables, F1, F2, and F3.

Variable	Description
F1	Receptiveness to Expertise
F2	Forecast Severity
F3	Forecast Credibility

F1 is how receptive the agents are to expertise (i.e., heed official warnings), that is, how receptive the agent is to a forecast. This is divided into three levels: 0.25, 0.5 and 1.0, with 0.25 being the least receptive and 1.0 being the most receptive. These are assigned to each of the agents through a random number generator at the beginning of the simulation and held fixed. F2 is the severity of the forecast. This is divided into two levels: 0.5 and 1.0, with 0.5 being a less severe snow event and 1.0 being a more severe snow event. This is randomized with equal probability with each snow event. F3 is forecast credibility. This is dependent on the previous forecast. This is set to 1.0 before the first snow event. If the previous forecast is poor, credibility is lost, and the value of F3 is multiplied by 0.5. If the forecast is good, credibility is gained back, and the value of F3 is multiplied by 1.5. F3 cannot be any greater than 1.0. Thus, a sequence of poor-good-good forecasts would result in F3 values of 1.0 (prior to the first event), 0.5 (after the first event and before the second event), and 0.75 (after the second event). In other words, after a poor forecast, subsequent good forecasts have less impact than otherwise but do increase over time. For each event, the prior forecast has a 50% probability of being a good forecast, regardless of severity.

These variables affect the agents' probability (Pr) of staying home, which is applied only to firm workers (who have an option of working remotely). Service workers always attempt the trip to work and thus Pr=0 for those agents. After each snow event, Pr is calculated for firm workers as:

$$\mathrm{Pr} = F1 * F2 * F3 \qquad (1)$$

An additional complexity is introduced by the possibility of traffic accidents, where the severity of events increases that chance. The accident rate is set following Blincoe et al. (2002) and Roebber et al. (2007). When an accident occurs, a flag is set that indicates the road there is blocked and the agent adjusts its search path. The accident time is recorded and it is assumed that the road blockage is cleared after one hour.

3. Results

The model, with randomized forecast severity and accuracy (and thus credibility), is run 15 times to explore agent sensitivity (Table 2).

Table 2. The sequences of forecast severity (F2) and credibility (F3) for each of the 15 runs.

		Event Number					
		Base	1	2	3	4	5
Run 1	F2	0	0.5	1	0.5	1	1
	F3	1	1	1	0.5	0.25	0.375
Run 2	F2	0	1	0.5	0.5	0.5	1
	F3	1	0.5	0.75	1	0.5	0.75
Run 3	F2	0	0.5	0.5	1	1	0.5
	F3	1	1	0.5	0.75	1	0.5
Run 4	F2	0	1	1	0.5	0.5	1
	F3	1	1	1	1	0.5	0.25
Run 5	F2	0	0.5	1	0.5	1	0.5
	F3	1	1	0.5	0.25	0.375	0.5625
Run 6	F2	0	1	0.5	1	1	0.5
	F3	1	0.5	0.75	1	0.5	0.75
Run 7	F2	0	0.5	0.5	1	1	1
	F3	1	1	1	1	1	0.5
Run 8	F2	0	0.5	0.5	0.5	1	0.5
	F3	1	1	0.5	0.75	1	0.5
Run 9	F2	0	0.5	1	0.5	1	0.5
	F3	1	0.5	0.75	0.375	0.1875	0.09375
Run 10	F2	0	0.5	1	0.5	1	0.5
	F3	1	1	1	0.5	0.75	1
Run 11	F2	0	1	0.5	1	1	0.5
	F3	1	1	1	1	0.5	0.75
Run 12	F2	0	1	1	1	0.5	1
	F3	1	0.5	0.25	0.375	0.5625	0.28125
Run 13	F2	0	1	0.5	0.5	1	0.5
	F3	1	0.5	0.75	0.375	0.1875	0.28125
Run 14	F2	0	0.5	1	1	1	1

	F3	1	1	1	0.5	0.25	0.125
Run 15	F2	0	1	0.5	1	1	1
	F3	1	1	0.5	0.25	0.375	0.5625

3.1 Number of People Traveling

The trends in the number of agents traveling to work vary between firm and service workers (Fig. 3). As the forecast severity and credibility increase, the number of firm workers traveling to work decreases (i.e., if the forecast is severe and the forecast credibility is high, more firm workers exercise their option for remote work). Since service workers do not have this option, there is no substantial change in this number for with forecast credibility. When the forecast severity is high, fewer service workers make it to work, owing to the weather itself and the accidents caused by the weather (Fig. 4). While this fraction of the overall service worker population is less than 0.2%, in absolute numbers this amounts to approximately 600 people.

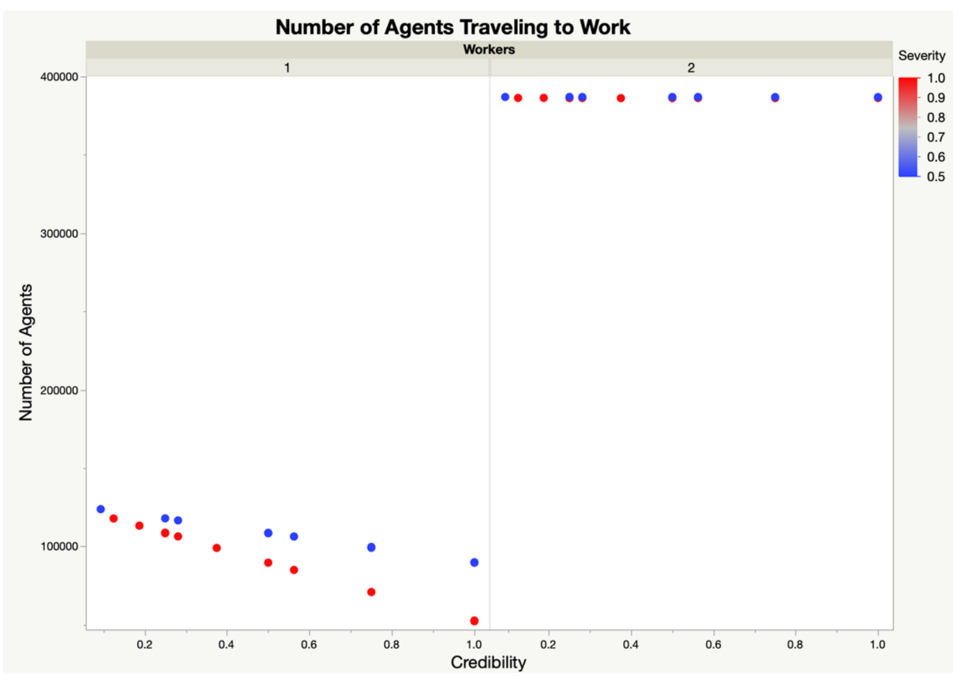

Figure 3. The number of agents traveling to work based on forecast severity and credibility separated by firm workers (1) and service workers (2).

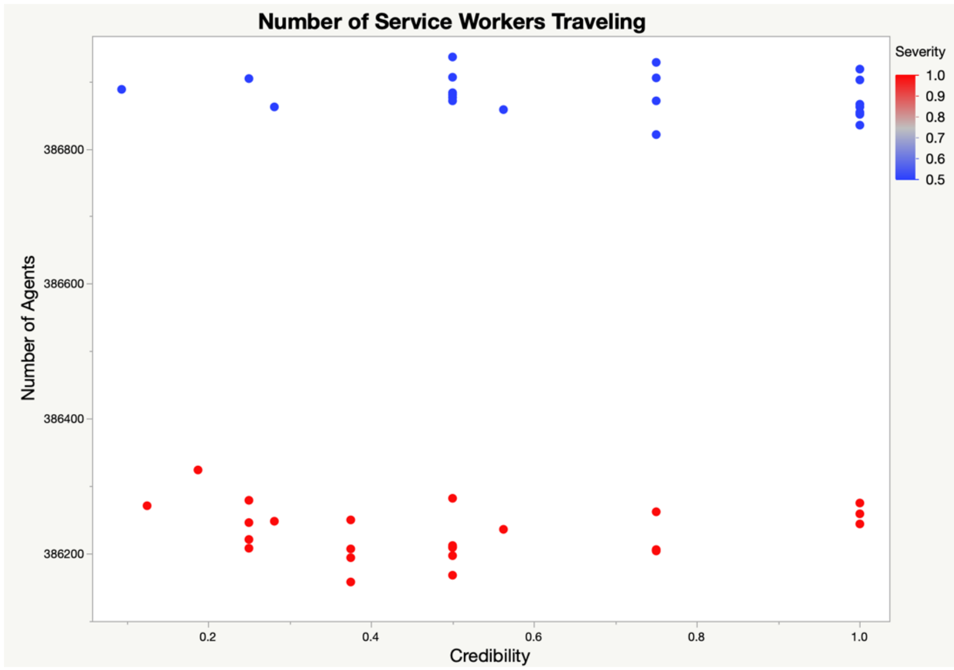

Figure 4. The number of service workers traveling to work based on forecast severity and credibility.

3.2 Travel Time

The difference in travel time (relative to the base case of no weather effect) is calculated by subtracting the median travel time (minutes) for the base case from the median travel time (minutes) for each event. Not surprisingly, both firm and service workers saw an increase in travel time with an increase in forecast severity (Fig. 5). Firm workers had a median travel time increase of roughly 8 minutes with a higher forecast severity while service workers had a median travel time increase of roughly 10 minutes. It appears, however, that while forecast credibility did not influence the travel time of service workers (for reasons previously stated), it likewise did not have a substantial influence on firm workers. This motivates further investigation of accidents in section 3.3.

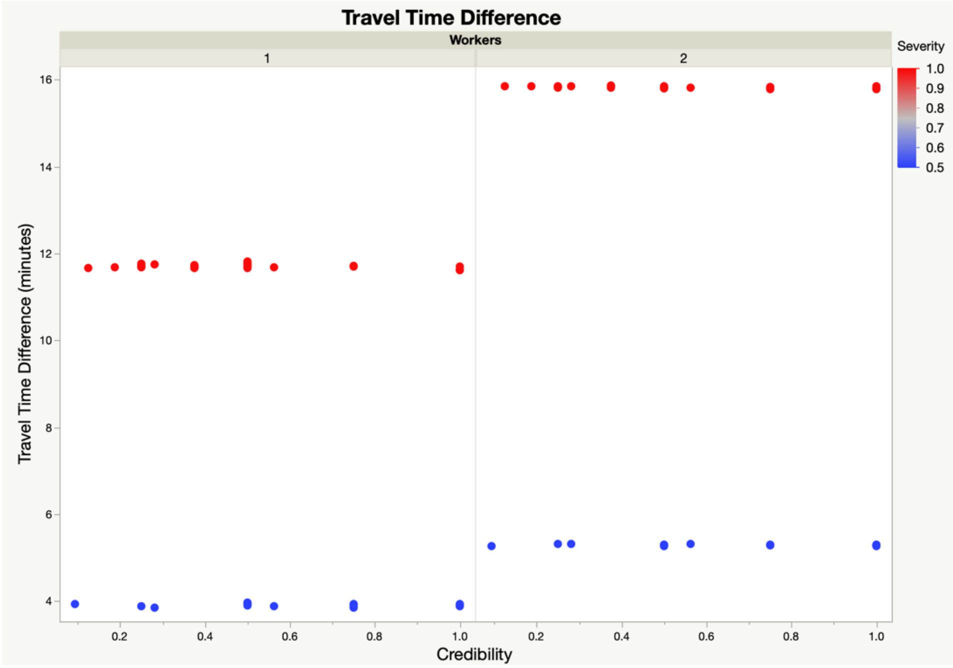

Figure 5. The difference in travel time to work in minutes based on forecast severity and credibility separated by firm workers (1) and service workers (2).

3.3 Accidents

In the model, accidents are random events whose probability for an individual agent is a function of distance traveled and weather severity. Thus, one might expect more accidents with more agents traveling and worse weather. However, perhaps due to the small number of runs, such a relationship was not evident in the model data, which instead features substantial case-to-case variability (Fig. 6). Overall, there is a higher percentage of service workers getting into accidents on the way to work compared to firm workers simply because there are more of them on the road. In order to test this effect further, rather than run thousands of simulations (which is computationally expensive), we ran an additional simulation where the accident rate has been increased by a factor of 10 (Fig. 7). In this instance, we find that there is a strong increase in accidents in severe weather, as expected (along with increases in travel time). Note that the accident rate assigned as the base rate in these simulations is not rigorously known, and in reality, is likely to differ depending on how used to driving in such conditions a population might be (Bello, 2014). Thus, we consider that our results apply to a northern climate, at a time of year when individuals have become readjusted to winter driving challenges.

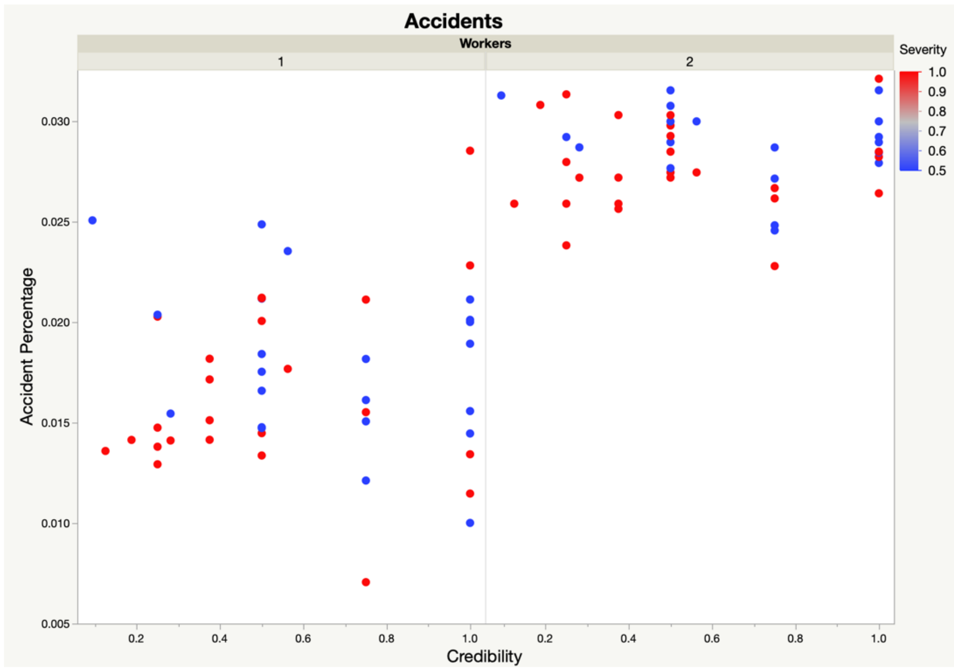

Figure 6. The percentage of accidents occurring on the way to work based on forecast severity and credibility separated by firm workers (1) and service workers (2).

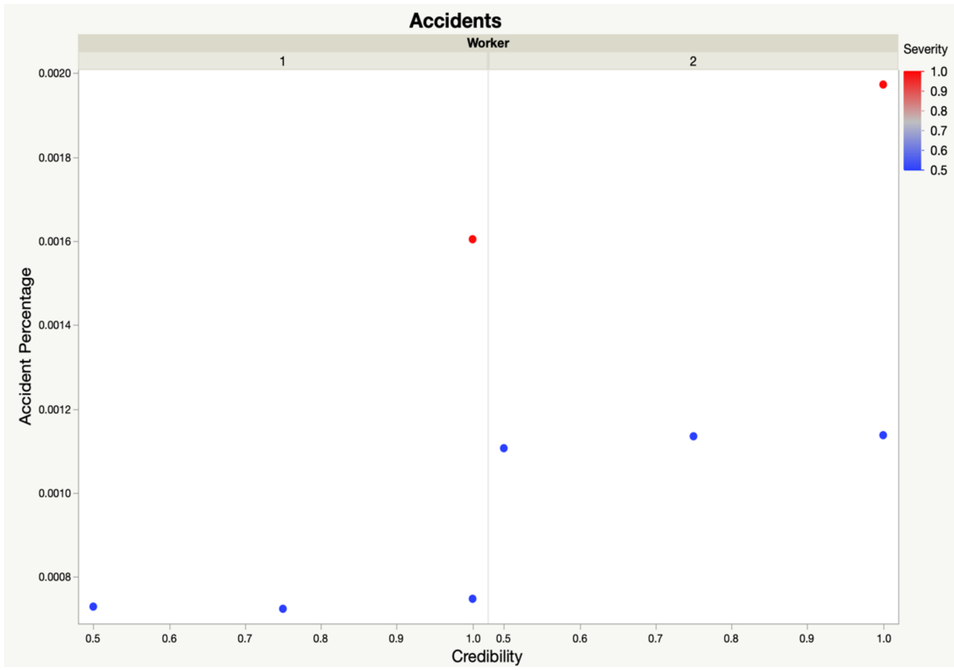

Figure 7. The percentage of accidents occurring on the way to work based on forecast severity and credibility separated by firm workers (1) and service workers (2). Accident rate in this simulation is increased by a factor of 10 relative to the other simulations in this study.

3.4 Receptiveness to Expertise

To test how the level of receptiveness to expertise factored into travel decisions, each agent in the model was next set to the same value for F1. The model was run three times for each value (0.25, 0.5, and 1.0). Through these model runs, it was found that receptiveness to expertise does not have a strong influence on the median travel time difference, number of agents traveling, and accidents. For firm workers, there is a small effect on the number that travel to work as receptiveness to expertise increases (Fig. 8). There appears to be a marginal increase in travel time, that results from a wide scatter in accident frequency, for those workers (Figs. 9-10). As discussed in section 3c, it is likely that there would be regional variability in this result, owing to differential accident rates depending on the ability of driver to accommodate winter driving conditions. Regrettably, social science data that might shed light on this issue are not available, but the present work does suggest a motivation for its collection. It is possible that a careful review of NTIS accident data might provide some insight, although the existing database references fatalities only and so likely substantially underrepresents the actual accident rates (see section 3c for the experiment with higher rates).

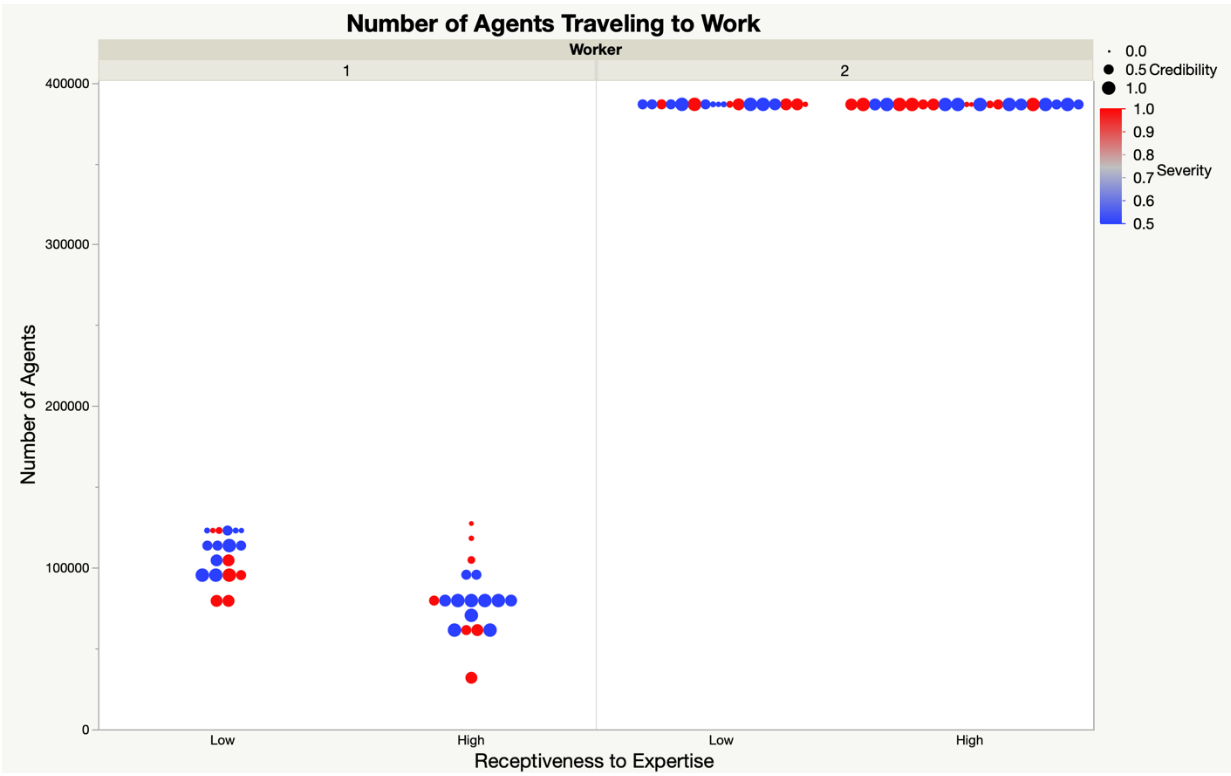

Figure 8. The number of agents traveling to work based on receptiveness to expertise (0.5 or lower is considered low while above 0.5 is considered high), forecast severity (color), and forecast credibility (symbol size, larger indicates higher credibility) separated by firm workers (1) and service workers (2).

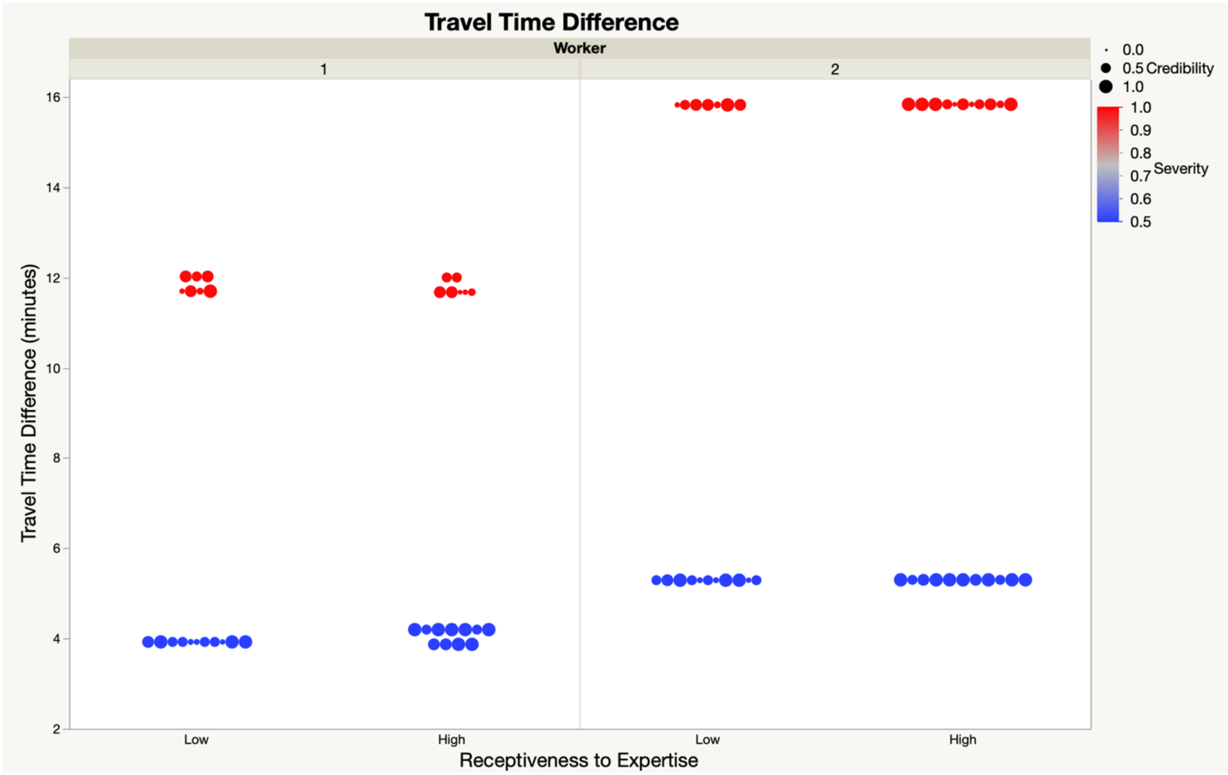

Figure 9. The difference in travel time to work in minutes based on receptiveness to expertise (0.5 or lower is considered low while above 0.5 is considered high), forecast severity (color), and forecast credibility (symbol size, larger indicates higher credibility) separated by firm workers (1) and service workers (2).

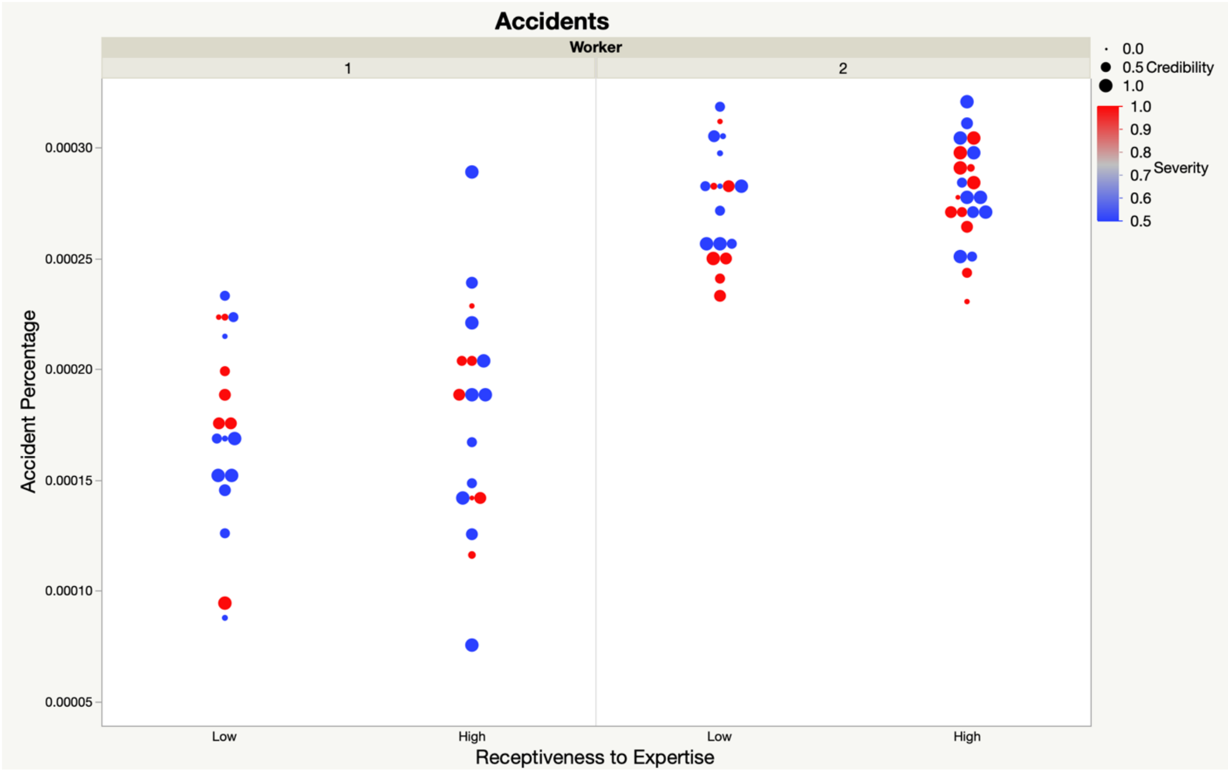

Figure 10. The percentage of accidents occurring on the way to work based on receptiveness to expertise (0.5 or lower is considered low while above 0.5 is considered high), forecast severity (color), and forecast credibility (symbol size, larger indicates higher credibility) separated by firm workers (1) and service workers (2).

4. Conclusion

This model performed as expected regarding the patterns in number of agents traveling and travel time differences. Since firm workers have the option to work from home, less of them are on the roadway when the forecast severity and credibility are higher. Since service workers do not have the option to work from home, forecast credibility does not factor into their travel decisions. Despite this, fewer service workers will make it into work when the forecast severity is higher due to the more difficult commute during those times. Forecast severity is the major factor in the difference in travel time. When the severity is higher, both firm workers and service workers have a longer commute time.

For the base accident rate explored in detail, there were no clear patterns in how forecast severity and credibility factor into the percentage of agents involved in accidents. We speculate that this result may be reasonable for areas in which drivers are most accustomed to winter driving hazards. To explore whether the model responds to a higher accident rate, which might apply to areas less exposed to severe winter weather, we performed additional simulations with an increased base accident rate. We found the expected response in this case: a strong increase in accidents and longer commute times. It would be beneficial to determine whether national data collected by the U.S. Department of Transportation can provide better insight into regional accident rates during snow events.

We did not see a strong effect of receptiveness to expertise. Instead, there were some minor differences in number of firm workers traveling to work depending on this factor. This makes sense, since if the agent is more receptive, they will more likely stay home when forecast severity and credibility are higher.

This model is necessarily simple as a first attempt, but there are a number of possible enhancements that could be added to this framework. For example, in the current version, agents do not receive weather information from different or multiple sources, whereas in reality individuals may hear about storms from the National Weather Service, local television stations, internet weather applications, and/or word of mouth. Variable workplace telework policies could be added. The current version of the model treats traffic simply, where cars do not interact except in the case of accidents. Traffic congestion is readily simulated in agent-based models, and adding this aspect here would increase the interactivity of agents. Further, experience with accidents could be factored into future decision making by agents.

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