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Exploring the Impact of Driver Adherence to Speed Limits and the Interdependence of Roadside Collisions in an Urban Environment: An Agent-Based Modelling Approach

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Abstract: Roadside collisions are a significant problem faced by all countries. Urbanisation has led to an increase in traffic congestion and roadside vehicle collisions. According to the UK Government's Department for Transport, most vehicle collisions occur on urban roads, with empirical evidence showing drivers are more likely to break local and fixed speed limits in urban environments. Analysis conducted by the Department for Transport found that the UK's accident prevention measure's cost is estimated to be £33bn per year. Therefore, there is a strong motivation to investigate the causes of roadside collisions in urban environments to better prepare traffic management, support local council policies, and ultimately reduce collision rates. This study utilises agent-based modelling as a tool to plan, experiment and investigate the relationship between speeding and vehicle density with collisions. The study found that higher traffic density results in more vehicles travelling at a slower speed, regardless of the degree to which drivers comply with speed restrictions. Secondly, collisions increase linearly as speed compliance is reduced for all densities. Collisions are lowest when all vehicles comply with speed limits for all densities. Lastly, higher global traffic densities result in higher local traffic densities near-collision sites across all adherence levels, increasing the likelihood of congestion around these sites. This work, when extended to real-world applications using empirical data, can support effective road safety policies.

Keywords: agent-based model; traffic simulation; urban environment; autonomous agents; data analysis; collisions; speed adherence

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1. Introduction

A lack of adherence to speed limits can have serious consequences and pose a significant risk to life for drivers, passengers and members of the public. According to UK Government reports, car users account for the largest proportion of casualties across all categories of injury. A total of 736 car passengers/drivers suffered fatal collisions in 2019 [1,2]. Furthermore, on 30 mph (miles per hour) roads, 54% of cars exceeded the speed limit in the first quarter of 2019. In addition, 6% of these cars exceeded the speed limit by over 10 mph. This increased in the second quarter of 2019 to 56%. Similarly, 37% of fatalities among car passengers/drivers in 2019 occurred on urban roads—an increase of 1% since 2018. An additional 57% of fatalities occurred in rural roads, down 3% since 2018. These trends are evident outside of the UK. According to [3], almost half of the reported driving offences in the Northern Territory of Australia are regulatory; these include speeding and non-adherence to road rules. In Norway, a longitudinal study conducted on 145 young drivers (up to 25 years old) found that speeding behaviour was the main factor (80%) in causing motor vehicle collisions [4].

Driving speeds are a vital component in exploring the factors that lead to collisions. Several empirical studies in speed and collision rates found evidence that crash rates increase faster given the increase in speed in minor roads compared to major roads. Two important factors related to collision rates are traffic density and traffic flow [5]. Furthermore, the authors in [6] found that population density is a contributory factor in accident frequency. The authors suggest that population densities in cities are higher than in rural areas; thus, people are more exposed to vehicle collisions. Similarly, the authors in [7,8] collected empirical data from drivers in the form of surveys to conduct studies in driver behaviour; this method was also adopted by [9]. These studies found that an increase in speed led to an increase in collision rates and that fast moving vehicles have a higher crash rate than slow moving vehicles. References [7,8] both reported a power function to describe this relationship, while the authors in [9–11] reported an exponential function. These latter three studies also found that the crash rate increases faster with increasing speed on urban than on rural roads. Methodological differences in the operationalisation of variables, and the influence of coincidental factors, all may account for differences in results at a detailed level [5].

Self-driving cars play an important role in vehicle collision research. Reference [12] found that human-like driving policies are necessary to ensure the safety of passengers in these vehicles. The authors apply deep-reinforcement learning algorithms to simulate collision avoidance in dynamic settings. By adopting human expert knowledge data and feeding these data into the model, the authors found that human-like driving policies can be achieved. Similarly, reference [13] developed a hybrid online POMDP planning and deep-reinforcement learning algorithm to enable self-driving cars to avoid collisions, including pedestrians. The research aims to deploy a collision-free navigation system such that vehicles are better equipped at handling high-risk scenarios. The authors found that their hybrid solution outperforms each applied technique, POMDP and deep-reinforcement learning on average. Moreover, the author in [14] attempts to explore how and if ethics can be adopted in self-driving cars by comparing real-world scenarios where self-driving cars fail to adopt human intuition to avoid a collision with a pedestrian as doing so would result in the vehicle breaking its own intrinsic rules. The author in [14] points out that self-driving cars cannot be sure that a road ahead is clear, such that it should cross and avoid hitting a person that it may encounter. These vehicles will estimate the confidence interval at 98 to 99 per cent, which ultimately means engineers would have to decide how high the confidence interval must be. Thus, engineers would need to consider what object is ahead, i.e., plastic bag or a person making this an essential line of enquiry in this field of research. While most of the research in self-driving car technologies is in its infancy, developing new technologies to handle collision is welcomed, which could, in turn, be adopted by regular non-self-driving vehicles.

Safety intervention policies in reducing variations in speed play an essential role in reducing collision rates. Interventions include speed humps, roundabouts, road markings, signposts and traffic lights. However, the measures that have been found to increase speed limit adherence are those that physically prevent a vehicle from driving faster than necessary, such as speed humps [15]. Safety measures deployed in vehicles have also lead to a decrease in collisions. The European Union has made it mandatory through legislative requirements for vehicles to be fitted with advanced emergency braking systems and other measures, which lead to a decrease of 5000 fatal collisions on European roads per year [16]. Alternatively, signposts that show the expected speed limit do not automatically imply that drivers will match the indicated speed limit. The authors in [17] refer to static speed limit signposts as passive speed control. They argue that passive control alone is generally only sufficient at sites where the hazards are obvious, and drivers understand and accept the speed limitation [15]. Ultimately, the authors in [18] found that active signalling, using dynamic signs informing a driver that they are exceeding the speed limit, has more effect than passive control since drivers may also interpret the signal as an indication for impending danger. In addition, the authors in [19] found that, when comparing a signpost with a marked police car in increasing speed adherence, the police car had a significant effect on driving speed the drivers were in active fear of being reprimanded. According to [20], features such as edge markings that visually narrow the road, the vicinity of buildings, reduced carriageway widths, barriers in the carriageway and pedestrian activity all tend to reduce speed.

The concepts discussed above provide insight into the literature on empirical evidence of collisions in Great Britain, the impact of speeding, safety intervention policies and road design. However, the decision to speed or comply with speed limits comes down to the individual driver. Speeding is a major contributory factor to roadside accidents [21]. To date, the majority of research in this area has investigated an extensive range of important factors from the viewpoint of those who exceed speed limits. This focus is understandable, given that faster vehicle speeds increase both risks of crash involvement and severity of crash outcomes [22].

The earlier statistics show that work needs to be done to curb the number of accidents on urban roads. This study will utilise a novel 3D Urban Traffic Agent-Based Model [23] to conduct several experiments by testing multiple traffic density and speed limit adherence parameters to illustrate how these measures impact vehicle collisions among a heterogeneous agent population of vehicles in a simplification of an urban environment. This study adopts the widely accepted definition of collisions, defined by [24] as: "an observational situation in which two or more road users approach each other in space and time to such an extent that a collision is imminent if their movements remain unchanged". The study ultimately aims to assess the impact traffic density and speed limit adherence have on collision rates by utilising a novel agent-based model to provide recommendations on reducing these rates and inform policy.

Section 2 introduces the agent-based modelling methodology by describing what it is and how it has been adopted in similar research. Section 3 will describe the agent-based model using established protocols such as the Overview, Design concepts and Details (ODD) [25]. This section outlines the purpose of the model, agents and environment characteristics. Section 4 describes the number of experiments conducted, the rationale behind them and an analysis of the subsequent outcomes. Lastly, Section 5 consists of the studies' initial aims, which was found after experimentation, and the recommendations made for future urban road infrastructure planning.

2. An Individual-Based Modelling Approach to Traffic Simulation

The traffic system is characterised by multiple individual actors (drivers) and a street network made up of individual rules such as right of way and speed limits. Given the nature of this system's individual-level components, it is evident that these systems are perfectly poised to be studied using individual-based modelling methods. According to [26], individual-based modelling refers to simulation models that treat individual entities as unique and discrete components with at least one property, for example, age, height, position and these properties change during the life cycle of these entities. Therefore, in this study, vehicles can be thought of as individual heterogeneous entities with their own rules, while the urban street network is the environment in which these vehicle entities are observed from within. The aim is to test various interventions in this simplified world and collect observational data from these entities to assess the impact of these interventions.

Agent-Based Modelling (ABM) is a tool that allows the study of emergent behaviour of a system by simulating the actions and interactions of a collection of autonomous agents. It is used in a wide variety of disciplines such as ecology [27], crime [28] and sociology [29]. Implementing simple rules for the agents can lead to the reproduction of complex phenomena observed in the real world. Like all models, an agent-based model simplifies the isolated study of the effect of particular agent behaviour. In light of these advancements, several scholars advocate for contemporary simulation models as better suited in studying the underlying mechanisms of crash occurrence. Furthermore, these methods represent a richer and more detailed set of alternatives than statistical models [30].

Traffic in an urban space is a complex system that includes the environment (a road network with a plethora of features like intersections, traffic lights, roundabouts, hills and weather conditions) and drivers' behaviour as individuals. Urban traffic management has reached utmost importance worldwide as cities battle congestion and its impacts on public health and fossil fuel emissions. Many computational models exist—SUMO [31], AIMSUN [32], ARCHISIM [33] and PARAMICS [34], to name several—which aim to simulate traffic flow and aid the design and layout of urban roads and thereby help to minimise the impact of congestion. However, these models are typically explicitly collision-free; driver behaviour is formulated to prevent collisions. However, some contemporary academic research has focused on various aspects of roadside collisions. The authors in [35] applied data mining techniques on data captured from intersection accidents to support real-time collision detection systems at intersections. A review of near-collision driver behaviour models by [36] found that most research has mainly been interested in the details of control in near-crash and crash-phases and have thus not needed to provide an account of why these states were reached in the first place. Furthermore, the authors in [36] argue that some authors have modelled reactions to collision warnings in various ways [37–39], while none of the models has addressed the phenomena of behavioural adaptation to long-term system exposure. The model adopted in this study [23] allows for the vehicle's life-cycle to be observed at an individual level while also observing the global patterns that emerge overtime at the street network level. The authors in [36] also found that almost all papers focused on a narrow set of collisions, namely rear-end collisions. Thus, they recommend looking at a more diverse range of pre-crash scenarios to achieve full credibility. The model adopted in this research deploys an environment that can observe multiple vehicle behaviours while applying the laws of physics. A variety of collisions among vehicles can then be observed. An example of this is where vehicles tip over if a collision occurs with a heavier, faster-moving vehicle, which ultimately captures a more realistic array of possible collisions and repercussions. Ultimately, collisions occur and contribute to various undesirable circumstances on roads, such as traffic jams and congestion. Furthermore, the rate, type, and severity of these collisions are emergent properties of the system, impacted by driver interaction, driver behaviour, and the environment.

Driver behaviour can be observed in many ways; these include surveys, camera footage, police reports, to name but a few. A prominent method within the literature is the Driver Behaviour Questionnaire (DBQ) introduced in 1990 by [40]. This questionnaire consists of 50 items describing various problems and violations while driving, which members of the public can fill out. After surveying 520 drivers, the authors in [40] identified that errors are statistically distinct from violations, indicating that different psychological mechanisms trigger errors and violations. The authors in [41] found that violations were more prevalent among young drivers compared to senior drivers. On the other hand, errors decreased for younger drivers but remained constant with age among older drivers. The differences between attitudes among drivers in rural areas and urban areas reflect the significant difference among collisions in these areas. The authors in [42] identified that urban road network design consisted of higher lengths of road and traffic volume, which in turn increased the collision rates. The authors in [43] add to this by highlighting the strongest predictors of fatality rates due to vehicle collisions as being age and number of residents in the geographical areas. The authors in [44] adopted Naturalistic Driving Study (NDS) data which contains driver, trip and vehicle specific information. These data represent driver behaviour before, during and after the adoption of high-visibility enforcement programs. Furthermore, the study focused specifically on aggressive driving behaviour; these include speeding and tailgating to explore the intensity and duration of these behavioural patterns. The study found that high-visibility enforcement programs are likely to reduce speeding only in some instances. A survey result showed that drivers in rural areas are more likely to drive without a seat belt on or while intoxicated with alcohol compared to drivers in urban areas [45]. The author in [46] identified two components that impact traffic risk. These are system risk and risk culture. The latter consists of factors independent of the driver, such as vehicle condition, weather and road plans. The former are human factors such as norms, feelings, attitudes and perceptions of risk. Adding to this, the authors in [47] attempted to analyse taxi driver speeding behaviours captured by GPS trajectory data. These data captured the hourly speeding frequency and average speeding severity of each driver. Their study concludes that aggressive driver behaviour among taxi drivers are linked to longer trips, short delivery time, high monetary value, driving at night, and, lastly, forced low-speed limits. Given all of the above, the authors in [43] highlight the impact physical changes to road networks can have by enforcing slower speeds such as road humps, while also indicating that driver behaviour may also be altered indirectly by influencing the public's attitudes and norms which links to the literature on "self-explaining" roads [48] mentioned earlier in the Introduction section.

Accident reduction is a crucial aim of transport management. It has been hypothesised that higher congestion leads to fewer road fatalities [49] as congestion leads to lower overall speeds, and therefore collisions are less likely to occur. While some evidence of this relationship has been found in some scenarios such as on single-carriage rural roads in the UK [50], results are much less conclusive in other scenarios such as in cities such as London [51] or on highways such as the M25 motorway around London [52]. Furthermore, it has been argued that, in many empirical studies, congestion is evaluated using proxy variables such as volume over capacity ratio or employment density [53] and that, to fully understand the impact of congestion, data with high levels of spatial and temporal resolution are needed [54]. Microscopic traffic simulations track all vehicles' positions and velocity in the simulated road network in small time steps, allowing traffic dynamics to be observed in high spatial and temporal resolution. These simulations could complement empirical investigations and yield further insight into the interactions between road environment, speed, traffic density, congestion and accidents, adding to the debate regarding the impact of vehicular congestion on the frequency of road accidents [55].

The ABM described in this study has been designed to investigate the relationship between driver adherence to speed limits and the subsequent impact on the number of collisions. Unlike the previously described models, it utilises a physics engine provided by the Unity development platform. This feature allows physical collisions to occur between vehicles. The interaction between traffic density, adherence level and collisions can be studied by increasing the number of agents. The study will ultimately aim to argue for various policy interventions such as reducing or increasing density to reduce collision rates and regulate speeding in dense road networks and, by utilising the agent-based model, show the extent to which these interventions impact the system as a whole.

3. Model Description

This section describes the agent-based model adopted for this study. A general description of the model can be found at [23]. The model description includes the purpose of the model, the parameters that can be selected, the output variables from the model post simulation run, overview of the model workflow, and, lastly, a detailed description of the vehicle agents and environment. The Overview Design and Details (ODD) protocol will be utilised to explain the model [25].

3.1. Purpose

The agent-based model used in this research is the 3D Urban Traffic Simulator in Unity [23], this includes the data produced during model experiments, found in the Supplementary Materials. The model was designed to provide researchers with the ability to simulate hypothetical vehicle drive–cycle activity scenarios in a 3D urban environment. The model utilises heterogeneous autonomous vehicle agents with granular control parameters such as vehicle mass, velocity, traction and downforce to name but a few. Similarly, the street network is developed around a built-up urban environment that contains the foundations of a dense urban street network with varying road speed limits and intersection rules.

3.2. Variables

The model requires input variables to run an experiment and output results that can later be analysed. The parameters that can be modified are listed in Table 1.

Table 1. Model entities and parameter values, where [X, Y] are a random uniform distribution of values (inclusive) [23].

Entity	Parameter	Values
Vehicle	Mass	[1, 7500] (kg)
	Top Speed	[30, 45] (mph)
	Ray-cast Length	[1, 20] (m)
Environment	N. Of Vehicles	[1, 500]
	Speed Adherence	[0, N]
	Roads	1295
	Intersections	354

The model consists of two entities: the vehicle agents and model environment. The vehicle parameters are:

- The vehicle mass parameter, each vehicle can weigh up to 7500 kg; the model distributes vehicles arbitrarily across the environment with varying weights, from small cars to large goods vehicles (LGVs) to capture heterogeneity, every vehicle must have a mass of at least one such that the laws of gravity apply during the simulation experiment. Mass only becomes significant when collision severity is of importance; however, all collisions are considered in this study.
- The top speed measure is between 30 and 45 mph, and is only applied to vehicles that do not adhere to speed limits (break speed limit rules), for example, vehicles that are driving on a 20 mph road can bypass the speed limit and drive at 45 mph which is more than double the speed limit. This measure is applied only if Speed Adherence is $\geq$1 (source [2]).
- The ray-cast length parameter can be between 1 to 20. The variable assigns a distance between two vehicles in meters (source [56]).

The environment specific parameters are:

- The number of vehicles in the model, N; this can be between 1 and 500.
- The speed adherence variable can be between $0 \leq x \leq N$. This assigns the proportion of vehicles that will not adhere to the speed limits (vehicles that break the local and fixed speed limits) applied to the road which they are driving on during simulation.
- The urban road network consists of 1295 roads which vehicles drive on and 354 intersections which consist of right of way rules. The street network has been developed to depict a small urban town.

The parameters mentioned above, once selected, are used to initialise the experiment (model-run) which lead to output variables. These variables observe data points every step of the simulation experiment. Table 2 describes the output variables that the model produces.

The model outputs thirteen variables (refer to Table 2). The agent ID variable allows for a micro-level analysis of the agent behaviours during model execution at the street level, and this helps identify specific agents in the environment. The collisions variable is a cumulative number that increases each time the vehicle collides with another; this includes contact made between two or more vehicles on all road types and intersections. Top speed is the speed limit associated with the road that the vehicle is currently on, and the vehicle is trying to match the speed; however, in scenarios where some vehicles do not adhere to speed limits, the top speed for those vehicles would be a value between 30 and 45 mph ultimately breaking the speed limit. The current speed variable is the vehicle's speed at the current time of the simulation run. The distance of travel is in meters which tracks the vehicle's distance from the starting position on the road network up until the current simulation step. The ray-cast length variable is the distance the vehicle can identify objects ahead, for example, other vehicles. Traction control is either 1 (on) or 0 (off). If the traction control is on, the vehicle has full traction capability such that each wheel can adapt to the surface; however, it is not utilised for this study as not all vehicles have access to traction control. The velocity magnitude is a scalar value demonstrating the rate of motion at a specific time. The vehicleMass variable assigns a weight to the vehicle between 1 to 7500 in kilograms to capture heterogeneity. The physics engine in Unity requires that every object has a mass assigned to it to ensure gravity is applied. Downforce coefficient is between 0.1 and 10; for this research, it is left at 0.1 to have no impact. Lastly, date-time stamps are included in each row of data recorded such that time-series analysis can be applied [23].

Table 2. Model output variables, source [23].

Variable	Output Type	Example Value
AgentID	Integer	−38,572
xAxisPos	Float	75.94560
zAxisPos	Float	20.1927
collisions	Integer	12
topSpeed(mph)	Float	20.0
currentSpeed(mph)	Float	18.0
distanceOfTravel(meters)	Float	13.0
raycastLength	Integer	6
tractionControl	Integer	0
velocityMagnitude(BETA)	Float	0.195808
vehicleMass	Integer	1500
downforce	Float	0.1
date-time	DateTime	18 January 2021 13:05:40

3.3. Model Overview

The agent-based model was developed using Unity. Unity is a 3D software development platform consisting of a rendering and physics engine and graphical user interface. Unity has received wide-spread acceptance in several industries, including gaming, automotive and film [57].

The following workflow diagram describes the processes that the model [23] undergoes during run-time.

The Urban Traffic Simulator [23] workflow (refer to Figure 1) takes input values for the five variables described earlier (refer to Table 1). The software then resets all parameters to start the simulation scene, producing the agents and environment. Once the model has reset, the model produces all agents, starting locations, and environment parameters before the simulation starts. Now, the model runs each frame, and every change that occurs is stored with a time-stamp. Fixed Update is used to compute any physics elements such as vehicle wheels, mass and velocity. The Update method computes variables in each frame. The model utilises Fixed Update due to the number of physics components used; therefore, multiple changes occur during simulation run-time for each frame, and these changes are captured to output the thirteen variables' (Table 2) post-simulation run; once this is done, the model is stopped (destroyed).

3.4. Agent

The vehicles are classed as autonomous agents; the vehicle population is heterogeneous (every vehicle has distinguishable characteristics). These agents apply similar characteristics to real-world motor vehicles; they have four wheels, steering angle, traction, mass, and drag. Each vehicle agent applies the following set of rules during its drive cycle, refer to Algorithm 1.

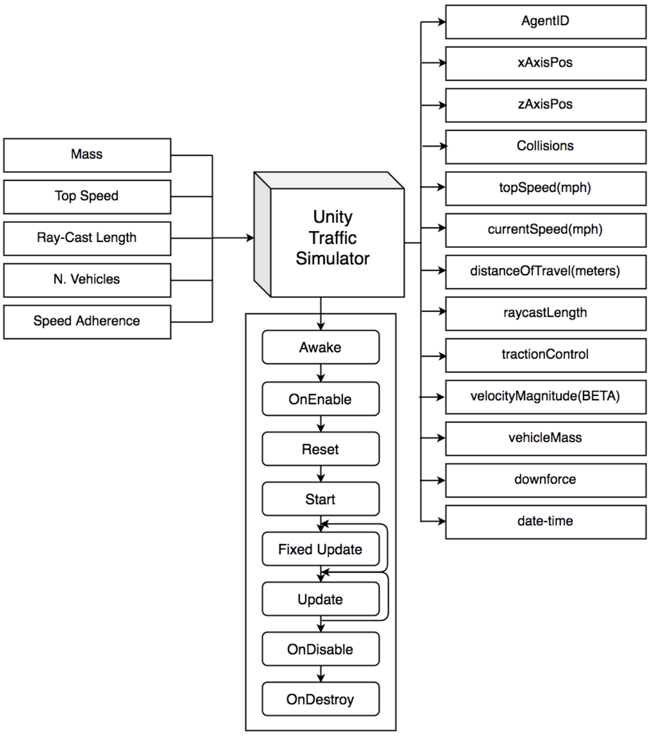


Figure 1. Workflow diagram depicting processes that the Urban Traffic Simulator undergoes during run-time.

Algorithm 1: Vehicle agent rules in pseudocode.

```
while Model running do
    Drive;
    if not_adherence == true then
        accelerate to top speed [30, 45];
    else
        accelerate matching road speed limit;
    end
    if vehicle_ahead == true then
        match speed of that vehicle;
    else
        continue at current speed;
    end
    if at_intersection == true AND vehicle_present == false AND right_of_way == true
     then
        reduce speed and drive out of intersection;
    else if at_intersection == true AND vehicle_present == true AND right_of_way ==
     false then
        halt till intersection_clear == true;
    else if at_intersection == true AND vehicle_present == false AND right_of_way ==
     false then
        reduce speed and drive out of intersection;
    else
        halt till intersection_clear == true;
    end
end
```

The rules described in Algorithm 1 allow vehicle agents to navigate the environment and collect data. Each vehicle follows the same rules. However, the features vary and depend on the input values from Table 1. These vehicle agents are a simplification of real vehicles. Therefore, it is not expected to perfectly simulate real-world vehicles but includes the fundamental features that all vehicles retain.

If a vehicle is not adhering to speed limits, it can increase its speed between 30 to 45 mph. If vehicle X is ahead of Y, Y given the rules in Algorithm 1 should decrease speed to match vehicle X's speed. When a vehicle arrives at an intersection, if it has the right of way, i.e., on a horizontal lane and no vehicles are at the intersection, it reduces its speed to 10 mph and drives through the intersection. If the vehicle is at the intersection and does not have the right of way, it should wait until the intersection is cleared. If the vehicle is at an intersection, it does not have the right of way, and there are no vehicles at the intersection, the vehicle is free to reduce speed to 10 mph and drive through the intersection. Lastly, all vehicles that adhere to the speed limit increase or decrease speed to match the road's speed limit [23].

3.5. Environment

The vehicle agents described earlier require an environment to function within. The model [23] deploys an urban street network that is described as a T-type network [58]. This street network contains similar characteristics to downtown Philidelphia [59] and San Francisco [60]. T-network patterns are like grid-shaped networks but include t-junctions. Several added features such as eight-lane intersections described in [61] are also utilised to add complexity. The street network contains 1295 roads and 354 intersections, which were arbitrarily generated to cover a small town. The individual roads, speed limits and intersection rules are described in the following Figure 2.

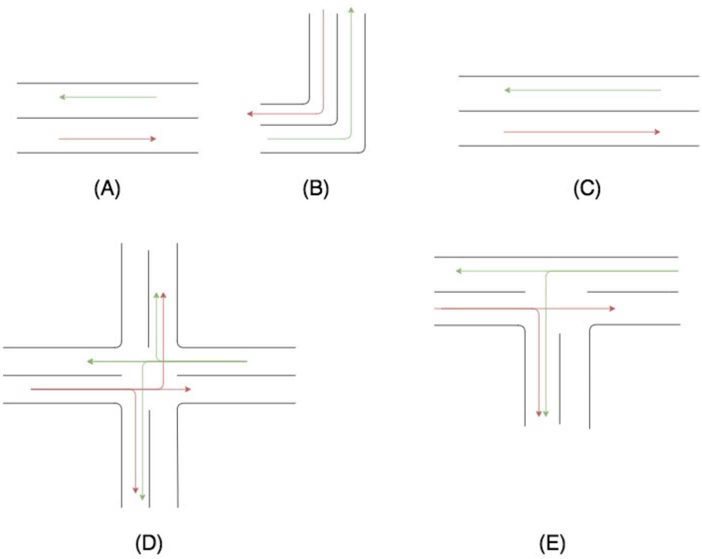


Figure 2. Urban Street Network roads and intersections, (**A**): two-way local road, (**B**): two-way corner road, (**C**): two-way fixed road, (**D**): eight-way intersection and (**E**): two-way T-junction.

The environment contains three road types with varying fixed and local speed limits and intersections with right of way rules. The environment is a simplification of the real world. Therefore, it does not utilise all intersection types. Moreover, overtaking is not utilised in the model as passing-lanes (overtaking lanes) do not exist in the street network and are commonly found in motorways or multi-lane highways [62]. However, it does contain the basic features of an urban street network which have also been observed in several cities across the United States [59,60]. The following list describes each road, intersection and the speed limits assigned to these roads from Figure 2:

- (A) Two-way local road with a speed limit rule of 20 mph.
- (B) Two-way corner road with a speed limit rule of 10 mph.
- (C) Two-way fixed road with a speed limit rule of 30 mph.

- (D) Eight-way intersection, where right of way is for traffic on horizontal lanes, speed limit rule of 10 mph.
- (E) Two-way T-junction, right of way is for horizontal lanes, speed limit rule of 10 mph.

The speed limits for the three road types (Figure 2A–C) were derived from UK government sources such as [2], where urban streets consist of local 20 mph and fixed 30 mph zones; however, corner roads sometimes require lower speeds such as 10 mph as vehicles require more room to turn. A UK Government report identifies roads in built-up areas as having a fixed speed limit of 30 mph. However, for dense areas—usually city centres—this may be designated 20 mph by local councils to keep pedestrians safe from collisions [63].

For comparison, the urban street network in the Urban Traffic Simulator [23] is roughly the same size as the town of Morley, UK (refer to Figure 3). Morley has 1526 roads compared to 1295, which the urban street network possesses.

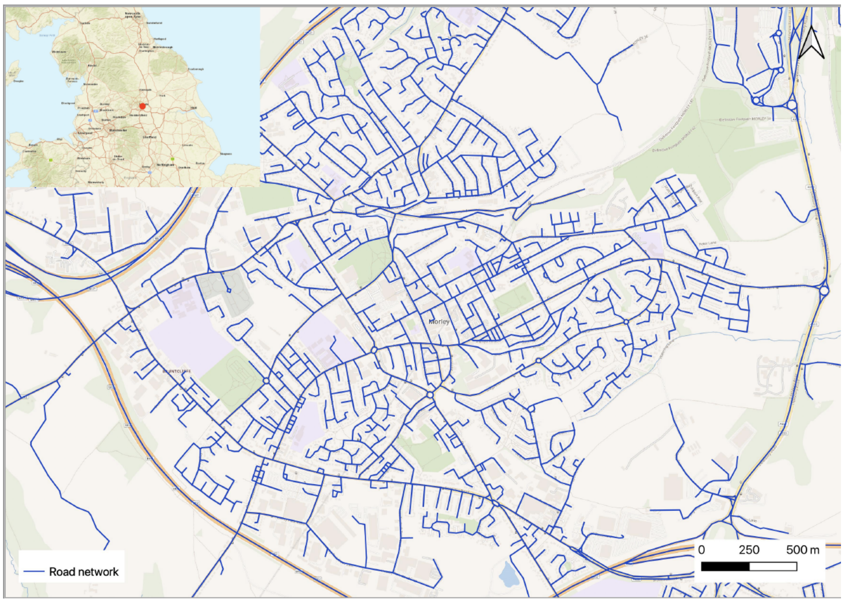


Figure 3. Urban Street Network of Morley, UK (data source: [64]).

3.6. Summary

The model description section describes the rules vehicle agents follow for every road type and intersection it encounters. Five rules govern the vehicle's behaviour; these broadly involve increased or reduce speed depending on road or speed adherence, interacting with intersections in a safe way to reduce the risks of collisions. The environment comprises three road types and two intersections, with varying local and fixed speed limits taken from empirical data via UK government sources. Lastly, the town of Morley, UK happens to be very similar in size to the urban street network applied in the model; this provides a realistic snapshot of the global scale of the street network involved. In the next section, the model is used to run nine hypothetical scenarios. The output data from these scenarios will be quantitatively analysed in several ways.

4. Experimental Results

As mentioned previously, this study aims to quantify the relationship between speed limit adherence within different population sizes and the subsequent impact on collisions. The experiments will conduct multiple model execution scenarios under nine conditions, refer to Table 3. The goal is to quantitatively identify the best and worst-case scenarios concerning the number of collisions in an urban street network. More specifically, low, mid and full adherence to speed limits will be compared across low, mid and high traffic density (number of vehicles); these are identified as the independent variables, while the dependent variable is the number of collisions. All other parameters will remain constant to ensure a heterogeneous population of vehicles across all experiments. The model is still in its infancy and can be thought of as a proof of concept. Thus, factors such as weather and time of day have not yet been implemented but will be considered for future extensions. The main variables of interest at this current time for this study are adherence to speed limit, vehicle density and collisions.

As described in the background section, the relationship between collision rate and traffic density has been theorised but not empirically verified. Since collisions in the real world can be caused by many factors, we will focus on collisions caused by speeding. Our question is: do higher traffic densities suppress the higher collision rates caused by speeding in an urban environment?

Table 3. Experiment conditions.

Independent Variable Measure	Low Adherence	Mid Adherence	High Adherence
Low traffic density	50 vehicles (25%) and 15 adherence (30%)	50 vehicles (25%) and 30 adherence (60%)	50 vehicles (25%) and 50 adherence (100%)
Mid traffic density	100 vehicles (50%) and 30 adherence (30%)	100 vehicles (50%) and 60 adherence (60%)	100 vehicles (50%) and 100 adherence (100%)
High traffic density	200 vehicles (100%) and 60 adherence (30%)	200 vehicles (100%) and 120 adherence (60%)	200 vehicles (100%) and 200 adherence (100%)

Each experiment ran five times with different random seeds for five minutes due to the computational demand required to render 3D agents. Final collision values were averaged across runs and normalised by the number of vehicles, with the standard deviation displayed in the error bars. The results are shown in Figure 4.

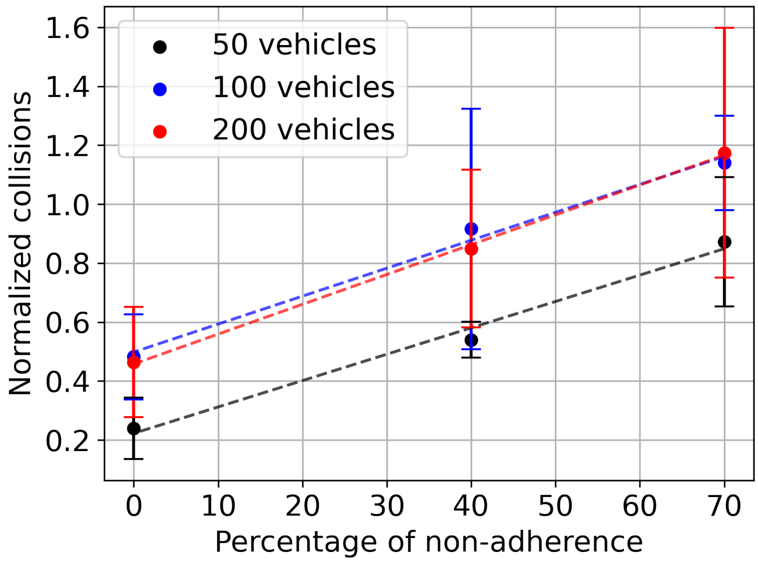


Figure 4. Number of collisions (normalised by number of vehicles) against the percentage of non-adherence to speed limits, refer to Supplementary Materials for data used.

Firstly, it is important to note the size of the error. While some variance in model runs is expected, the extent of the overlap between scenarios makes drawing firm conclusions from these experimental results difficult. However, in future studies, this will be taken into account.

While keeping account of this variance, it is still clear that there is a greater difference in collision rates between 50 and 100 vehicles than between 100 and 200. This suggests that there exists a critical density at which the number of collisions begins to scale linearly with traffic density; prior to this critical point, an increase in vehicles results in a disproportionately large increase in collisions. Similar patterns were found in empirical data collected in the subsequent studies [7–9]. In Figure 4, we see little evidence of reduction (either proportional or absolute) in the number of collisions as traffic density increases. Higher traffic density also does not appear to suppress the effects of low-speed limit adherence on collisions. As can be seen from the trend lines in Figure 4, collisions increase at a near-identical rate as a function of the percentage of non-adherence. Higher traffic densities also appear to loosely correlate with greater variance in collisions between runs.

While collision prevention is a primary goal of traffic management, the prevention of congestion—and its impact on public health and CO_2 emissions—is equally crucial [65,66]. As described in the background, it has been suggested that these goals could conflict [49,54].

There is no single definition of congestion—several different definitions have been developed for different congestion scenarios [67] or for identifying congestion from the available data [68]. In this study, congestion will be understood both as a decrease in the overall traffic speed in the system and as an increase in the number of vehicles with speeds under 5 mph at a given time. Local traffic density (the number of vehicles in a particular area of the network) will also be considered under the assumption that this correlates with congestion and being of interest in its own right.

To compare traffic flow for the different scenarios, the average speed of all vehicles was calculated. The results are shown in Figure 5. Lower adherence to speed limits leads to higher average speed for systems of varying density. However, the average speed of systems with low adherence is impacted more by increasing the density. For example, when increasing the number of vehicles from 50 to 200 for 100% speed limit adherence, the average speed decreases by 3.6%. When increasing the number of vehicles from 50 to 200 for 30% speed limit adherence, the average speed decreases by 13.3%; therefore, as density increases, the average speed of vehicles decreases.

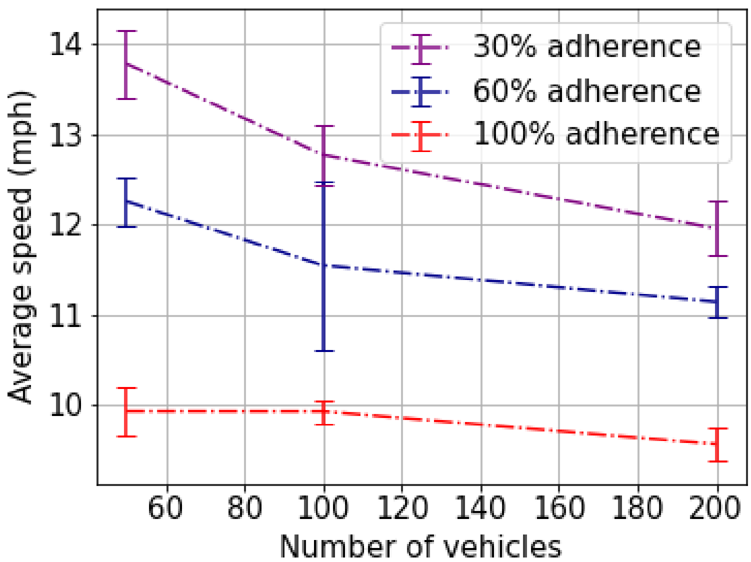


Figure 5. Average speed of vehicles against number of vehicles for each adherence scenario, refer to Supplementary Materials for data used.

While the average speed of traffic is an essential factor for considering the overall efficiency of the system (at least concerning average journey times), it does not communicate the distribution of speeds (for example, some vehicles may enjoy short journey times while others are stuck in congestion) or how these are spatially located.

The average agents' speed, the spread of agents' speed, and the percentage of vehicles below 5 mph at the final time step of each scenario are presented in Table 4. The spread of speed, which is the standard deviation of all agents' speeds, increases with lower adherence by a factor of more than 1.6 from 100% adherence to 30% adherence for all traffic densities.

This increase is expected since non-adhering drivers can access a broader range of speeds up to 45 mph while adhering drivers cannot exceed 30 mph. The fraction of vehicles below 5 mph includes vehicles that have collided and cannot move, including vehicles stuck behind these collisions. There is an increase in this fraction for 100 and 200 vehicles as adherence decreases. This increase is not evident for 50 vehicles.

Table 4. Average speed, spread of speeds, and fraction of vehicles moving below 5 mph for each scenario (where v = vehicles and ad = adherence percentage).

Scenario	Speed (mph)	Spread (mph)	Vehicles under 5 mph (%)
50 v, ad 30%	13.49	5.69	7.6
50 v, ad 60%	11.74	5.8	12.0
50 v, ad 100%	9.96	3.34	6.0
100 v, ad 30%	12.24	6.93	17.0
100 v, ad 60%	11.21	5.84	13.4
100 v, ad 100%	9.9	3.56	6.2
200 v, ad 30%	11.59	6.85	20.6
200 v, ad 60%	11.17	5.52	12.7
200 v, ad 100%	9.42	4.08	11.1

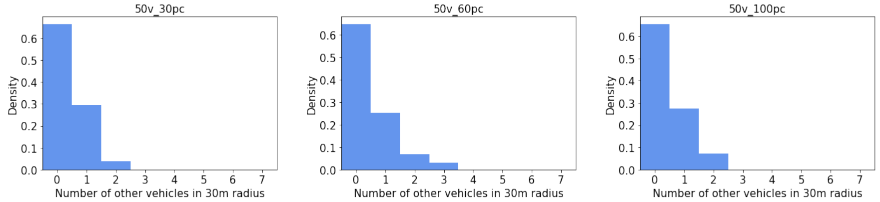
The above Table 4 shows that higher traffic densities and lower speed adherence result in a greater fraction of vehicles travelling at very low speeds at any given point in time, even though the average speed is higher. Similarly, low-speed adherence with low traffic densities increases the average speed without increasing the fraction of vehicles at very low speeds.

This study is concerned with the spatio-temporal analysis of the whole urban street network. However, Figure 6 shows that local micro-level phenomena can also be observed. We hope to conduct a comprehensive analysis of micro-level interactions between density, congestion and collisions for future studies.

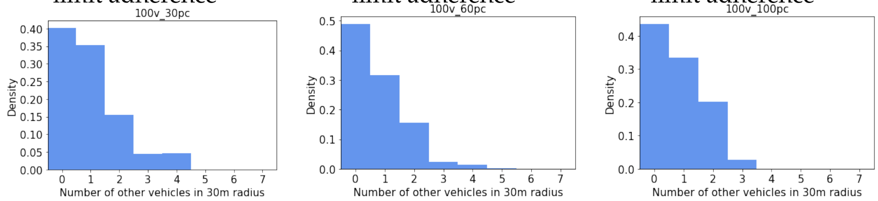
The local traffic densities within 30 metres of a collision site, one second before the collision takes place, is shown in Figure 6. Higher global traffic densities result in higher local traffic densities near-collision sites across all adherence levels. This is highlighted when comparing Figure 6c,f,i, where the modal value of the number of additional vehicles present near a collision increases from 0 to 1; that is to say that, for lower global vehicle densities, we typically observe that no additional vehicles are present at a collision site. Whilst for a large population of 200 vehicles, we observed that it is common for at least one other vehicle to be present. Furthermore, lower adherence results in higher local traffic densities near collision sites for 100 vehicles (Figure 6d–f) and 200 vehicles (Figure 6g–i) but not 50 vehicles (Figure 6a–c).

Collisions, when they occur, appear to be more likely to take place in the presence of other vehicles both when global traffic density is increased and when adherence level is lowered. However, an increase in local traffic density alone does not appear to cause an increase in collisions; a similar pattern was observed in [69]. This can be seen by comparing local traffic density results for 100 vehicles and 200 vehicles, which Figure 4 shows to have a near-equal collision rate despite Figure 6 showing that 200 vehicles have a higher local traffic density near collision sites.

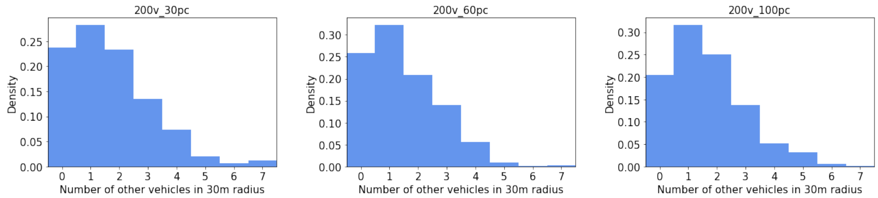
However, according to Figure 6, there is also an increase in local traffic density as adherence decreases, which always results in more collisions. This indicates that local traffic density may have a contributory effect towards collisions when combined with low adherence to speed limits, a higher average speed, or greater speed variance.



(**a**) 50 vehicles, 30% speed limit adherence (**b**) 50 vehicles, 60% speed limit adherence (**c**) 50 vehicles, 100% speed limit adherence



(**d**) 100 vehicles, 30% speed limit adherence (**e**) 100 vehicles, 60% speed limit adherence (**f**) 100 vehicles, 100% speed limit adherence



(**g**) 200 vehicles, 30% speed limit adherence (**h**) 200 vehicles, 60% speed limit adherence (**i**) 200 vehicles, 100% speed limit adherence

Figure 6. Distribution of number of additional vehicles involved in simulated collisions based on number of vehicles in system and proportion of vehicles adhering to speed limits.

4.1. Summary

To conclude, the experiments found that a higher traffic density results in more vehicles travelling at lower speeds through space and time. This is the case even when 70% of vehicles do not adhere to speed limit rules, i.e., driving between 30 to 45 mph. Furthermore, collisions increase linearly as the non-adherence measure is increased. This is the case for all traffic densities; however, lower densities lead to fewer collisions. Lastly, collisions are at their lowest amount when all vehicles comply with speed limits for all densities.

In the next section, an overview of the results is provided. Furthermore, the findings from the paper will be validated by comparing the results with empirical findings. Additionally, recommendations for reducing collisions will be made, and, lastly, future avenues for research will be discussed.

5. Discussion

The goal of this study was to understand the relationship between traffic density and the number of collisions. Moreover, the paper aimed to look at the concept of higher traffic density serving to suppress collisions by regulating driver speed, especially if drivers were not adhering to prescribed speed limits. Previous studies indicate that higher levels of congestion can result in fewer road accidents. This theory was the case for a single highway segment in Detroit [70]. Similarly, the authors in [71] found this to be the case on two to three-lane motorways in France. However, this is not true at intersections [72], or on urban roads in London [51,71], where the number of accidents was found to increase linearly at low to mid-levels of traffic and nonlinearly at high levels of traffic.

This study found that higher levels of traffic density do not reduce the frequency of collisions. Furthermore, higher traffic levels do not suppress the increased collision rates caused by non-adherence to speed limits. Empirical findings found that traffic congestion has little or no impact on the frequency of road accidents; however, it should be noted that the results are constrained to the M25 London motorway [52]. The author in [42] found that an increase in collision rates resulted from the road network design of urban roads, which consisted of higher lengths of road and high traffic density. This study aims to contribute to the ongoing debate as to whether traffic congestion impacts the frequency of road accidents [55].

This study found that high-density systems are affected to the same degree as low-density systems and provide no protective effect. This would suggest that the traffic management goals of congestion-reduction and accident-reduction are not in conflict for urban road networks.

This study also suggests that lower traffic density on average leads to fewer collisions regardless of adherence levels, as was observed in [72]. However, as adherence decreases, this leads to increased collisions relative to the number of vehicles in the urban environment. These findings were also observed in [73].

Empirical evidence from UK government sources in 2019 shows that, on average, 55% of vehicles in 2019 exceeded the speed limit on urban roads. During this time, 63% of all collisions occurred on these urban roads [1,2]. This study also shows that increases in collisions are more likely as more vehicles break speed limit rules.

This study's results do not reflect the same linear-to-nonlinear relationship between accidents and traffic levels as [71,72]. At low to mid traffic densities, collisions increase disproportionately as traffic density increases. Collisions begin to increase proportionately at a critical point in density, so an individual vehicle's risk of colliding does not increase as traffic increases. However, the results reflect the global number of collisions against an urban road network's global traffic density rather than studying micro-level intersections or specific urban roads. The study also attempted to provide a micro-level analysis to supplement the findings of the research. The analysis observed the distribution of the number of additional vehicles involved in collisions based on the global number of vehicles and the proportion of vehicles adhering to speed limits. We found that higher global traffic density resulted in higher local traffic density near collision sites. Furthermore, we found that lower adherence results in higher local traffic densities near collision sites for 100 to 200 vehicles; this is not the case for 50 vehicles. This indicates that local traffic density may contribute to collisions when combined with low adherence to speed limits, a higher average speed, or greater speed variance. Lastly, this micro-level analysis shows that additional vehicles are present within 30 m of a collision, ultimately leading to congestion at the local level.

The results in this study do show that higher traffic density results in higher levels of congestion. Even when maximum adherence is achieved, increased density resulted in reduced average vehicle speed, and this effect was greater for systems with lower adherence. Therefore, with high density, non-adhering vehicles are more likely to reduce their speeds more often as they find slower-moving vehicles ahead of them.

It should also be noted that conclusions drawn from this study are from the tested traffic densities. Studying a greater range of densities may reveal a more complex relationship. Conducting this study with a greater number of model runs per scenario may yield more precise insights into the relationship between collisions, traffic density, speed adherence, and speed distribution.

Since non-adherence to speed limits was found to increase collision rates for all traffic densities, this study recommends implementing measures to increase adherence to speed limits on all roads regardless of their traffic level. This may include the introduction of more speed cameras, which have been found to reduce speeding significantly [74]. Feedback signs which broadcast the percentage of drivers who have stayed within the speed limit of an area have also been found to be effective at reducing speeding and resulting accidents [75].

Another important finding from this study suggests that, if fewer vehicles occupy a street network, the total number of collisions is reduced. The most dramatic reduction in collisions may be areas that shift from medium traffic density to low traffic density. These findings support pedestrianisation policies, as these policies should reduce collision rates among vehicles in these urban environments and reduce CO_2 exposure. A report titled "The effect of pedestrianisation and bicycles on local business" published in 2017 found that: According to the 2012 Economic Impact Study, pedestrian activity has risen by 11%, with 35% fewer accidents with pedestrians and 63% fewer traffic accidents in New York Times Square [76].

6. Conclusions

This study aimed to explore the relationship between vehicle density and adherence to speed limits with collision rates through agent-based modelling. This area of research is still in its infancy but has shown that agent-based modelling is a powerful method that can provide the means to simulate hypothetical yet realistic properties of the real world and produce insight into these properties that can be empirically validated. Thus, this study will allow traffic practitioners and safety scientists to test their hypotheses through agent-based modelling in a safe, low-cost way prior to advising real-world policies.

In this study, the severity of collisions is not quantified. Since each vehicle's momentum is recorded in the model, this is a potential avenue for further study. Quantifying collision severity would allow future studies to categorise severe collisions (life-threatening) to mild collisions (dent in a vehicle), thus providing a more realistic snapshot of collision types. Some past studies have tried to quantify collision severity using alternate means such as the ordered logit model and the ordered probit model [77]. Similarly, empirical research found that mild collisions such as those that are not fatal were more likely to occur in cities across the UK [55]; this can be a future avenue to explore using ABMs.

Another avenue to explore would be to incorporate changing weather into the agent-based model. Weather plays a significant role in having an impact on driver behaviour, which can, in turn, lead to higher collision rates, i.e., vehicles are more likely to collide during snowy conditions [78–80]. Given the ABMs drag, traction control and downforce parameters, the phenomena mentioned above can be modelled in future studies.

Supplementary Materials: To download the data and software scripts used in the analysis of results, visit: https://github.com/SedarOlmez94/TrafficSimulatorResults, accessed on: 07 June 2021. Download the 3D Urban Traffic Simulator here: https://www.comses.net/codebases/32e7be8c-b05c-46b2-9b5f-73c4d273ca59/releases/1.1.0/, accessed on: 07 June 2021.

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