

Research Article

A Compartmental Model of Traffic Congestion with Adaptive Driver Behavior: Role of Awareness-Driven Interventions in Congestion Control

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ABSTRACT

Urban traffic congestion imposes substantial societal costs through time delays, fuel waste, and environmental degradation. Traditional mathematical models often overlook the influence of driver awareness and adaptive behavior, despite their increasing relevance in the era of real-time traffic information systems. This study presents a novel SIR-based compartmental model that integrates behavioral adaptation by introducing an "Aware" class of drivers who modify their travel decisions to avoid congestion. Qualitative analysis confirms the model's positivity and boundedness, while a stability analysis identifies a threshold condition governed by a basic congestion reproduction number, \mathcal{R}_0 . Results indicate that when $\mathcal{R}_0 < 1$, congestion dissipates over time, while $\mathcal{R}_0 > 1$ leads to sustained congestion. Numerical simulations reveal that increasing the rate of awareness acquisition significantly lowers \mathcal{R}_0 , reducing both the peak and duration of congestion. These findings highlight the potential of awareness-driven such as real-time traffic advisories and navigation systems, as effective and low-cost strategies for congestion mitigation. The results provide theoretical insights that can inform the design of integrated traffic management policies combining behavioral and infrastructure-based approaches.

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1. INTRODUCTION

Traffic congestion is defined as a state in which vehicular demand exceeds the available road capacity, leading to diminished speeds, increased travel times, and unstable traffic flow characterized by frequent stop-and-go patterns (Herdiana et al., 2024). This phenomenon emerges from multifactorial causes, including accelerated urbanization, rapid motorization, insufficient roadway expansion, and suboptimal traffic signal coordination (Rahman et al., 2022). The implications of persistent congestion extend beyond individual inconvenience, manifesting as substantial macroeconomic losses through reduced labor productivity, elevated fuel consumption, and increased operational costs of transportation networks (Faheem et al., 2024). Furthermore, congestion exacerbates environmental stressors by intensifying greenhouse gas emissions and local air pollutants, thereby contributing to public health risks and climate change (Bharadwaj et al., 2017; Samal et al., 2021). In rapidly urbanizing economies, such as those in Southeast Asia, traffic congestion has evolved into a systemic challenge that highlights sustainable urban development and demands integrated, data-driven mitigation strategies (Zhang, 2023).

Existing studies have increasingly employed epidemiological modeling frameworks, particularly susceptible-infected-recovered (SIR) models, to describe the propagation of traffic congestion. Originally developed for infectious disease dynamics (Dayap et al., 2025; Dayap & Rabajante, 2025), the SIR framework has been adapted to traffic systems by classifying vehicles into susceptible (free-flow), infected (congested), and recovered (cleared) states, thereby establishing a useful analogy between congestion dynamics and contagion processes. Within this perspective, congestion spreads through interactions among vehicles in a manner analogous to disease transmission. Several SIR models have been proposed to capture different aspects of congestion dynamics. For instance, Wu et al. (2004) modeled congestion spreading across network nodes, demonstrating how localized bottlenecks can propagate to neighboring links if not mitigated. Similarly, Pu et al. (2016) investigated the role of network structure, showing that higher network density and homogeneity can accelerate the spread of congestion. Saberi et al. (2020) further extended the SIR framework to urban traffic networks, using simulations across multiple metropolitan cities to analyze large-scale congestion patterns. In addition, Herdiana et al. (2024) incorporated control variables into the SIR model to represent traffic signal regulation, particularly the adjustment of green light durations. Rafsanjani et al. (2023) adapted the classical SIR model to reflect urban road characteristics, focusing on congestion propagation without incorporating explicit recovery interventions.

Despite these advancements, existing SIR-based traffic models largely assume homogeneous driver behavior and do not explicitly incorporate awareness-driven adaptation, which has become increasingly important in modern transportation systems. With the widespread adoption of intelligent transportation systems (ITS) and real-time navigation applications, drivers are no longer passive participants but actively adjust their routes, departure times, and driving behavior in response to traffic information (Azadani & Boukerche, 2021). Empirical evidence suggests that such adaptive behavior can significantly influence congestion dynamics, either mitigating or amplifying congestion depending on the responsiveness of drivers and the timeliness of information dissemination (Caspersen et al., 2023). However, the distinction between preventive adaptation, where drivers act before encountering congestion and reactive adaptation, where adjustments occur after experiencing congestion, remains insufficiently explored in existing models. Consequently, current frameworks may not fully capture the behavioral mechanisms that govern congestion propagation in information-rich environments.

Motivated by this gap, this study proposes an extended SIR-based traffic congestion model that incorporates an aware compartment to explicitly represent drivers who adjust their travel decisions in response to congestion information. The model distinguishes between preventive awareness, acquired while drivers are still free-flowing, and reactive awareness, gained after experiencing congestion. This extension enables the examination of how awareness dynamics interact with congestion transmission and clearance processes. The primary contributions of this work are threefold: (i) formulation of a four-compartment system capturing susceptible, congested, aware, and recovered vehicles; (ii) rigorous mathematical analysis, including positivity, boundedness, and stability assessments, as well as derivation of the basic congestion reproduction number using the next-generation matrix method; and (iii) numerical simulations illustrating the mitigating impact of awareness-related parameters on congestion dynamics.

Through this approach, we aim to contribute to the growing body of research in traffic modeling by incorporating a behavioral dimension that can potentially lead to more effective congestion management strategies. The inclusion of adaptive driving behavior could inform policymakers and urban planners on how to design smarter traffic management systems that account for real-time driver adjustments, ultimately leading to more efficient traffic flow.

2. METHODOLOGY

2.1. Model Formulation

The traffic congestion model developed in this paper is a modification of the classical SIR compartmental framework inspired by epidemiological dynamics. Unlike traditional SIR traffic models (Rafsanjani et al., 2023; Herdiana et al., 2024), the proposed model introduces an additional aware compartment to capture both preventive and reactive behavioral adaptations of drivers in response to congestion information. The structure of the model, including the transitions between driver states and the role of awareness, is illustrated in Figure 1. This framework aims to characterize the dynamics of congestion propagation along a major urban road segment and evaluate the mitigating impact of real-time awareness.

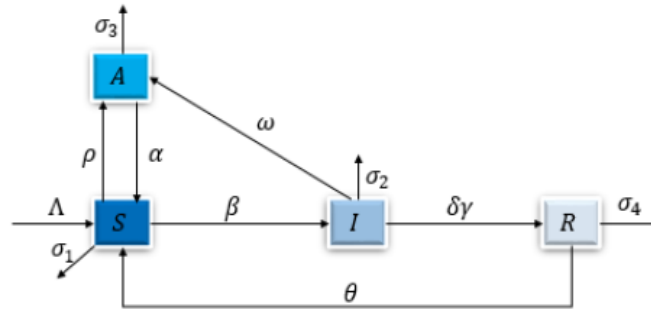


Figure 1. Schematic diagram of the traffic congestion dynamics with awareness

The system of differential equations governing the model is given by:

$$\begin{aligned} \frac{dS}{dt} &= \Lambda - \beta SI + \alpha A - \rho S + \theta R - \sigma_1 S, \\ \frac{dI}{dt} &= \beta SI - \omega I - \delta \gamma I - \sigma_2 I, \\ \frac{dA}{dt} &= \rho S + \omega I - \alpha A - \sigma_3 A, \\ \frac{dR}{dt} &= \delta \gamma I - \theta R - \sigma_4 R, \end{aligned} \quad (1)$$

where the variables and parameters are defined in Tables 1 and 2, respectively. The initial conditions are:

$$S(0) > 0, I(0) > 0, A(0) > 0, R(0) > 0. \quad (2)$$

The flow diagram corresponding to model (1) is shown in Figure 1, illustrating the transitions between susceptible (*S*), congested (*I*), aware (*A*), and recovered (*R*) vehicle classes. The model formulation is based on the following assumptions:

- A1 Vehicles enter the road segment at a constant rate Λ and initially join the susceptible class *S*.
- A2 Susceptible vehicles become congested through interaction with congested vehicles at a rate proportional to βSI , where β is the congestion transmission rate.
- A3 A fraction of susceptible vehicles acquires awareness at rate α , transitioning to the aware class *A*. Additionally, congested vehicles may also gain awareness and divert routes at rate ω , moving directly to *A*.
- A4 Aware vehicles may lose awareness at rate ρ and return to the susceptible state.
- A5 Congested vehicles clear the bottleneck at rate $\delta \gamma$, moving to the recovered class *R*.
- A6 Recovered vehicles may re-enter the susceptible class at rate θ , modeling return trips or re-exposure.
- A7 Permanent exits occur for susceptible, congested, aware, and recovered vehicles at rates σ_1 , σ_2 , σ_3 , and σ_4 respectively, representing trip completions or departures from the study segment.

Table 1. Description of the variables in the traffic congestion model

Variables	Description
<i>S</i>	Susceptible (free-flow) vehicles on the road segment
<i>I</i>	Congested vehicles trapped in the traffic buildup
<i>A</i>	Aware vehicles adapting behavior to avoid congestion (preventive or reactive)
<i>R</i>	Recovered vehicles that cleared the congestion zone (downstream)

Table 2. Description of the parameters in the traffic congestion model

Parameters	Description
Λ	Vehicle arrival rate into the segment
β	Congestion transmission rate due to vehicle interactions
ρ	Awareness (Adaptive) acquisition rate from susceptible vehicles (preventive)
ω	Awareness (Adaptive) acquisition rate from congested vehicles (reactive)
α	Awareness (Adaptive) decay rate (return from aware to susceptible)
δ	Proportion of green light in a single traffic-light cycle
γ	Vehicle clearance rate during the green light
θ	Re-exposure rate of recovered vehicles back to susceptible
$\sigma_1, \sigma_2, \sigma_3, \sigma_4$	Permanent exit rate of vehicles from susceptible, congested, aware, and recovered states

This study adopts a theoretical mathematical modeling approach and does not involve the collection or use of primary empirical data. The results are derived from qualitative analysis and numerical simulations of the proposed model. Parameter values are obtained from existing literature where available or specified within plausible ranges to illustrate the qualitative behavior of the system.

2.2. Preliminary Characteristics

In this section, fundamental properties of system (1) were established, including positivity, boundedness, congestion-free equilibrium point, and the basic congestion reproduction number \mathcal{R}_0 . These properties are essential to ensure the mathematical and physical validity of the proposed traffic congestion model.

2.2.1. Boundedness of Solutions

Theorem 1. All solutions of system (1) are bounded in the positively invariant region:

$$\Omega = \{(S, I, A, R) \in \mathbb{R}_+^4 : S + I + A + R \leq M\},$$

where $M = \frac{\Lambda}{\min \{\sigma_1, \sigma_2, \sigma_3, \sigma_4\}}$.

Proof. Let $N(t) = S(t) + I(t) + A(t) + R(t)$ denote the total vehicle population. Summing the equations of (1) yields:

$$\frac{dN}{dt} = \Lambda - \sigma_1 S - \sigma_2 I - \sigma_3 A - \sigma_4 R.$$

Since $\sigma_1, \sigma_2, \sigma_3, \sigma_4 > 0$ and $S, I, A, R \geq 0$, we have:

$$\frac{dN}{dt} \leq \Lambda - \sigma_{\min} N,$$

where

$$\sigma_{\min} = \min \{\sigma_1, \sigma_2, \sigma_3, \sigma_4\}.$$

Solving gives

$$N(t) \leq \frac{\Lambda}{\sigma_{\min}} + \left(N(0) - \frac{\Lambda}{\sigma_{\min}}\right) e^{-\sigma_{\min} t}.$$

Hence

$$\limsup_{t \rightarrow \infty} N(t) \leq \frac{\Lambda}{\sigma_{\min}}.$$

Thus, all state variables $S, I, A,$ and R are bounded within the feasible region.

$$\Omega = \{(S, I, A, R) \in \mathbb{R}_+^4 : N(t) \leq \frac{\Lambda}{\sigma_{\min}}\}.$$

□

2.2.2. Positivity of Solutions

Theorem 2. Let the initial conditions, $S(0) \geq 0, I(0) \geq 0, A(0) \geq 0,$ and $R(0) \geq 0$ be non-negative. Then the solutions $(S(t), I(t), A(t), R(t))$ of system (1) remain non-negative for all $t \geq 0$.

Proof. To establish positivity, we examine the behavior of the system on the boundary of the feasible region.

At $S = 0,$

$$\frac{dS}{dt} = \Lambda + \alpha A + \theta R \geq 0.$$

At $I = 0$,

$$\frac{dI}{dt} = 0.$$

At $A = 0$,

$$\frac{dA}{dt} = \rho S + \omega I \geq 0.$$

At $R = 0$,

$$\frac{dR}{dt} = \delta \gamma I \geq 0.$$

Thus, along each boundary, the corresponding derivative is non-negative, implying that trajectories cannot cross into the negative region. Therefore, all solutions remain non-negative for all $t \geq 0$. The results of Theorems 1 and 2 establish that the model is mathematically well-posed and physically meaningful, ensuring that all state variables remain non-negative and bounded for all time.

2.3. Congestion-Free Equilibrium

The congestion-free equilibrium (CFE) represents a steady-state configuration in which no vehicles occupy the congested class, that is, $I(t) = 0$. This state represents a traffic regime where congestion is absent and all vehicles operate under free-flow or adaptive conditions. To determine this equilibrium, the right-hand side of system (1) is set to zero under the constraint $I = 0$. Solving the resulting algebraic system yields:

$$\bar{A} = \frac{\rho \bar{S}}{\alpha + \sigma_3}, \quad \bar{R} = 0,$$

and

$$\bar{S} = \frac{\Lambda(\alpha + \sigma_3)}{\rho\sigma_3 + \sigma_1\alpha + \sigma_1\sigma_3}.$$

Accordingly, the congestion-free equilibrium is given by:

$$E_0 = \left(\frac{\Lambda(\alpha + \sigma_3)}{\rho\sigma_3 + \sigma_1\alpha + \sigma_1\sigma_3}, 0, \frac{\rho \bar{S}}{\alpha + \sigma_3}, 0 \right).$$

The congestion-free equilibrium characterizes a stable traffic regime in which congestion does not persist. The local stability of this equilibrium is governed by the basic congestion reproduction number \mathcal{R}_0 , which determines whether small perturbations in the congested class decay or amplify over time.

2.4. The Basic Reproduction Number

The basic congestion reproduction number, \mathcal{R}_0 , quantifies the expected number of newly congested vehicles generated by a single congested vehicle introduced into an otherwise congestion-free traffic stream. This threshold parameter is derived using the next-generation matrix method (Van den Driessche, 2002) where the congested compartment I constitutes the infected subsystem. The new infection term is

$$\mathcal{F} = \beta SI,$$

and the transition term is

$$\mathcal{V} = (\omega + \delta\gamma + \sigma_2)I.$$

Evaluating at the congestion-free equilibrium E_0 , we have

$$\mathcal{R}_0 = \frac{\beta \Lambda (\alpha + \sigma_3)}{(\omega + \delta\gamma + \sigma_2) [\rho\sigma_3 + \sigma_1(\alpha + \sigma_3)]}.$$

2.5. Local Stability Analysis Of The Congestion – Free Equilibrium

The local stability of E_0 is established through linearization of system (1). The Jacobian matrix of the system at any point $E = (S, I, A, R)$ is

$$J = \begin{pmatrix} -\beta I - \rho - \sigma_1 & -\beta S & \alpha & \theta \\ \beta I & \beta S - \omega - \delta\gamma - \sigma_2 & 0 & 0 \\ \rho & \omega & -\alpha - \sigma_3 & 0 \\ 0 & \delta\gamma & 0 & -\alpha - \sigma_4 \end{pmatrix}$$

Evaluating at $E_0 = (\bar{S}, 0, \bar{A}, 0)$, we obtain the Jacobian matrix as

$$J(E_0) = \begin{pmatrix} -\rho - \sigma_1 & -\beta \bar{S} & \alpha & \theta \\ 0 & \beta \bar{S} - \omega - \delta\gamma - \sigma_2 & 0 & 0 \\ \rho & \omega & -\alpha - \sigma_3 & 0 \\ 0 & \delta\gamma & 0 & -\alpha - \sigma_4 \end{pmatrix}$$

It is evident that the first three eigenvalues of the Jacobian matrix at the congestion-free equilibrium, namely $\lambda_1 = -\alpha - \sigma_3$, $\lambda_2 = -\theta - \sigma_4$, and $\lambda_3 = -\rho - \sigma_1$, are strictly negative for all biologically and physically feasible parameter values. Consequently, the local stability of the equilibrium is governed entirely by the sign of the remaining eigenvalue, $\lambda_4 = \beta \bar{S} - (\omega + \delta\gamma + \sigma_2) = (\omega + \delta\gamma + \sigma_2)(\mathcal{R}_0 - 1)$. If $\mathcal{R}_0 < 1$, then $\lambda_4 < 0$, implying that all eigenvalues are negative and the congestion-free equilibrium is locally asymptotically stable. Conversely, when $\mathcal{R}_0 > 1$, $\lambda_4 > 0$, indicating that perturbations around the equilibrium will grow and the system will evolve toward a congested state.

Thus, we have the following theorem. Theorem 3: The congestion-free equilibrium $E_0 = (\bar{S}, 0, \bar{A}, 0)$ of system (1) is locally asymptotically stable if $\mathcal{R}_0 < 1$ and unstable if $\mathcal{R}_0 > 1$.

2.6. Sensitivity Analysis of \mathcal{R}_0

Sensitivity analysis quantifies the relative influence of each parameter on the basic congestion reproduction number \mathcal{R}_0 . This is critical for identifying key control levers for traffic management interventions. We adopt the normalized forward sensitivity index, defined for a parameter p as:

$$\gamma_p^{\mathcal{R}_0} = \frac{\partial \mathcal{R}_0}{\partial p} \cdot \frac{p}{\mathcal{R}_0}$$

Figure 2 illustrates the sensitivity indices derived from the parameter values in Table 3. Positive sensitivity indices (β , Λ , and α) indicate that an increase in these parameters proportionally increases \mathcal{R}_0 , promoting congestion. Negative indices (ρ , ω , δ , γ , σ_1 , σ_2 and σ_3) imply that higher values of these parameters reduce \mathcal{R}_0 , thus mitigating congestion. The results highlight that β (congestion transmission rate) and Λ (vehicle inflow rate) exert the strongest positive influence on \mathcal{R}_0 , highlighting the importance of reducing traffic inflow or interaction rates. Conversely, enhancing awareness transition rate (ρ and ω) and increasing clearance efficiency ($\delta\gamma$) substantially reduce \mathcal{R}_0 , supporting their role as effective control strategies.

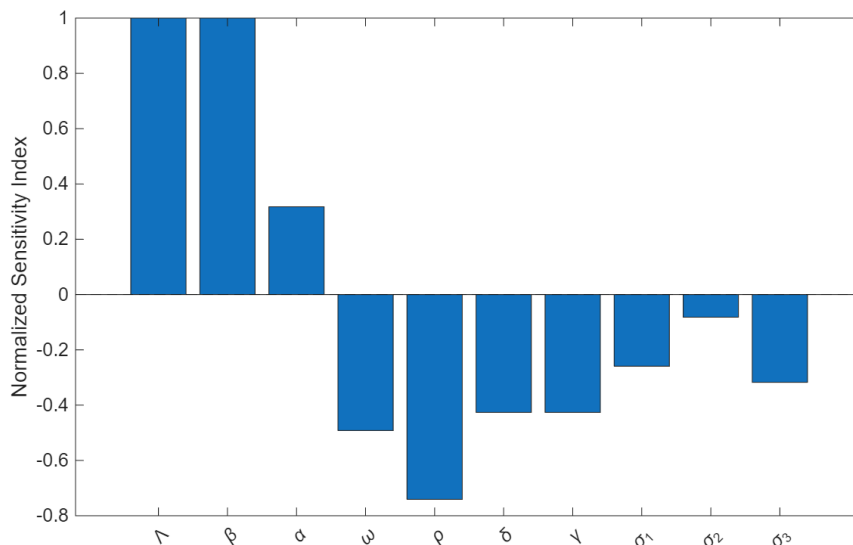


Figure 2. Normalized sensitivity indices of \mathcal{R}_0 with respect to key parameters. Positive values increase \mathcal{R}_0 , while negative values reduce it.

3. RESULTS AND DISCUSSION

To validate the analytical results and explore the dynamic behavior of the proposed traffic congestion model (1), numerical simulations were conducted under realistic parameter settings. The simulations aim to (i) illustrate the impact of awareness dynamics on congestion levels, (ii) examine the role of traffic signal timing parameters δ and γ , and (iii) verify the theoretical threshold condition governed by the basic reproduction number \mathcal{R}_0 . The system of nonlinear ordinary differential equations was solved using a fourth-order Runge–Kutta method with adaptive step size control to ensure accuracy and stability. The simulations were implemented in Matlab with a time horizon of $t \in [0, 180]$ minutes, corresponding to typical rush-hour durations in a main road in the city. Baseline parameter values were drawn from empirical studies on urban traffic flow (Rafsanjani et al., 2023; Herdiana et al., 2024), and are summarized in Table 3. Initial conditions were set to reflect moderate congestion at the onset of rush hour: $S(0) = 100$, $I(0) = 20$, $A(0) = 10$, $R(0) = 5$.

Table 3. Baseline parameter values in simulations.

Parameter	Value	Source	Parameter	Value	Source
λ	0.6	Rafsanjani et al., 2023	γ	0.5	Rafsanjani et al., 2023
β	0.08	Rafsanjani et al., 2023	θ	0.01	Rafsanjani et al., 2023
α	0.03	assumed	σ_1	0.03	Azadani & Boukerche, 2021
ω	0.06	assumed	σ_2	0.01	Azadani & Boukerche, 2021
ρ	0.15	assumed	σ_3	0.04	Azadani & Boukerche, 2021
δ	0.104	assumed	σ_4	0.06	Azadani & Boukerche, 2021

The parameters α , ω , ρ , and δ are not directly measurable from available traffic datasets and, as such, cannot be empirically calibrated within the scope of this study. These parameters characterize behavioral and control-related mechanisms, including awareness decay, reactive and preventive driver adaptation, and signal timing efficiency. Accordingly, their baseline values are specified within plausible ranges (0 – 1) to capture the qualitative dynamics of the system. To account for the uncertainty associated with these assumptions, a sensitivity analysis is performed to assess the impact of these parameters on the basic congestion reproduction number. The results indicate that the qualitative behavior of the model is robust over a range of parameter values, supporting the validity of the theoretical insights derived.

3.1. Numerical Solution of the Model

Figure 3 illustrates the temporal evolution of the traffic system under two threshold scenarios of the basic congestion reproduction number, \mathcal{R}_0 . In panel (a), where $\mathcal{R}_0 < 1$ ($\beta = 0.01, \mathcal{R}_0 = 0.43$), the congested class $I(t)$ decreases monotonically and approaches zero as time progresses. Simultaneously, the remaining state variables converge to steady-state values, indicating that the system asymptotically approaches the congestion-free equilibrium. This numerical behavior is consistent with the analytical findings, which establish that the congestion-free equilibrium is locally asymptotically stable whenever $\mathcal{R}_0 < 1$. In contrast, panel (b) corresponds to the case $\mathcal{R}_0 > 1$ ($\beta = 0.08, \mathcal{R}_0 = 3.40$), where the congested class persists at a strictly positive level over time. The system trajectories converge to a non-trivial steady state characterized by sustained congestion, indicating the presence of an endemic equilibrium. This observation confirms that when the $\mathcal{R}_0 > 1$, congestion is able to invade and persist within the system, resulting in long-term traffic accumulation.

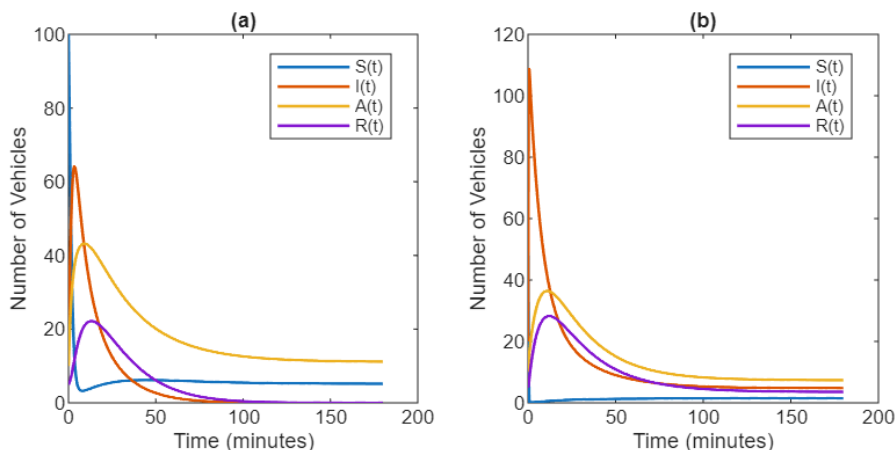


Figure 3. Numerical solution of the model showing traffic dynamics when (a) $\mathcal{R}_0 < 1$ and (b) $\mathcal{R}_0 > 1$.

3.2. Impact of Awareness-Related Parameters on Traffic Congestion Dynamics

Figure 4 presents the effect of awareness-related behavioral parameters on the temporal dynamics of congestion. Panel (a) shows that increasing the awareness rate of susceptible vehicles (ρ) leads to a faster decline in the number of congested vehicles, indicating that early awareness reduces congestion. Panel (b) demonstrates that higher adaptive response rates of congested vehicles (ω) result in a steeper decrease in congestion levels, highlighting the importance of behavioral adjustments during congestion episodes. These results emphasize the significance of incorporating both anticipatory and responsive driver behaviors in traffic management strategies to effectively reduce the overall burden of congestion and support the model's theoretical analysis that such interventions help maintain $\mathcal{R}_0 < 1$.

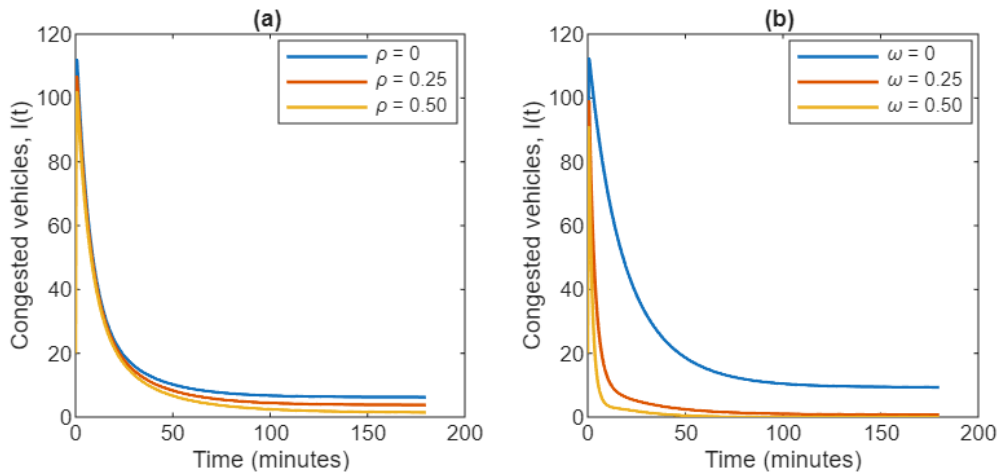


Figure 4. Effect of Awareness-Driven Parameters on Congestion Dynamics: (a) Susceptible Awareness Rate and (b) Congested Adaptation Rate.

3.3. Effect of Key Parameters on the Reproduction Number

The sensitivity analysis in Figure 5 reveals how key behavioral and infrastructural parameters affect the basic congestion reproduction number, \mathcal{R}_0 , which serves as an indicator of whether traffic congestion will persist or die out over time.

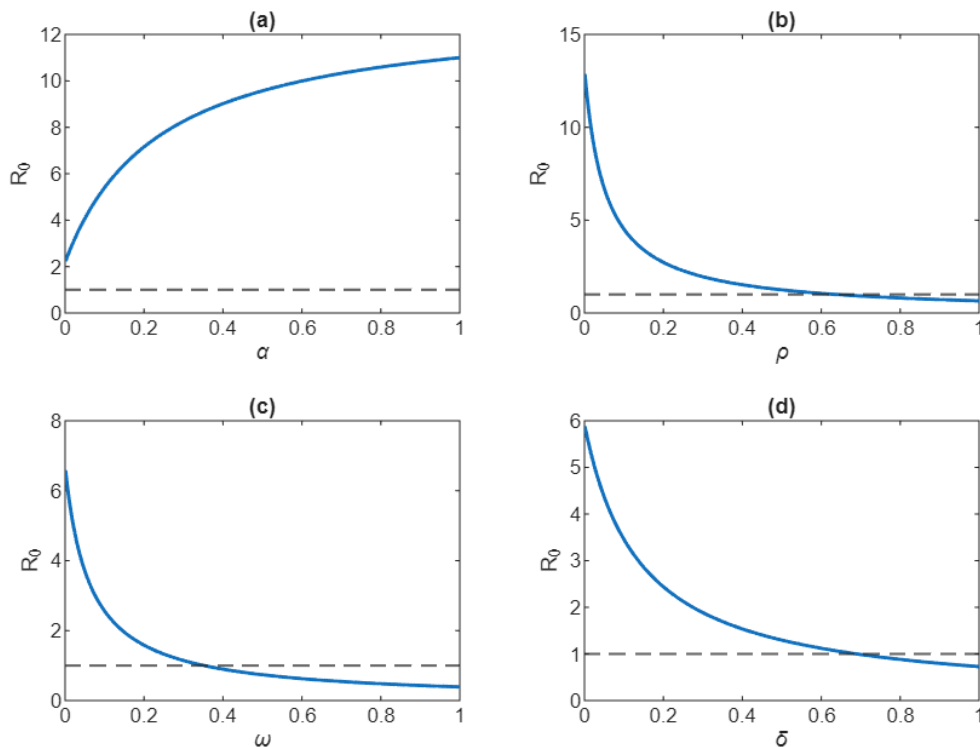


Figure 5. Influence of key parameters on the basic congestion reproduction number \mathcal{R}_0 : (a) awareness decay rate (α), (b) preventive awareness acquisition rate (ρ), (c) reactive awareness acquisition rate (ω), and (d) proportion of green light (δ)

In Panel (a), an increase in awareness decay rate (α) leads to a corresponding rise in \mathcal{R}_0 , indicating that the rapid loss of adaptive driving behavior intensifies congestion and reinforcing the need for sustained informational interventions. Panel (b) demonstrates a monotonic decline in \mathcal{R}_0 as the preventive awareness rate (ρ) increases, with a threshold near 0.7 necessary to reduce \mathcal{R}_0 below 1, signifying the effectiveness of proactive behavior among uncongested drivers. Panel (c) shows a similar, though less pronounced, impact of the reactive awareness rate (ω), with a threshold of approximately 0.4; this suggests that while responses from already congested drivers help, preventive strategies are more influential in halting congestion spread. Panel (d) indicates that increasing the proportion of green light (δ) effectively reduces \mathcal{R}_0 , with a critical threshold around 0.7 for achieving a congestion-free state. These results emphasize the importance of awareness-driven behavioral adaptation and optimized signal timing in traffic management. The integration of intelligent transportation systems (ITS) and the widespread availability of real-time traffic data through mobile navigation applications can further reinforce preventive and reactive awareness, ensuring timely behavioral responses and supporting the systemic maintenance of \mathcal{R}_0 across urban networks.

3.4. Managerial Implications

The findings of this study offer practical guidance for transport planners and traffic managers seeking to mitigate congestion in urban road networks. In particular, increasing the preventive awareness rate (ρ), through timely traffic advisories, navigation applications, and real-time route guidance, can substantially reduce both the severity and duration of congestion. This suggests that enabling drivers to make informed decisions prior to encountering congestion is one of the most effective strategies for improving traffic flow. At the same time, improving the reactive awareness rate (ω), that is, how drivers respond once they experience congestion, can further support faster recovery of traffic conditions. Tools such as incident alerts and adaptive rerouting play an important role by enabling drivers to adjust their behavior in real time. From an infrastructure perspective, optimizing traffic signal operations, represented by the proportion of green signal time (δ), also contributes significantly to congestion reduction. The results support the use of adaptive signal control systems that adjust signal timing dynamically based on prevailing traffic conditions, thereby enhancing overall network performance.

Taken together, these findings highlight the importance of an integrated approach that combines behavioral and infrastructure-based strategies. Investments in intelligent transportation systems (ITS), together with data-driven signal optimization, can work synergistically to improve traffic conditions. Within the framework of this model, such coordinated interventions help maintain the congestion reproduction threshold $\mathcal{R}_0 < 1$, ensuring that congestion does not persist over time. For policymakers, this implies prioritizing scalable and cost-effective solutions such as real-time information systems, complemented by targeted infrastructure improvements. For traffic managers, it emphasizes the value of incorporating behavioral insights into operational strategies to enhance system efficiency, reduce delays, and improve the overall reliability of urban transport networks.

4. CONCLUSION

This study developed and analyzed a novel SIR-type traffic congestion model incorporating an aware compartment to represent adaptive driver behavior influenced by real-time traffic information. The model was shown to be mathematically well-posed, and the basic congestion reproduction number was derived to characterize the threshold dynamics governing the stability of the congestion-free equilibrium. Numerical simulations supported the analytical results, demonstrating that increasing preventive and reactive awareness acquisition rates, as well as the proportion of green signal time, reduces the intensity and persistence of congestion. These findings suggest that integrating behavioral adaptation with infrastructure-based strategies can enhance congestion mitigation. However, it is important to emphasize that these results are theoretical and based solely on numerical simulations, without empirical validation. Consequently, the actual effectiveness of awareness-driven interventions in real-world traffic systems remains to be established. Future research should therefore focus on validating the model using real-world traffic data and extending it to incorporate network structure, stochastic driver behavior, and hybrid control strategies.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTION

Jonecis Dayap: Conceptualization, methodology, data analysis, review and editing, supervision. Fahad Al Basir: Conceptualization, methodology, review and editing. Vincent Banot: Conceptualization, review and editing. Jeanievic Idjao: Conceptualization, review and editing. Mark Vincent Cortez: Conceptualization, review and editing.

DATA AVAILABILITY

All data generated or analyzed during this study are included in this published article.

DECLARATION OF GENERATIVE AI

During the preparation of this work the author(s) used Grammarly in order to assist with grammar refinement, and improving the clarity of written content. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

ETHICS

Not applicable.

REFERENCES

- Azadani MN, Boukerche A. (2021). Driving behavior analysis guidelines for intelligent transportation systems. *IEEE Transactions on Intelligent Transportation Systems*, 23(7), 6027-6045. doi:10.1109/TITS.2021.3076140
- Bharadwaj S, Ballare S, Chandel MK. (2017). Impact of congestion on greenhouse gas emissions for road transport in Mumbai metropolitan region. *Transportation Research Procedia*, 25(1), 3538-3551. doi:10.1016/j.trpro.2017.05.282
- Caspersen E, Orving T, Tennoy A. (2023). Capacity reduction on urban main roads: How truck drivers adapted, and what effects and consequences they experienced. *Transport Policy*, 130, 68-83. doi:10.1016/j.tranpol.2022.10.016
- Cole G, Wolshon B, Schmidt J. (2023). Incident diversionary routing: Survey of influences and decisions. *Transportation Research Record*, 2677(12), 830-839. doi:10.1177/03611981231170009
- Dayap J, Amazona G, Verano A, Ybañez CJ. (2025). Mathematical assessment of dengue control interventions in Cebu City, Philippines. *Journal of Science and Mathematics Letters*, 13(2), 120-131. doi.org/10.37134/jsml.vol13.2.9.2025
- Dayap, J. A., & Rabajante, J. F. (2025). Mathematical model of dengue transmission dynamics with adaptive human behavior. *Communication in Biomathematical Sciences*, 8(1), 93-109. doi.org/10.5614/cbms.2025.8.1.7
- Faheem HB, Shorbagy AME, Gabr ME. (2024). Impact of traffic congestion on transportation system: Challenges and remediations-a review. *Mansoura Engineering Journal*, 49(2), 18. doi:10.58491/2735-4202.3191
- Ferrara A, Sacone S, Siri S. (2018). First-Order Macroscopic Traffic Models. In: Freeway Traffic Modelling and Control. Advances in Industrial Control. Springer, Cham. doi:10.1007/978-3-319-75961-6_3
- Herdiana R, Rafsanjani ZA, Tjahjana R, Erlangga YA, Ansori MF. (2024). Analysis of SIR model with optimal control strategy for a simple traffic congestion process. *Communications in Mathematical Biology and Neuroscience*, Article-ID 6. doi:10.28919/cmbn/8336
- Pu C, Li S, Yang X, Xu Z, Ji Z, Yang J. (2016). Traffic-driven SIR epidemic spreading in networks. *Physica A: Statistical Mechanics and its Applications*, 446, 129-137. doi:10.1016/j.physa.2015.11.028
- Rafsanjani ZA, Herdiana R, Tjahjana RH, Erlangga YA. (2023). Traffic congestion analysis using SIR Epidemic Model. *Barekeng: Jurnal Ilmu Matematika dan Terapan*, 17(4), 2471-2478. doi:10.30598/barekengvol17iss4pp2471-2478
- Rahman MM, Najaf P, Fields MG, Thill J.C. (2022). Traffic congestion and its urban scale factors: Empirical evidence from American urban areas. *International Journal of Sustainable Transportation*, 16(5), 406-421. doi:10.1080/15568318.2021.1885085
- Saberi M, Hamedmoghadam H, Ashfaq M, Hosseini SA, Gu Z, Shafiei S. (2020). A simple contagion process describes spreading of traffic jams in urban networks, *Nature Communications*, 11, 1616. doi:10.1038/s41467-020-15353-2
- Samal SR, Mohanty M, Santhakumar SM. (2021). Adverse effect of congestion on economy, health and environment under mixed traffic scenario. *Transportation in Developing Economies*, 7(2), 15. doi:10.1007/s40890-021-00125-4
- Van den Driessche P, Watmough J. (2002). Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission. *Mathematical Biosciences*, 180(1-2), 29-48. doi:10.1016/S0025-5564(02)00108-6
- Wu J, Gao Z, Sun H. (2004). Simulation of traffic congestion with SIR model. *Modern Physics Letters B*, 18(30), 1537-1542. doi:10.1142/S0217984904008031
- Zhang R. (2023). Spatial Analysis of Transportation Networks for Urban Planning. *International Journal of New Developments in Engineering and Society*, 7(1), 1-5. doi:10.25236/IJNDES.2023.070801