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The development of BPR models in smart cities using loop detectors and license plate recognition technologies: A case study

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A B S T R A C T

The trend toward sustainable city development is associated with intelligent transportation systems (ITS). Automation, efficiency, safety, security, and cost-effectiveness are critical factors in establishing each aspect of a smart city. Real-time data obtained from ITS play an essential role in improving the level of service of road segments, enhancing road safety, and supporting road users with road circumstances information. Travel time information is applicable in travel time maps, decision makings for traffic congestion, dynamic pricing of the network, emergency relief services, traffic flow monitoring, traffic jams management, and air quality analysis. Travel time on a road segment highly depends on geometrical specifications, environmental and weather conditions, traffic flow, and driving behavior. Due to specific driving behavior and road conditions, the above parameters are not essentially applicable in another region. The present research uses the data collected from loop detectors and License Plate Recognition (LPR) systems to develop a Bureau of Public Roads (BPR) model for Iran's freeway network (Tehran-Qom Freeway). Because of the large amount of data, the SQL server program was used for creating and organizing the database and the BPR model was calibrated using SPSS statistical software. The results of the BPR model were evaluated with an ANOVA test, indicating that the derived model can estimate the travel time at freeway sections with a %5.2 error for the volume-to-capacity ratio (V/C) of less than 0.8.

1. Introduction

As a fundamental measure in the performance evaluation of traffic facilities, travel time is used by many users, including travelers, transportation engineers, and planners (Yanying Li and McDonald, n.d.). Travel time is defined as the required time to traverse a route from one specified location to another. Generally, travel time data is employed to identify problem locations on facilities, measure the level of service at arterials, and develop traffic assignment models (Roess *et al.*, 2004). Travel time data can be utilized in different fields. It enables road users to get informed of the operational characteristics of traffic flow, reduce travel costs, increase reliability in route selection, and avoid getting stuck in a traffic jam. It also reduces costs and increases the reliability and quality of the cargo and public transportation (Menglong Yang *et al.*, 2010). Generally, the users who deal with travel time data can be categorized into three groups:

I) **Road users**: Those who use the road, such as drivers and travelers. This group selects the route and departure time according to their information about traffic flow proportional to their personality trait and travel purpose.
II) **Transportation engineers**: This group needs an appropriate awareness of influential factors in travel time, its variations, and the drivers' reaction to these variations. Their effort is to minimize travel costs.

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III) **Public or commercial transportation managers**: This group needs travel time data in planning, road network management, and increasing fleet performance. To this group, reducing delay and improving the precision of time estimation is of great importance (Ishak and Al-Deek, 2002).

Travel time information can be provided through the Variable Message System, Radio Data System, and Radio Advisory System to inform drivers about the road condition, weather, alternative paths, and safety warnings and to pre-inform them of probable road events in order to prevent drivers' sudden reactions. Furthermore, the Timetable Management System makes public transportation users aware of departure times and possible delays (Ishak and Al-Deek, 2002). Travel time can be measured, estimated, or forecasted. Measurements can be classified into direct and indirect. Direct measurements are done using transportation instruments such as the Global Positioning System or Advanced Vehicle Technology and the LPR cameras or through the usage of a floating car or test vehicle technique. When the direct measurement of travel time is not possible, it can be calculated or predicted (extrapolation method) using the recorded data from vehicle counting systems (Holt *et al.*, 2003).

Many researchers have been using travel time information in recent years to build traffic models and simulate and analyze traffic behavior on streets, highways, and freeways, especially in large cities. Based on traffic network features, the provided models can be used to provide sensitivity analyses for the assessment of the current state of the traffic network, as well as to suggest alternatives to optimize the transportation network. To accomplish so, the purpose of this study is to develop a model to predict travel time on a major freeway in Iran using Loop Detector data and LPR systems. In order to boost the performance of the transportation network, planners are going to benefit from the proposed model. It offers a clear picture of the current state of the transportation network and allows them to make informed decisions.

The rest of the paper is organized as follows. Section 2 presents the theoretical background and literature review. In Section 3, the collected data has been explained. Section 4 describes the analysis method as well as the results. The discussion and conclusion have been presented in Section 5 and Section 6, respectively.

2. Theoretical background and literature review

Since 1920, engineers and designers have used travel time and delay variables to evaluate and improve transportation facilities. Travel time has been the subject of hundreds of studies. Berry et al. (Berry, 1952; Berry and Green, 1950) presented general research on travel time. Institute of Transportation Engineers (ITE) has published "The Manual of Transportation Engineering Studies" as a reference for the travel time study for engineers (Hummer *et al.*, 1994). In 1994 the "Highway Capacity Manual" (HCM) introduced the general principles of travel time as a criterion for assessing the performance quality of arterial roads. The second volume of the National Cooperative Highway Research Program (NCHRP) Report No. 398 presented an instruction for measuring the density and travel time (Lomax *et al.*, 1997). Also, numerous researchers have carried out studies on travel time on freeway sections and urban road networks. Most studies focused on providing algorithms to forecast travel time based on inductive loop counters data.

Recently, engineering and transportation challenges are being addressed with technological advances, especially in system management, scheduling, and safety concerns (Aghakhani & Rajabi, 2022; Omer *et al.*, 2022; Rajabi, Radzi, *et al.*, 2022; Rajabi, Rezaeiashtiani, *et al.*, 2022). Particularly, in recent years transportation researchers tried to utilize emerging Artificial Intelligence (AI) and Machine Learning (ML) tools to predict and simulate traffic behavior, especially in megacities (Aghakhani *et al.*, 2022; Beigi *et al.*, 2022; Lotfi *et al.*, 2022; moeinifard *et al.*, 2021; Mudiyanselage *et al.*, 2021; Rajabi, Beigi, *et al.*, 2022; Rajabi, Taghaddos, *et al.*, 2022; Shakerian *et al.*, 2022). In terms of the scope of this paper, when traffic conditions are relatively stable, a reasonably simple estimation can be used, but a prediction model is required when conditions are rapidly changing. Travel time is an element that is sensitive to many factors. An incident can cause a trip to be delayed considerably. Current applications of travel time information in transportation and logistics are driven mainly by travel time prediction. The goal of forecasting traffic information instead of relying on real-time data is to make travel decisions more proactive, both before and during the trips (Lin *et al.*, 2005).

Research on the estimation of travel time started in 1960. Smock (Lomax *et al.*, 1997) provided Eq. (1) for the Detroit study:

$$T = t_0\, e^{\left(\frac{v}{Q_s}\right)} \tag{1}$$

where T is the travel time per unit distance (minute per kilometer), t_0 is the travel time per unit distance under free-flow conditions, v is the flow on a link (equivalent vehicle per hour), and Q_s is the steady-state capacity of the link. Overgaard (1967) generalized the Smock function to Eq. (2) (Lomax *et al.*, 1997):

$$T = t_0 \alpha \beta \left(\frac{v}{Q_p}\right) \tag{2}$$

where Q_p is the link's capacity, and α and β are the parameters for calibration. The Department of Transport in the UK has proposed many travel time-flow functions for various link types based on speed volume curves. The general forms of these functions are as follows (Lomax *et al.*, 1997):

$$S(V) = \begin{cases} S_0 & V < F_1 \\ S_0 - \dfrac{S_0 - S_1}{F_2 - F_1} = (V - F_1) & F_1 \le V \le F_2 \\ \dfrac{S_1}{\left[1 + \left(\frac{S_1}{8d}\right)\left(\frac{V}{F_2} - 1\right)\right]} & V > F_2 \end{cases} \tag{3}$$

where S_0 is the free-flow speed (kilometer per hour), S_1 is the speed at capacity flow F_2 (kilometer per hour), F_1 is the maximum flow at which free-flow conditions prevail, and d is the distance or length of the link. Then the time-flow function is presented as follows:

$$V = \begin{cases} \dfrac{d}{S_0} & V < F_1 \\ \dfrac{d}{S_{(2)}} = \dfrac{d}{S_0 + SS_{01}.F_1 - SS_{01}.V} & F_1 \le V \le F_2 \\ \dfrac{d}{S_1} + \left({}^{V}/_{F_2} - 1\right)/8 & V > F_2 \end{cases} \tag{4}$$

with SS_{01} given by:

$$SS_{01} = (\frac{S_0.S_1}{F_2 - F_1}) \tag{5}$$

2.1 BPR model

A mathematical formula for representing the traffic impedance quantitatively is a road impedance function (Tan *et al.*, 2017) (2). The most used impedance calculation model is the BPR function, which acknowledges that the saturation of traffic flow is essential to traffic speed (Roads, 1964).

The US BPR function is the theoretical regression model (Tan *et al.*, 2017). The function largely took into account the effects of traffic flow and demonstrated enhanced impedance changes (Tan *et al.*, 2017). The model is straightforward, user-friendly, and capable of simple parameter calibration (Tan *et al.*, 2017). In light of the fact that this model is based on data from a highway, which differs from the circumstances on a city road, researchers should concentrate on the model's practical implementation (Tan *et al.*, 2017). The BRP in the USA provided their well-known function in 1964 as Eq. (6):

$$T = t_0 \, [1 + \alpha \left(\frac{v}{C}\right)^{\beta}] \tag{6}$$

where T is the travel time per unit distance at flow Q, t_0 is the travel time per unit distance at zero flow, v is the flow on a link, C is the “practical capacity” of a link (equivalent vehicle for one meter of link width per hour), α and β are dependent on the type of the link. α is the ratio of travel time per unit distance at practical capacity C to the capacity at zero flow, and β represents the rate of changes in travel time (Roads, 1964). The BPR engineers suggested 0.15 and 4 for α and β, respectively. Dowling and Skabardonis (2008) evaluated the BPR function experimentally. They declared the underestimation of travel time resulted from the function for the values of V/C between 0.8 and 1 and its overestimation in queuing conditions. Moreover, their study revealed another flaw of the function: the offline estimation of travel time. It means that the travel time estimated by the BPR function is based on the previously recorded data and does not necessarily account for the present traffic flow condition (Dowling & Skabardonis, 2008). The BPR formula was included in the HCM book (Hansen, 2020) back in 1965. Afterward, in 1985, a function similar to the BPR was proposed by HCM, with more sensitivity to low traffic flow conditions. In 1994, another function based on experimental data was presented on HCM, which could account for the other forms of relationship between speed and flow. Recently, in the HCM (2000), new speed-flow curves for different levels of service were provided, which could not estimate travel time for the values of V/C more than 1. Kurth, Singh, and Hansen conducted the calibration of the BPR function for different values of α and β. Portland Metropolitan Planning Organization (METRO) calibrated the formula by using α equal to 0.15 and β equal to 7. Their proposed function is as follows (Saberi & Figliozzi, 2010):

$$T = t_0 \left(1 + \alpha \left(\frac{v}{0.75C}\right)^{\beta}\right) \tag{7}$$

Also, for the first time in Iran, Pourzahedi and Ashtiani (1995) developed a time-flow function for the Zayanderoud riverside road and calibrated the BPR model. Furthermore, a road network study by Tabibi and Mohseni (2012) using neural networks didn't significantly change travel time for the volume-to-capacity ratio of less than 0.6. They also calibrated the BPR model for the Iran highway network and two-way suburban roads. Sun et al. (2018) used YOLO detectors for Chinese car license plate detection. They found that one network can recognize a license plate with a different number of characters. Luo et al. (2019) used LPR to estimate queue length for signalized intersections. The obtained results were fully consistent with the experimental findings (Luo *et al.*, 2019). Laroca *et al.* (2018) presented a robust automatic LPR based on the YOLO object detector with better system performance and a recognition rate of %78.33.

Using four years of Virginia Interstate data, a modeling methodology was developed based on classification trees in Babiceanu Lahiri's work (Babiceanu & Lahiri, 2022). As independent variables, this model used the Hourly Volume, Volume/Capacity Ratio, Truck Percentage, Equivalent Property Damage Only Rate, Lane Impacting Incident Rate, Number of Lanes, Presence of Safety Service Patrol, Terrain, and Urban Designation to predict the reliability class (reliable or unreliable) of each segment in a year. Applied sensitivity analyses revealed that the predicted PMTR-IS (Percent of the Person-Miles Traveled on the Reliable Interstate) was reactive to capacity increase in unreliable sections at the local level, slower to respond to increases in AADT (annual average daily traffic) at the local level, and stable to small oscillations of AADT at the statewide level.

Global Positioning System (GPS) raw data were analyzed to identify trips in the study conducted by Zhao and Li (2022). A five-step procedure was utilized to extract trips based on origin-destination pairs (OD). Based on OD trips for each dedicated truck, three metrics were used to estimate the performance of travel time reliability. According to the application, trucks traveling long distances have less reliable travel times as compared to trucks traveling short distances. They used GPS data to study travel time for freight performance and similar punctuality requirements in logistics without providing further information.

2.2 Research objectives

Based on the literature review, there are few studies focused on travel time estimation based on loop detector data. Moreover, LPR systems always end up with high procurement and maintenance costs, therefore, the main objective of this research is to estimate the travel time based on vehicle counting itself. In this research a BPR model was also calibrated to predict travel time based on the traffic flow data and LPR system in Iran freeway network (Tehran-Qom). It is noted that to simplify the study, other variables such as weather conditions, traffic incidents and topography along the road were not considered.

3. Data collection

The traffic speed and volume data used for this study were collected by loop detectors and travel time data was gathered from LPR systems during a one-year period, as shown in Fig. 1. Since LPR cameras were not installed in all highway toll gates and were not activated sometimes, especially in heavy traffic situations and some night hours, the corresponding data in both systems have to be aligned.

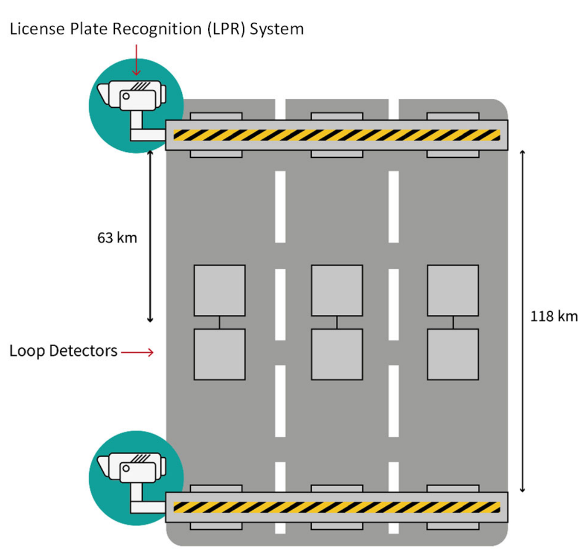

Fig. 1. The position of the LPR system and loop detectors in Tehran-Qom freeway lanes

The following method is employed in the present research based on the available data from the loop detectors and LPR systems. The LPR cameras record the entrance and exit time data, as presented in Table 1.

Table 1
Sample of plate count system output

Vehicle License plate No.	Departure from Tehran	Arrival at Qom	Travel Time(seconds)
65T85933	14:36:38	15:42:26	3948
18S59254	14:17:04	15:23:34	3990
47D94616	13:22:42	14:29:14	3993

Loop detectors have recorded speed, time, and date of passing vehicles for the specified period, ac-cording to Table 2.

Table 2
An output sample of loop detectors.

Start time	End time	Time period (min)	Volume	Heavy Veh. percentage	Speed
13:45	14:00	15	166	19	115
13:30	13:45	15	189	17	116
13:15	13:30	15	185	15	113

In conjunction with the lighting on the Tehran-Qom freeway, there is no difference in speed and travel time between daytime and nighttime; therefore, the entire recorded data is used in developing the model. It is noteworthy that the cameras and loop detectors were activated approximately 98 percent of the time during both day and night. Consequently, an algorithm was employed to extract the time intervals with overlapping data in the database management software. Table 3 illustrates a sample of SQL-Server output.

Table 3
A sample of SQL-Server output.

Starting time	Ending time	Observation No.	Average travel time (sec.)	Vol-ume	Speed at loop detector (km/hr)
13:45	14:00	10	3720	213	115
13:30	13:45	29	3678	237	116
13:15	13:30	11	3901	227	113

3. Research method and data analyzing

3.1 Evaluating the Distribution of Data

Device measuring error–based on the extracted results, equals %3.5. The amount of collected data for achieving %95 reliability in each interval was sufficient according to the equation (1.96s2/e2). The model was developed using 1333 pairs of travel time and flow data out of 1800 total data, randomly selected using Excel software. The remaining data were utilized in the model validation. The presented histogram in Fig. 2 shows the symmetric shape of data frequency around the mean.

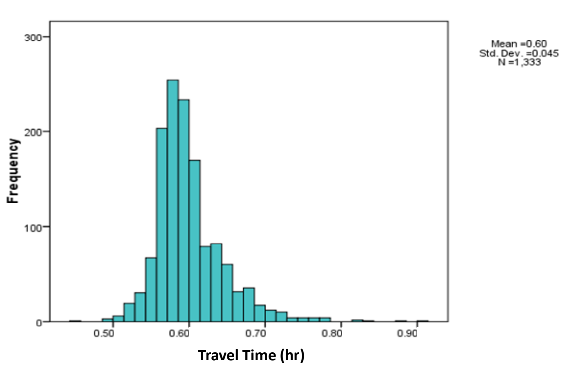

Fig. 2. Histogram of travel time variable in Tehran-Qom freeway

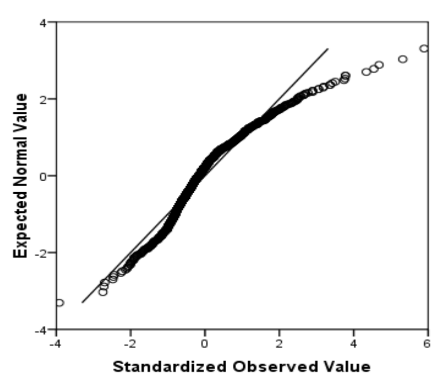

Fig. 3. Q-Q plot of response data (travel time) in the Tehran-Qom freeway

As presented in Fig. 2, the travel time variable has a mean value of 0.6 and a variance of 0.045. A Q-Q plot was used to demonstrate the normality of data, as shown in Fig. 3. As the values are mainly along the 45-degree line, the normality of the distribution may be indicated.

3.2 Capacity Calculation

The output data of vehicle counting devices in suburban routes show that on most highways of the country (except a few ones such as Tehran-Karaj, and Karaj-Chalous), the traffic volume is less than the capacity, and it is nearly free flow most of the time (except for holidays and last days of summer). Some famous models were assessed based on the dataset randomly selected out of the total one-year vehicle counted data on the Tehran-Qom freeway and using fundamental traffic flow functions. Finally, a linear regression model between speed and flow was established. Then the equation was multiplied by density, which ended up with a flow-density relationship. Finally, the maximum value for capacity was obtained by derivation of flow-density relationship. Moreover, the maximum capacity value of 6596 (Veh/hr) was attained based on the linear regression model relating speed and density, like Greenshield's model (Fig. 4).

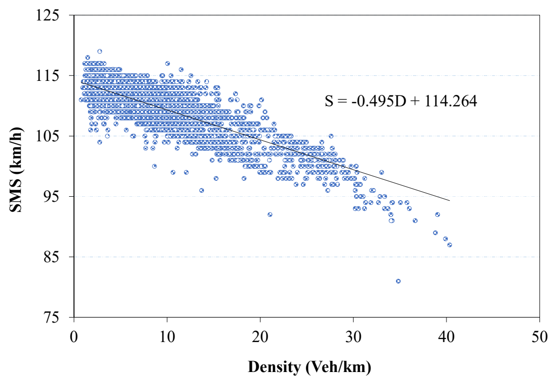

Fig. 4. Speed-density diagram on Tehran-Qom freeway

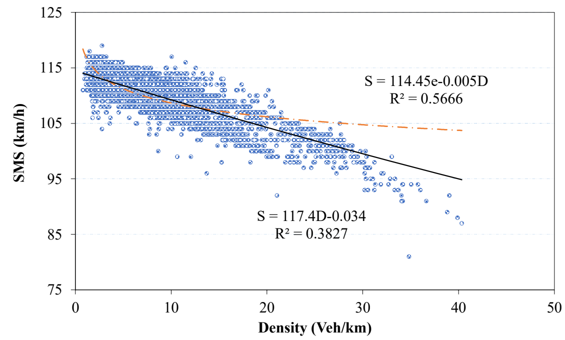

Fig. 5. Other types of regression between speed and density in the Tehran-Qom freeway

The derived formulas for the other regression types are presented in Fig. 5. The goodness of fit parameters for the linear regression model and the capacity analysis results are provided in Table 4 and Table 5, respectively.

Table 4
Goodness of fit for capacity analysis model for Tehran-Qom freeway.

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.8342	0.696	0.696	2.432

Table 5
Summary of capacity analysis results for Tehran-Qom freeway.

Section	Lane No.	Lane width(m)	Shoulder width(m)	Capacity (vehicle per hour)
Tehran-Qom	3	10	1	6596

3.3 Developing the BPR Model

Based on the literature review, the BPR model is one of the most common models for forecasting travel time. Therefore, in the present research, in order to develop a BPR model adopted for specific traffic conditions of the country, the values of α and β are calibrated based on the input values of capacity and free flow travel time using SPSS Statistical software. The final regression model and the results of the ANOVA test are presented in Eq. (8) and Table 6.

$$T = t_0(1 + 0.451(v/c)^{0.963}) \qquad (8)$$

Table 6
ANOVA test results for the BPR model

Source	Sum of Squares	df	Mean Squares
Regression	480.117	2	240.059
Residual	1.787	1331	0.001
Uncorrected Total	481.905	1333	
Corrected Total	2.682	1332	
R-squared = 1 - (Residual Sum of Squares) / (Corrected Sum of Squares) = 0.334			

In this study, %85 of the dataset is used for establishing the model and the rest was used for evaluating the model. Finally, it was showing that the model was able to predict the travel time with %5.2 accuracy level.

5. Discussion

As a key component of traffic engineering, travel time can be used for a variety of purposes. Travel time estimation and prediction in transportation networks are clearly critical components to implementing ITS and developing smart cities. As a result of providing travel-time information to travelers, they can save time and improve the reliability of their trips by selecting routes and times in advance and during their travels. Logistics applications that utilize accurate travel-time estimation can reduce delivery costs, enhance the quality of service, and increase delivery reliability. Traffic planners use travel-time information to evaluate the efficiency of their traffic systems. With the accurate estimation of travel time, transportation costs can be reduced by avoiding congested sections, and the service quality of commercial deliveries can be improved by delivering goods within the specified timeframe (Laroca *et al.*, 2018). In order to accomplish this, this study also attempted to develop a BPR model using travel time and traffic flow data obtained from loop detectors on a major freeway in Iran. In response to the expensive costs related to installing and maintaining an LPR system, an estimate of travel time has been presented based solely on the number of vehicles. It was shown that the proposed method resulted in accurate results in estimating the travel time, which could be used in subsequent applications. It is important to note that one of the major limitations of this study is that it only considered basic conditions and neglected to examine other variables, such as weather conditions, traffic incidents, and topography along the route. As a best practice, future studies should examine the same approach in inclement weather conditions as well.

6. Conclusions

In the past few years, ITS has become an invaluable part of sustainable city development. Establishing a smart city depends on automation, efficiency, safety, security, and cost-effectiveness. ITS real-time data contribute significantly to improving the level of service on road segments, improving road safety, and providing road users with information about road conditions. Travel time as a fundamental index of traffic facilities performance is typically used by road users and transportation managers. The presented research on travel time was conducted based on data collected by LPR cameras installed at toll gates and inductive traffic counters, which were placed in the middle of the route. Additionally, on the basis of the collected data on the freeway network (Tehran-Qom Freeway), the BPR model was calibrated. Due to the large amount of data, the SQL server was used to storage and organize the data and SPSS statistical software was utilized to analyze data. Based on the result of ANOVA test, the BPR model was able to predict travel time at freeway segments with a %5.2 error for volume-to-capacity ratios less than 0.80. According to the results, the maximum capacity of the Tehran-Qom freeway was approximately around 2200 vehicles/hour per lane, and the achieved speed-density model was linear (as per Greenshields's model). The results of this research can be employed in freeway network (Tehran-Qom freeway) travel time estimation with similar circumstances (topography, V/C ratio, weather). However, for different situations other models should be developed.

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Institutional Review Board Statement

Ethical review and approval were waived for this study, due to the study involving anonymous data collection.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to some data being proprietary or confidential in nature. Therefore, the data may only be provided with restrictions.

Conflicts of Interest

The authors declare no conflict of interest.

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