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Characterizing Peak-Time Traffic Jam Incidents in Kampala Using Exploratory Data Analysis

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Abstract

Traffic congestion is associated with increased environmental pollutions, as well as reduced socio-economic productivity due to significant delays in travel times. The consequences are worse in least developed countries where motorized road transport networks are often inefficiently managed in addition to being largely underdeveloped. Recent research on traffic congestion has mostly focused on infrastructural aspects of road networks, with little or no emphasis at all on motorists' on-the-road behavior (MB). The current study thus aimed to bridge this knowledge gap by characterizing traffic jam incidents (TJI) observed over a period of 80 days in Uganda's Capital City, Kampala. MB as well as road network infrastructural factors such as road blockage (RB), were captured for each of the observed TJI. A total of 483 peak-time TJI were recorded, and exploratory data analysis (EDA) subsequently performed on the TJI dataset. EDA involved Hierarchical clustering analysis (HCA) and K-means clustering of the TJI dataset, as well as a detailed descriptive statistical analysis of both the entire dataset and the emerging TJI clusters. A highlight finding of this study is that 48.2% of the observed TJIs were as a result of on-the-road motorist behavior. Furthermore, the intervention of traffic police officers in a bid to regulate traffic flow was equally responsible for 25.9% of the TJIs observed in this study. Overall, these results indicate that whereas road infrastructural improvement is warranted in order to improve traffic flow, introducing interventions to address inappropriate on-the-road motorists' behavior could alone improve traffic flow in Kampala, by over 48%. Additionally, in-order to effectively regulate traffic flow in Kampala and other least developed cities with similar traffic congestion management practices, motorists' on-the-road behavior ought to be factored into any data-driven mechanisms deployed to regulate traffic flow and thus potentially significantly curbing traffic congestion.

Keywords

Motorist Behavior, Traffic Jam, Traffic Congestion, Urban Road-Networks, Motorized Transport, Traffic Clusters

1. Introduction

Road traffic congestion refers to a scenario where traffic flow along a route slows down primarily due to demand for space exceeding the road network's capacity [1]. Road networks in cities and urban areas experience traffic congestion either recurrently such as during peak-times of the day, or as once-off occurrences resulting from a specific on-the-road incident [2]. Traffic jam on the other hand, is worse than traffic congestion, as it implies a total halt to traffic flow as a result one or more causal factor, consequently leading to an even more complex congestion. Traffic jam incidents (TJI) leading to total halt of traffic flow include, road accidents, road blockage (RB) possibly as a result of both natural or man-made factors, motor vehicle failures, and inappropriate on-the-road motorists' behavior (MB) [1] [3].

The socio-economic cost and impact of traffic congestion has been emphasized numerously in literature [1] [3]-[18]. Economically, time wastage as a result of the persistent delays of motorists (commuters) in traffic has been associated with the undesired non-conduciveness of the business environment in and around cities often as a result of increased costs of business operations [7] [16] [19] [20] [21]. This association explains why traffic congestion in cities and urban areas has often been used as a determinant factor in as far as attracting foreign investors to a country is concerned, particularly in the least developing countries. With regards to quality of life and the health of residents in cities and urban areas, traffic congestion and traffic jam have been associated with increase in air pollution-related illnesses such as lung cancer and respiratory diseases [6] [10] [11] [12] [17] [18]. This is so due to the increase in carbon emissions into the atmosphere, a direct implication of fossil fuel-based motorized transport systems popularly used in most cities and urban areas. While traffic congestion affects both the most developed [10] [18] and least developed countries [2] [7] [13] [15] [21], the consequences on the latter are more severe given that more often than not, the under pressure motorized road transport infrastructure in underdeveloped countries and largely lacking.

Research related to traffic congestion globally, can be categorized into four themes: studies aimed at understanding and describing traffic patterns both quantitatively and qualitatively [1] [2] [3] [22] [23] [24], research work aimed at predicting and estimating traffic congestion using various parameters [25]-[38], studies aimed at modelling road networks with a primary aim of decongesting cities and urban areas [23] [24] [25] [39] [40] [41] [42] [43], and studies aimed at quantifying the impact of traffic congestion on other socio-economic aspects such as air quality, health, economic performance, etc. [5] [6] [7] [8] [9] [11] [12] [13] [18] [19] [20] [44] [45] [46] [47]. The current study falls in the first thematic category, *i.e.* understanding and profiling traffic jam in Uganda's capital, Kampala, both quantitatively and qualitatively. While previous research pertaining traffic congestion has been impactful in various aspects, it should be noted that majority of it has largely studied the phenomenon from a road network infrastructural view-point with little emphasis on real-time on-the-road motorists' behavior (MB). This work therefore aimed to bridge this information gap by observing and profiling the traffic jam causing incidents (*i.e.* both MB-related as well as RB-related) in Uganda's capital city, Kampala. Recent research that has aimed to profile motorist's behavior has mainly been through simulation-generated data such as driver behavior towards signalized traffic-light junctions [48]. To the best of authors' knowledge, the current study is the first of a kind to attempt to profile on-the-road MB using real-time on-site road observation data. Moreover, traffic congestion or traffic jam data particularly in the least developing cities and urban areas in largely lacking in literature.

Kampala is Uganda's Capital City and has a resident population of about 1.7 Million people and a total day-time population estimated to be about 4 Million people as of 2022 [49] [50]. The city is part of the Greater Kampala Metropolitan Area (GKMA) occupying approximately 1000 square kilometers, consisting of Kampala, Wakiso, Mukono, and Mpigi districts. The GKMA is Uganda's major industrial and business hub and contributes over 60% of Uganda's Gross Domestic Product (DGP) [50]. Majority non-resident day-time occupants in Kampala City commute daily from their places of residence mostly within the GKMA, either for official and business work or for education purposes, among other reasons. This early morning and late afternoon inflow and outflow of people in and out of Kampala, coupled with the inefficient commonly utilized motorized modes of transport and the narrow road network, are the major contributors of traffic jam in Kampala [2]. Therefore, the outcomes of the current study presented in this manuscript offer a significant contribution to the existing body of knowledge on traffic congestion, especially in as far as Cities and Urban towns of the developing world is concerned.

The contribution of this exploratory cross-sectional study is therefore threefold: Firstly, this work is providing quantitative data on the role of motorist's on-the-road behavior in as far as causing traffic jam (congestion) is concerned. This is a vital contribution as it offers potential immediate remedies to the traffic jam menace, especially in Kampala and similar cities particularly within the least developed world where road infrastructural upgrades may not happen anytime soon. Secondly, by quantifying the contribution of the different traffic jam causing incidents studied in this work with respect to traffic jam duration, a more data-driven approach taking into account real-time updates of traffic jam incidents could now be developed and deployed to objectively manage road traffic along interconnected routes within congestion-prone cities. Finally, this manuscript reports descriptive statistics of the entire dataset of traffic jam causing incidents generated in this cross-sectional study, following exploratory data analysis. These statistics offer insights into the degree of how each individual traffic jam causing factor studied in this work, individually and collectively contributes to the overall impact of traffic jam in Kampala and other similar cities. This quantitative data could also potentially aid the design and development of a data-driven traffic monitoring and thus regulation model within Kampala and similar cities, that takes into account real-time traffic incidents data along interconnected routes. Such a model could feasibly be deployed over a mobile-application accessible to all traffic regulation officers as well as City dwellers including motorists, there by significantly contribute to improving on-the-road experiences and the general quality of life within Kampala and other similar cities.

2. Methods

2.1. The Current Exploratory Study in Stages

This exploratory cross-sectional study involved three main stages as illustrated in Figure 1 below.

2.2. Profiling Incidents Causing Traffic Jam

This study focused on traffic jam incidents observed along routes leading to and out of Kampala's Central Business District (CBD) [51], during the early morning (M) and late afternoon (A) rush hours/peak-times respectively. We define a traffic jam incident (TJI) as an incident resulting into a temporary total halt to traffic flow. Our interest was to identify the main factor that led to the occurrence of a TJI as well as the total duration (in minutes) of the observed TJI (TJI duration). As most of the recent related works primarily focused on traffic jam from

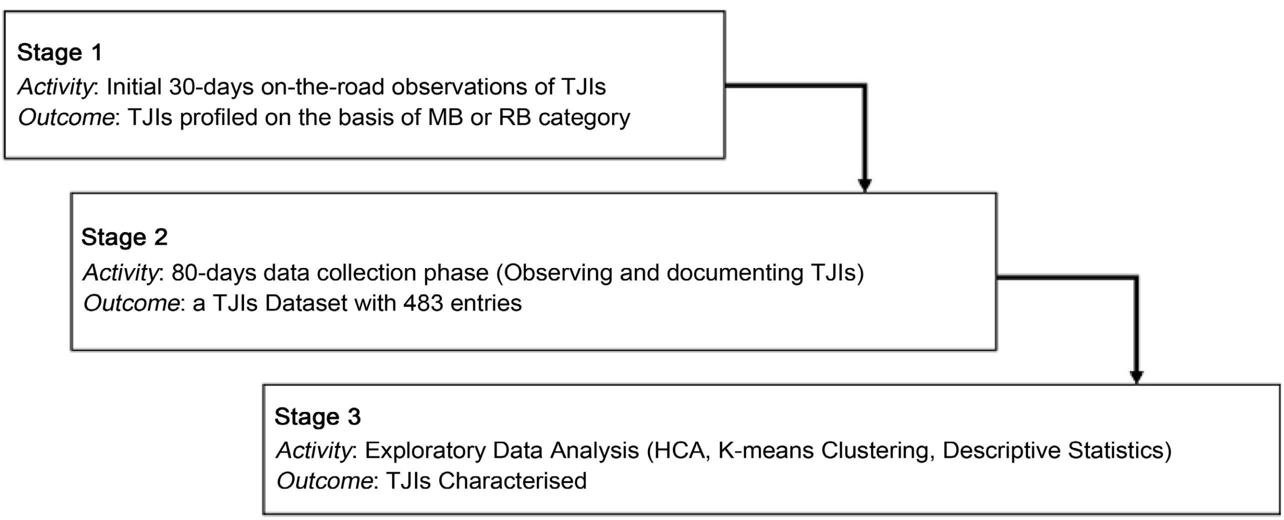


Figure 1. The 3 main stages of the current study.

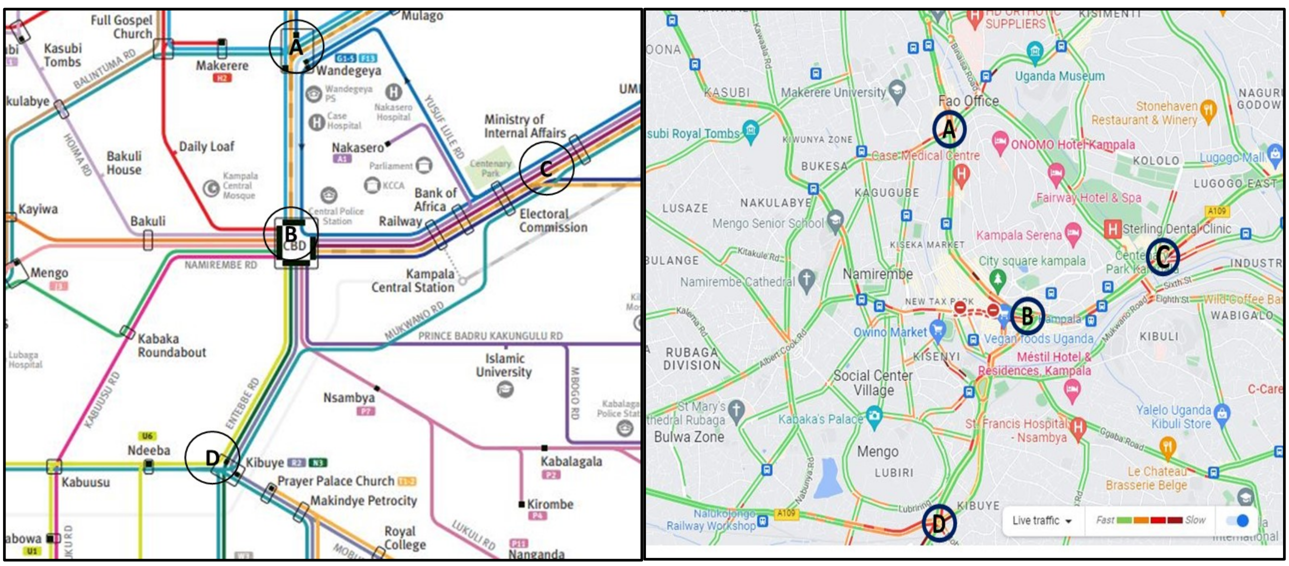
a road infrastructural view point, in the current study focus was on both TJI causing factors arising from both motorists' behavior (MB) as well as from an infrastructural view point of road blockage (RB).

Therefore, in order to profile the TJIs on the basis of MB and RB, the data collection team stationed in 3 prominent routes leading to and out of the CBD, spent a total 30-days observing traffic flow during both the early morning (*i.e.* 6:30 AM-8:30 AM) and late afternoon (*i.e.* from 5:30 PM-7:30 PM) peak-time rush hours to and out of the CBD. As illustrated in **Figure 2**, the routes included: the Bombo Road-Kampala Road route, Kampala Road-Jinja Road route, as well as the Kampala Road-Entebbe Road route. These three routes are some of the main entries into and out of Kampala's CBD, and therefore most traffic jam and congestion during peak-hours is often experienced here.

Following a 30-day observation of traffic flow along the main routes as illustrated in **Figure 2** below, it was observed that the most frequent on-the-road MB and RB TJI causing cases included the following:

2.2.1. Motorist Behavior

- Abrupt stop (AS)—This is a TJI caused when a motorist suddenly stops in the middle of the road thereby blocking traffic flow along the route resulting in a temporary halt of other motorists' movement.
- Abrupt turn (AT)—This is a TJI caused when a motorist abruptly makes a wrong turn in the middle of the road, resulting into a temporary halt of traffic flow.
- Lane disruption (LD)—This is a TJI resulting from a motorist joins a lane they should not be joining thereby disrupting traffic flow from the opposite



(a) (b)

Figure 2. (a) Shows the studied area on the public transport routes' map for Kampala City [52]. (b) Shows a Google Map showing live traffic in the 3 main routes that experience traffic jam in and out of Kampala's CBD [53]. Points A to B is the Bombo Road-Kampala Road route, B to C is the Kampala Road-Jinja Road route, and B to D is the Kampala Road-Entebbe Road route.

direction leading to a temporary halt in traffic flow.

- Road rage (RR)—This is a TJI resulting from a motorist or a group of motorists stopping their motor vehicles or motorcycles in the middle of the road and raging about a matter they are unhappy about (e.g. another motorist scratching their vehicle). This RR consequently often leads to a temporary halt of traffic flow in part due to the narrow road networks, but also because very often other non-involved motorists stop, in trying to understand the cause of the RR, often a scuffle ensues before traffic police intervenes.

2.2.2. Road Blockage

- Accident incident (AI)—This is when traffic along a route is halted as a result of an accident incident along the same route or feeder route.
- Poor drainage (PD)—This is when traffic flow along a route is halted as a result of flooding of the road after a heavy downpour or a bust underground water pipe, often due to poor drainage.
- Ongoing construction (OC)—This is when traffic flow has to be temporary halted at different time intervals due to ongoing road constructions works along a route or a feeder route.
- Motor vehicle failure (MF)—This is when traffic flow along a route is halted as a result of a mechanical failure of a motor vehicle thereby blocking other trailing motorists. This also includes cases where motorists run out of fuel (gas) thereby suddenly stopping mid-way the road and have to be pushed out of the way.
- Traffic diversion (TD)—This is when traffic flow is temporarily disrupted because an exit or entry route has been blocked for public access by traffic police due to either an ongoing road traffic operation or as a mechanism of reserving the route for very important persons (VIP), often government officials.
- Traffic officer (TO)—This is when traffic flow along a route comes to a complete halt because a traffic officer (or officers) are physically manning a multi-intersection junction as opposed to signalized traffic lights regulated junctions. This happens frequently especially during peak hours in the morning and evening.

Motorists involved in both the MB and RB TJIs mentioned above, included public taxis, private motor vehicles (private car), government (gov't car) and non-government (org car) vehicles as identified from their number plates, motorcyclists also known as boda-boda in Uganda. The outcome of this 30-day TJIs profiling exercises resulted in the generation of the TJI data capture tool (DCT) shown in **Table 1** below, which was utilized for real-time data collection of TJIs along the identified TJI-prone routes using on-site observation by the data collection team. As shown in the DCT specimen, the route along which the TJI occurred is recorded (*i.e.* either A-B, or B-C, or B-D as per **Figure 1**), together with the exact location along the route as well as the time stamp of the incident

Table 1. The TJI data collection tool populated during TJI data collection.

Route:

Location of TJI (*i.e.* feeder junction):

Day/Date/Time:

TJI #	Cause of TJI (Traffic Jam Incident)			
	A Motorist Behavior (MB) case		A Road Blockage (RB) case	
	Tick observed TJI	Specify motorist involved	Tick observed TJI	Specify motorist if AI/MF
1.	AS	Gov't Car	AI	Gov't Car
	AT	Org Car	PD	Org Car
	LD	Boda-Boda	OC	Boda-Boda
	RR	Public Taxi	MF	Public Taxi
		Private Car	TD	Private Car
			TO	

TJI Duration = ……………. Minutes

(*i.e.* the Day of the week, date, and peak-time range). The TJI is categorized as either a MB case or a RB case, and the specific type of TJI and the type of motorist involved are accordingly captured.

2.3. The Data Collection Process

Following the 30-days TJI observation and profiling phase explained in the previous section, a data collection protocol was designed. The protocol required a human data collection agent to stand at specific points along the targeted routes, in possession of a wearable pocket-size stopwatch, print out of the data collection tools, and a pen. The points along the routes were selected on the basis of the safety of the data collection agents as well as the degree of visibility so as to enable them continuously monitor the traffic flow along the identified routes.

Once a TJI is observed, the data collection agent immediately starts their stopwatch, and only stops it when traffic flow resumes, and then accordingly records the TJI's duration as the reading at stop moment in minutes as per the DCT shown in **Table 1**. The stopwatch is then reset and the agent continues to observe traffic flow for any other TJI occurrences. The TJI observation and recording process continues until the end of the peak-hours for that particular peak-time (*i.e.* either early morning or late afternoon). A total of 12 data collection agents were sufficiently trained for this data collection protocol prior to the beginning of the real data collection process.

The agents collected data for a period of 80 days, both during the early-morning peak-hours as well as during the late-afternoon peak hours. By the end of the 80-days long data collection phase, a total of 483 traffic jam causing incidents had been observed along the targeted routes and accordingly recorded, hence the TJI dataset with 483 entries presented and characterized in this work.

The data collection protocol adopted in this work was approved by the University's research committee on ethics and safety.

2.4. Data Pre-Processing and Exploratory Data Analysis

The total 483 TJI entries that were captured on hardcopy were saved into a spread sheet file, resulting into a 483 by 6 dataset. An entry (TJIe) in the total dataset is defined by the six main TJI attribute as per Equation (1). A snapshot of the resulting dataset is shown in Figure 3

$$\text{TJIe} = f\left(\text{TJI id}, \text{Motorist Involved}, \text{Peak Time}, \text{TJI cause}, \text{TJI class}, \text{TJI duration}\right) \tag{1}$$

where e is any of the TJI entries 1 to 483.

Hierarchical Clustering and K-Means Clustering

Hierarchical clustering analysis (HCA) and K-means clustering were performed on the TJI dataset sub-set of dimension 483 by 1, to establish whether natural subgroups would emerge within the observed TJIs on the basis of their duration (TJI duration). The clustering was performed used the open-source Python 3.7 software on a core i7 dell laptop computer with 8 GB RAM.

K-means: We used the elbow joint method [54] [55] is to establish the optimal number of clusters. Using this method, the number of clusters (K) is varied from 1 to 10, and for each Kth value, the within-cluster sum of square (WCSS) is computed as per Equation (2). WCSS is basically the sum of squared distance between each data point and the centroid in a cluster. When WCSS was plotted against each K value for our TJI dataset, the elbow joint in Figure 4 from the goodness of split principle suggests 2 as the optimal number of clusters for our k-means clustering.

$$\text{WCSS} = \sum_{i \in n}\left(X_i - Y_i\right)^2 \tag{2}$$

A	B	C	D	E	F
TJI ID	TJI Cause	Motorist	TJI Time	TJI Class	TJI Duration
1	LD	Gov	A	MB	8
2	TD	TD	A	RB	6
3	AT	Org	A	MB	6
4	LD	Tax	A	MB	7
5	AS	Tax	A	MB	5
6	AS	Tax	A	MB	7
7	MF	Tax	A	RB	20
8	AS	Prv	A	MB	7
9	TD	TD	A	RB	6
10	AT	Bob	A	MB	5
11	AT	Tax	A	MB	7
12	AS	Tax	A	MB	6
13	TD	TD	A	RB	5
14	LD	Tax	A	MB	5
15	TO	TO	A	RB	16
16	TO	TO	A	RB	10

Figure 3. A snapshot of the 483 by 6 TJI dataset in a spreadsheet.

where X is the ith member data point and Y is its cluster's centroid, for all n data points.

After visually confirming 2 as the number of optimal clusters as seen in **Figure 4**, K-means clustering is performed on the 483 by 1 dataset with the number of clusters set to 2. The resulting two subgroups' compositions are further analyzed on the basis of the descriptive statistics for the other dataset features (*i.e.* TJI cause, motorist type, peak-time of the day, and TJI category).

Hierarchical Clustering: In performing HCA on the 483 by 1 TJI dataset feature subset (*i.e.* clustering only 1-D data of TJI duration for the 483 TJI entries), Euclidean distance method was used to compute pairwise distances between points as per Equation (3). Following computation of Euclidean distances, Ward's linkage method as per Equation (4), is then applied to pair the objects which consequently and continuously form binary cluster groupings until a dendrogram is produced as was applied in [56] [57]. Besides visual inspection of the emerging dendrogram, the subgroups are further confirmed using the cophenetic correlation coefficient. *i.e.* a measure of how faithfully the pairwise distances between original data points are preserved by the hierarchical tree. As in K-means clusters, the emerging HCA subgroups' composition is further analyzed through descriptive analysis.

$$d_{pq}^2 = \left(x_p - x_q\right)\left(x_p - x_q\right)' \tag{3}$$

where x_p and x_q are row vectors in the input matrix.

$$d\left(k,m\right) = \sqrt{\frac{2n_k n_m}{n_k + n_m}}\left\|\overline{X_k} - \overline{X_m}\right\|_2 \tag{4}$$

where $\overline{X_k}$ and $\overline{X_m}$ represent k and m clusters' centroids respectively, while n_k and n_m represent the number of elements in clusters k and m respectively.

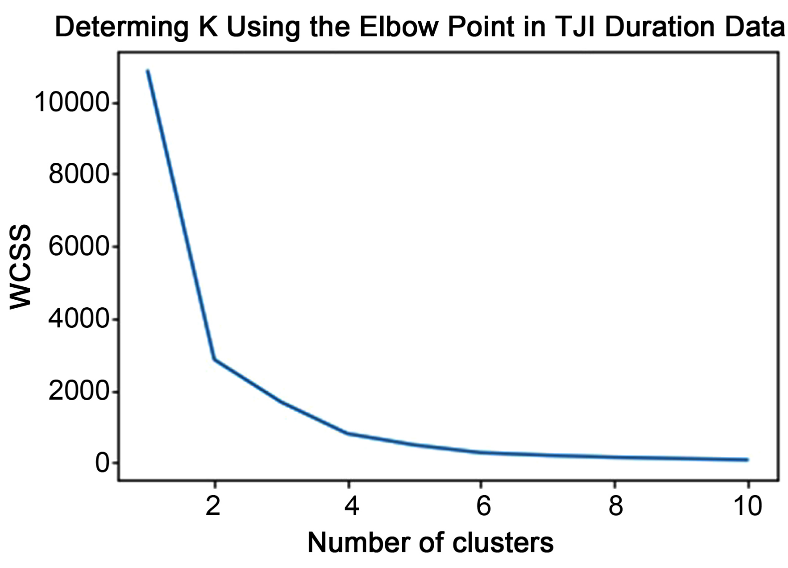


Figure 4. Within-cluster sum of square distance for k-means clusters 1 - 10.

2.5. Data Visualization and Descriptive Statistics

2.5.1. Data Visualization

Using Seaborn, a Python data visualization library, statistical graphics are created to visualize the TJI dataset generated in this research work. The current research particularly aimed to visualize the extent to which motorists on-the-road behavior contributes to daily traffic jam incidences in Kampala, in addition to the other road infrastructural aspects especially common within cities and urban areas of the least developed countries, Uganda inclusive. Graphical visuals of the following TJI are particularly a salient contribution of this work:

- A graphical visualization of time wasted in traffic as observed for each of the TJI causes reported in this work (*i.e.* TJI duration plotted against TJI cause).
- A graphical visualization of time wasted in traffic as observed for each of the TJI categories (MB or RB) studied in this work (*i.e.* TJI duration plotted against TJI type).
- A graphical visualization of time wasted in traffic as observed for each of the daily peaks hours (early morning or late afternoon) investigated in this work (*i.e.* TJI duration plotted against Peak-time).
- A visual representation of the frequency of TJI occurrences for each of the TJI causes studied in this work (*i.e.* TJI frequency plotted against TJI cause).
- A visual representation of the frequency of TJI occurrences for each of the TJI categories studied in this work (*i.e.* TJI frequency plotted against TJI type).
- A visual comparison of the frequency of TJI occurrences between early morning and late afternoon peak times (*i.e.* TJI frequency plotted against Peak-time).
- A visual representation of the TJI durations for the identified clusters following HCA and K-means clustering of the entire TJI dataset on the basis of TJI duration parameter (*i.e.* TJI duration plotted against Clusters for both HCA and K-means clustering).

2.5.2. Descriptive Statistics

Using IBM's Statistical Package for Social Sciences (SPSS) version 22, several quantitative descriptive statistics (mean, standard deviation, range) are computed from both the entire TJI dataset as well as from the identified subgroups following HCA and K-means clustering. These descriptive statistics are necessary to quantitatively qualify the contributions of each traffic jam aspect studied and reported in this work. Non-parametric statistical tests are also performed to establish whether there is any significant difference in the TJI duration between the TJI clusters emerging from both HCA and K-means clustering conducted in this work.

3. Results and Discussion

3.1. HCA and K-Means Clustering Results

Both HCA and K-means clustering processes produced two subgroups (clusters) as is visualized in Figure 5 and Figure 6 for HCA and in Figure 7 and Figure 8 for K-means clustering, respectively.

3.2. Visualizing TJI Dataset in Statistical Graphs

The frequencies of the different TJI causes in the total TJI dataset are graphically visualized in Figure 9 and as quantified in Table 2. It was observed that from a motorist behavior viewpoint, abrupt stops (22.80%) by motorists produced the most cases of TJIs. Lane disruptions came second (14.10%), followed by abrupt turns (10.60%), and finally road rage (0.80%) by motorists contributed the fewest TJIs in the MB-TJI category. The low road rage cases are perhaps attributable to the collective normalization of the observed motorist behavior, which consequently makes motorists more persevering of inappropriate behavior of other

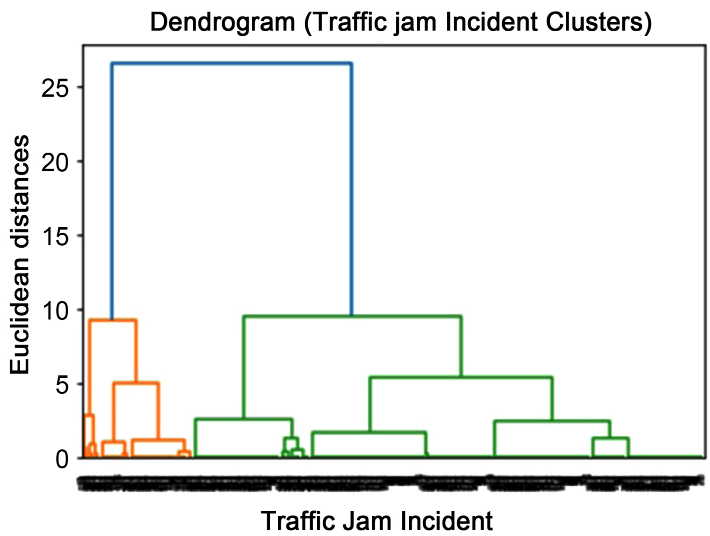


Figure 5. Dendrogram resulting from HCA of 1-D TJI Duration dataset.

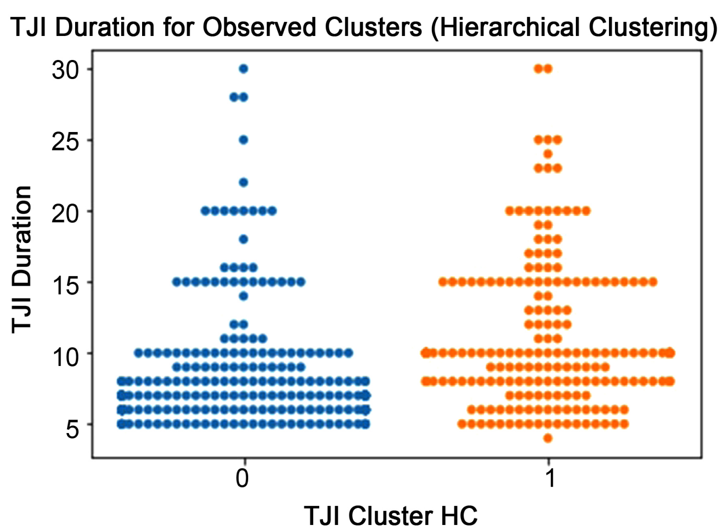


Figure 6. Visualization of TJI duration for the 2-subgroups from HCA of TJI dataset.

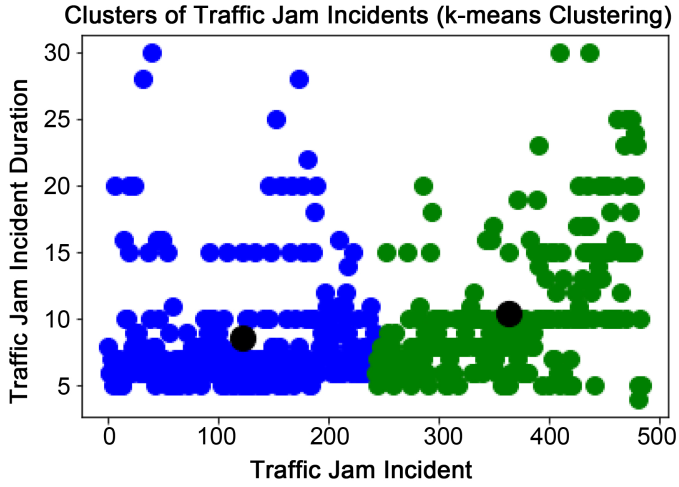


Figure 7. Visualization of subgroups (2—clusters) emerging from K-means of TJI dataset.

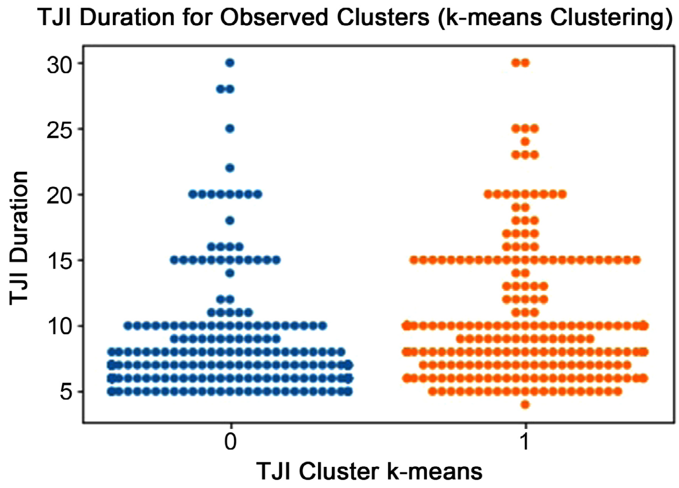


Figure 8. Visualization of TJI duration for the Subgroups (2—clusters) emerging from K-means.

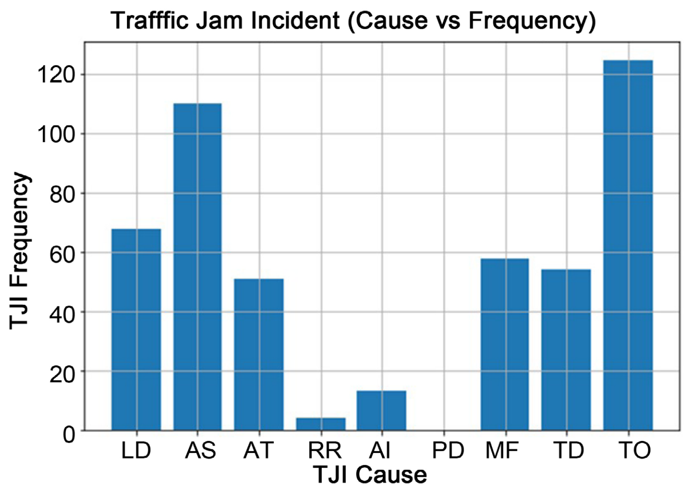


Figure 9. TJI frequency visualization with respect to TJI Cause.

Table 2. Descriptive statistics of the TJI dataset.

TJI Parameter	TJI Duration (Minutes)				
TJI Cause/Motorist involved (N = 483)	n	Mean (SD)	% of N	Minimum	Maximum
Boda-Boda	42	7.24 (3.53)	8.70%	5	24
Gov't Car	47	8.53 (2.91)	9.70%	5	20
Org Car	23	7.61 (3.58)	4.80%	5	20
Private Car	48	12.58 (6.79)	9.90%	6	30
Public Taxi	144	8.56 (4.27)	29.80%	5	30
Traffic Diversion	54	7.20 (1.41)	11.20%	5	10
Traffic Officer	125	11.81 (4.85)	25.90%	4	25
	Total = 483				
TJI Cause (N = 483)	n	Mean (SD)	% of N	Minimum	Maximum
Accident Incident (AI)	13	17.85 (8.61)	2.70%	5	30
Abrupt Stop (AS)	110	7.04 (1.82)	22.80%	5	17
Abrupt Turn (AT)	51	7.06 (1.89)	10.60%	5	15
Lane Disruption (LD)	68	7.51 (2.56)	14.10%	5	20
Motor-vehicle Failure (MF)	58	13.71 (5.54)	12.00%	5	28
Road Rage (RR)	4	11.25 (4.78)	0.80%	5	15
Traffic Diversion (TD)	54	7.20 (1.41)	11.20%	5	10
Traffic Officer (TO)	125	11.81 (4.85)	25.90%	4	25
	Total = 483				
TJI Category (N = 483)	n	Mean (SD)	% of N	Minimum	Maximum
Motorist Behavior (MB)	233	7.25 (2.20)	48.20%	5	20
Road Blockage (RB)	250	11.57 (5.48)	51.80%	4	30
TJI Peak-time (N = 483)	n	Mean (SD)	% of N	Minimum	Maximum
Morning Peak-time (M)	211	9.29 (4.32)	43.70%	5	28
Afternoon Peak-time (A)	272	9.64 (5.05)	56.30%	4	30
	Total = 483				

motorists. From a view point of road blockage aspects, traffic officers manning the investigated traffic jam hotspots were responsible for the most cases (25.90%) of the overall observed TJIs. This was followed by motor-vehicle failures (12.00%) and then traffic diversion (11.20%). It should be noted however, that while traffic officers contributed over 25% of the reported TJIs in this work, their absence would surely have results in even worse TJIs, especially at junctions without traffic lights management systems in place.

Considering the different types of motorists leading to the observed TJIs, public taxis (mini-buses) were responsible for the most of TJIs (29.8%) as can be seen in Figure 10 and statistically quantified in Table 2. This was followed by privately owned motor-vehicles (9.90%), then government owned motor-vehicles (9.70%). Motorcycles (boda-bodas) came next (8.70%), and finally motor-vehicles owned by non-government organizations (4.80%) identified using the vehicle number plate system of Uganda. While government owned motor vehicles appear to have caused fewer TJIs, it should be noted that halting and diversion of traffic flow by traffic officers as indicated in Figure 9, often involves making way for motor-vehicle convoys of very important persons usually in government owned motor-vehicles.

As expected, it was observed that the different TJI causing factors, resulted in TJIs of varying durations as presented in Figure 11 and Table 2. It was observed

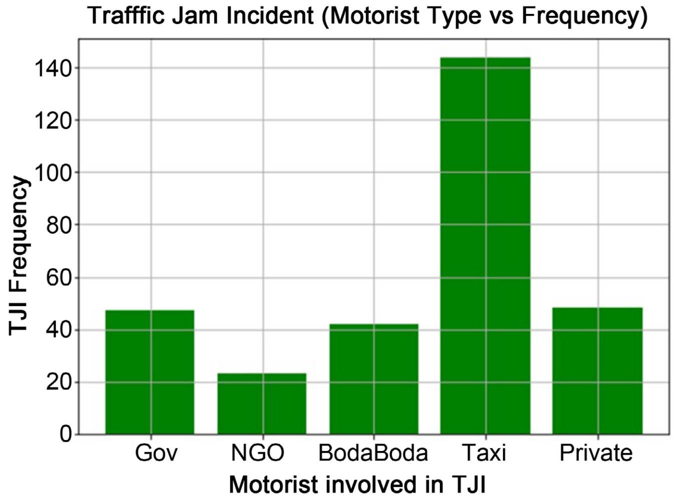


Figure 10. Visualizing TJI frequency with respect to type of motorist causing the TJI.

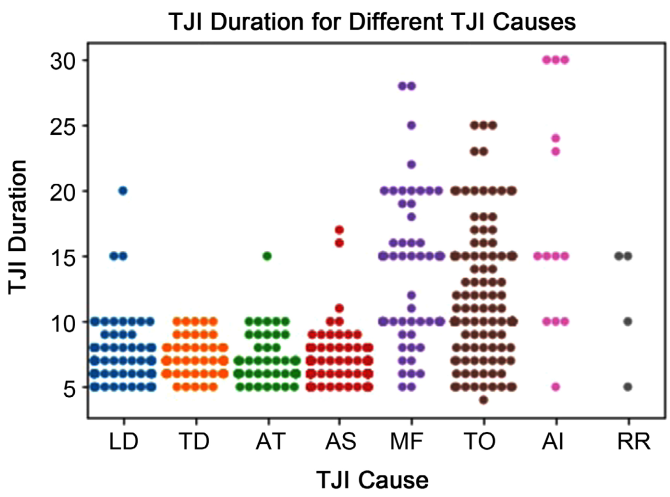


Figure 11. Visualizing TJI duration variations for the different TJI causes.

that accident incidents resulted in the highest mean (SD) TJI duration of 17.85 (8.61) minutes and a range of 25 minutes (*i.e.* minimum of 5 and maximum of 30 TJI duration). This is quite obvious as serious accident incidents often require intervention of multiple response teams before traffic can normalize again. This was followed by motor-vehicle failure cases which had an average (SD) TJI duration of 13.71 (5.54) minutes and a range of 23 minutes (*i.e.* minimum of 5 and maximum of 28 TJI duration). This observation is also quite obvious, as very often, broken motor-vehicles have to physically removed from the road for normal traffic flow to resume. While abrupt stops were responsible for the most motorist behavior TJIs, it was observed that they take the least time to resolve before normal traffic flow resumption, averagely (SD), 7.04 (1.82) minutes with a range of 12 minutes (*i.e.* minimum of 5 and maximum of 17 TJI duration). This observation quantitatively reveals the extent to which the motorists are accustomed to this peer behavior, that it is resolved quite seamlessly with minimal traffic flow delays.

Furthermore, the descriptive statistics reveal that private owned cars resulted in the averagely longest traffic jam incidents to resolve, with mean (SD) TJI duration of 12.58 (6.79) minutes and a range of 24 minutes (*i.e.* minimum of 6 and maximum of 30 TJI duration), as shown in **Figure 12** and **Table 2**. This is perhaps due to the observed statistical fact that motor vehicle failures and accident incidents often involving privately owned motor vehicles, produced the longest lasting TJIs. This was followed by traffic police officers who manually manning traffic jammed routes, with an average (SD) TJI duration of 11.81 (4.85) minutes and a range of 21 minutes (*i.e.* minimum of 4 and maximum of 25 TJI duration). This statistical revelation points to the fact that, due to traffic flow decisions by traffic police officers being primarily subjectively enforced, it is practically impossible to effectively regulate traffic flow manually while ensuring minimal traffic jam delays. This notwithstanding however, without the intervention of traffic

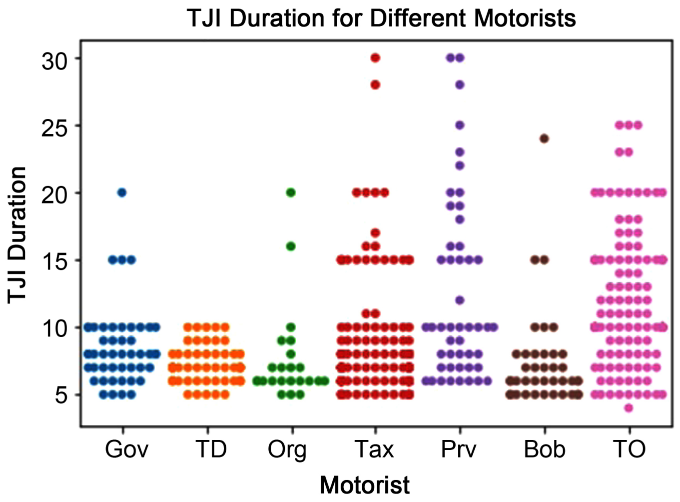


Figure 12. Visualizing variation of TJI duration for the different Causes/Motorists leading to TJIs.

police officers at grid-locked routes as is currently the practice, traffic jam delays would have undoubtedly been worse, particularly at multi-intersection routes without the traffic lights infrastructure, such as seen in **Figure 13**.

While it was observed that road blockage factors contributed to the most TJIs, it is quite a revelation that motorist behavior was responsible for 48.2% (*i.e.* 233 TJIs) of the 483 TJIs studied in this work, as can be visualized in **Figure 14**, **Figure 15** and **Table 2**. This is practically even worse, because the intervention of traffic officers (which was categorized as a road-infrastructure related factor) at grid-locked traffic jam prone routes and junctions, is often due to the failure of motorists to self-regulate during peak hours. Furthermore, it was noted that road blockage factors resulted in the longest averaged TJI duration (*i.e.* 11.57 (5.48) minutes) compared to motorist behavior caused TJIs which averagely lasted 7.25 (2.20) minutes, as reported in **Table 2**.

Figure 13. Early morning traffic grid-lock at one of the traffic-unregulated feeder routes into junction C of one of the studied routes (**Figure 2**). Image source: Authors.

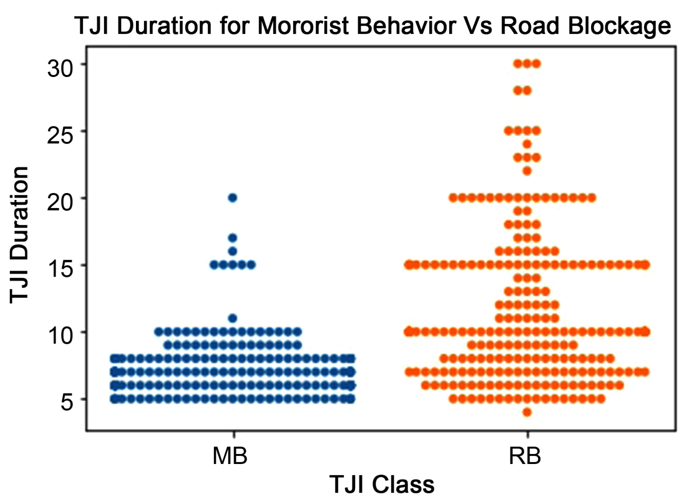


Figure 14. Visualizing TJI Duration variations between MB and RB related TJIs.

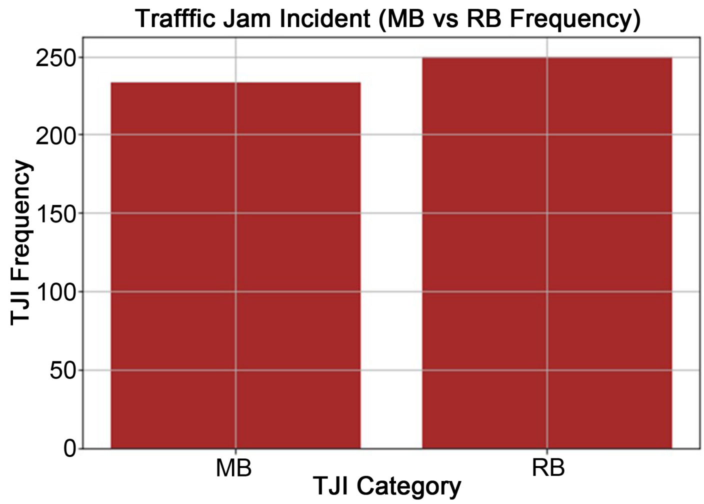


Figure 15. Visualizing TJI frequency between MB and RB Types of TJI.

Furthermore, as can be visualized in **Figure 16** and **Figure 17**, and **Table 2**, the most TJIs were reported in late-afternoon/early-evening (56.30%, 272 TJIs) traffic jam peak-hours, compared to the early-morning peak-hours (43.70%). This is more likely due to the fact that motorist have a wider time window to enter Kampala's CBD in the morning, than they have in the evening. This is also logical from a viewpoint of varying reporting times to work especially for the self-employed and business motorists, when compared to the nearly uniform exit times from the CBD. Interestingly it was observed (see **Table 2**) that the average TJI durations for evening and early morning peak-hours did not vary significantly, *i.e.* mean (SD) TJI duration of 9.29 (4.32) minutes and 9.64 (5.05) minutes respectively.

3.3. Descriptive Statistics of the TJI Dataset and the HCA—K-Means Clusters

Table 2 presents descriptive statistics of the different features characterizing the TJI dataset produced in this work.

Table 3 presents descriptive statistics of the different clusters identified through HCA and K-means clustering.

The descriptive statistics presented in **Table 3** are a result of further exploration of the emerging clusters following HCA and K-means clustering as shown in **Figure 5** and **Figure 6**, and **Figure 7** and **Figure 8** respectively. Interestingly as presented in **Table 3**, both HCA and K-means clustering produced two subgroups primarily split on the MB-RB classification of TJIs as adopted in this work. In HCA clusters, cluster 1 was MB dominated (*i.e.* by 53.57%, 150 out of the total 280 TJI data points in the cluster), while cluster 2 was RB dominated (*i.e.* by 59.11%, 120 out of the total 203 TJI data points in the cluster). Similarly, with K-means clustering, cluster 1 was MB dominated (*i.e.* by 50.40%, 122 out of the total 242 TJI data points in the cluster), while cluster 2 was RB dominated

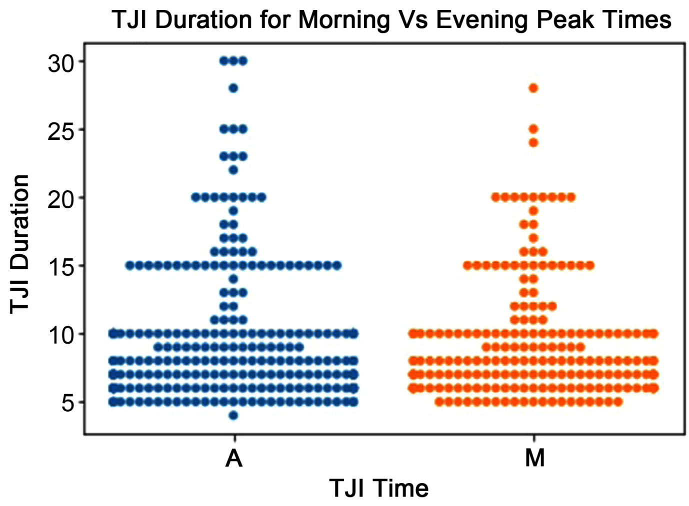


Figure 16. Visualizing TJI duration variations between morning and evening peak-time TJIs.

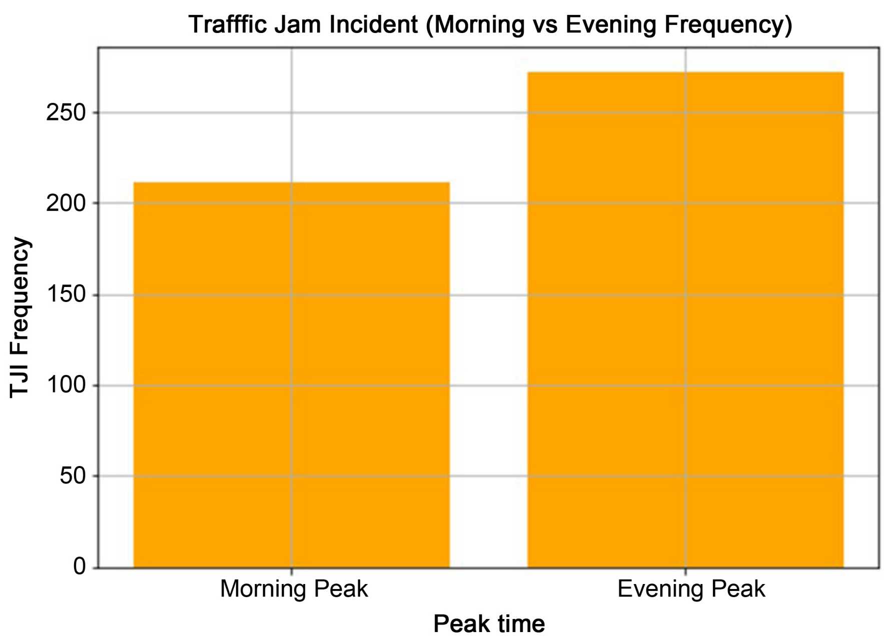


Figure 17. Visualizing TJI frequency between early morning and late afternoon peak-times.

(*i.e.* by 53.94%, 130 out of the total 241 TJI data points in the cluster). This revelation suggests that natural TJI subgroups emerge on the basis of TJI category (*i.e.* MB or RB), when TJI duration is clustered. Practically, this implies that MB-related and RB-related traffic jam incidents seem to be easily identifiable on the basis of their corresponding average traffic jam durations, a factor that could facilitate data-driven TJI-category centered approaches, in as far as management of peak-time traffic jam incidents in concerned. Whereas the non-parametric statistical test (*i.e.* Mann-Whitney U test) indicates a significant difference (*i.e.* $p < 0.05$) between the clusters for both HCA and K-means generated clusters (see

Table 3. Descriptive statistics of clusters identified through HCA and K-means clustering.

Cluster	Cluster Composition				TJI Duration (Minutes)		Inter-Cluster TJI duration difference
	n (MB) vs n (RB)		n (M) vs n (A) Peak-times		Mean (SD)	Min-Max	p-value (95% CI of the difference)
HCA Clusters	MB	RB	M	A			
Cluster 1 (n = 280)	150	130	125	155	8.38 (4.15)	5 - 30	0.000 (1.82 - 3.47)
Cluster 2 (n = 203)	83	120	86	117	11.02 (5.08)	4 - 30	
K-Means Clusters	MB	RB	M	A	Mean (SD)	Min-Max	p-value (95% CI of the difference)
Cluster 1 (n = 242)	122	120	105	137	8.55 (4.36)	5 - 30	0.001 (1.04 - 2.70)
Cluster 2 (n = 241)	111	130	106	135	10.42 (4.93)	4 - 30	

Table 3), it is worth realizing that the 483 TJIs reported in this work are numerically insignificant so as to deem these results significant, from a general application viewpoint.

3.4. Implications of the Outcomes of This Exploratory Study

The results of this exploratory cross-sectional study have several implications in as far as traffic jam in Cities and urban areas, particularly in least developed countries such as Uganda where the physical road network infrastructure is still largely lacking. Much as infrastructural road network features (such as traffic flow regulation lights, multiple lanes, road signage, etc.) are undoubtedly crucial to traffic jam reduction in Kampala and similar cities, the fact that 48.2% of traffic jam incidents reported in this research were as a result of inappropriate on-the-road motorists' behavior, is an objective statistical indication that calls for multi-stakeholder interventions to address motorists' behavior. Conversely, this statistical revelation implies that by effectively addressing only motorists on-the-road behavior (specially for the studied routes and the characterized motorists' behavior), the overall traffic jam problem would see a reduction of over 48%. Traffic regulators could therefore begin with interventions directed at addressing motorists' on-the-road behavior characterized in this work (*i.e.* abrupt stop, lane disruption, abrupt turns, road rage, and other related inappropriate on-the-road behavior). This similar inference has previously been made by [38] [57].

Furthermore, future studies could aim to understand the indirect factors associated with the motorist behavior characterized in the current study, an aspect that was beyond the scope of the current work. For instance, a TJI might ensue as a result of lane disruption by a motorist who is trying to evade arrest by traffic police over a pending traffic violation or other indirect reason. Therefore, a further exploration of these indirectly TJI associated factors could be crucial in initiating effective corrective measures to address a wider spectrum of motorists' behavior investigated in this work and beyond, so as to complement on some of the recent related work that has aimed to understand and profile driver pattern behavior in traffic congestion [46] [58] [59].

Whereas traffic officers intervening to regulate traffic flow during peak hours (see **Figure 18**) have been found to contribute to over 25% (*i.e.* 125 out of the total 483 TJIs) of the traffic jam incidents characterized and reported in this work, their absence would have resulted in even worse traffic jam situation within the studied routes, especially at multi-intersection junctions lacking installations of traffic lights systems (sew **Figure 13**). Potentially, a data-driven traffic flow control model that takes into account the TJIs reported along interconnected routes, could be developed to aid the traffic police officers in making real-time objective decisions with regards to traffic flow regulation. Future phase of the current study will therefore aim to design and build such a data-driven traffic police assistive tool, that could be deployed over a mobile application. This human factor in road traffic management, has previously been highlighted as a necessary input in the design of resilient road traffic systems [24].

Additionally, whereas both HCA and K-means clustering produced two subgroups with traffic jam duration proving a dissimilarity factor, more TJIs data involving new parameters (both motorist behavior related as well as road infrastructural aspects) could be collected in future studies to further affirm this fact. This is particularly important so as to enable design and d deployment of data-driven traffic management models that are dynamic enough, to take into account the real-time traffic jam incident data arising from either motorists' behavior or infrastructural factors.

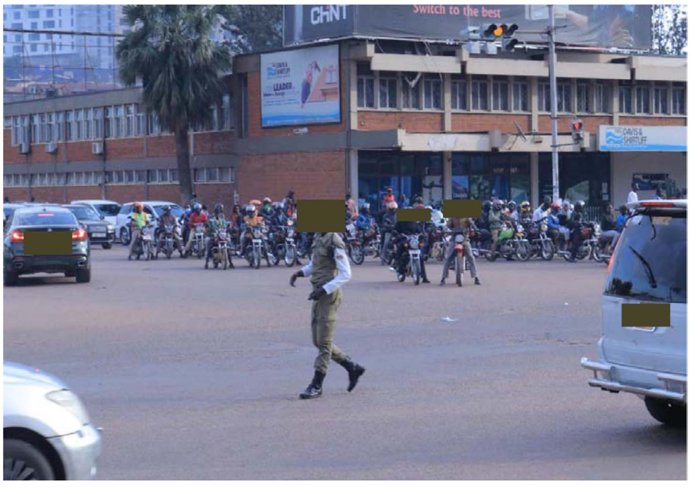


Figure 18. A traffic police officer regulates traffic during peak hours at junction C of one of the studied routes (as shown in **Figure 2**). Image source: Kikomeko Jackson.

4. Conclusion

This exploratory cross-sectional study aimed to characterize traffic jam causing incidents along the main entry and exit routes into and out of the central business district of Uganda's capital, Kampala. The rationale was to establish, beyond the road infrastructural factors, the extent to which motorists' on-the-road behavior contributes to traffic jam incidents during both the dawn and sunset traffic peak-hours. Motorists' behavior included on-the-road tendencies such as abrupt stops, abrupt turns, lane disruption, as well as road rage. Road blockage factors included traffic flow disruption factors such as poor drainage, motor vehicle failure, accident incidents, traffic diversions, on-going construction works, as well as intervention of traffic police officers. A total of 483 traffic jam incidents including traffic duration for each incident were observed and values of the defining parameters recorded and accordingly characterized both quantitatively and qualitatively. Descriptive statistics reveal that motorists' behavior was responsible for over 48% of the traffic jam incidents characterized in this work. Furthermore, it was observed that in trying to regulate traffic flow during peak-time hours (both early-morning and late-afternoon), traffic police officers were found to have caused over 25% of the total traffic jam incidents, primarily because their on-site traffic flow decisions are largely subjective in nature and are not backed by real-time traffic jam incident data along the connected routes. Additionally, results reveal that majority (over 29%) of the traffic jam incidents reported and characterized in this work, were caused by motorists driving public taxis, the most commonly used mode of public transport in Kampala. These results offer traffic regulatory and urban planning authorities, quantitative insights into possible feasible approaches to addressing traffic jam in Kampala and similar cities of least developed countries like Uganda, both in the short-term and long-term. For instance, the results obtained in this work suggest that, conversely, by addressing motorists' inappropriate on-the-road behavior could alone reduce traffic flow along the observed routes by over 48%. Moreover, the descriptive statistics of the observed traffic incidents and their corresponding associative factors (*i.e.* MB or RB), could be used as quantitative input into a data-driven traffic management model to serve as a traffic assistive tool for managing traffic flow along the often grid-locked multi-intersection joints usually manned manually by traffic police officers. Overall, this work adds to the existing body of knowledge on urban traffic jam management, particularly in least developed countries where road network infrastructure is largely inefficient. Moreover, descriptive data on traffic jam such as one presented in this work, is still largely lacking in literature especially for much of the developing world, and at best it is not current.

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out in this research work.

Data Availability

The traffic jam incident dataset generated in this research is readily available to anyone who needs it, upon request.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

[1] Falcocchio, J.C. and Levinson, H.S. (2015) Road Traffic Congestion: A Concise Guide. Vol. 7, Springer, Berlin. https://doi.org/10.1007/978-3-319-15165-6

[2] Kampala Capital City Authority (2015) The Kampala Mobility News Bite. *Entambula YO*, **1**, 3.

[3] Falcocchio, J.C. and Levinson, H.S. (2015) Overview of the Causes of Congestion. Springer Tracts Transp. *Traffic*, **7**, 35-37. https://doi.org/10.1007/978-3-319-15165-6_4

[4] Van Driel, C.J.G., Hoedemaeker, M. and van Arem, B. (2007) Impacts of a Congestion Assistant on Driving Behaviour and Acceptance Using a Driving Simulator. *Transportation Research Part F*: *Traffic Psychology and Behaviour*, **10**, 139-152. https://doi.org/10.1016/j.trf.2006.08.003

[5] Ghaffarpasand, O., Talaie, M.R., Ahmadikia, H., *et al*. (2021) How Does Unsustainable Urbanization Affect Driving Behavior and Vehicular Emissions? Evidence from Iran. *Sustainable Cities and Society*, **72**, Article ID: 103065. https://doi.org/10.1016/j.scs.2021.103065

[6] Levy, J.I., Buonocore, J.J. and von Stackelberg, K. (2010) The Public Health Costs of Traffic Congestion: A Health Risk Assessment. Environ. Harvard Center for Risk Analysis, Harvard School of Public Health, Boston, 1-12. https://doi.org/10.1186/1476-069X-9-65

[7] Sutandi, A.C. (2009) ITS Impact on Traffic Congestion and Environmental Quality in Large Cities in Developing Countries. *Proceedings of the Eastern Asia Society for Transportation Studies*, **7**, 10.

[8] Bivina, G.R., Landge, V. and Kumar, V.S.S. (2016) Socio Economic Valuation of Traffic Delays. *Transportation Research Procedia*, **17**, 513-520. https://doi.org/10.1016/j.trpro.2016.11.104

[9] Bigazzi, A.Y. and Clifton, K.J. (2015) Modeling the Effects of Congestion on Fuel Economy for Advanced Power Train Vehicles. *Transportation Planning and Technology*, **38**, 149-161. https://doi.org/10.1080/03081060.2014.997449

[10] Higgins, C.D., Sweet, M.N. and Kanaroglou, P.S. (2018) All Minutes Are Not Equal: Travel Time and the Effects of Congestion on Commute Satisfaction in Canadian Cities. *Transportation* (*Amst*), **45**, 1249-1268.

https://doi.org/10.1007/s11116-017-9766-2

[11] Rossi, R., Ceccato, R. and Gastaldi, M. (2020) Effect of Road Traffic on Air Pollution. Experimental Evidence from Covid-19 Lockdown. *Sustainability*, **12**, Article No. 8984. https://doi.org/10.3390/su12218984

[12] Zhang, K. and Batterman, S. (2013) Air Pollution and Health Risks Due to Vehicle Traffic. *Science of the Total Environment*, **450**-**451**, 307-316. https://doi.org/10.1016/j.scitotenv.2013.01.074

[13] Chakrabartty, A. and Gupta, S. (2015) Estimation of Congestion Cost in the City of Kolkata—A Case Study. *Current Urban Studies*, **3**, 95-104. https://doi.org/10.4236/cus.2015.32009

[14] Fattah, A. and Riad Morshed, S. (2021) Assessing the Sustainability of Transportation System in a Developing City through Estimating CO_2 Emissions and Bio-Capacity for Vehicular Activities. *Transportation Research Interdisciplinary Perspectives*, **10**, Article ID: 100361. https://doi.org/10.1016/j.trip.2021.100361

[15] Fattah, M.A., Morshed, S.R. and Kafy, A.-A. (2022) Insights into the Socio-Economic Impacts of Traffic Congestion in the Port and Industrial Areas of Chittagong City, Bangladesh. *Transportation Engineering*, **9**, Article ID: 100122. https://doi.org/10.1016/j.treng.2022.100122

[16] Falcocchio, J.C. and Levinson, H.S. (2015) The Costs and Other Consequences of Traffic Congestion. In: Falcocchio, J.C. and Levinson, H.S., Eds., *Road Traffic Congestion*: *A Concise Guide*, Springer Tracts on Transportation and Traffic, Vol. 7, Springer, Berlin, 159-182. https://doi.org/10.1007/978-3-319-15165-6_13

[17] Pope, C.A., *et al*. (2002) Lung Cancer, Cardiopulmonary Mortality, and Long-Term Exposure to Fine Particulate Air Pollution. *JAMA*, **287**, 1132-1141. https://doi.org/10.1001/jama.287.9.1132

[18] Muller, N.Z. and Mendelsohn, R. (2007) Measuring the Damages of Air Pollution in the United States. *Journal of Environmental Economics and Management*, **54**, 1-14. https://doi.org/10.1016/j.jeem.2006.12.002

[19] Ali, M.S., Adnan, M., Noman, S.M. and Baqueri, S.F.A. (2014) Estimation of Traffic Congestion Cost—A Case Study of a Major Arterial in Karachi. *Procedia Engineering*, **77**, 37-44. https://doi.org/10.1016/j.proeng.2014.07.030

[20] Gulian, E., Glendon, A.I., Matthews, G., Davies, D.R. and Debney, L.M. (1990) The Stress of Driving: A Diary Study. *Work Stress*, **4**, 7-16. https://doi.org/10.1080/02678379008256960

[21] Fattah, M.A., Esraz-Ul-Zannat, M., Morshed, S.R. and Roni, A.T. (2022) Modeling the Impact of Motorized Vehicles' Activities on Emissions and Economic Losses in a Fast-Growing Developing City, Dhaka, Bangladesh. *Journal of Transport & Health*, **25**, Article ID: 101377. https://doi.org/10.1016/j.jth.2022.101377

[22] Driver Behavior Influences Traffic Patterns as Much as Roadway Design. ScienceDaily. https://www.sciencedaily.com/releases/2020/11/201117133914.htm

[23] Wang, W.X., Guo, R.J. and Yu, J. (2018) Research on Road Traffic Congestion Index Based on Comprehensive Parameters: Taking Dalian City as an Example. *Advances in Mechanical Engineering*, **10**, 1-8. https://doi.org/10.1177/1687814018781482

[24] Prasolenko, O., Lobashov, O., Bugayov, I., Gyulyev, N. and Filina-Dawidowicz, L. (2019) Designing the Conditions of Road Traffic in the Cities Taking into Account the Human Factor. 2019 6*th International Conference on Models and Technologies for Intelligent Transportation Systems* (*MT-ITS*), Cracow, 5-7 June 2019, 1-8. https://doi.org/10.1109/MTITS.2019.8883381

[25] Kerner, B.S., Rehborn, H., Aleksic, M. and Haug, A. (2004) Recognition and Tracking of Spatial-Temporal Congested Traffic Patterns on Freeways. *Transportation Research Part C: Emerging Technologies*, **12**, 369-400. https://doi.org/10.1016/j.trc.2004.07.015

[26] Dong, H., Ma, S., Guo, M. and Liu, D. (2012) Research on Analysis Method of Traffic Congestion Mechanism Based on Improved Cell Transmission Model. *Discrete Dynamics in Nature and Society*, **2012**, Article ID: 854654. https://doi.org/10.1155/2012/854654

[27] Akhtar, M. and Moridpour, S. (2021) A Review of Traffic Congestion Prediction Using Artificial Intelligence. *Machine Learning Applications in Transportation Engineering*, **2021**, Article ID: 8878011. https://www.hindawi.com/journals/jat/2021/8878011

[28] Huang, D., Deng, Z., Wan, S., Mi, B. and Liu, Y. (2018) Identification and Prediction of Urban Traffic Congestion via Cyber-Physical Link Optimization. *IEEE Access*, **6**, 63268-63278. https://doi.org/10.1109/ACCESS.2018.2875239

[29] Zhang, S., Yao, Y., Hu, J., Zhao, Y., Li, S. and Hu, J. (2019) Deep Autoencoder Neural Networks for Short-Term Traffic Congestion Prediction of Transportation Networks. *Sensors* (*Switzerland*), **19**, 2229. https://doi.org/10.3390/s19102229

[30] Xing, Y., Ban, X., Liu, X. and Shen, Q. (2019) Large-Scale Traffic Congestion Prediction Based on the Symmetric Extreme Learning Machine Cluster Fast Learning Method. *Symmetry* (*Basel*), **11**, 730. https://doi.org/10.3390/sym11060730

[31] Wang, X., *et al.* (2019) Data-Driven Short-Term Forecasting for Urban Road Network Traffic Based on Data Processing and LSTM-RNN. *Arabian Journal for Science and Engineering*, **44**, 3043-3060. https://doi.org/10.1007/s13369-018-3390-0

[32] Di, X., Xiao, Y., Zhu, C., Deng, Y., Zhao, Q. and Rao, W. (2019) Traffic Congestion Prediction by Spatiotemporal Propagation Patterns. 2019 20*th IEEE International Conference on Mobile Data Management* (*MDM*), Hong Kong, 10-13 June 2019, 298-303. https://doi.org/10.1109/MDM.2019.00-45

[33] Liu, Y., Feng, X., Wang, Q., Zhang, H. and Wang, X. (2014) Prediction of Urban Road Congestion Using a Bayesian Network Approach. *Procedia—Social and Behavioral Sciences*, **138**, 671-678. https://doi.org/10.1016/j.sbspro.2014.07.259

[34] Jain, S., Jain, S.S. and Jain, G. (2017) Traffic Congestion Modelling Based on Origin and Destination. *Procedia Engineering*, **187**, 442-450. https://doi.org/10.1016/j.proeng.2017.04.398

[35] Kim, J. and Wang, G. (2016) Diagnosis and Prediction of Traffic Congestion on Urban Road Networks Using Bayesian Networks. *Transportation Research Record*, **2595**, 108-118. https://doi.org/10.3141/2595-12

[36] Yang, X., Luo, S., Gao, K., Qiao, T. and Chen, X. (2019) Application of Data Science Technologies in Intelligent Prediction of Traffic Congestion. *Journal of Advanced Transportation*, **2019**, Article ID: 2915369. https://doi.org/10.1155/2019/2915369

[37] Rehborn, H. and Klenov, S.L. (2009) Traffic Prediction of Congested Patterns. In: *Encyclopedia of Complexity and Systems Science*, Springer, Berlin, 9500-9536. https://doi.org/10.1007/978-0-387-30440-3_564

[38] Ito, T. and Kaneyasu, R. (2017) Predicting Traffic Congestion Using Driver Behavior. *Procedia Computer Science*, **112**, 1288-1297. https://doi.org/10.1016/j.procs.2017.08.090

[39] Lu, S. and Liu, Y. (2018) Evaluation System for the Sustainable Development of Urban Transportation and Ecological Environment Based on SVM. *Journal of Intelligent & Fuzzy Systems*, **34**, 831-838. https://doi.org/10.3233/JIFS-169376

[40] Alajali, W., Zhou, W., Wen, S. and Wang, Y. (2018) Intersection Traffic Prediction Using Decision Tree Models. *Symmetry* (*Basel*), **10**, 386. https://doi.org/10.3390/sym10090386

[41] Wang, H., Liu, L., Dong, S., Qian, Z. and Wei, H. (2016) A Novel Work Zone Short-Term Vehicle-Type Specific Traffic Speed Prediction Model through the Hybrid EMD-ARIMA Framework. *Transportmetrica B*, **4**, 159-186. https://doi.org/10.1080/21680566.2015.1060582

[42] Lee, C., *et al*. (2020) A Visual Analytics System for Exploring, Monitoring, and Forecasting Road Traffic Congestion. *IEEE Transactions on Visualization and Computer Graphics*, **26**, 3133-3146. https://doi.org/10.1109/TVCG.2019.2922597

[43] Qi, W., Wen, H. and Wu, Y. (2015) Method and Application of Grade Division for Road Traffic Congestion Based on Driver's Feeling. *Advances in Mechanical Engineering*, **7**, 1-9. https://doi.org/10.1177/1687814015618860

[44] Hennessy, D.A. and Wiesenthal, D.L. (2010) The Relationship between Traffic Congestion, Driver Stress and Direct versus Indirect Coping Behaviours. *Ergonomic*, **40**, 348-361. https://doi.org/10.1080/001401397188198

[45] Ito, T. and Kaneyasu, R. (2017) Review under Responsibility of KES International Predicting Traffic Congestion Using Driver Behavior-Review under Responsibility of KES International. https://doi.org/10.1016/j.procs.2017.08.090

[46] Li, G., *et al*. (2020) Influence of Traffic Congestion on Driver Behavior in Post-Congestion Driving. *Accident Analysis and Prevention*, **141**, Article ID: 105508. https://doi.org/10.1016/j.aap.2020.105508

[47] Graham, D.J. and Glaister, S. (2004) Road Traffic Demand Elasticity Estimates: A Review. *Transport Reviews*, **24**, 261-274. https://doi.org/10.1080/0144164032000101193

[48] Karri, S.L., De Silva, L.C., Lai, D.T.C. and Yong, S.Y. (2021) Classification and Prediction of Driving Behaviour at a Traffic Intersection Using SVM and KNN. *SN Computer Science*, **2**, 1-11. https://doi.org/10.1007/s42979-021-00588-7

[49] U.B. of Statistics (2022) Uganda Bureau of Statistics. https://www.ubos.org

[50] Kasimbazi, E. (2018) Urban Expansion in the Greater Kampala Metropolitan Area, Uganda. United Nations Habitat.

[51] Angel, A.M., *et al*. (2012) Central Business District, Kampala, Uganda, 1990 in EarthWorks. [Shapefile]. Lincoln Institute of Land Policy. https://earthworks.stanford.edu/catalog/stanford-xz507pv3399

[52] Kampala Capital City Authority (2020) Kampala Public Transport Routes. Ministry of Works and Transport, Kampala. https://www.kcca.go.ug/media/docs/Kampala%20Public%20Transport%20Routes.pdf

[53] Google (2022) Google Maps. Google Map Data. https://www.google.com/maps/@0.3186714,32.5922711,14z/data=!5m1!1e1

[54] Satopää, V., Albrecht, J., Irwin, D. and Raghavan, B. (2011) Finding a "Kneedle" in a Haystack: Detecting Knee Points in System Behavior. 2011 31*st International Conference on Distributed Computing Systems Workshops*, Minneapolis, 20-24 June 2011, 166-171. https://doi.org/10.1109/ICDCSW.2011.20

[55] Thorndike, R.L. (1953) Who Belongs in the Family? *Psychometrika*, **18**, 267-276. https://doi.org/10.1007/BF02289263

[56] Yahya, U., Senanayake, S.M.N.A. and Naim, A.G. (2022) Characterising Leg-Dominance in Healthy Netballers Using 3D Kinematics-Electromyography Features' In-

tegration and Machine Learning Techniques. *International Journal of Biomedical Engineering and Technology*, **39**, 65-92. https://doi.org/10.1504/IJBET.2022.123259

[57] Yahya, U., Senanayake, S.M.N.A. and Naim, A.G. (2018) Cluster Analysis-Based Classification of Healthy Female Netball Players Using Wearable Sensors. 2017 *Eleventh International Conference on Sensing Technology* (*ICST*), Sydney, 4-6 December 2017, 1-7. https://doi.org/10.1109/ICSensT.2017.8304484

[58] Qi, W., Wen, H., Wu, Y. and Qin, L. (2017) Effect Model of Urban Traffic Congestion on Driver's Lane-Changing Behavior. *Advances in Mechanical Engineering*, **9**, 1-12. https://doi.org/10.1177/1687814017724087

[59] Qi, W., Pei, Y., Song, M. and Bie, Y. (2013) Pattern Analysis of Driver's "Pressure-State-Response" in Traffic Congestion. *Discrete Dynamics in Nature and Society*, **2013**, Article ID: 853845. https://doi.org/10.1155/2013/853845