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# Small Autonomous Vehicles in Pedestrian Contexts: A First Analysis of Logistics Performances in Terms of Commercial Speed

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**Abstract:** There is a lot of talk about autonomous vehicles, and Europe is very much focusing on their use and deployment. However, the field use of these vehicles is still very limited. The proposed research refers to a specific category of autonomous vehicles, that is, small ground autonomous vehicles circulating in pedestrian environments, with a focus on their use in operating logistical services. More precisely, this paper presents data collected during a challenging experiment carried out in the city of Trikala, Greece, in the context of the major European project "SHOW". A statistical analysis of these sampled data concerning service times, in terms of commercial speed, for collecting organic waste from cafeterias is presented. The aim of this paper is to verify whether data collected from autonomous vehicles used for this service are reliable and whether accurate estimates can be derived from these data to be used as standard parameters of these vehicles. For these reasons, we analyze the operational performance of the service performed by small autonomous vehicles, with particular attention to the interactions between them and pedestrians and the ability of users to load and unload small vehicles. More precisely, we verify whether there is an adaptation period in which human–vehicle interactions become smoother and whether commercial speed varies at different times of day, that is, if there are peak periods in which droid speed is limited because of the intensity of interactions with pedestrians. A statistical analysis of these data is proposed to find answers to these research questions. It made it possible to highlight an adaptation curve of humans to droids and that no peak periods emerged where droid speed was limited because of the intensity of interactions with pedestrians. This result is probably related to the fact that stability of service operation was not achieved. Had the period of experimentation been extended, it would probably have been possible to identify peak and off-peak periods and the relative commercial speeds. However, it is important to note that the achievement of service operation stability takes a long time. The results obtained are interesting and contribute to the current state of knowledge. In fact, data analyzed here are collected on public land, refer to interactions that take place between small autonomous ground vehicles and a heterogeneous population, and therefore constitute a starting point for the development of technologies that facilitate human–driver interactions and thus lead to an improvement in the performance of sustainable logistics services managed by autonomous vehicles and facilitate their dissemination.

**Keywords:** commercial speed; logistics; operative performance; real field data; small autonomous vehicles



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## 1. Introduction

Small Ground Autonomous Vehicles (sGAVs), also known as Sidewalk Autonomous Delivery Robots (SADRs), Autonomous Delivery Robots (ADRs), droids, or Ground Autonomous Delivery Devices (GADDs), are compact autonomous vehicles designed to perform indoor and outdoor operative tasks in pedestrian-centric environments. These operational tasks are most often logistical services of delivery/collection of small parcels [1] but can also be understood as environmental monitoring or environmental cleaning/sanitization.

Equipped with sensors and mapping technologies, these robots can safely maneuver through crowded spaces while avoiding obstacles and ensuring pedestrian safety. However, their successful integration into human-populated environments depends, first, on their ability to interact seamlessly and safely with them: e.g., pedestrians, bikes, and cars [2] and second, on their sustainability and operative performances [3,4].

Logistics services operated by sGAVs in pedestrian areas seem to promise greater sustainability. Last-mile distribution is increasingly critical because of the rapid growth in e-commerce, sGAVs, and moving in pedestrian areas, which could help reduce freight traffic volumes on urban roads [5]. Furthermore, being electric, their carbon footprint is negligible [6,7]. In dense neighborhoods such as historical city centers, it has been shown that sGAVs are not only more sustainable but also show great potential and are expected to be economically profitable [8]. With regard to droid-operated logistics services in hospitals, these are more sustainable as they reduce direct physical contact between people, which helps limit the spread of infections. They also allow for more accurate environmental cleaning/sanitization. As far as air quality monitoring is concerned, sGAVs can identify the attainment of critical levels earlier and thus enable the implementation of earlier mitigation actions that, in turn, ensure environmental sustainability in both indoor and outdoor pedestrian contexts.

Logistical delivery services operated by sGAVs in pedestrian areas are thought not only to be sustainable but also to be economically profitable, being able to save up to 90% of operating expenses when compared with traditional truck-based deliveries when they are implemented in a two-tier structure [9].

Although promising to be sustainable and economically profitable, these technologies are at an early stage of development; thus, real-life applications are infrequent and take place mainly in private contexts, for instance, in industries that address operations in challenging and dangerous areas [10]. As examples of real services operated by sGAVs fleets in private contexts, we can mention the following:

- Outdoors, automated parcel delivery services are operated across private campuses. Examples are:
- on the Northern Arizona University campus, where food deliveries are performed by Starship robots [11];
- in the Joint Research Centre (Ispra, Italy), where deliveries are performed by Yapes;
- on the Heilbronn University campus, where coffee delivery services are operated by an sGAV based on an electric golf cart [12].
- Indoors,
- At Roma Fiumicino airport (Italy), droids bring packages that have been purchased in the various shops at the airport to their buyers who are waiting at the gates. This service allows customers to move around easily without having to carry the purchased products, which can be heavy and bulky.
- In hospitals, sGAVs are used for disinfection purposes [13]. These robots can autonomously navigate a hospital facility and then complete the disinfection operation of hospital rooms or surgical theaters without any human interaction. Droids in hospitals are also used for carrying medications, lab samples, and other critical items [13]. These droids aim to handle deliveries quickly, safely, and reliably, increasing productivity and sustainability while improving the staff experience and patient outcomes.

While in private contexts, droid-operated logistics services are beginning to be implemented, in public contexts, this is still difficult because of problems with permits, safety regulations, authorizations for their movement, and liabilities. As it concerns public contexts, the first experience was made in Germany, where the robot Obelix navigated autonomously from the campus of the Faculty of Engineering of the University of Freiburg to the city center of Freiburg during a busy day in August 2012 [14]. Later, logistics services operated by autonomous vehicles on public land were implemented during long-lasting pilots in the context of the European project SHOW. Pilots of Logistics services are those implemented in Karinthia (Austrian state), Trikala (Greece), and Karlsuhe (Germany). A very interesting parcel delivery system has been implemented recently in a pedestrian area in the new city district of Heilbronn, Germany. It was operated by two autonomous vehicles based on an electric golf cart for several months [15]. These innovative solutions are often still prototype solutions and often rely on sGAVs with very different characteristics: several companies such as Starship [16], Robby [17], and Marble [18] have developed their own versions of delivery robots, which are currently evaluated in field tests.

From these experiences in the field, it seems sustainable and economically profitable to operate logistical delivery services in pedestrian areas with autonomous vehicles; therefore, several models have been proposed to optimize their performance. Vehicle routing problems with time windows and delivery robots (VRPTWDR) can be found in the literature [19,20]. If the optimization of the routes, which determines the points that must be traveled by an SGAV to reach the destination, is based on time, a history of the performed routes is required, as well as a classification according to the parameters regarding the weather conditions (season) and the time period (day and time or rush hours). However, there is little available representative data for these targets [15], and in most cases, the traveling speed and service times for robots are often assumed to be constant [21]. When travel times and service times are considered uncertain in robust optimization [22–24], it is assumed that the realizations of travel time and service time always fall within given ranges since in most real-life applications, the probability distributions of travel time and service time could be hard to obtain. Considering the high uncertainty of these input parameters, a sensitivity analysis of the models is often performed. Bakach et al. [9] consider instead stochastic travel times, given the presence of zones with varying pedestrian levels of service, in pathfinding and routing heuristics.

However, most studies on sGAVs have been theoretical in nature, and there is a clear need for case studies and real implementations in the public field, as pointed out by Alverhed et al. [25]. There is a lack of empirical data necessary for the definition of efficient optimization algorithms for logistic services in pedestrian areas that can also be used for training and testing machine learning algorithms. Indeed, these learning-based methods require representative data that do not exist for pedestrian environments [26]. Moreover, it is also important to take into account that logistics systems with different characteristics and operated by different autonomous vehicles must be optimized with data appropriate to the specific system. This makes the need for empirical data specific to different categories of sGAVs even more critical.

The research presented in this article is similar to that of Kocsis et al. [15], but the autonomous vehicles used for last-mile distribution are very different in size and load capacity. The electric golf car adapted by Kocsis et al. [15] has a length of 240 cm and a width of 119 cm with a maximum load capacity of 360 kg; this research, on the other hand, refers to a small droid called Yape produced by the company YAPE [27], which has a length of 70 cm and a width of 70 cm with a maximum load capacity of 10 kg. Due to these differences in the characteristics of sGAVs, the logistical performance, e.g., in terms of travel time and service, and the impact that sGAVs have on pedestrian flows in the area in which they operate are different.

The present research proposes a statistical analysis of empirical data collected in the field relating to one of the three logistics services that were implemented in Trikala, Greece. In particular, this paper focuses on the commercial speeds of Yape. Note that the commercial speed is an aggregated measure that considers the distance between the origin and the delivery point and the overall time required to complete the delivery at the destination point, therefore making it available for a new delivery.

The aim of the proposed statistical analysis is twofold. First, commercial speeds are affected by interactions with humans. Humans interact with sGAVs on the one hand because they share the same physical space and, on the other hand, because they have to collaborate with sGAVs in logistic activities. Therefore, our goal is to understand if there is an adaptation period for humans in both dodging Yapes moving in pedestrian environments and/or collaborating with Yape during loading and unloading activities. Second, since commercial speeds are influenced by interactions with pedestrian flows and pedestrian flows change during the day, we wish to verify whether Yape's commercial speeds are correlated with daily time. Specifically, we verify whether their commercial speeds are higher when pedestrian flows are lower (off-peak periods) and vice-versa (peak periods).

The remaining paper is structured as follows. Section 2 describes the technical features of the used sGAV and the public context in which the logistics service has been operated and in which these data were collected. Section 3 reports on the statistical analysis of these empirical data. Section 4 assesses the implications of our empirical findings. Finally, Section 5 concludes the paper by presenting future research directions.

## 2. The Vehicle, the Real Context, and Empirical Data Collection

### *2.1. The Vehicle*

Yape has been designed for both indoor and outdoor low-contact services and last-mile delivery operations. The overall system that allows autonomous navigation is described below.

- ADMIN PLATFORM allows the management of digital maps of the site where the robot navigates. The admin platform also provides the latest release of the Control Room and Robot software (V0.2_2023).
- CONTROL ROOM allows the operator to monitor the fleet during the delivery and, if needed, allows the operator to take control and manage critical operations.
- DELIVERY PLATFORM allows the user to place a delivery request.
- FLEET OF DROIDS (1+) Yapes, SAE level 4 and TRL 7, have 3 different movement modes: autonomously traveling, driven by a remote controller (Wi-Fi connection), and operated by a local controller via joystick (Bluetooth). Yapes are characterized by compact size and high maneuverability. Each droid has its docking station to automatize daily operations. Yape is a compact size droid (Yape's dimensions are 70 L–70 W–90 H [cm]) that weighs 50 kg and can carry up to 10 kg of load. Yape's maximum speed is 6 Km/h, but it was limited to 3 Km/h (0.833 m/s) for safety reasons. Yapes are equipped with one lidar sensor (LiDAR type 360 ~ 3D) to detect obstacles or detect the path to move autonomously, Li-ion batteries which allow the droid to operate 8 h without interruptions, 3 HD and 1 stereo camera to monitor the delivery operations of the droid by the operator. Yape can go up to 12° of inclination. The procedure of localization makes use of a GNSS (Global Navigation Satellite System) by giving an absolute position, whose accuracy depends on the signal's precision; this guarantees global localization. The 4G/5G coverage must be guaranteed on the whole area where the droids operate.

The Control Room laptop is connected to the network through Wi-Fi or Ethernet. The droids are connected through their internal modem to a 4G or 5G network. However, each droid can be provided with a 4G SIM card.

Yape's behavior in case of an expected conflict is very simple: Yape stops, stands still, and waits for the obstacle to move. In case the obstacle does not move, Yape calls the remote controller.

### *2.2. The Public Context Where the Logistic Service Has Been Operated*

In the pedestrian area in the Trikala city center, a prototype homogeneous fleet of 5 identical Yapes collects coffee residuals from the coffee shops in the area and delivers them to the deport/control station. The length of the round trip is about 4500 m. The delivery path includes Asklipiou Street and Buronos Street; the number of service stops is 2 at the coffee shop locations. In Figure 1, the control station location is indicated by an arrow, the stop locations are displayed with cycles, and the delivery path is displayed with a black line. Figure 1 includes the coordinates of the main stops.


**Figure 1.** Yape's path for coffee residual collections from 2 cafe shops on Asklipiou Street (Ασκληπιου) and Buronos Street (Βυρωνοσ).

Delivery trips start and end in the control station. Figure 2 shows the control station interior with the Yape fleet and the Control Room with the digital map of the area. The control station also acts as a parking area, a deposit and charging station for Yapes, and a storage area for the goods. The control station is directly connected to the real urban pedestrian area where Yapes operate. These droids do not need to cross the roads and vehicular flows. In the real urban pedestrian area where Yapes operate, commercial vehicles and bicycles may occasionally pass by.

This is a demand-responsive service. Coffee shop owners use the special reservation system through the Delivery Platform. The collection service can be single-stop or multi-stop. In the first case, the collection service is requested by a single café. At this time, Yape leaves the deportation station and reaches a coffee shop. Then, the shopkeeper leaves the shop, and upon Yape's arrival, the lid opens. The coffee residue is loaded into Yape, and the lid is closed. Finally, Yape returns to the deport station, where an operator unloads it.

In the case of a multi-stop, both shops request the service. The service takes place as in the previous case, but after the shopkeeper of the first shop has closed the lid of the droid, it does not return to the deport station but proceeds to the second coffee shop, where the shopkeeper also loads the coffee residues. Only when the second shopkeeper closes the lid of Yape does it return to the deport station. Here, the operator unloads the coffee residues from the 2 coffee shops.

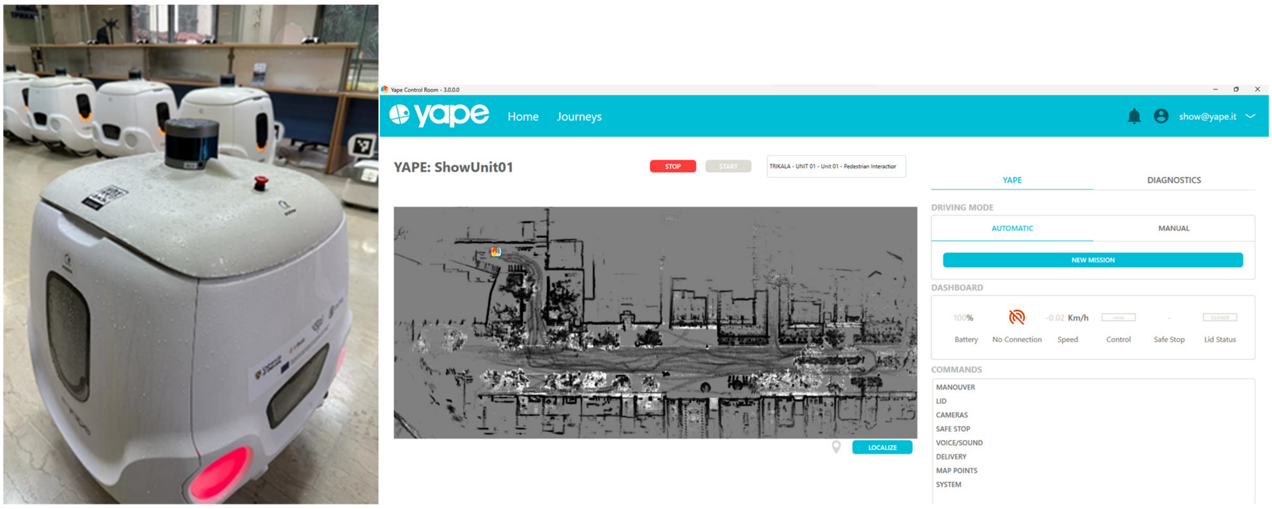


**Figure 2.** The control station interior (right) and the Control Room display the digital map of the Trikala pedestrian area and the trajectories of Yapes.

## 3. The Empirical Data Collection

Data collection was performed in Asklipiou Street and Buronos Street (Figure 1) during the operation of the logistic services in the following conditions:

- working days, peak hours (from 11 a.m. to 13 a.m. and from 4 p.m. to 6 p.m.), and off-peak hours (from 9 a.m. to 11 a.m.) in order to have different pedestrian densities;
- different weather conditions (rainy and non-rainy days).

Data collection was performed for about 1 month: from mid-January 2023 to the end of February 2023. In total, 34 successful deliveries were performed.

These data were recorded autonomously by Yapes and were downloaded to a PC at the end of the day by an operator. These data include:

the timestamp of Yape's departure from the control room,

then, for each delivery $i$ that takes place at stop $i$:

- $ShipmentStartDT^i$ = the timestamp of Yape's departure from stop $i - 1$;
- *Lid opening time*$^i$ = the timestamp when Yape's lid is opened at stop $i$;
- *Lid closing time*$^i$ = the timestamp when the lid is closed in stop $i$ = $ShipmentEndDT^i$: the timestamp when the delivery in $i$ ends;

the timestamp of when Yape returns to the control room.

- Note that *Lid closing time*$^i$ = $ShipmentEndDT^i$ is equal to the timestamp of when Yape departs from stop $i$: = $ShipmentStartDT^{i+1}$

The linear relationship between space and time is called a time-track: its angular coefficient measures the speed of the vehicle and is commonly used in rail. A Yape's time track is shown in Figure 3. It refers to the multi-stop collection service: Yape leaves the depot station and reaches the first coffee; the shopkeeper puts the residues into Yape and closes the lid. Then, Yape reaches the second coffee. Here, the shopkeeper loads the coffee residue into Yape. More specifically, referring to Figure 3, at the time ShipmentStartDT1, Yape left the deport station. It travels from the deport station to coffee shop 1. The arrival time at stop 1 is unknown since it has not been recorded. At Lid opening time1, Yape lid is opened at stop 1 by the first shopkeeper, and at Lid closing time1, the lid is closed. At this time, the first shipment ends (Lid closing time1 = $ShipmentEndDT^1$), and Yape starts the second shipment ($ShipmentEndDT^1$ = $ShipmentStartTD^2$). The second shipment ends at time $ShipmentEndDT^2$. Both Yape's trips, as shown in Figure 3, are performed at a constant speed. In fact, note that the angular coefficient is constant.

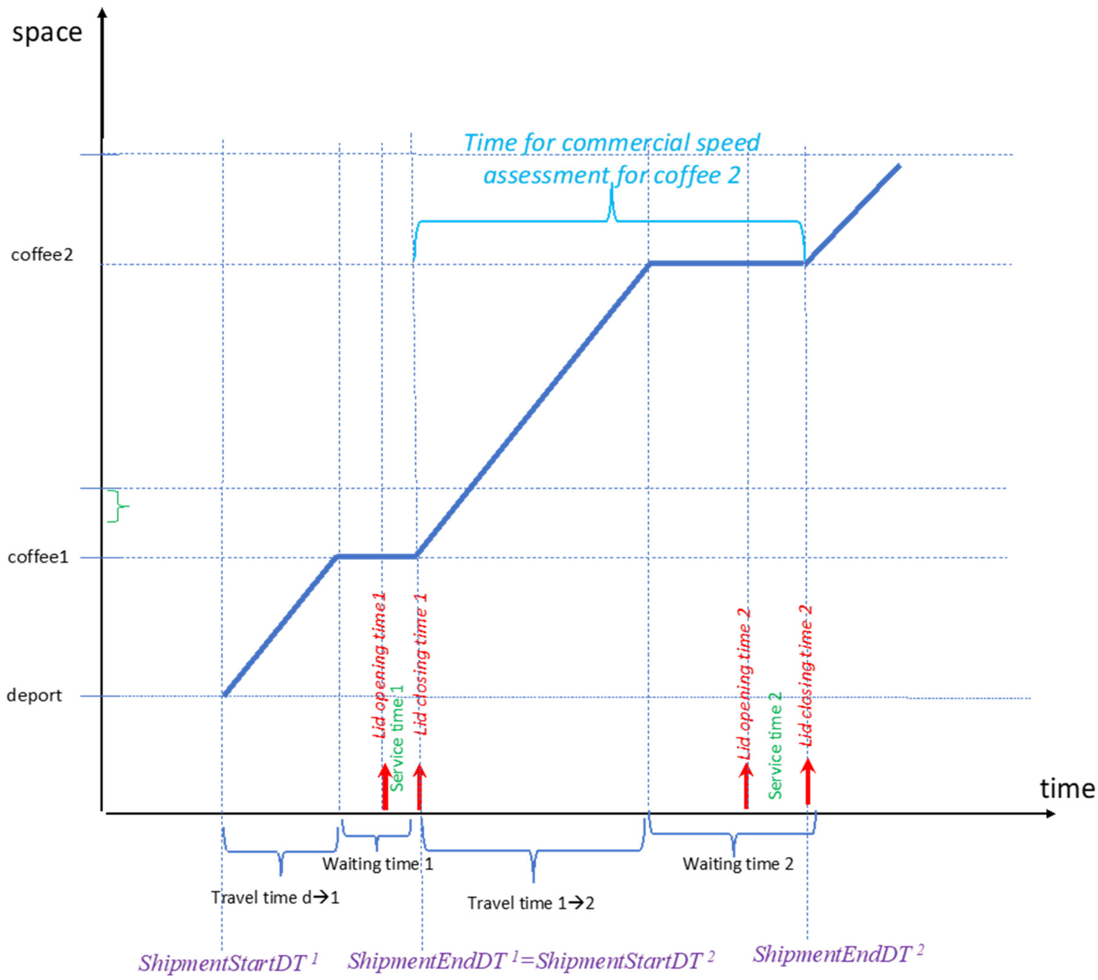


**Figure 3.** Multi-stop collection service.

The reordered timestamps have been converted into human-readable format dates, that is, year, month, day, hour, minutes, and seconds; for instance, timestamp 23012023T172138 has been converted in year 2023, month January, day 23 at time 17:21:38.

Data collection aims to assess the operative logistics performances of delivery services operated by the Yape fleet. The relevant KPIs considered in the present study are travel time, waiting time, acknowledgment time, service time, and commercial speed. These indexes are collected as follows.

Travel time: it is the time Yape takes to reach the second stop ($i$ + 1) starting from the first one ($i$). This time depends on Yape's speed and the number of interactions with pedestrians, bicycles, and cargo vans during the trip.

Waiting time: it is computed from the time Yape arrives to the stop to the lid closing time. This time is given by the sum of 2 contributions:

Acknowledgment time: this time depends on how long it takes the shopkeeper to realize that Yape has arrived at the stop and to reach it.

Service time: the time taken by the shopkeeper to load or unload Yape. In practice, it is the time interval between the lid opening and lid closing and depends on the human-AV interaction: $Lid\ closing\ time^i - Lid\ opening\ time^i$

Commercial speed in $i$ + 1: it is given by the rate between the distance between 2 service points ($i$ and $i$ + 1) and the time interval: $ShipmentEndDT^{i+1} - ShipmentStartDT^{i+1}$ which, in turn, is given by the sum of travel time between $i$ and $i$ + 1 and the waiting time in $i$ + 1.

In the following, the results related to the analysis of commercial speed are reported.

Statistical Analysis

Collected data have been elaborated, and in the resulting database, each dataset is composed of a commercial speed value and the related timestamp (*ShipmentStartDT*$^{i}$). These data are shown in Figure 4.

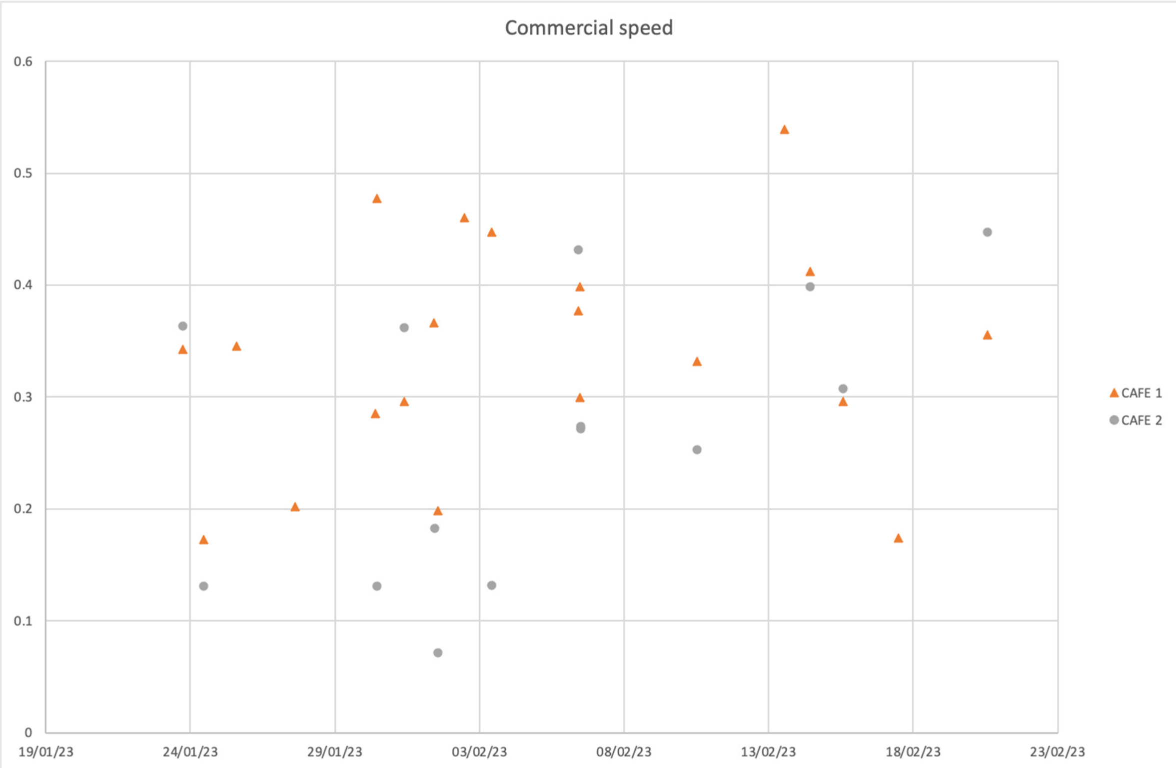


**Figure 4.** Commercial speed time series.

Figure 4 reports the *ShipmentStartDT* on the x-axis (it refers to the time from 19 January to 23 February 2023) and the related commercial speed [m/s] on the y-axis. Data related to coffee shop 1 are displayed as triangles and those related to coffee shop 2 as circles.

A total of 20 datasets refer to delivery trips to coffee shop 1, and 14 datasets refer to delivery trips to coffee shop 2.

The Inter-Quartile Range (IQR) Method of Outlier Detection has been adopted. We call Q1 the first quartile: the value under which 25% of data points are found when they are arranged in increasing order. Q3 the third quartile: the value under which 75% of data points are found. The difference between Q3 and Q1 is called the Inter-Quartile Range (IQR). To detect the outliers using the IQR Method, we define a new range called the decision range, and any data point lying outside this range is considered an outlier and is dealt with accordingly. The range is: [Q1 − 1, 5(Q3 − Q1); Q3 + 1, 5(Q3 − Q1)]. Any data point less than the lower bound or more than the upper bound is considered an outlier. Since all data collected in the present study are within the decision range, no data are considered outliers.

In the following, the criteria for data analysis are reported:

- The first question is: can we join data related to coffee shop 1 with data related to coffee shop 2, or are there statistically important differences between these two datasets? The trip length to reach coffee shop 2 is 160 m, and the distance to reach coffee shop 1 is 260 m. Does this make these two datasets statistically different?
- The second question is: can it be said that commercial speed changes at different times of the day? So, are there peak and off-peak hours at which low or higher commercial speeds correspond?

- The third question is: is there an increase in commercial speed over time during the pilot study? Does commercial speed increase, increasing the experience of pedestrians in dodging Yape and shopkeepers in loading and unloading Yape? Does the time series have a positive trend component?

### *3.1. First Question: Are the two Datasets Statistically Different?*

Having chosen a significance level α (0.05) for the test, the equality of the averages of the two datasets is set as null hypothesis H0.

It has been assumed that both groups of data are sampled from populations that follow a normal distribution. The histogram method has been used, even if the database dimensions are quite limited, by plotting a histogram of the variable of interest and visually checking the shape of the distribution. The two histograms are shown in Figure 5.

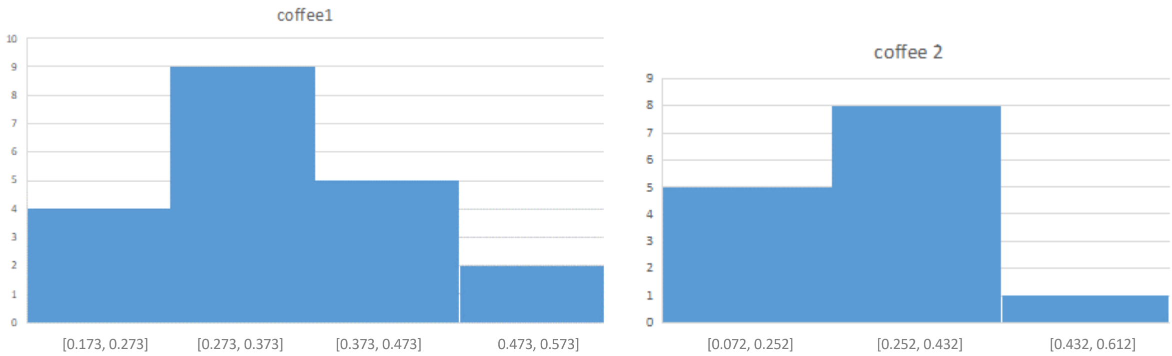


**Figure 5.** Histograms of the two datasets.

Since the two datasets can be considered independent of each other, it is necessary to evaluate the variances of the datasets. According to Derrick et al. [28], if these are similar, then a classical two-sample *t*-test is applied; if they are different, then a Welch test, whose proprieties make it also Type I error robust [28], must be applied. Therefore, since the variances assessed on the two datasets are specifically equal to 0.01 and 0.02, in accordance with Ahad [29], the Welch test has been applied.

The statistical analysis performed with the Microsoft Excel Analysis Toolpak, version number 16.78.3 (Data/Test analysis: two samples assuming different variances) is reported in Table 1. Since the absolute calculated t-value (1.76) is lower than the critical two-tail value (2.06), there is no statistically significant difference between the means of the coffee shop 1 and coffee shop 2 datasets. In addition, the two-tailed *p*-value of the test is 0.09, which is higher than the significance level of 0.05, and we can accept the null hypothesis, while we do not have sufficient evidence to say that the two population means are different. Therefore, the two datasets have been analyzed as a unique dataset since we do not have sufficient evidence to say that the two datasets are statistically different. This allows us to have a fairly large database and, therefore, gives greater reliability to the proposed analysis.

**Table 1.** Test analysis: two samples assuming different variances.

| | **Variable 1** | **Variable 2** |
|---|---|---|
| Mean | 0.34 | 0.27 |
| Variance | 0.01 | 0.02 |
| number of observations | 20 | 14 |
| difference assumed for averages | 0 | |
| degree of freedom | 25 | |
| t-value | 1.76 | |
| two-tailed *p*-value | 0.09 | |
| critical two-tail value | 2.06 | |

### 3.2. Second Question: Does Commercial Speed Change at Different Times of the Day?

These data were processed by aggregating commercial speed values according to the time of day to which they refer, irrespective of the day of the week and the month to which they refer. The relative dataset is the (commercial speed and daily time) dataset and is plotted in Figure 6, where the y-axis refers to commercial speeds [m/s], and the x-axis refers to daily time. So, in Figure 6, the speeds of two collection trips made at 9 a.m., one on 19 January and the other on 20 February, have the same value on the x-axis, while in Figure 4, they have different values on the x-axis.

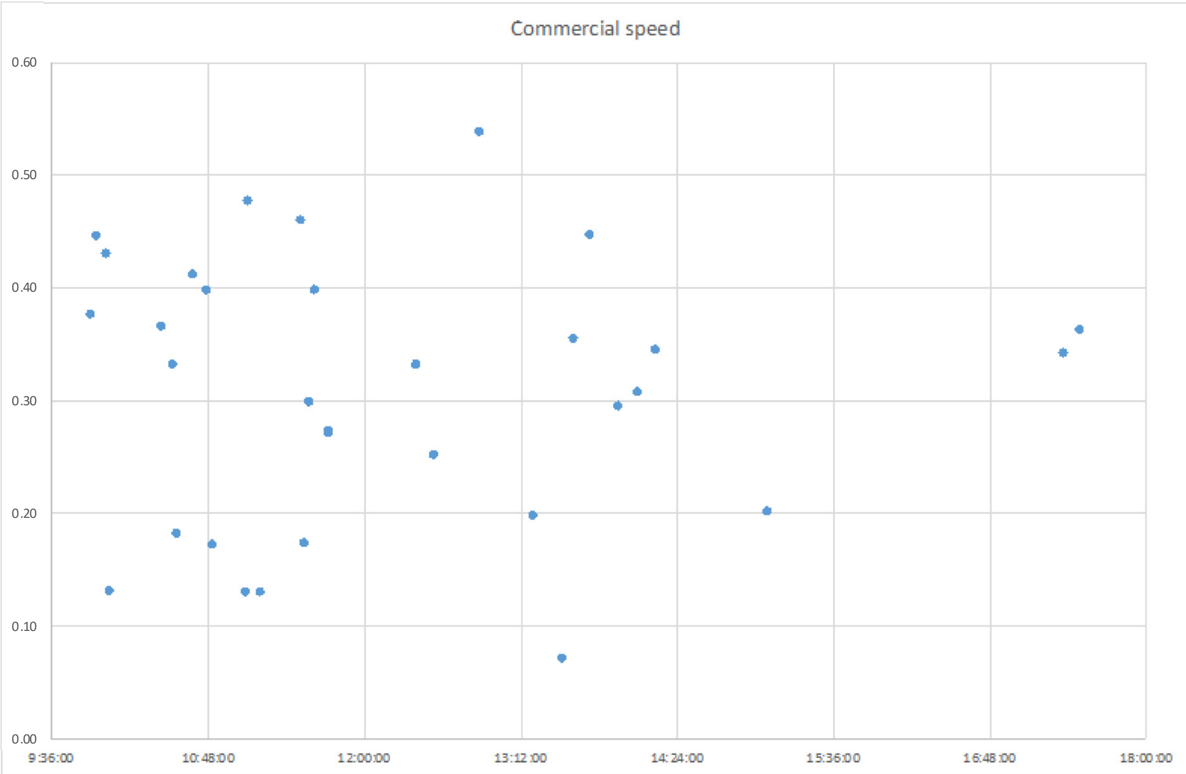


**Figure 6.** Commercial speed [m/s] vs. daily time [hh:mm:ss].

All data refer to working days from mid-January to mid-February 2023. The early data were collected at 9.30 a.m. and the last at 6 p.m. However, most observations refer to the period from 9.30 a.m. to 2.30 p.m.

According to the qualitative observations on pedestrian flows we made during the field trial, we assume a peak period consisting of two time intervals, namely, 11 a.m. to 1 p.m. and 4 p.m. to 6 p.m., and an off-peak period from 9 a.m. to 11 a.m.

We checked whether the peak period corresponds to a lower average commercial speed than the average commercial speed in the off-peak period. The statistical analysis results, reported in Table 2, show that the defined peak and off-peak periods do not correspond to significant differences in the average commercial speeds of Yapes.

**Table 2.** Statistical analysis of the (commercial speed; daily time) dataset.

| | Off-Peak Hours | Peak Hours |
|---|---|---|
| mean [m/s] | 0.323 | 0.303 |
| standard error | 0.029 | 0.026 |
| median | 0.362 | 0.303 |
| mode | - | - |
| Standard deviation | 0.103 | 0.121 |
| Sample variance | 0.0107 | 0.0146 |

Based on the above data, instead of defining the number of clusters and their characteristics a priori, we performed an inductive technique to search for latent structures without making any a priori assumptions about peak and off-peak periods. For this purpose, hierarchical clustering algorithms were implemented through Python. The results are reported in Figure 7. The code calculates the linkage matrix using the Ward method [30]. This method is used to measure the distance/dissimilarity between clusters. The dendrogram is then created and reported in Figure 7.

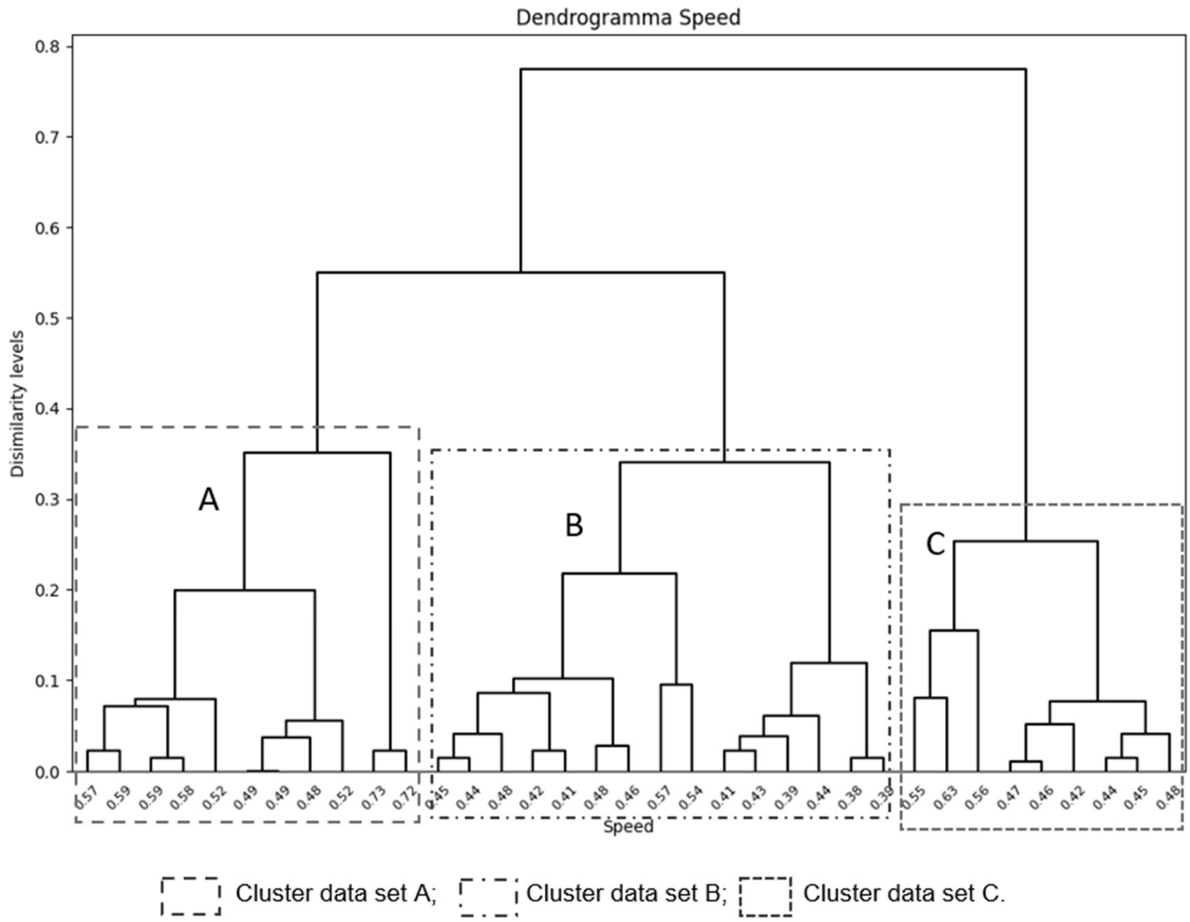


**Figure 7.** Dendrogram. Clustering of the commercial speeds.

The algorithm is iterative and proceeds by successive aggregations.

In the first step, every point is in its own cluster. Then, at each iteration, it proceeds in two steps:

For each cluster, the mean for all the elements is computed: let $\vec{c}_i$ be the mean of cluster *i*.

The distance matrix between clusters is calculated by establishing a criterion for assessing distances. The chosen criterion is the squared Euclidean distance to the cluster means according to Ward's method. The method is a variance method that attempts to generate clusters to minimize the within-cluster variance. The distance between two clusters, say A and B, is assessed according to Equations (1) and (2), respectively,

$$d_{AB} = \sum_{i \in A \cup B} \|\vec{x}_i - \vec{c}_{A \cup B}\|^2 - \sum_{i \in A} \|\vec{x}_i - \vec{c}_A\|^2 - \sum_{i \in B} \|\vec{x}_i - \vec{c}_B\|^2 \quad (1)$$

$$d_{AB} = \frac{n_A * n_B}{n_A + n_B} \|\vec{c}_A - \vec{c}_B\|^2 \quad (2)$$

where:

$d_{AB}$ is the distance/dissimilarity or merging "cost" of combining clusters A and B.
$x_i$ is an element,
$n_g$ is the number of elements in cluster g.
$\vec{c}_{A \cup B}$ is the mean of the cluster resulting from combining Cluster A with Cluster B.

Group the clusters that have the lower merging "cost". In practice, the two clusters with the smallest increase in the overall sum of squares within-cluster distances are combined.

The algorithm stops when all elements are aggregated into a single cluster. With this hierarchical clustering approach, the sum of squares starts at zero (because every point is in its own cluster) and then grows as we merge clusters. Ward's method keeps this growth as small as possible. Given two pairs of clusters whose centers are equally far apart, Ward's method will prefer to merge the smaller ones. Ward's method is both greedy and constrained by previous choices [31].

In the dendrogram displayed in Figure 7, the y-axis reports the dissimilarity levels. Distance/dissimilarity is based on commercial speed values. As already said, the elements to be grouped are daily times. The number of items on the x-axis is equal to the number of observations (34). For each observation, a label is placed on the x-axis with an indication of the time of the day to which the observation refers. The time values have been obtained by the Microsoft Excel TIME function that returns a value between 0 and 0.99988426, indicating an hour between 0.00.00 and 23.59.59. Therefore, every 14.4 min, the label value increases by 0.01. Table 3 shows the moments of the day (hours and minutes) in which commercial speed values were recorded and the corresponding values belonging to interval [0, 0.99] obtained with the Excel TIME function and reported on the x-axis in Figure 7.

**Table 3.** Daily times in the form of *hh:mm* and in the related TIME scale [0;0.99].

| Hours | Minutes | TIME | Hours | Minutes | TIME | Hours | Minutes | TIME |
|---|---|---|---|---|---|---|---|---|
| 9 | 11 | 0.38 | 10 | 49 | 0.45 | 12 | 52 | 0.54 |
| 9 | 16 | 0.39 | 11 | 5 | 0.46 | 13 | 17 | 0.55 |
| 9 | 20 | 0.39 | 11 | 6 | 0.46 | 13 | 30 | 0.56 |
| 9 | 53 | 0.41 | 11 | 11 | 0.47 | 13 | 36 | 0.57 |
| 9 | 56 | 0.41 | 11 | 30 | 0.48 | 13 | 43 | 0.57 |
| 10 | 0 | 0.42 | 11 | 31 | 0.48 | 13 | 56 | 0.58 |
| 10 | 2 | 0.42 | 11 | 34 | 0.48 | 14 | 5 | 0.59 |
| 10 | 26 | 0.43 | 11 | 36 | 0.48 | 14 | 13 | 0.59 |
| 10 | 31 | 0.44 | 11 | 43 | 0.49 | 15 | 5 | 0.63 |
| 10 | 33 | 0.44 | 11 | 43 | 0.49 | 17 | 21 | 0.72 |
| 10 | 40 | 0.44 | 12 | 23 | 0.52 | 17 | 29 | 0.73 |
| 10 | 47 | 0.45 | 12 | 31 | 0.52 | | | |

In this table, the observations are ordered on the x-axis as commercial speed increases.

The observations are grouped into clusters according to the merging "costs" of combining the clusters. The algorithm starts by assigning each observation to a different cluster. Then, in the first step, there are 34 clusters. At each subsequent step, the number of clusters is reduced by grouping more observations in each cluster. Clearly, as the steps of the procedure increase, the merging "costs" increases, and the number of clusters decreases. The algorithm stops when all observations are aggregated into a single cluster.

It is worth observing that a critical level of dissimilarity can, therefore, be defined. We look for this critical value on the y-axis. Sectioning the dendrogram at this level of dissimilarity yields a partition into disjointed groups. A horizontal line is drawn that intersects the y-axis at the chosen critical value. The number of vertical segments that this line intersects corresponds to the number of clusters into which the observations have been divided, respecting the critical value.

Looking at Figure 7, assume a critical value equal to 0.36. At this critical value correspond 3 clusters. Cluster A contains 11 observations which correspond to the lowest recorded values of commercial speeds. Cluster B is the one that groups together the greatest number of observations (15) to which average values of commercial speeds correspond. Cluster C contains nine observations representing the highest recorded values of commercial speeds.

It is possible to note that there are two labels on the x-axis with a value of 0.57 (corresponding to daily time 11.40 a.m.). One observation belongs to Cluster A and one to Cluster B, as the commercial speeds recorded are equal to 0.36 and 0.45, respectively. So, the commercial speed values recorded on different working days at the same daily time are quite different.

According to the reported data analysis, we can state that commercial speed does not change significantly at different times of the day, and it is not possible to find peak and off-peak periods in the working day that allow trust in a given value of commercial speed.

### *3.3. 3rd Question: Does the Time Series Have a Positive Trend Component?*

Figure 4 represents a time series of commercial speed values [m/s]. The x-axis refers to the month during which observations have been collected. Commercial speed values are reported on the y-axis. To eliminate some of the randomness in these data and smooth out short-term fluctuations, the simple moving average (MA) technique was applied. Of the alternative methods that fulfill this objective, MA is among the simplest to implement [32] and, despite this, has enabled the identification of the trend in the dataset, therefore achieving our target. Simple MA can be defined as a succession of means. Given a series of values and a fixed subset size, the first element of the moving average is obtained by taking the average of the initial fixed subset of the number series. Then, the subset is modified by "shifting forward," that is, excluding the first number of the series and including the next value in the subset. The fixed subset size is called *m*, and the related MA is called a moving average of order m (m-MA). The order *m* should be any odd number, and there are two options: two-sided averaging or one-sided averaging. Assuming an order $m = 3$, the two-sided averaging is given by Equation (3), and it is centered around *t*. One-sided averaging is given by Equation (4) and presents two elements on the left of *t*.

$$\widehat{T}_t = \frac{Y_{t-1} + Y_t + Y_{t+1}}{3} \tag{3}$$

$$\widehat{T}_t = \frac{Y_{t-2} + Y_{t-1} + Y_t}{3} \tag{4}$$

where $\widehat{T}_t$ is the average of the values belonging to a subset of fixed size equal to 3. These values are: $Y_{t-1}$, $Y_t$, $Y_{t+1}$ in Equation (3) and $Y_{t-2}, Y_{t-1}, Y_t$ in Equation (4).

The choice of the order m must consider that as m increases, the size of the new database formed by the averages (m-MA) is reduced, but more reliable trend indicators are obtained that are less subject to temporary fluctuations. Therefore, taking this into account and considering the temporal distribution of these collected data and their stability, an order of 5 was chosen (5-MA). In fact, for stable data, short periods may be sufficient to eliminate short-term fluctuations [32].

The 5-MA technique has been applied to commercial speed values in the dataset. The two-sided averaging has been adopted to have average values centered on each subset. The plot of resulting data representing 5-MA commercial speed values against time is reported in Figure 8. A time period of 24 h corresponds to a time period equal to 1 on the x-axis, that is $\Delta x = 1$. Using moving averages helps in estimating the trend in the dataset. A linear regression line, estimated by the least squares method, was added in Figure 8. The equation of the regression line is shown in Equation (5).

$$y = 0.004x + 0.26 \quad (5)$$

where $x$ is the value time starting from the beginning of the field data collection. The results show a positive linear trend. In particular, every day, the commercial speed increases by 0.004 m/s, starting from an initial value of 0.26 m/s. After one month, the observed speed reached 0.38 m/s. The r-squared ($R^2$) value for the linear regression is 0.39.

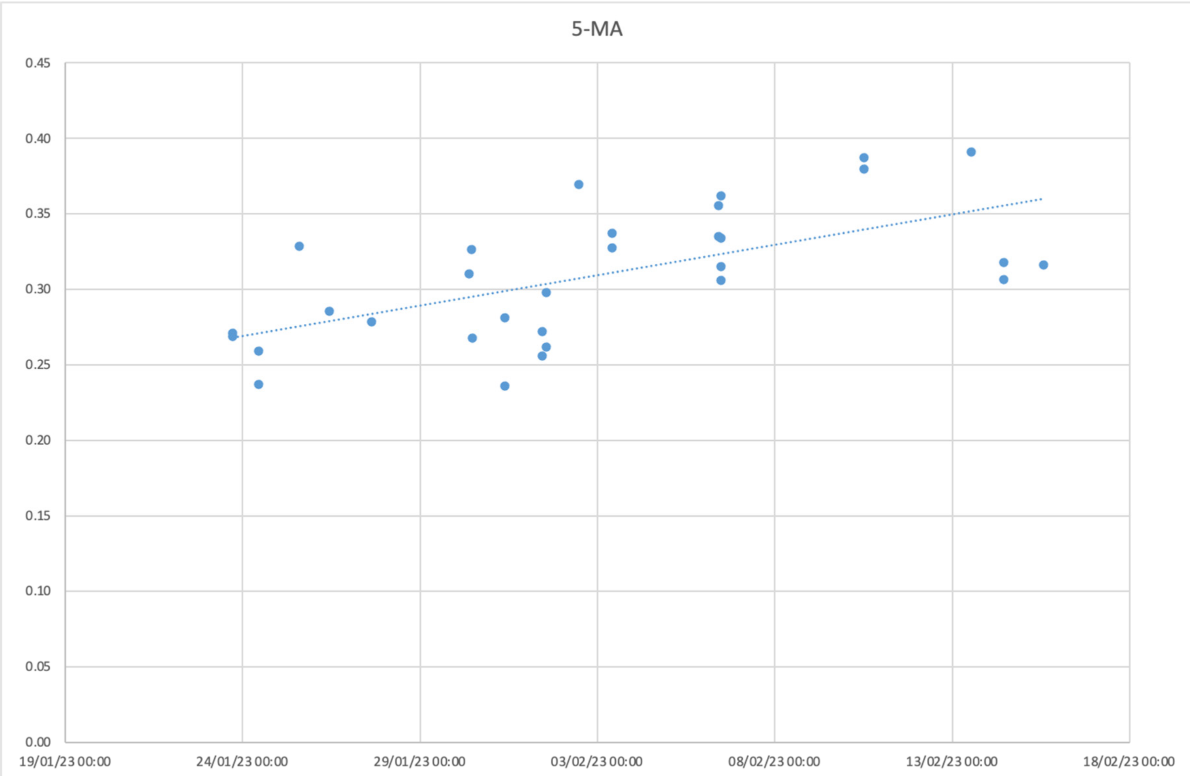


**Figure 8.** 5-MA commercial speed [m/s] vs. time.

From Figure 8, the authors concluded that there is a slow increase in commercial speed over time. If the commercial speed increases over time it means that the time for commercial speed assessment decreases over time. As can be seen from Figure 3, the time for commercial speed assessment is the sum of two contributions: the travel time, that is, the time Yape takes to move from one stop to another, and the waiting time at the stop. From these collected data, it is not possible to understand which of the two components decreases, but we know that their sum decreases over time. Now, if it is the first component to decrease over time, then over time, the pedestrians learn to dodge Yapes, and thus the slowdowns reduce during its motion. Remember that Yape proceeds at a constant speed until it finds an obstacle. At this point, it stops and waits for the obstacle to move out of its path. If it is the second component that decreased over time, then over time, shopkeepers learn to meet Yape as soon as it arrives at their shop, to open Yape's lid more quickly, to reduce the time needed to load Yape with coffee residuals and close the lid immediately. In addition, in this case, we have no knowledge of all the times that make up the waiting time as we do not know the exact time when Yape arrives at the stop. However, we know that their sum will probably decrease over time. In this case, we can say that as time passes, shopkeepers become faster, and the waiting time for Yape at stops decreases. As time goes by, humans learn to interact with droids better and better. We call this case an adaptation period. Similar conclusions were drawn by Etminani-Ghasrodashti et al. [33] regarding the use of autonomous vehicles in public transport. In fact, their results indicated that perceived usefulness and restriction factors can positively motivate individuals to use autonomous vehicles more easily and frequently.

From Figure 8, it is also evident that, in the observed period, commercial speed does not reach a value and then remains constant over time. In fact, throughout the observed period, the commercial speed showed an increasing trend over time. Therefore, a further increase in the commercial speed of droids is possible, extending the experimentation time.

Currently, the authors are preparing additional experiments to discriminate these phenomena, for instance, using Yapes during social events in parks and patios. During these different cases, characterized by very high density and many users accessing Yapes to collect drinks from lateral bags, it became evident that the people and their movements resulted in a major obstacle to the droid's movements and slowed down its speed drastically. It would be interesting to model the obstacle avoidance behavior of Yape and introduce it to existing microscopic models of pedestrian behavior as proposed by Cepolina and Tyler [34]. This would also allow changes in Yape's obstacle avoidance behavior to be evaluated at a simulation level.

## 4. Discussion/Conclusions

The research proposed in the article refers to empirical data collected in the field during a pilot application lasting a total of three months and concerning logistics services operated by small autonomous vehicles. It is the first pilot application in Europe involving the use of a fleet of small autonomous vehicles in public urban pedestrian areas. Numerous problems arose during the pilot application, related, for example, to the acquisition of movement permits for droids, the stability of the data connection, and the reactions of the population. Numerous were unsuccessful deliveries because of these problems. In total, out of all the logistics services operated, about 10% of deliveries were unsuccessful. Numerous measures to mitigate the causes of these problems were implemented in the initial phase.

Once the operational problems were fixed, the database definition phase took a long time. These data automatically collected by the small autonomous vehicles were a posteriori integrated with other data indispensable for the elaborations proposed in the article. The proposed statistical analysis made it possible to highlight that reaching a steady state for a logistic service operated in pedestrian areas by the sGAVs requires a long time: more than 1 month for the Trikala pilot.

Two interesting phenomena emerged. The first is the existence of an adaptation curve of humans to droids. Both non-users (i.e., the pedestrians sharing the pedestrian path with the droids) and users (the recipients of the logistics service), during the analyzed period, learned better and better how to interact with the droids, making the interactions smoother, and this led to a slight but steady increase in commercial speed. However, the commercial speed did not reach a value and then remained constant over time because a steady state was not reached. We therefore believe that if we had extended the experimental period, we could have observed further improvements in the way humans interact with droids, thus further increasing the commercial speed. Stability could have been achieved earlier by training the population and users of the logistics service who will have to interact with the droids or even by acting on the human–machine interface [35]. Indeed, an improvement in logistical and operational performance (increased in commercial speed) is possible with external Human–Machine Interfaces (eHMIs). In particular, interfaces that facilitate mutual obstacle avoidance between pedestrians and droids and that facilitate shopkeepers in loading and unloading droids are crucial. The impact of eHMIs in interactions between pedestrians and autonomous vehicles was studied in pedestrian crossing situations [36,37]. Again, data from these research studies show a crucial role of eHMIs in pedestrians' decisions and actions when crossing the road in the presence of autonomous vehicles. It is therefore believed that, just as eHMIs can help to improve the safety of pedestrians by providing them with clear and concise information about the intentions of the autonomous vehicles in pedestrian crossings, they could also make it easier for pedestrians to navigate around droids, leading to an improvement in the commercial speed of droids performing logistics services in pedestrian areas. In addition, the findings from Sun et al. [38] provide guidance for interaction designs to increase trust, thereby enhancing the acceptance and sustainability of AVs.

The second phenomenon that occurred was that no peak periods emerged: hours within the day when the droids' commercial speed was lower. In fact, the commercial speed of Yape does not change significantly during the hours of the day at different values of pedestrian density. This could be simply due to the fact that the operational stability of the service was not achieved. It would have been useful to continue the experiment until the operational stability of the service is reached and, under these stable conditions, to test whether the different pedestrian density significantly affects commercial speed. The identification of peak periods would be important for logistics service planning and optimization, considering that sGAVs must slow down or completely stop in the presence of objects, such as pedestrians. Operating in off-peak periods or addressing a routing problem to avoid the most congested roads at a given time would lead both to improved logistical and operational performance (reduced delivery times) and also to a reduction in the size of droid fleets required to meet a given delivery demand. Research is moving in this direction: for instance, Bakach et al. [9] explore the effect on deliveries of sGAV travel times, depending on the pedestrian density of the different areas crossed.

It may also be relevant that in the proposed analysis, the total time given by the sum of the travel time and waiting time was used to calculate the commercial speed. It would be interesting to have the possibility of further disaggregating these collected data and repeating the analysis by referring only to point-to-point transit and thus referring only to travel time. In this way, the travel times that were realized in Trikala during the experiment could be compared with those recorded in the field by Kocsis et al. [15], taking into account the different types of vehicles used in the two pilots. However, it was not possible to conduct this at the moment as we did not have data relating to the instant arrival of Yapes at the shop location. However, it relates to the moment when the shopkeeper opened the droid lid.

## 5. Future Research Lines

The authors are currently working on a Virtual Framework for the Certification of Urban Autonomous Vehicles by conducting research on Certification and by creating digital twins of Yapes. These activities are in conjunction with MEDUSAE (Multi-domain testing Environment and Dataset for certification of Unmanned Systems and Autonomous vehicles in order to enable their use in industrial, civil, and urban applications), developed by the simulation team, which creates a framework and a procedure to certify the use of droids in urban environments. Indeed, it is crucial for the diffusion of autonomous systems to solve the current problem related to certification and authorization for their use [39,40]. In fact, this is strongly related to the possibility of using new Autonomous Systems (AS) for safety within municipalities. MEDUSAE aims to develop an environment for VV&T (verification, validation, and testing), and its goal is to create a framework and guidelines to develop AS Digital Twins that can interoperate. MEDUSAE is a common multi-domain test environment (MdtE) that includes a physical test area (MdtE r) and a virtual world (MdtE s) devoted to completing these tests. This allows both real and virtual tests to be conducted on a new real physical autonomous system and its digital twins. Authors have developed part of the virtual test environment to support VV&T and are currently conducting tests to integrate these systems, as proposed in Figure 9.


**Figure 9.** 2-wheel Auton2-wheel system moving on the Simulated Virtual Framework (MdtE s).

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