Baltic J. Modern Computing, Vol. 10 (2022), No. 4, pp. 665–688
https://doi.org/10.22364/bjmc.2022.10.4.05

A Study into Elevator Passenger In-Cabin Behaviour on a Smart-Elevator Platform

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Abstract. With the advancement of technology, elevators have evolved into complex systems transporting people and goods between floors. The trend is towards smart elevators, adding not only value to services provided but enabling capabilities to study passenger behaviour more closely. Have you ever wondered why some people always choose the same spot to stand in an elevator cabin, or what is your favourite location to stand in an elevator? In this study, we use a smart elevator platform to explore elevator passengers' in-cabin behaviour. We develop a location analysis model, passenger behaviour evaluation method, and analyse the data of real elevator passengers. We show that elevator passengers have their favourite spots in elevators to stand in, and common movement patterns they follow, which depend on the operational context. In general, the results we obtain are applicable to any elevator type, and beyond for several use cases of cyber-physical social systems.

Keywords: Smart-elevator, human behaviour, moving patterns, Socio-Cyber-Physical Systems

1 Introduction

The history of modern elevators as a transport means for exclusively transporting humans goes back to the beginning of the 1800s when steam and hydraulic power were introduced for lifting. The first passenger elevator powered by a steam engine was installed in 1857 but received a cold reception from passengers with a refusal to accept it (Bernard, 2014). Today, elevators are a norm for modern commercial and residential buildings, especially in high-rise buildings equipped with several elevators, providing an easy way for people to move between floors. In Estonia (since 2019), new buildings with five or more floors must be fitted with an elevator, as required by the law.

The ever-increasing computerization has also shaped the development of elevators, and today we can address these as Cyber Physical (Social) Systems (CPSS) (Cassandras, 2016; Dressler, 2018; Lee and Seshia, 2016; Zhuge, 2014) having a high impact on our daily lives. Elevator systems have become complex, including rope-free and side-ways moving systems (e.g., ThyssenKrupp Multi) for elevator cabins. The development trend today is towards smart elevators equipped with various sensors allowing to sense and interpret the operational context of the elevator and deliver better service, safety, maintenance, and comfort for passengers. From the perspective of passengers, the underlying mode of exploitation of elevators has stayed the same – we wait for the elevator cabin to arrive and take us from a floor to the desired one. However, the capabilities of smart-elevators today let to study the exploitation of elevators closely. With the emergence of smart cities, the social aspect of elevators is also becoming important and future (smart-)elevators can be addressed as Socio-Cyber-Physical Systems (SCPS) (Calinescu et al., 2019), driving the necessity to model and understand human involvement and behaviour within such systems, and allow engineers to reason about the latter.

A lot of research is available on CPSS, yet smart elevators as SCPS have still received little attention with a focus on reducing waiting time and energy consumption (Bamunuarachchi and Ranasinghe, 2015; Bharti et al., 2017; Chou et al., 2018; Fernandez and Cortes, 2015; Fujimura et al., 2013; Wang et al., 2011) and thereby carbon footprint, optimal parking in group elevator control (Brand and Nikovski, 2004), use of floor sensors and RFID technology for elevator scheduling (Kwon et al., 2014), and the use of mobile phones to improve the flow of people (Turunen et al., 2013). A thorough overview of elevator control systems is provided by Fernandez and Cortes (2015); Ge et al. (2018), and passenger behavioural patterns while using elevators are discussed by Liang et al. (2013).

In this paper, we focus on elevator passengers' movement behaviour inside the elevator cabin during travelling from one floor to another. We take advantage of the existing smart elevator infrastructure and study human location preferences and movement behaviour, and the dependencies on cabin occupancy. The results can be later used in various fields, such as passenger movement behaviour prediction using machine learning, better layout of sensors in a smart-elevator environment, and enabling personalization for future smart elevators. To the best of our knowledge, human movement behaviour inside an elevator cabin has not yet been studied in the context of and using the equipment of a smart elevator platform.

For our study, we use the smart-elevator system (Leier et al., 2021; Reinsalu et al., 2020; Robal et al., 2020) set up at TalTech (Tallinn University of Technology), located in the ICT-building on the university campus. This is a single shaft single car elevator in a typical eight-floor office building, equipped with many smart devices such as cameras, speakers, microphones, and various sensors to collect a variety of data. The system also facilitates passenger identification and profiles.

In this study, we use and model real passengers' travel data to answer the following four research questions:

RQ1: *What are the most preferred standing positions of passengers in an elevator cabin while travelling alone, or in a crowded elevator?* We hypothesize that with single occupancy passengers prefer to stand near the doors or in the middle of the elevator, whereas in a crowded elevator distance is kept.

RQ2: *How likely is an elevator passenger to choose the same standing location for successive travels?* The hypothesis is that each traveller tends to have a preferred location(s) to stand in the elevator cabin.

RQ3: *What are the usual movement paths passengers take in an elevator cabin while travelling?* We hypothesize that the cabin layout and elevator operational context defines the moving paths of passengers, and the majority of passengers tend to follow the same paths.

RQ4: *What are the in-cabin movement path patterns passengers follow during their travels, if any?* We hypothesize that each passenger has a certain path (s)he follows in the elevator cabin environment while entering and exiting.

The results of our study indicate that passengers favour standing in the middle of the elevator cabin, within the reach of the floor buttons while travelling alone, and tend to choose the same spot to stand in the elevator for successive travels. Moreover, certain movement patterns exist, dependent on the operational context of the elevator, and the cabin layout.

This paper is a continuation of our previous work and an extended version of an already published conference paper (15th International Baltic Conference on Digital Business and Intelligent Systems (DB&IS 2022)) on the same topic by Basov, Robal, Reinsalu and Leier (2022), first published in Communications in Computer and Information Science (vol 1598) pp. 3–18, 2022 by Springer Nature. In this extended version, we have expanded the related works section, described in more detail the used smart-elevator system, study setup and analysis, and presented new results.

The rest of the paper is organized as follows. Section 2 is dedicated to related works, while Section 3 presents the Smart-Elevator System (SES) used for the study. Section 4 discusses the location analysis model and the experiments, Section 5 studies the passengers' in-cabin behaviour and answers the set research questions, and in Section 6 we draw conclusions.

2 Related works

The research on human behaviour regarding elevators has mainly focused on passenger arrival at elevator lobbies (Sorsa et al., 2013, 2021), passenger flow influence on lift control systems (Lin et al., 2016), finding patterns in usage (Liang et al., 2013), or exploring evacuation models (Heyes and Spearpoint, 2012; Ronchi and Nilsson, 2013).

Sorsa et al. (2013, 2021) rejected the assumption that passengers arrive at the elevator lobbies separately, showing that in multi-storey office, hotel and residential buildings people tend to arrive in batches of variable size depending on the time of day. The results show that arrivals were batches of two or more persons, especially during lunch hours. Considering batch arrival helped to improve elevator group performance by reducing car loading, round-trip time and passenger waiting times by 30-40%.

Liang et al. (2013) gathered real-world traces of human behaviour data from 12 elevators in an 18-story office building, showing that elevator usage patterns vary depending on the layout of the building (e.g., whether the stairs as an alternative are available next to the elevator, or not) and the main function of the building (e.g., in hospitals and hotels most of the vertical movement is done using elevators). They also claim that high-rise buildings with multiple elevators benefit more than low-rise buildings from human behavioural patterns on elevator usage since waiting time is minimal in smaller buildings and a single elevator can reach all floors quickly.

Ronchi and Nilsson (2013) focused on investigating the capabilities of evacuation models in high-rise buildings and showed that the use of elevators can reduce the evacuation time in a non-fire emergency, while for fire events the elevator was less valuable due to the layout of the particular building used in the study. Heyes and Spearpoint (2012) explored evacuation behaviour of building residents in case of a fire. The intention was to develop parameters that could be used for designing an evacuation system that uses elevators. The results of their study show that the number of building occupants that are likely to use the elevator as an evacuation method was increasingly dependent on the floor level. The primary factor in whether to choose stairs or an elevator is the prediction of how much time it takes to reach the ground level via the evacuation route.

Susi et al. (2004) researched the effect of human behaviour in a simulation case of the elevator traffic flow by studying the effect of passenger behaviour. The work describes the model of human decision-making in a transportation system, which can be used for more accurate elevator traffic flow simulations to achieve realistic results. Previously elevator traffic simulations have not included passenger behaviour. They found that the simulation results are affected by the characteristics and behaviour of passengers.

Cameras and deep learning were used by Chou et al. (2018) not only to minimize the average waiting time for passengers but also to decrease energy consumption by re-scheduling elevator movements. In this research cameras were placed in front of elevators and Region Based Convolutional Neural Network (R-CNN) was used to detect the number of passengers queuing for an elevator, and dispatch elevators according to the detected demand such that the elevator with the smallest energy consumption was serving the waiting passengers.

To the best of our knowledge, human movement behaviour inside an elevator car has not yet been studied in the context of and using the equipment of a smart elevator. While Liang et al. (2013) studied human behavioural patterns in the context of exploiting modern elevators through indicators such as elevator load factor, the number of floors travelled, and the doors-opened events to describe general behavioural patterns of office-building inhabitants, using the data (logs) generated by the elevator system itself, we in contrary focus not on the external events caused by the passengers but the passengers' behaviour in travelling situation inside the elevator cabin, and for this advantage from special equipment to collect such data on passengers.

Our previous work has focused on establishing and using the existing smart elevator platform (Leier et al., 2021) to profile passengers for travel behaviour characterization and floor prediction (Reinsalu et al., 2020; Robal et al., 2020) for enhanced travel experience in smart elevators. Here, we continue our work on this track and contribute to fill the gap in the existing literature for social research in the context of elevators as CPSS. We develop a new method to study and evaluate passengers' behaviour during their travels and apply the method in a real-life scenario using real-world data on real elevator passengers.

3 Smart elevator system

A smart elevator system can be considered as a CPSS and SCPS advantaging of data mining, Artificial Intelligence (AI) (Russell and Norvig, 2009), for instance, facial image recognition (Robal et al., 2018; Silva et al., 2018; Stark, 2019; Zhao et al., 2003) and human speech recognition (Allen, 2003; Goetsu and Sakai, 2019; Ketkar and Mukherjee, 2011; Ross et al., 2004). Our passenger in-cabin movement behaviour study is carried out using the smart elevator system (SES) (Leier et al., 2021) developed and installed at TalTech ICT-building.

To better understand the context of the smart-elevator and our study, let us take a closer look at the system setup. The TalTech ICT-building is a typical office building with 8 floors (0 to 7) with the main entrance at level 1. The building has two KONE (a global leader in the elevator and escalator industry) elevators installed, one on each side of the building. Each elevator is a single car running in its allocated elevator shaft. The building resides at the university campus and hosts offices for university staff, labs, computer classes, and offices for private and start-up companies.

Out of the two elevators, one (on the North-side of the building) is equipped with additional hard- and software to deliver the features of the smart elevator. These devices include an RGB camera (Basler acA2040-25gc) for facial recognition, four depth cameras (Intel Real Sense D435) to detect passengers' location within the cabin, a speakerphone (Senheiser SP20) enabling voice commands to the elevator system, and a mini-PC (Intel NUC Mini PC NUC5i7RYB) for processing sensor data. The smart elevator is operating between all eight floors of the ICT-building. As common, the elevator can be called to a floor by up and down travel buttons located at each floor next to the elevator entrance, and operated by push-button controls inside the cabin. The main passengers of the elevator are the employees of the university and the companies having offices in the building, and students accessing classrooms and working-places. Figure 1 provides an overview of the smart-elevator setup used for our studies.

For our passenger in-cabin behaviour studies, we use the four depth cameras located over the elevator ceiling (Fig. 1) to capture passenger movement data in the cabin. The known passengers are identified by the SES through facial recognition using the Basler RGB camera and matched to existing profiles (stored as anonymous passenger profiles with facial features and numeric IDs; no facial data as photos/video is stored). Also, in accordance with the law, passengers of the elevator are notified of the existence of the cameras within the elevator cabin, and in case they disagree, they have the option to use the second elevator of the building. In the scope of this study, we use passenger profiles just as numerical ID's to distinguish between known travellers while addressing RQ2 and RQ4.

We now proceed to define the terms we use in this paper in the context of the smart-elevator system. A *travel* is defined as a ride of an elevator passenger between departure and destination floors, such that it starts with a passenger entering the elevator cabin and ends with exiting the cabin. Each travel is assigned a new travel identification number (travel ID) in the SES stored alongside with track data. A *track* is the location of the passenger inside the elevator cabin attributed with travel ID, position coordinates (x, y), and timestamp. A *single travel* is a travel with only one passenger occupying the elevator cabin, whereas *crowded travel* with at least two passengers in the cabin.

Fig. 1. The smart-elevator system used for the passenger studies, and its operational environment – a view into the elevator cabin.

The passenger position data is gathered using the SES positioning service, which allows the collection of position data individually for each passenger by tracking and retrieving sensor data from the four depth sensors located in the ceiling of the elevator cabin. Detection of travellers is done using an image processing algorithm. The algorithm delimits the heads of passengers in the elevator cabin regardless of their height. The system starts to locate heads at the height of 120 cm and with every iteration increases the detection height by 5 cm. Every height layer is run through until the ceiling height is reached. All the detected heads' movements will be monitored throughout the travel and track data stored periodically (every 200ms). Whenever a passenger with an existing profile (the passenger has travelled previously) is identified, the track is associated with the profile ID in the SES. The coordinates in the SES positioning service are expressed in the metric system using centimetres as the unit (Fig. 2). The numerical values of coordinates for the x-axis are in a range from 0 to 220 cm and for the y-axis from 0 to 110 cm, reflecting the central position of the detected object position at 120 cm or higher above the floor. Figure 2 outlines the elevator cabin context with the equipment and the coordinates system used by the SES positioning service.

4 Passenger study setup and experiments

Our passenger study is based on the location data of real elevator passengers captured by the smart-elevator system (SES) positioning service. Therefore, to be able to properly interpret the data collected by the system, we carried out a ground truth study consisting of a series of validation experiments, based on the developed passenger location analysis model.

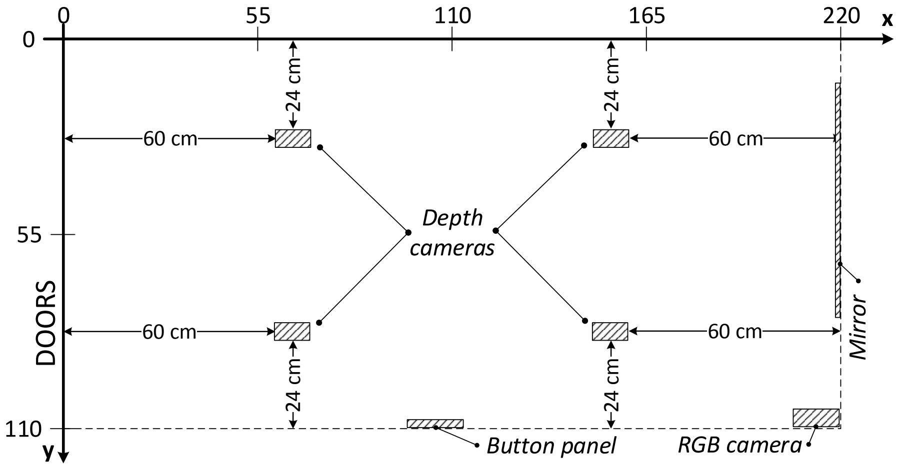

Fig. 2. Elevator cabin context and the coordinates system of the SES positioning service (Basov et al., 2022).

4.1 Passenger location analysis model

To be able to analyse the passenger's travel data and answer the set research questions, we first developed a model for passenger location interpretation. After several simulations and experiments, we ended up with a two-dimensional model that divides the elevator floor area into eight equal square-sized sections with an additional section of the same size overlaying the sections in the middle of the cabin (Fig. 3). Each of the 9 sections identifies a potential location of an elevator passenger.

The division into the given nine sections was carried by a hypothesis that a passenger takes space with a diameter of approximately 50 cm (together with space between other passengers) in a two-dimensional room. A study by Randall et al. (1946) for Army Air Force reports that 95% of cadets have shoulder-width (biacromial) of 42.90 cm. Considering the latter, the division of the elevator floor into nine equal sections, where the width of each section is 55cm, is justified, and gives passengers enough individual space, taking into account that not every passenger might be in the ideal shape of a 'cadet'. Thus, the centre point of a passenger is at ca 22 cm according to the passenger's shoulder width, which correlates with the centre point of the location model sections (27.5 cm). As usually passengers do not stand against the wall, there is a high probability that the passenger centre point aligns well with the section centre point in the model. For a crowded travel situation, the elevator producer KONE has limited the maximum number of people for this elevator type to 13. Figure 3 outlines the location model with 9 sections, and the context of the elevator cabin environment, i.e., the position of doors sliding open from left-to-right while standing in the cabin and facing the doors, location of the floor buttons, back-wall mirror, and the Basler RGB camera used for face recognition by the SES.

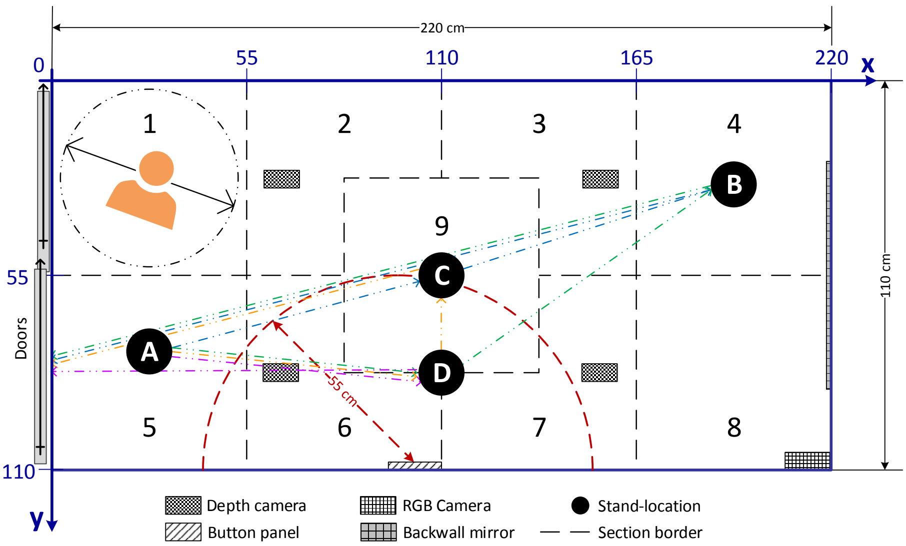

Fig. 3. The model for passenger location analysis with nine sections (1–9), and the context of the elevator cabin environment. Letters A–D mark the stand-location points used in the ground truth study. Dash-dot-dot coloured lines mark the movement path for the continuous location detection study: Route#1 – blue, Route#2 – green, Route#3 – orange, and Route#4 – magenta.

We use this zoned location model to validate the SES passenger positioning service, and in further to analyse passenger in-cabin location behaviour based on real travel data captured to answer the set RQs.

4.2 Ground truth study

On 6 April 2021 late evening (after 20:00), a ground truth study was carried out by a single test passenger to evaluate the technical setup and its precision in detecting passengers' location in the smart elevator cabin according to the location analysis model (Section 4.1). We chose a late hour to have minimum disturbance for other potential travellers, as well as for the continuity of the experiments. During the study, the performance and accuracy of the SES positioning service were validated whereas the test passenger location inside the elevator cabin was known in advance. Multiple locations inside the elevator cabin were selected with the goal to determine the accuracy of passenger position detection in a given section according to the location analysis model and to identify the variability of detection within the model. The study assumed that the test subject was always standing in the middle of the designated zone of the location analysis model. For the experiments, a grid according to the analysis model was marked down on the elevator floor with paint tape (Fig. 4).

For the ground truth study two experiment series were carried out: (i) *static stand positions* (Section 4.3), and (ii) *continuous position detection for path* (Section 4.4). Although the total number of planned test travels was 60 – 10 for each static stand

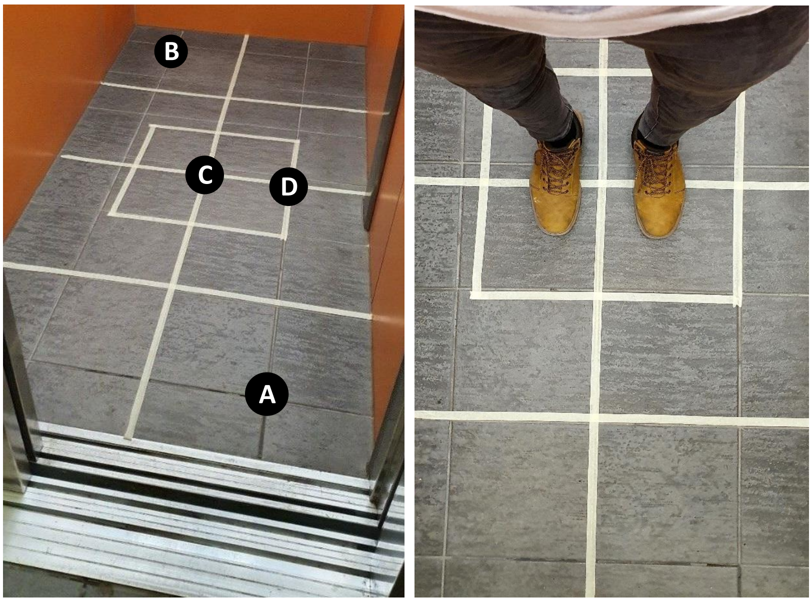

Fig. 4. The ground truth study: markings on the elevator floor to divide the area into sections of the location analysis model (left), and the test passenger standing at position C in the middle of the elevator cabin, facing the doors (right).

position, and 5 for every continuous position detection experiment – the actual number of travels captured was 61 (due to miscounting). Four additional travel records appeared in the captured data as other passengers entered the cabin mid-experiment. These travels were removed from the analysis data, leaving thereby a dataset of 59 travel and location tracks data of $37,044$ coordinate pairs.

The collected data was analysed using a high-level interpreted general-purpose programming language Python (ver. 3.7), often used for scripting, and data processing and analysis due to its extensive standard library and wide range of modules and packages. For the analysis, we used the following libraries: *Psycopg*[1] PostgreSQL database adapter, and *XlsxWriter*[2], Python module for writing files in the Excel XSLX format, *DateTime*[3], *numpy*[4] and *Matplotlib*[5] packages.

4.3 Static stand positions

First, a static stand-still study to validate the SES positioning service against the location analysis model was carried out with four different purposefully selected stand-positions A–D (Fig. 3) in the elevator cabin:

[1] https://pypi.org/project/psycopg2/
[2] https://pypi.org/project/XlsxWriter/
[3] https://pypi.org/project/DateTime/
[4] https://pypi.org/project/numpy/
[5] https://pypi.org/project/matplotlib/

- Position A – represents a zone right in front of the elevator doors on the opening side (doors open in the direction from Section 5 to 1),
- Position B – this location in Section 4 marks the back corner of the elevator cabin in front of the mirror,
- Position C – represents the middle of the elevator cabin (Section 9),
- Position D – located on the border of Sections 6 and 7 represents an ambiguous multi-section area in front of the elevator floor buttons, which can be reached for pressing from Sections 6, 7 or 9 in an approximate reach radius of 55 cm (Fig. 3).

Each position A–D was tested with a series of ten travels (except C for which 1 series appeared invalid and was removed) between two floor levels (e.g., floor 3 to 5), with a travel lasting about 20 seconds. The top-ceiling depth camera system setup captures passenger position tracks with a sample rate of 200 ms – roughly 100 position data points for each travel in the experiment. The collected data indicated 104 tracks on average per experiment travel (min 88 and max 112). For the sake of data completeness, for each travel, a new elevator call was made. In addition, the test passenger was required to follow the same route when entering the elevator and to stand in the centre of the agreed position (A, B, C, or D), and turn around to face the doors once reaching the position.

Standing in each position A–D was analysed separately. To evaluate the accuracy of measuring the static stand location, the data coordinates describing the movement into the required position A–D were filtered out as follows: first, any coordinate outside of the planned stand position section was deemed as movement into the section and thus eliminated; and further, the movement points from the section edge to the centre of the planned stand position section were additionally removed until five consecutive points (ca 1 second) were captured at the planned stand position section (the points counted as standpoints would start from the sixth point) to assure a safe margin for reaching a stand position. Similar filtering action was carried out for data describing exiting a section and the elevator. Figure 5 visualises the experiment data before and after filtering (dashed callout) for position C located in Section 9.

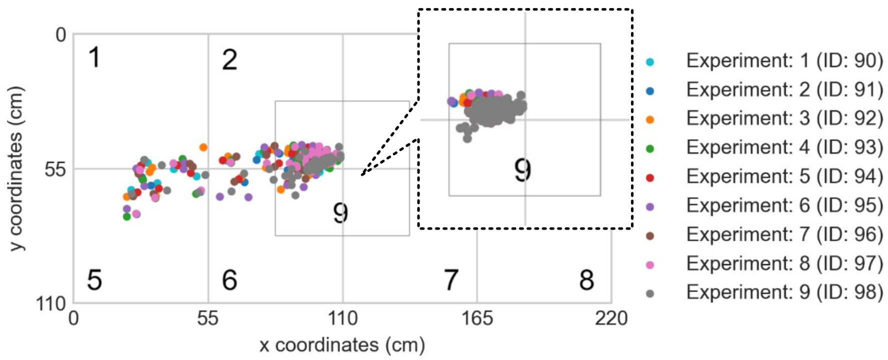

Fig. 5. Captured location data visualisation before and after (callout with a dashed line) data filtering for location point C in Section 9 of the location analysis model (Basov et al., 2022).

Table 1 outlines the results of the static stand positions experiment series. On average 210 location points for each series were deemed to describe moving to a location and thus removed from the analysis – more for positions further away from the doors (e.g., position B). We noted that for position B the deviation for determining the x-coordinate differs from all other findings, which could be the misalignment of the positioning service or also the effect of the back-wall mirror. In further analysis, this blind-spot area has been accounted for.

Table 1. Experiment results for the static stand position study

	# track coordinates		$M_{x,y}$*		$E_{x,y}$**		Average deviation	
Position		Filtered	x	y	x	y	x	y
A	983	893	27.5	82.5	32	76.5	4.9 ± 4.4	-7.3 ± 4.2
B	1156	759	192.5	27.5	170.4	28.5	-21.3 ± 4.8	1.4 ± 3.3
C	962	778	110	55	100.9	52.6	-9.4 ± 2.9	-2.8 ± 1.5
D	1042	873	110	82.5	103.9	80.9	-7.1 ± 4.5	-2.8 ± 4.9
Avg	1036	826	n/a	n/a	n/a	n/a	-8.2 ± 4.2	-2.9 ± 3.5
Sum	4143	3303	n/a	n/a	n/a	n/a	n/a	n/a

* central section coordinates in the model [cm].
** median central coordinates of section in experiments [cm].

The results of static stand position experiments indicate that the coordinates captured by the elevator positioning system are slightly off-centred on the x-axis, while the y-coordinates are rather accurate. The misalignment may have been caused by several reasons, one of which could be the test passenger's posture, but also an alignment shift in the SES positioning service. Overall, the system is able to locate the passenger in a section centre with a deviation of 8 cm on x-axis and 3 cm on the y-axis, which considering the technical setup is satisfactory. With this study, besides validating the positioning service, we also determined the viewing range of the four depth cameras and confirmed the elevator coordinate system in SES. The experiment forms a benchmark for interpreting the travel track dataset of real passengers.

4.4 Continuous position detection for a movement path

Next in the ground truth study, was to validate the detection of passenger movement path inside the elevator cabin using the SES positioning service. For this, we planned four different routes starting and ending at the cabin doors in between the positions A–D, as indicated with the dash-dot-dot lines on Figure 3:

- Route#1: $A \rightarrow C \rightarrow B \rightarrow A$, as a scenario when a passenger enters the elevator, moves to the middle, reaches the floor buttons and proceeds to move to the back corner of the cabin for the duration of travel.

- Route#2: $A \rightarrow D \rightarrow B \rightarrow A$, a scenario similar to Route#1, except the floor buttons are reached right in front of these at the position D.
- Route#3: $A \rightarrow D \rightarrow C \rightarrow A$, where after pressing the floor buttons the passenger proceeds to stand in the middle of the elevator at the position C.
- Route#4: $A \rightarrow D \rightarrow A$, where the passenger reaches the button panel and then immediately steps back to the closest position to the doors on the opening side.

The test passenger followed each route for five times during the experiments. Each travel was through four floor levels (e.g., floor 1 to 5) with an average travel duration of 25 seconds, during which on average 112 track points for each travel were captured by SES. We chose a longer distance of four floors to prolong the travel time, allowing the test passenger to successfully implement the movement through the determined paths. At each point (A–D) the test passenger made a short stop, yet keeping the movement as natural as possible. While exiting, the shortest path through the opening side of the doors (position A) was taken.

Even though the test passenger was following a predetermined route (1–4) while moving inside the elevator cabin during travel, the results of the ground truth study indicated deviations caused by human body movement and posture on the path. This called for a method of data filtering, to match passenger movement to the location analysis model. Figure 6 presents the unfiltered data of five experiments conducted for Route#2.

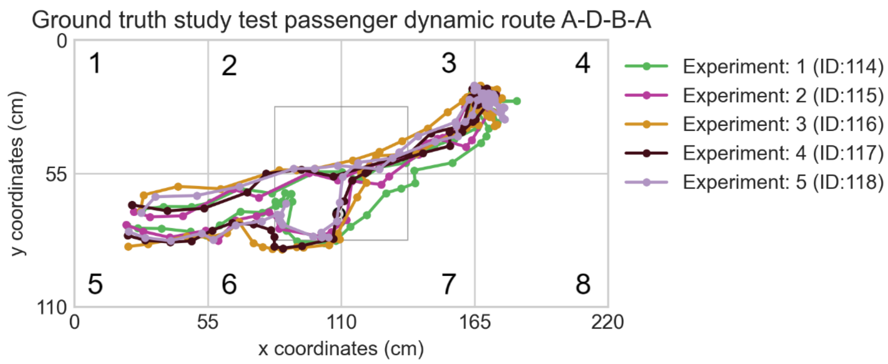

Fig. 6. Test passenger movement path on Route#2 in the ground truth study experiments.

To be able to match the passenger movement in the cabin to the location analysis model, and further compare the moving patterns, we decided in favour of path construction based on the sections of the location analysis model. To construct the movement path, we first ordered the captured test passenger's location data by time, and then proceeded to process, filter and compress the processing results as follows: a section and location coordinates were added to the movement path whenever five consecutive points were captured by SES in the same section (data capturing by SES at the rate of 200 ms), and only if the section was a neighbouring section to the previous one in the already detected movement path list of sections passed. This approach, we elaborated through experimenting with the collected ground truth data, enabled a realistic movement path construction and tackled the problem of a passenger fluctuating between sections, while for example moving from one section to another (border cases). Thereby, the passenger movement path is constructed as a sequence of sections of the location analysis model (identified by the location coordinates) passed by the passenger, where each section is sequentially counted only once.

For instance, let us consider the following case. The passenger enters the elevator from the opening side of the doors (Section 5), then moves directly towards the floor buttons (Section 6) and then locates herself to stand in the middle of the elevator (Section 9) for the travel, and finally follows the same route to exit the elevator. The latter sequence of passenger actions would form a movement path of $5-6-9-6-5$.

Figure 7 demonstrates the paths detected in the ground truth study for the five experiments (ID: 114 – 118) on the planned Route#2 together with the intended ideal route set for the experiments. We see that the time-wise fluctuating coordinates (Fig. 6) over sections are now matched to the location analysis model, allowing to identify movement paths according to the model and compare the paths of different or the same passenger.

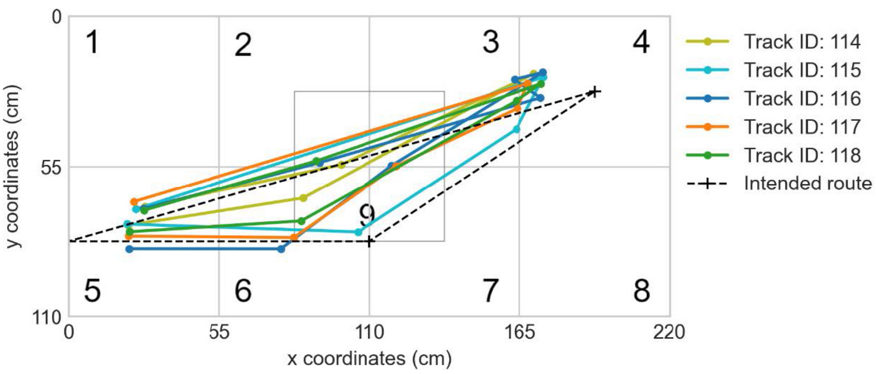

Fig. 7. Movement path construction with applied data filtering for Route#2 in the experiments. The dashed black line indicates the planned route for the experiment (Basov et al., 2022).

From the continuous position detection study for the paths, we also notice that there is a certain blind-spot area of approximately 15 cm from the wall into which no coordinates fall. First of all, the SES positioning service estimates the centre point of the passenger, and second, even if a passenger stands against the wall, the detected centre point of the person would still be around 15 cm away from it.

The ground truth study on continuous location detection confirmed that the smart-elevator system positioning service tracks passengers' location and movement within the elevator cabin with sufficient accuracy throughout the travel, and the collected data can be successfully matched against the developed location analysis model using the noise removal and data point reduction techniques described. The results will be applied to answer $RQ3$ and $RQ4$.

5 Behaviour analysis

In this section, we apply the knowledge gained from the ground truth study to answer the research questions about passengers' preferred location and movement behaviour in the elevator cabin. For this, we use the track data of real passengers collected through 61 days (2 months, April – May 2021) and consisting of $11,731$ travels, out of which 67.9% of travels were made by a single passenger, and in 32.1% of cases there were multiple passengers in the cabin. The period of data collection matches with the enforced COVID-19 restrictions where the $2 + 2$ rule and facial mask mandate were enforced, which affected the available number of travels as well as the ability of the SES to differentiate between known travellers through facial recognition (recall, no data used in this study is personalized). In addition, the ICT-building was partially closed to students due to the pandemic. We also noticed that people preferred stairs over the elevator once the pandemic started. Travels performed by the test passenger for the ground truth study have been excluded. Table 2 characterizes the used data.

Table 2. Smart elevator passenger data used for the behaviour analysis

	# Travels	# Tracks	ntp_{avg}*	d_{avg}**
Total (count)	$11,731$	$1,414,740$	120	24
Travelling alone in cabin (count)	$7,790$	$1,034,162$	130	26
Travelling in a crowded cabin (count)	$3,761$	$380,578$	101	20

* avg. tracks per travel per passenger. ** avg. travel duration per passenger [s].

5.1 RQ1: Preferred standing positions

The first question we consider is the most preferred standing location while travelling alone or in a crowded elevator cabin. To answer *RQ1* we look at all track data on passengers' position in two groups: travels with one passenger in the cabin (*single travel*), and travels with more than one passenger in the cabin (*crowded travel*), in two categories: (i) *coordinate-based positioning* into sections of the analysis model for the whole travel, and (ii) *travel-based standing position*, i.e., the most occupied section is deemed the standing position of the travel. The analysis for *RQ1* is based on all the available data for all the passengers during the study period regardless of whether they had an existing profile or not. The data is analysed according to the location analysis model and the method described in Section 4, according to which for each track coordinate a section (Section 1–9) is identified.

The analysis of passenger travel data (Fig. 8 and 9) reveals that for single travel situations in most cases passengers tend to stand in the middle of the elevator (i.e., Section 9). Whenever there are fellow passengers in the elevator, distance is kept and the central location is chosen only in a fifth of the cases, having a dramatic drop of two times compared to a single travel situation. The least desirable position to stand is in front of the facial recognition camera (Section 8). The passengers are four times more likely to stand next to the door on the closing side (Section 1) when travelling in a crowded elevator than travelling alone. There is almost no difference in standing in front of the doors on the opening side (Section 5). Also, we notice that passengers prefer to stand on the opposite side to the button panel and level indicator above it (compare Sections 2 and 3 to Sections 6 and 7). We believe this is due to have a better view of the travel status from the floor indicator panel and also not to block the (de-)boarding passengers. Figure 10 presents the location density maps for passenger locations in the category of coordinate-based positioning through all track data.

We acknowledge that these findings apply to this particular elevator cabin type with the floor buttons located in the middle of one of the sidewalls. However, in many larger elevators the buttons are doubled on both sides of the elevator doors, and doors open to both sides, which is likely to change the favourable standing positions layout. It would be interesting to carry out this experiment on different elevator layouts, equipment permitted, to explore whether the general findings, e.g., for single travel the centre of the elevator is preferred, hold or not.

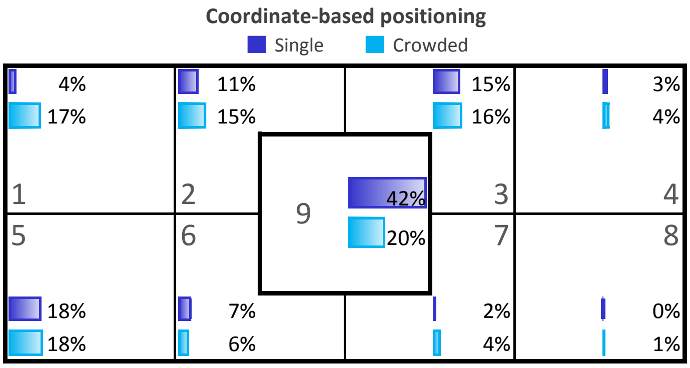

Fig. 8. Preferred standing positions according to the section model for single and crowded cabin travel situation based on all coordinates of a travel.

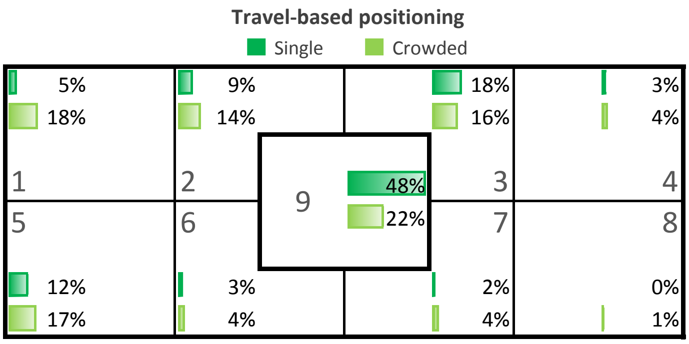

Fig. 9. Preferred standing positions according to the section model for single and crowded cabin travel situation based on the most occupied section during a travel.

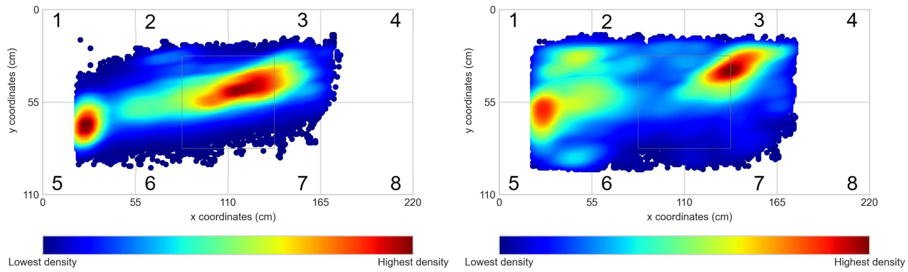

Fig. 10. Density maps for elevator passengers positions in cabin trough travels: single passenger in cabin (left), multiple passengers in cabin (right) (Basov et al., 2022).

5.2 RQ2: Preferred standing position for successive travels

The second research question we consider is the likelihood of a passenger choosing the same standing location in the elevator cabin for re-occurring travels, i.e., do passengers have their favourite spots to stand in the elevator cabin? To answer $RQ2$, we analyse only the track data of known (profiled) passengers by their travels.

These passenger profiles are created and identified by the smart elevator system automatically using the implemented face recognition system (Leier et al., 2021; Robal et al., 2020) with an identification success rate of 98.2%. Unfortunately, during the study Covid-19 restrictions (including the mask mandate) were effective, which significantly reduced the travel data available for profiled passengers – the SES was unable to recognise all known passengers. We obtain only 793 travels with 305 distinct profiles, which we once again separate into two groups: travelling alone (*single*: 30.0%) and travelling with other passengers also occupying the elevator cabin (*crowded*: 69.7%). Figure 11 characterises the data of profiled passengers over these two groups.

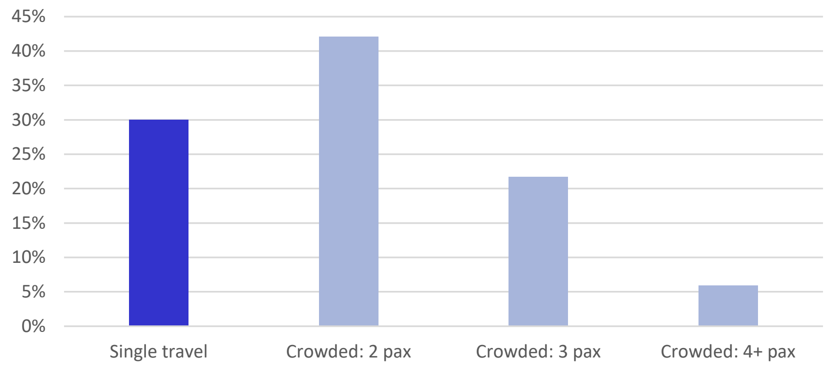

Fig. 11. Characterisation of profiled passenger data grouped by travel situation (single travel, crowded travel).

Next, we reject any profile that has less than three travels associated. This is a minimum setup to separate the travels into two sets. Further, we organize the travels of each profile in chronological order and split the set into two and use the first 2/3 to determine the preferred standing position and the last 1/3 to verify the hypothesis of choosing mostly the same standing location. This leaves us with 361 travels (46%), 83 as single, and 278 as crowded cabin travels, with 17 and 60 profiles correspondingly. Table 3 describes the data used to answer RQ2.

Table 3. Characterisation of data used to answer RQ2

Travel situation	# Profiles	# Travels Total	# Travels Determination	# Travels Validation	Average # trips
Single travel	17	83	55	28	4.9
Crowded travel	60	278	190	88	4.0

In order to determine the preferred location of elevator passengers, we apply the same approach as for RQ1 based on the location analysis model, determining the preferred standing position as one of the nine sections. For each passenger, we find over her travels a list of standing positions (Section 1–9) in decreasing order and use the top two items as the most likely standing positions as *Top 1* and *Top 2* of this list. We then compare these to the remaining 1/3 of the data to validate the determined preferred standing location. Table 4 shows the analysis results. We see that for successive travels in a single travel situation passengers tend to choose the same standing locations as previously, while in the situation of a crowded cabin, no favourable position as a choice can be detected as a random open spot is occupied. In the case of single travel the most preferred standing location was the centre of the elevator (Section 9), preferred in 65% of cases, and also conforming to the findings of RQ1.

Table 4. Probability of choosing the same standing position for re-occurring travels

Travel situation	# Profiles	# Travels	Top 1	Top 2	Top 1 or Top 2
Single travel	17	83	60%	31%	91%
Crowded travel	60	278	26%	9%	35%

5.3 RQ3: Passenger movement patterns

Having explored the preferred standing positions of elevator passengers, we proceed to study their usual movement paths inside the cabin. For this, we construct passenger movement paths according to the model discussed in Section 4.1 and validated through the conducted ground truth study (Section 4.4).

In order to answer RQ3 – what are the usual movement paths of passengers in the cabin, and if these are connected to the layout and operational context – we first separate from the data crowded travels. The reasoning is that if there are already passengers inside the elevator cabin, the path of a boarding passenger is greatly affected by the location of other passengers already in the cabin. Thereby, we continue with $7,790$ single travels (Table 2) only and establish a passenger movement path for each of these.

Looking at the established movement paths, we quickly learn that a large amount of them are overlapping – passengers take the same movement paths in the cabin while using the elevator. We also notice from the data that sometimes passengers tend not to locate themselves to stand at a certain standing point but rather walk around the elevator cabin while it relocates to a selected floor. We further decide to focus only on *Top 10* and *Top 20* movement paths correspondingly indicating 73% and 81% of the total single travels. In the *Top 10* and *Top 20* of movement paths, a third of single travels have the passenger path of entering the elevator from the opening side of the doors, proceeding directly into the cabin to stand in the middle of the elevator, and exiting the same route (i.e., path: $5-6-9-6-5$). In one-fourth of the travels, passengers reach a bit further into the cabin to Section 3. A fair amount of almost a fifth of single travel paths end in the area in front of the door on the opening side, i.e., passengers walk in from Section 5, proceed to Section 6 to push the floor buttons and then move out the same route. Other paths account for less than 10% of overall single travels. Figure 12 outlines the *Top 10* movement paths in the elevator.

The *Top 10* passenger moving paths inside the moving elevator cabin for single travels are listed in Table 5, showing the percentage of such paths among the total amount of paths detected, and the *Top 10* and *Top 20* movement path sets. As can be seen, the vast amount of movement is considered with the first half and the section opposite to the floor button panel in the third quarter of the elevator cabin depth from the floors. A low number of passengers enter the elevator from the closing side of the doors through Section 1 but opt to exit also from the opening side. Also, Sections 7

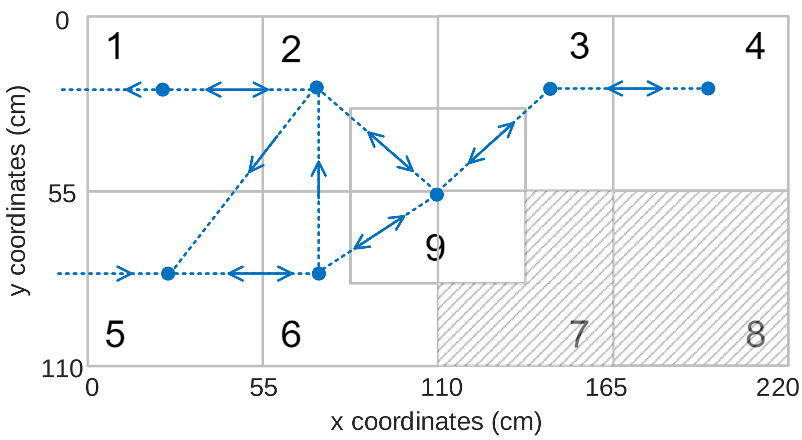

Fig. 12. Top 10 movement paths in the elevator cabin for single travel situation.

Table 5. Top 10 elevator passenger movement paths for single travel situation, and their corresponding proportion in the Overall, Top 20 and Top 10 path sets

Path	Overall	Top 20	Top 10
5-6-9-6-5	23.6%	29.2%	32.1%
5-6-9-3-9-6-5	19.1%	23.7%	26.0%
5-6-5	12.9%	15.9%	17.5%
5-6-9-2-5	5.0%	6.2%	6.8%
5-6-9-3-9-2-5	2.7%	3.4%	3.7%
5-6-2-1	2.3%	2.9%	3.2%
5-6-9-3-4-3-9-6-5	2.2%	2.8%	3.0%
5-6-2-5	2.0%	2.5%	2.8%
5-6-9-2-1	1.9%	2.4%	2.7%
1-2-9-6-5	1.6%	2.0%	2.2%

and 8 never make it into the movement paths in the *Top 10* (streaked on Fig. 12), being present in movement paths only in 0.5% of single travels.

We also look at the *entry-exit* behaviour of passengers, and their movement path maximum depth into the cabin (Fig. 13). The data clearly indicates that passengers choose to exit through the same section they used to enter the elevator, doing so in 85.5% of cases, and choosing an exit section different than the entry section in case of 14.5% of travels. For 89% of single travels, passengers enter the elevator from the opening side of the door (Section 5). For the maximum path depth into the cabin, we see that in the majority of cases the movement behaviour takes passengers to the middle section or the nearby Section 3 opposite to the floor buttons and indicator panel. The trend is the same regardless of which entry section the passengers use. Figure 13 indicates the depths of paths through sections for each of the entry sections. Interestingly, regardless of the entry section, the same proportion of movement paths (47%) take the passengers no further than the middle of the elevator.

In summary, the passenger movement paths are largely influenced by the elevator operational context, starting with how the doors operate, which in the case of the elevator we used for our study slide open from one side to another (Section 5 to Section 1 in the analysis model), causing the majority of passengers to enter the elevator through the opening side (Section 5), and ending with the location of floor buttons in the middle of the same side of the wall, where the doors open. We conclude that certain patterns of movement paths exist for elevator passengers, determined by the operational context and layout of the elevator cabin.

5.4 RQ4: Recurring movement patterns

The last question we address when studying passenger in-cabin behaviour is whether passengers tend to follow the same movement path through the cabin during their travels. To answer *RQ4* we analyse the successive travels of profiled passengers (single travel only) and use the same dataset as for RQ2. From RQ2 we already know that passengers tend to choose the same standing location in 60% of cases when travelling

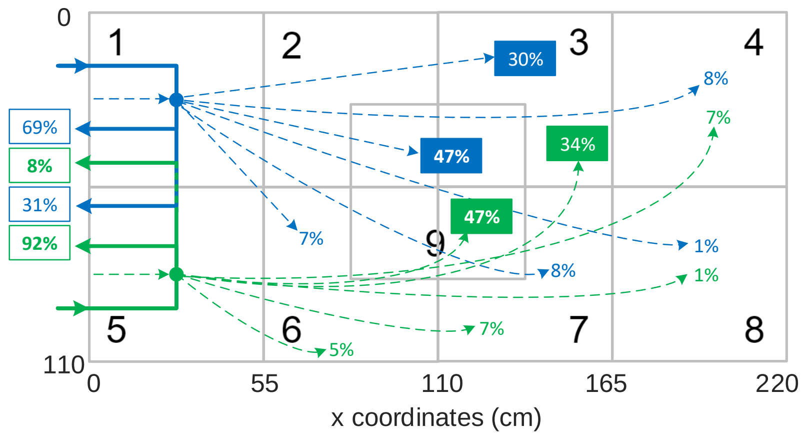

Fig. 13. Entry-exit behaviour (solid lines on the left over Sections 1 and 5), and maximum depth into cabin on passenger movement paths in single travel situation (dashed lines).

alone. We decide not to analyse movement routes while travelling in a crowded elevator as the route would greatly depend on the occupancy of the elevator cabin and the locations of fellow passengers.

For each travel associated with a profile, we construct a movement path based on the sections the traveller has been found to be present in (passing or standing) using the method described in Section 4.4, producing a path (e.g., $5 - 6 - 9 - 1 - 5$) for every single travel of a profiled passenger. Table 6 characterises the movement paths for the 83 single travels available for 17 profiled passengers.

Table 6. Characterisation of constructed movement paths and re-occurrence match

	# travels/profile	L_{path}*	$L_{pax-path}$**	M*** [%]	$M_{partial}$**** [%]
Avg	5±2	6	6,4±1,0	13%	62,3%
Min	3	3	5,2±1,3	75%	100,0%
Max	12	11	7,8±1,4	0%	0%

* path length over all travels. ** avg. path length per passenger.
*** exact path match rate. **** partial path match rate on the first three positions.

Based on the small sample of data we have, we do not find that on an individual level passengers would follow the same movement path when entering, standing, and exiting the elevator for travelling between floors. The average movement path for passengers consists of four to eight sections of movement with a maximum of 11 sections. The same path is followed only in 13% of travels observed. However, for two profiled travellers we notice the exact path match to be 75% and 67%. Analysing the first three positions of a path, we interestingly find that the same passenger who had the exact match rate at 75% had a movement path match by the first three positions at 100%, whereas the general rate for all single-travelling profiled passengers was at 62%. This is somewhat expected, as passengers usually enter from Section 5 (as confirmed by RQ3), move to Section 6 to press a floor button, and then to Section 9 to stand in the middle of the elevator cabin. With the availability of a larger set of data on profiled passengers over a longer period of time, there might be some interesting findings in the future.

6 Conclusions

With the advancement of technology, smart-elevators as CP(S)S are increasingly becoming a reality. These smart-elevators provide an excellent platform to study passengers' behaviour – once used to be possible only with surveillance cameras and manual work – to improve elevator systems, quality of provided service and passenger experience, and further enhance the concept of smart-elevators.

In this paper, we established an elevator passenger location analysis model, formulated a method to evaluate passengers' movement behaviour, benchmarked it against the smart-elevator positioning service, and investigated elevator passenger in-cabin behaviour using an existing smart-elevator platform. Although our study was limited to one type of elevator cabin, the established zone-based location analysis model and method can be applied to any elevator type with the same or larger floor area. Thus, the model and methods established can be applied in case of an elevator able to carry more than 10 persons at a time. Such elevators are typically found in large commercial buildings, shopping malls, hotels, hospitals etc. With the model, method and experiments we have filled the gap in the existing literature regarding studies of human behavioural patterns in the context of elevator travels. The results of our study can be used to improve (smart-) elevator cabin layout design, placement of sensors, and to enhance the overall quality of service by knowing how the passengers take advantage of the existing elevator in their operational context in real-life situations – *all in all, little things do matter*!

In our study of elevator passenger in-cabin behaviour, we took advantage of an existing smart-elevator platform. First, we explored whether there are favourable standing positions for passengers in general. The study showed that passengers tend to prefer to stand in the middle of the elevator while being the only occupant of the elevator cabin, which however is not the case for crowded cabin situations, where a random open spot is occupied. Further, we used the smart-elevator system passenger profiling capabilities to identify passengers repeatedly travelling to investigate whether they tend to have personally preferred standing locations in the cabin. The analysis revealed that passengers tend to choose the same standing location quite often (60%) in the case they are the only occupant of the elevator cabin. Next, we investigated the passengers' movement behaviour in the cabin by constructing movement paths. We found that in general passengers tend to follow the same trajectory to exploit the elevators to travel between the floors and that the operational context and layout of the cabin strongly affect this behaviour. We however failed to find confident results that passengers would always follow the same movement path while entering, travelling and exiting the elevator. This could be possibly due to the small sample of data we had for profiled passengers due to covid-restrictions intervening our study. Although herein we limited our study to travel situations with a single passenger in the cabin, in the future it would be interesting to study also the influence of fellow passengers on the passengers' behaviour.

The behaviour analysis model and the methods we established are not bound only to the context of elevators. On the opposite, we see our work to be applicable in many other situations, be it the in the context of mass public transport passengers, open-plan office workers, etc. where the focus is a better flow of people and the improvement of cyber-physical social systems for the good of humankind.

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Received October 27, 2022 , accepted November 29, 2022