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▶ To cite this version:

Mehdi Baali, Christine Buisson, Rémi Coulaud, Mehdi Moussaïd. The impact of passenger noncompliance during alighting and boarding on railway stations. 2024. hal-04811675

HAL Id: hal-04811675 https://hal.science/hal-04811675v1

Preprint submitted on 29 Nov 2024

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The impact of passenger non-compliance during alighting and boarding on railway stations

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Abstract

In dense train networks, the alighting and boarding process involves complex pedes-9 trian flow dynamics. A common rule to facilitate this process is to wait until alighting 10 is complete before boarding. However, many passengers do not adhere to this rule 11 in real-world scenarios. Here we present an experimental study to assess the impact 12 of such non-compliance on pedestrian flow and compare the results with field data 13 collected from infrared sensors. Our findings indicate that pedestrian discomfort in-14 creases considerably with increasing non-compliance. However, the average alighting 15 and boarding times are similar regardless of non-compliance levels. We show that this 16 counter-intuitive effect is due to a compensatory mechanism between lower densities 17 at lower degrees of non-compliance and higher densities at higher degrees of non-18 compliance. This research opens new perspectives in understanding and managing 19 pedestrian flows in dense railway environments. 20

21 **1** INTRODUCTION

In major cities, daily commuting is an essential aspect of urban life. People travel to city 22 centers for work in the morning and return home in the evening, leading to significant 23 crowding on suburban trains. For example, in the Paris suburban rail network (RER), 24 over three million journeys are made daily across its five lines. In particular, the processes 25 of boarding and alighting involve complex pedestrian dynamics that directly affect train 26 dwell times and can contribute to delays, thus impacting the network's overall efficiency. 27 Therefore, understanding the pedestrian flows during the alighting and boarding phases is 28 29 crucial.

The collective dynamics of pedestrian flows emerge from the interactions between multiple individuals. These interactions include, among others, imitation, avoidance, and scrambling. A comprehensive overview of these interactions has been provided by Moussaid (2010).

Collective behaviors are characterized by macroscopic variables such as pedestrian density 34 and flow. The relationship between these variables is frequently represented using fun-35 damental diagrams (Hankin & Wright, 1958; Carstens & Ring, 1970; Lam et al., 1995). 36 Experimental approaches have also been employed to refine these models in various con-37 texts (Weidmann, 1993). However, it is important to report that the fundamental diagram 38 is formed to be highly context-dependent. For instance, stress levels have been shown to 39 influence pedestrian behavior in non-trivial ways (Helbing et al., 2000), and the form of the 40 relationship between density and flow can differ for bi-directional flows (Motsch et al., 2018; 41 J. Zhang et al., 2012). In some cases, bi-directional flows are more efficient at high den-42 sities due to self-organizing patterns, such as the formation of lanes (Kretz, Grünebohm, 43 Kaufman, et al., 2006; Moussaïd et al., 2012). Similarly, the presence of bottlenecks can 44 significantly alter flow patterns (Helbing et al., 2005; Kretz, Grünebohm, & Schreckenberg, 45 2006). See Vanumu et al. (2017) for a discussion on how the fundamental diagrams change 46 under varying contexts, including bi-directional flows, cross-flows, and bottlenecks. 47

48 The situation at train doors presents a unique case characterized by bi-directional pedes-

⁴⁹ trian flows in a confined space, often complicated by compliance to rules—such as alighting

⁵⁰ before boarding—that are not consistently observed.

Pedestrian flows at train doors have rarely been studied at the individual level, with a few 51 exceptions, such as the study by Q. Zhang et al. (2008), which proposed a simulation based 52 on cellular automata. More often, research has focused on more aggregated variables, such 53 as alighting and boarding times (Wiggenraad, 2001; Daamen et al., 2008). Several models 54 have been proposed to estimate these times. For example, Weston (1989) developed an 55 analytical model based on the number of alighting and boarding passengers and various 56 geometric parameters. However, this model appeared inadequate under high passenger 57 loads (Harris, 2005). Additionally, Coulaud et al. (2023) highlighted that the dwell time 58 of trains is related to the passenger flow data at critical door locations. 59

Seriani et al. (2019) explored the relationship between alighting and boarding times and the ratio of boarding to alighting passengers, along with the level of congestion. Their study found that the boarding time (and, similarly, the alighting time) increased when there were more alighting passengers than boarding, and vice versa. They also observed the formation of alighting lanes, which had narrower widths when the number of boarding passengers exceeded the number of alighting passengers. This observation suggests that self organization patterns can enhance efficiency.

⁶⁶ self-organization patterns can enhance efficiency.

Furthermore, when platform-edge doors were present, De Ana Rodríguez et al. (2016) observed shorter alighting and boarding times. This improvement was interpreted through better positioning of passengers on either side of the door, which reduces interference between boarding and alighting passengers. Generally, operators promote compliance with the rule of waiting for alighting to be completed before boarding, assuming the alighting and boarding process to be improved. In this study, we refer to this behavior as non-

73 compliance.

Despite being common in daily commuting, non-compliance with boarding and alighting 74 rules has rarely been the subject of detailed study. Wahaballa et al. (2022) conducted 75 observations using video footage from Cairo metro stations but found no significant rela-76 tionship between non-compliance and the overall alighting and boarding time. In contrast, 77 Seriani et al. (2022) observed a slight increase—ranging from 1 to 2 seconds—in alighting 78 and boarding times under non-compliance conditions in a controlled laboratory setting. 79 Similarly, Li et al. (2020) investigated the effects of non-compliance using microscopic sim-80 ulations. Their findings indicated no significant impact on alighting and boarding times 81 under low passenger loads; however, they noted a considerable influence under higher pas-82 senger loads. 83

While these studies have primarily focused on the duration of alighting and boarding processes, they have not provided strong explanations for the observed effects, nor have they explored the related flow and density patterns. Furthermore, so far, no research has evaluated the impact of non-compliance on passenger comfort

⁸⁷ evaluated the impact of non-compliance on passenger comfort.

There are limited tools available for studying comfort in pedestrian flows. Instead, the concept of Level of Service (LOS) is more commonly used to assess pedestrian comfort situations. Originally developed for vehicular traffic analysis (see TRB (1956) and TRB

⁹¹ (2022) for a more recent version), LOS was adapted for pedestrian flows by Fruin (1970).

⁹² LOS categorizes pedestrian environments into letter grades (from A to F), with each grade

⁹³ representing decreasing levels of comfort (related to increasing density). These categories

⁹⁴ also take into account different contexts, such as waiting, walking, or ascending stairs
 ⁹⁵ (TRB, 2022; FGSV, 2015), though they are typically defined in discrete terms.

⁹⁶ Kretz (2011) proposed a formula to unify various pedestrian scenarios and calculate LOS

97 on a continuous scale. This continuous LOS measurement offers a more nuanced tool

⁹⁸ for evaluating complex pedestrian flows, such as those occurring during the alighting and

⁹⁹ boarding processes.

¹⁰⁰ The goal of the present study is to quantitatively assess the impact of varying degrees

of non-compliance on flow and density patterns in pedestrian traffic, where the degree of non-compliance refers to the number of passengers who begin boarding before alighting is complete. We design an experiment to measure these effects under controlled conditions, and the experimental findings are validated using field data. Additionally, we provide a quantitative evaluation of the LOS for each level of non-compliance based on the experimental results.

This paper is organized as follows: Section 2 details the experimental setup, including data collection and preprocessing methods for both experimental and field data. Section 3 presents the effects of non-compliance on cumulative profiles, as well as on alighting and boarding times, followed by an analysis of the flow and density patterns. This section concludes with an estimation of the LOS for different levels of non-compliance. Finally, Section 4 provides a discussion of the results and offers concluding remarks.

113 **2 METHOD**

In this section, we present the experimental setup and the data collection framework.
We also present field data and how they were pre-processed to be compared with the
experimental data.

117 Two kind of data; experimental data and field data

118 Experiment

We designed an experiment to quantitatively measure the impact of passenger non-compliance 119 during the alighting and boarding process. We used a real train (called Z20500) dwelling 120 at a dedicated platform at *Gare de Lyon* (Paris) available during the whole morning. This 121 rolling stock was chosen for its small doors (1,3m wide). We wanted to make sure enough 122 hindrance would occur with a small number of participants as there was uncertainty on 123 the number of participants we would reach. We called on colleagues to participate in the 124 experiment to play "passengers". To do so, we spread a form in the company to register 125 interested people to participate. Despite the no-shows, we reached 32 participants. 126

The experiment has been divided into scenarios (S) of non-compliance to extract the 127 influence of increasing non-compliance, and scenarios were replicated (R). In each scenario 128 replication (S,R), half of the participants (16 people) were positioned inside the train (to 129 alight), the other half (16 people) outside the train (to board) in a designated waiting zone 130 marked by chalk. The zone was divided into two (both sides of the door) and the same 131 number of participants had to stand on both sides. After a signal to the train driver, the 132 door was unlocked and one participant inside pressed the button to open the door. An 133 alighting and boarding process then occurred. 134

We evaluated five different scenarios of non-compliance. A scenario of non-compliance 135 corresponds to a given number of boarding passengers trying to board as soon as the door 136 is open before the alighting is complete. The five scenarios match five different numbers 137 of non-compliant boarding passengers, see Table 1. For each scenario, we performed 12 138 replications. The sequence of scenarios and replications is sorted by replication and for each 139 replication, the five scenarios are performed in randomized order, for example, the sequence 140 for the two first replications was: (S1, R1), (S5, R1), (S4, R1), (S2, R1), (S3, R1), (S2, R1), (S3, R1), (S2, R1), (S3, R1), (S2, R1), (S3, R1)141 R2), (S4, R2), (S3, R2), (S5, R2), (S1, R2). Randomising enabled mitigating the impact 142 of fatigue perceived by the participants during the experiment. We did 45 minutes of 143 experiment followed by a 15-minute break followed by 30 minutes of experiment for a total 144 duration of 90 minutes. 145

Before starting the experiment, participants had to sign an informed consent form and were
briefed on the experiment's functioning and some security information. Each participant
was given a colored chasuble (red or blue) and a number (from 1 to 16). At each replication,

Scenario	Number
(S)	of non-compliant
	passengers
<i>S1</i>	0
S2	3
S3	6
S4	9
S5	12

Table 1: Presentation of the five scenarios assessed in the experiment. Twelve replications (R) were performed for each scenario (S).

- ¹⁴⁹ the non-compliant passengers were designated by their number.
- ¹⁵⁰ Finally, each replication follows this sequence:
- 151 1. Indication of the scenario and call for non-compliant passengers,
- 152 2. Signal to the train driver and closing of the door,
- 3. Unlocking of the door by the train driver and opening of the door (one alighting
 participant had to push a button),
- 4. Alighting and boarding process,
- 5. Repositioning of participants (alighting participants becoming boarding participants
 and vice-versa).
- ¹⁵⁸ The whole experiment was captured by a camera fixed above the train door.
- ¹⁵⁹ Two kinds of data have been extracted from the video of the experiment:
- The passenger flow (number of people alighting and boarding at each second),
- The passenger density (number of people in one square meter).

For both of these variables, two steps were followed. First, the videos were subsampled 162 into pictures every second. Second, manual counting was done on each picture to get flow 163 and density data. For the passenger flow, the counting was validated by comparing the 164 total number of counted people to the known number of participants. In other words, if 165 we did not count 16 people alighting and 16 people boarding, the counting had to be done 166 again. For the density, a surface was fixed, in which the counting was done. The surface 167 was $1.5m^2$ included in the camera view where all participants were fully viewable. The 168 density was obtained by dividing the counted number by this surface. Flows and density 169 are time-dependent with data extracted every second. For each (S,R) time 0 corresponds 170 to the door's opening. 171

172 Field data

Some new-generation trains (called Regio2N) are equipped with infrared sensors that count 173 the number of people alighting and the number of people boarding every several seconds 174 at each door and each stop of a train. The time separating two counting events is truly 175 random, having a standard deviation of 3s for an average of 3s. The data has been collected 176 over six months (September 2022 to February 2023) on line N which is the main line 177 operated by this rolling stock. Unfortunately, it is rare to see important bi-directional 178 flows on this line. There are 205 observations for ten people alighting and ten people 179 boarding (see Table 2) which is the studied case. Considering more alighting and boarding 180 people leads to an excessively small sample. On line N, the platforms are all at the same 181 height (except for two excluded stations) which leads to negligible differences in flows for 182 different stations or doors and all the doors are 1.6m wide. 183

	Degree of non-compliance	Number of observation
ten alighting	0	34
and	3	4
ten boarding	6	4
people	Others (excluded)	163

Table 2: Number of observations for the different studied cases from field data.

We defined the number of non-compliant passengers slightly differently than in the experi-184 ment: the degree of non-compliance will be the number of passengers boarding before 90%185 of the alighting passengers have got off. A more strict definition considering the number of 186 passengers boarding before alighting is complete (as for the experiment) is not appropri-187 ate. Indeed, in real-world scenarios, some passengers may alight lately. For example, if the 188 latest alighting passengers are not standing close to the door they may not be seen by the 189 boarding passengers right away. Then, the passengers boarding after 90% of the alighting 190 flow and before the 10% remaining may not necessarily hinder the alighting flow. 191

Notice that these sensors only capture the flow and do not capture the density. Then, we are studying only cumulative profiles and flows from this field data for three degrees of non-compliance (0, 3, and 6 non-compliant passengers).

195 Variables of interest

- ¹⁹⁶ In Section 3, we analyse the results through several variables:
- The cumulative profiles (cumulative alighting, cumulative boarding, and total) over time;
- The alighting and boarding times computed as the time of the last alighting or boarding;
- The alighting, boarding, and total flows (number of people crossing the door each second);
- The alighting, boarding, and total densities (number of people in the vicinity of the door by square meter).

From flows and densities, we plot the fundamental diagrams (flow versus density). Then, we compute the capacity (maximal flow) and the critical density (density where the maximal flow is obtained). Two methods were used to estimate them. First, we used a raw method: we compute the maximum of the flow and the density where this maximum is obtained. Second, we fitted a parabola (using the polyfit function from the numpy library in Python) over the data of the fundamental diagram and took capacities and critical densities from this parabola.

Finally, we studied the comfort during the alighting and boarding process through the notion of level of service (LOS). To do so, we use the formula proposed by Kretz (2011). The formula needs to be calibrated with two speed parameters (c_1 and c_2). The chosen values correspond to existing categories (Fruin, 1970; TRB, 2022; FGSV, 2015), for example, A being from 0 to 1, B being from 1 to 2, and so on. This formula is the following:

$$LOS = \rho \left(1 + \frac{\overline{v}}{c_1} + \frac{Var(\mathbf{v})}{c_2^2} \right),\tag{1}$$

²¹⁸ where ρ is the density,

217

$$\overline{v} = \frac{1}{N} \sum_{i}^{N} \|\mathbf{v}_{i}\|$$

220 221

$$Var(\mathbf{v}) = \frac{1}{N} \sum_{i}^{N} \left(\mathbf{v}_{i} - \frac{1}{N} \sum_{i}^{N} \mathbf{v}_{i} \right) \cdot \left(\mathbf{v}_{i} - \frac{1}{N} \sum_{i}^{N} \mathbf{v}_{i} \right),$$

v_i being the speed vector of passenger *i*. The term proportional to the mean speed illustrates that the faster is the crowd the less comfortable it is. The term proportional to the variance captures how messy the flow is. Taking $c_1 = 0.67$ m/s and $c_2 = 3.06$ m/s, we get a LOS corresponding to Fruin categories (according to Kretz (2011)).

226 Preprocessing of the data

Experimental and field data were then processed to compare the average profile by degree of non-compliance. For experimental data, for each couple (S,R), the profiles of variables of interest against time are smoothed by a sliding mean (using a 4s window). We then took the average and standard deviation of the variable of interest over a given number of non-compliant passengers. For field data, the same treatment is performed over the three scenarios referenced in Table 2.

233 **3 RESULTS**

In this section, the above-mentioned variables of interest from both experimental and field data are plotted and interpreted.

236 Cumulative profile: differences that compensate

First, the cumulative profile of alighting, boarding, and total (i.e. the sum of alighting 237 and boarding) are plotted in Figure 1 with their confidence intervals (at 95% threshold) 238 from experimental data (left) and field data (right). For alighting only and boarding only 239 respectively, the small intersection between the confidence intervals shows good distinction 240 between the profiles for different degrees of non-compliance. Both the alighting process 241 duration and the boarding process duration are longer with increasing non-compliance. As 242 expected, for lower non-compliance boarding starts later and alighting ends sooner, both 243 suffering less hindrance. What is more interesting is the width of the confidence interval 244 which also increases with non-compliance for both alighting and boarding (meaning more 245 variability). If we focus on the total, the average profile is very similar for all the degrees 246 of non-compliance with particularly little differences at the end of the process, meaning 247 very close alighting and boarding times. Table 3 confirms this observation. Such little 248 differences in alighting and boarding times, although already observed in the literature 249 (Wahaballa et al., 2022; Seriani et al., 2022; Li et al., 2020), are counter-intuitive and 250 suggest compensation somewhere in the process. The profiles from field data are similar to 251 the experimental ones, this disproves an experimental bias as the origin of the pattern. 252 The study of flows and densities helps to understand this compensation. 253

254 Flows: uneven transitions between alighting and boarding processes

255 Figure 2 shows the alighting, boarding and total passenger flows for the different degrees of non-compliance from both experimental and field data. On experimental data (left of 256 Figure 2), for lower non-compliance, the alighting flow reaches a sharp and high peak at 257 the beginning while the boarding flow reaches one at the end. As the non-compliance 258 increases, both peaks in alighting and boarding flows flatten and widen meaning two more 259 simultaneous but less effective flows. The total flow illustrates the compensation. For 260 lower non-compliance, we see two peaks separated by a gap: both alighting and boarding 261 flows are very effective but a latency is observed in between. By contrast, the total flow 262 is roughly constant for higher non-compliance, lower at the beginning and the end but 263



Figure 1: Cumulative alighting (top), boarding (center), and total (bottom) average profiles versus time from experimental data with confidence intervals at 95% (left) and field data (right). A good distinction between degrees of non-compliance is possible for the alighting and the boarding while there is little difference in the total profile.



Figure 2: Alighting (top), boarding (center), and total (bottom) average flows versus time from experimental data (left) and field data (right). Alighting flows and boarding flows flatten as non-compliance increases. In the total flow, the observed drop in experimental data corresponds to a transition between the alighting and the boarding. Such drop is not observed for field data.

Degree of non-compliance	Average alighting and boarding time	Standard deviation
[P]	[s]	[s]
0	19.1	0.89
3	20.1	0.94
6	20.6	1.03
9	21.3	1.92
12	21.3	2.11

Table 3: Means alighting and boarding time and their standard deviations measured for each studied degree of non-compliance from experimental data. Little difference is observed in the mean values while the standard deviation increases with non-compliance.

higher in between. In other words, the transition between the alighting and the boarding
for lower non-compliance leads to a loss in flow overall, explaining such small differences
in alighting and boarding times across degrees of non-compliance.

Concerning the field flows (right of Figure 2), the pattern is not fully the same. On 267 the one hand, the alighting flows and the boarding flows follow a similar pattern as for 268 the experiment. On the other hand, the total flow does not undergo two clear peaks 269 for lower non-compliance contrary to experimental flows. The total flow profile is more 270 similar between degrees of non-compliance. One explanation could be the granularity of 271 the field data where observations are reported with an interval often greater than one 272 second, leading to an excessively smoothed curve. Another explanation comes from the 273 definition of non-compliance chosen for field data: for lower non-compliance, a slightly 274 better transition between the alighting and the boarding should be observed as boarding 275 starts as soon as 90% of the alighting is complete. Yet, some compensation is still observed 276 with a higher flow at the beginning and at the end for lower non-compliance while the flow 277 is maximal at the middle of the exchange for higher non-compliance. 278

Besides, one may notice that the total flow is on average less for field data than for ex-279 perimental ones while the door is larger for field data. This might be explained by flows 280 lower than the capacity resulting from insufficient densities (more details in the seque). 281 These insufficient densities can be due to fewer people overall, or a propensity to keep more 282 distance between each other in real-world scenarios compared to the experiment (where the 283 participants generally know each other). Unfortunately, density data are not available from 284 field alighting and boarding processes. Then, in the sequel, we only focus on experimental 285 data to study density and its implications. 286

287 Density: higher non-compliance means higher density

Figure 3 shows the density in the vicinity of the door from experimental data, for only 288 alighting people, only boarding people, and the total. Similar to flows, for lower non-289 compliance, the alighting density reaches a peak at the beginning and the boarding density 290 at the end, coherent with the two phases of the scenario. When non-compliance increases, 291 the alighting density is high for a longer duration whereas the emergence of a second 292 peak at the beginning of the process is observed for boarding. The height of this second 293 peak increases with non-compliance while the height of the original peak decreases. This 294 pattern is coherent with the principle of the experiment: a given number of participants 295 have to board as soon as possible which generates high densities at the beginning; after non-296 compliant participant have boarded, the density decreases until alighting is complete and 297 boarding may resume. If we focus on the total density, higher non-compliance corresponds 298 to higher density overall but does not necessarily lead to much lower flows as seen in Figure 299 2. 300



Figure 3: Alighting (top left), boarding (top right), and total (bottom) average density versus time from experimental data. The density is higher for boarding and for higher non-compliance.



Figure 4: Pedestrian fundamental diagrams in this experiment (dots) and parabolic fit (line) for the five studied degrees of non-compliance. The five profiles are similar.

Degree of	Critical density	Critical density	Capacity	Capacity	R^2
non-compliance	(raw)	(fitted)	(raw)	(fitted)	(fit)
[P]	$[P/m^2]$	$[P/m^2]$	[P/s]	[/s]	
0	1.8	2.0	2.0	1.8	0.96
3	1.8	2.4	1.9	1.8	0.95
6	1.9	2.6	1.9	1.8	0.95
9	2.9	2.9	1.7	1.8	0.99
12	2.6	3.0	1.9	1.9	0.97

Table 4: Critical densities and capacities for each studied degree of non-compliance extracted from the fundamental diagrams with the two methods presented in Section 2. The critical density seems to increase with non-compliance but the capacity is stable.

301 Capacity & compensation pattern explanation

From the flows and densities, we plot the fundamental diagrams for the studied degrees of non-compliance (see Figure 4). As commonly observed in the literature, all the flowdensity curves are concave parabolas. The observed profiles for the different degrees of non-compliance are quite similar but the data might be insufficient to spot differences. In particular, the observed densities are not high enough to study properly the decrease in flow at high density, and the measurement of the capacity (the maximal flow) and the critical density is quite imprecise.

Table 4 presents the obtained critical densities and capacities for the different degrees of 309 non-compliance along with the coefficients of determination of the fit (that show decent 310 correspondence). The capacity does not vary with method and degree of non-compliance. 311 By contrast, the estimated critical density might differ with the method (in particular for 312 3, 6, and 12 non-compliant people). Besides, the critical density slightly increases with 313 non-compliance (no matter the method) which could be explained by self-organization in 314 the flow. Lanes formation is a commonly observed example where the bi-directional flow 315 is made more efficient (see Section 4 for further discussion). 316

The study of the fundamental diagram helps to explain the compensation observed in alighting and boarding times (see Section 3). For lower non-compliance, the total density drops (until 1-1.5 P/m²) at the transition between the alighting process and the boarding process. It leads to sub-maximal flows (between 1 P/s and 1.5 P/s), as seen in Figure 4. For higher non-compliance, the flow (around 1.5 P/s) remains close to maximum despite





Figure 5: Average level of services (LOS) versus degree of non-compliance. Colors correspond to Fruin LOS. The discomfort increases with non-compliance.

higher densities. Then, in the studied context, non-compliance does not significantly affect the duration of the alighting and boarding process. Nevertheless, higher non-compliance

³²⁴ increases the uncertainty in the alighting and boarding time and might decrease comfort.

325 A quantitative assessment of comfort loss due to non-compliance

In this section, we estimate the level of service (LOS) during the alighting and boarding process. The average LOS in the vicinity of the door is presented for each degree of non-compliance in Figure 5. We see that despite important spread, the average LOS increases with non-compliance. The size of the confidence interval also increases with non-compliance.

From these experimental results, although the alighting and boarding time is relatively independent of non-compliance, the LOS significantly increases with non-compliance. However, the LOS is not measurable with the field data available for this study.

334 4 DISCUSSION AND CONCLUSION

In this study, we designed an experiment to evaluate the influence of non-compliance on 335 pedestrian flows in alighting and boarding processes. The experiment showed no significant 336 impact on the alighting and boarding time, which is coherent with existing literature 337 (Wahaballa et al., 2022; Seriani et al., 2022; Li et al., 2020). However, flows and densities 338 over time had different profiles and this observation was confirmed by field data. This 339 phenomenon was interpreted thanks to the fundamental diagram: a decrease in density 340 during the transition between alighting and boarding for lower non-compliance extends the 341 alighting and boarding time as much as the hindrance at higher non-compliance. 342

Some processes at the microscopic level may explain this result but are not captured by the fundamental diagram. A well-documented example is the formation of lanes (Moussaïd et al., 2012). People from both directions (alighting and boarding) cross the door using a fraction of its width without hindering each other. Figure 6 shows an illustration from our experiment. Existing works show efficient bidirectional flows when lanes appear. Kretz, Grünebohm, Kaufman, et al. (2006) see such an example in a corridor. Helbing & Vicsek (1999) shows that the formation of lanes enhances the flow by decreasing the friction



Figure 6: Pictures showing the formation of lanes: an example of self-organization leading to a more efficient process. Pictures captured from the experiment.

³⁵⁰ between pedestrians from both directions. This concurs in explaining the relatively high
 ³⁵¹ flows for higher densities in the fundamental diagrams no matter the non-compliance.

Besides, for lower non-compliance, alighting flows drop at the end of the alighting process. Such a drop has already been discussed in the literature (Heinz, 2003). Two potential explanations were raised: either people in the main flow undergo stress within the crowd that leads them to hurry, or the several lanes during the process break down into one single lane at the end, reducing the density. These two potential explanations are not incompatible and could be true simultaneously.

Concerning flow management, a common rule of thumb is to ask boarding passengers to wait for the alighting to be complete before boarding. Surprisingly, our results contradict this usage (as already mentioned). Nevertheless, this rule may be relevant to cases other than the one studied here. In this sense, notice that we considered:

- A balanced flow (as many alighting people as boarding people),
- Little to medium demand (16 alightings and 16 boardings in the experiment, 8 alightings and 8 boardings for field data),
- An initial position where boarding passengers wait at both sides on the edge of the door (with no additional order).

Although the studied case represents most situations in the Paris suburban railway network, our conclusions are obtained in this specific context. Our conclusion should hold for lower demand or a more significant number of alighting (compared to boarding) since the non-compliance dynamic is not expected to change. By contrast, we cannot extend our conclusions for higher demand, more boarding compared to alighting, more load inside the train (see the results of Li et al. (2020)), or a more organized initial position (in organized lanes, for example).

The studied initial position is known to be sub-optimal (Heinz, 2003). Yang et al. (2019) shows, for example, an improvement in alighting and boarding time by having all the boarding people waiting at one side of the door. Yet, several works observed the initial position in real-world scenarios (Wu & Ma, 2013; Dell'Asin & Hool, 2018) where people wait at both sides of the door, similarly to our experimental instructions. Our experimental protocol was adapted to fit real-world scenarios as well as possible.

In conclusion, this study shows that, with a symmetric moderate total flow, the passengers'
compliance with the rule "alighting before boarding" does not impact the alighting and
boarding duration. By contrast, we showed significant improvement in comfort with lower
non-compliance, which advocates for such a rule.

Our future research includes designing another experiment to investigate cases where the 384 alighting and boarding time could be increased by higher non-compliance. Given the 385 above-discussed results, alighting and boarding time could be increased by a density that 386 is high enough to decrease the total flow significantly (cf fundamental diagram). There is 387 uncertainty on whether such a density is reachable in an alighting and boarding process: 388 people could self-organize to avoid an excessively high density. Future work will aim to 389 design an experiment that produces an appropriate environment for high enough densities 390 to be observed. Besides, we faced two challenges in creating the experiment presented 391 in this paper. The first was to assess only a few scenarios to perform enough replication 392 for each scenario in a restricted time (including some margin). The second was to en-393 roll enough colleagues to participate in a non-paid experiment on a Saturday morning. 394 Designing another experiment should meet these constraints while assessing the case for 395 more participants overall or higher degrees of non-compliance. Such an experiment will be 396 realized in future work. 397

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