How do we wait? Fundamentals, characteristics, and modeling implications

Michael J. Seitz, Stefan Seer, Silvia Klettner, Oliver Handel and Gerta Köster

Abstract Pedestrian simulation models predominantly focus on the flow or motion of agents. However, in many real-world scenarios a large amount of pedestrians' time is spent waiting. Furthermore, the initial spatial distribution of visitors of a mass event may contribute significantly to the overall evacuation time. In this paper, we discuss social science concepts related to waiting, such as personal space requirements, and identify relevant aspects for the modeling of pedestrian behavior. With this background, we develop measures and hypotheses for pedestrian waiting behavior and apply them to a field observation of a train station platform in Vienna. We discuss implications for modeling approaches to waiting, which could be an important future extension to pedestrian simulations.

Michael J. Seitz
Munich University of Applied Sciences, Lothstr. 64, 80335 Munich, Germany.
Technische Universität München, Boltzmannstr. 3, 85747 Garching, Germany.
e-mail: m.seitz@hm.edu

Stefan Seer
Austrian Institute of Technology, Giefinggasse 2, 1210 Vienna, Austria.
e-mail: stefan.seer@ait.ac.at

Silvia Klettner
Austrian Institute of Technology, Giefinggasse 2, 1210 Vienna, Austria.
e-mail: silvia.klettner.fl@ait.ac.at

Oliver Handel
Technische Universität München, Arcisstr. 21, 80333 Munich, Germany.
e-mail: oliver.handel@tum.de

Gerta Köster
Munich University of Applied Sciences, Lothstr. 64, 80335 Munich, Germany.
e-mail: gerta.koester@hm.edu

1 Introduction

Pedestrian simulations can be useful for a wide range of applications, such as safety engineering, transportation planning, or computer animation. The requirements for simulations vary across disciplines, but the underlying model always has to be validated according to some criteria. Hence, developing such a model must be based on knowledge of real pedestrians' behavior, and its predictions are often compared to empirical data [1] gathered in field observations [2] or controlled experiments [3].

So far, research on emergent collective pedestrian behavior has predominately focused on certain observable aspects, especially density and flow [4]. Although the flow is important for safety and efficiency considerations, humans often do not move but remain at a position for some time. They may have to wait or rest, or simply stay to chat with others. Waiting is also a common human activity in transportation systems but has been largely ignored in simulation models. Simulation approaches have been proposed for distributing pedestrians in waiting zones [5] and for modeling pedestrians to remain at a specified position within the social force model [6]. However, the individual choice of pedestrians to wait at a certain location and the respective underlying causes are widely unexplored.

We study *waiting* as a type of behavior by individuals remaining at a position to pass time until an event they expect occurs. Waiting – according to this definition – stands in contrast to remaining at one position for other reasons, such as chatting with someone or enjoying the scenery. Standing in line can be considered a specific form of waiting – with distinct characteristics – but is not studied in this work.

In this paper, we focus on passengers waiting at a train station. We draw on the literature, especially from a social science perspective. Since the usage of space is correlated to the context, such as the built and social environment, we pay special attention to the context. This background from social sciences allows us to develop measures and hypotheses about pedestrian behavior. We then evaluate the hypotheses with empirical data from a field observation.

2 Social science background

Environments are built with intent such that their functions and usage aim at regulating activities of individuals and groups [7]. According to Ruesch [8], both objects and spaces convey information just as spoken language, creating some symbolic meaning, categorizations or beliefs about a place. In that sense, what distinguishes one environment from another is "the nature of the rules embodied or encoded in it" ([9], p.14). Albeit the influence of environmental characteristics on human responses, their relation ought to be comprehended in a probabilistic way, i.e. the setting providing possibilities for choices by increasing or decreasing the probability for activities and behaviors [9]. In other words, choices and activities are not to be understood as determined by the environment, but as being mediated by an individual's characteristics (e.g. abilities, motivation, cognition), by subjective evaluations of space, as well as by (cultural) norms and conventions [10]. According to this understanding, it is the subjective reading of the context which affects activities in and the uses of space [11, 12].

Possibilities for such activities and behaviors can be communicated by the physical environment, its features [13], and/or by the subjective meaning of space [11, 14]. For example, being in public is different from being in private, revealing that individuals regulate their behaviors more in public environments [12]. At the same time, distinct physical features can trigger certain behaviors, such as position changes. Such influences can be grouped into two categories: push and pull factors. While push factors move individuals away from physical features, such as platform edges, pull factors attract and increase densities, such as by advertising screens.

Besides the physical environment which provides possibilities for activities and decisions, it is the social environment and cultural accepted norms that regulate behavior and social interactions, such as interpersonal distances to social group members (pull factors) or to non-social group members (push factors). Invisible boundaries around individuals and groups – often referred to as "small protective sphere or bubble" ([15], p.119) – are maintained to separate one from others [16] and to regulate privacy [15]. Entering somebody's intimate or personal sphere is normally an indication of familiarity and sometimes intimacy. While intimate distance (< 0.45 m) is reserved for close relationships, friends, and family members, personal distance ($0.45 - 1.2$ m) is used for conversations with friends and associates. Social distance ($1.2 - 3.6$ m) on the other hand is held when being with strangers, newly formed groups, and new acquaintances, whereas at public distance ($3.6 - 7.6$ m), individuals are well outside the circle of involvement.

Another model used to understand spatio-temporal patterns and that takes into account the social environment is Schelling's segregation model [17]. Applied in a microscopic context, its fundamental assumption is that individuals decide to change their waiting location once the share of neighboring people with different social characteristics exceeds an individual-dependent threshold. In other words, the whereabouts of an individual depends on the social characteristics of the surrounding environment. Even though people are quite tolerant towards such differences (high acceptance threshold), segregation processes occur quite rapidly.

However, in modern society, especially in crowded urban communities, it can be difficult to maintain personal space requirements, such as when being in dense, impersonal situations, e.g. on crowded trains, elevators, or streets. In such situations, physical proximity might be perceived as psychologically disturbing and uncomfortable. Privacy and personal space may, however, be re-established by adjusting social interaction to a desired level by verbal, nonverbal, and physical processes [18], such as by increasing physical or perceived interpersonal distances (e.g. stepping away from others, avoiding eye contact).

3 Material and methods

The empirical data presented in this paper originates from observations in a metro station in Vienna consisting of a center platform with tracks on each side, as illustrated in Fig. 1. The observed platform area was directly accessible for passengers via escalators and included tactile paving as well as yellow markings at the platform edges. Positions of waiting passengers were manually annotated in single video frames captured from an oblique camera view. Furthermore, all annotated waiting passengers were manually tracked over consecutive frames. We determined the point mapping between the image coordinate system and the world coordinate system using multiple reference points which were measured on-site. For our investigations, we used manual annotations from two video sequences each of 15 minutes length, which were recorded in the morning (7:00 AM with 38 passengers in 5 phases between consecutive trains) and evening (6:30 PM with 91 passengers in 4 phases between consecutive trains) with average train intervals of 80 seconds.

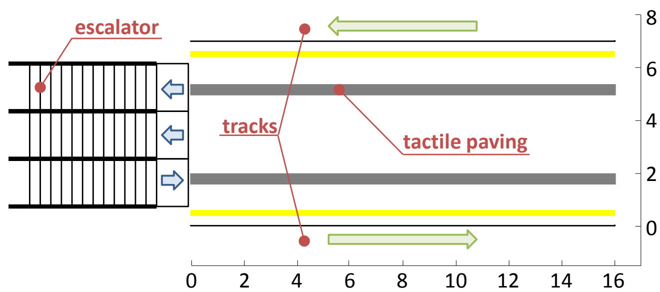

Fig. 1 Observed platform area in the metro station. The tactile paving is shown in gray and the line indicating a safety distance is shown in yellow.

4 Results and discussion

We analyzed the data collected from the observation by clustering the Spatial data in quadratic bins with a side length of 1 *m*. Fig. 2 illustrates the spatial distribution of waiting passengers and the respective waiting times.

On the left in Fig. 2, the number of passengers occupying each bin was counted every second. The sum was divided by the overall observation time yielding a normalised measure for the occupancy. Warmer colors indicate positions that were occupied more often. We observed higher levels of occupancy in the evening compared to the morning. In both cases, passengers seemed to stay clear of close positions next to the platform edge, yet some individuals remained close to it. Additionally, only very few passengers waited close to the escalators on the left of the observation area.

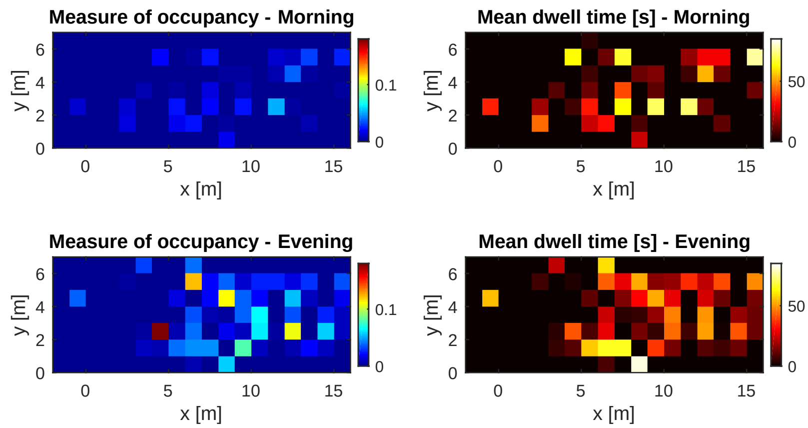

Fig. 2 On the left, passengers occupying one measurement bin were counted every second, and this sum was divided by the overall observation time. Warmer colors indicate a higher level of occupancy. On the right, the mean remain time was measured for each measurement bin. In both cases, measurement bins have side lengths of 1 *m*.

On the right in Fig. 2, the mean remain time in seconds was calculated for each bin. Brighter colors indicate positions were passengers remained longer on average. Here, a similar picture can be observed as for the level of occupancy. We did not find any additional systematic distribution of the remain time. However, with additional data, this measurement methodology may yield interesting insights into waiting behavior.

Looking at the data in detail, we evaluated two working hypotheses we expected to reject with the empirical observation. The first hypothesis states that passengers distribute uniformly over the platform. The second hypothesis postulates an exponential distribution for remain times. Both hypotheses were selected because of their simplicity and the assumption that they are used frequently in simulation models. In order to decide whether to reject the hypotheses, we explored the data with a series of histograms as reported in Fig. 3.

In Fig. 3a, the frequency of chosen positions over the width of the platform is shown. Again, this representation of the data reveals that passenger kept clear of close positions – up to 0.5 *m* – to the platform edge. Taken together with the spatial representations in Fig. 2, this strongly suggests that the hypothesis that passengers distribute uniformly can be rejected. Apart from the gaps close to the platform edge, a uniform distribution may still be a plausible statistical model for the data.

In Fig. 3b, the empirical distribution of remain times is shown. The hypothesis that the remain times are distributed exponentially seems implausible for two reasons. First, there is little weight for very short remain times, leaving a gap close to 0 *s* in the morning observation. Second, both distributions appear to be more heavy tailed compared to an exponential distribution – especially in the morning. From investigating the data we can conclude that the second hypothesis can be rejected

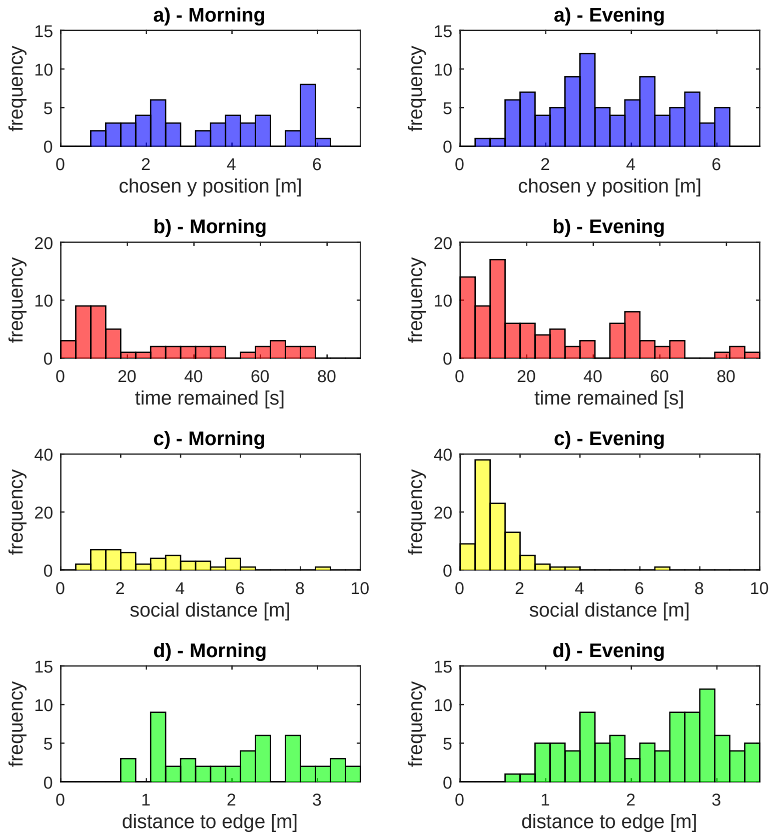

Fig. 3 Histograms summarizing the waiting behavior during the observation: a) the frequency of chosen positions over the width of the platform, b) the times passengers remained at one position, c) minimum distance kept to other passengers (position were ignored when there were no other passengers on the platform) and d) distance kept to the border of the platform.

as well. However, an exponential distribution may still be a useful simplified model for practical purposes.

In Fig. 3c, we report the distance kept for the chosen waiting position to the next waiting passenger. In the morning, passengers kept a mean interpersonal distance of 3.0 m. In the evening, pedestrians awaiting the train kept a mean distance of 1.2 m. Both empirical distributions could be modeled with a Gamma distribution, yet, with different parameters. In the morning, greater distances seemed to be more frequent. However, it is important to mention that densities were higher in the evening and hence interpersonal distances are also more likely to decrease. Another reason for greater distances in the morning could be that more commuters who did not know each other were present. In contrast to that, in the evening, more passengers in social groups who stay closer together can be expected.

In reference to Hall (1966), proximities of 1.2 and 3.0 *m* are within the range of social distance. When chosen voluntarily, it reflects the distance held between strangers, newly formed groups, and new acquaintances. Following Hall (1966), one would expect larger distances, which are characteristic for public occasions. Yet, due to the limited space available, the platform does not allow for much larger physical interpersonal distances.

Finally, in Fig. 3d, the empirical distribution of distances kept to the next platform edge are shown. As it was also observed in Fig. 2, passengers did not wait in a range from 0 up to 0.5 *m* and with low frequency in a range of 0.5 to 1 *m*. We propose two possible explanations for this. First, there was a yellow line indicating a safety distance people have to keep from the rails. This line is likely to encode the intended instruction to stay away from the platform edge and thus may suggests the observed behavior (see [13, 11]). Second, the platform edge and the knowledge that trains arrive and departure there might induce a possible threat leading to the observed behavior. Hence, the built environment itself and the familiarity of passengers with this context could be dominant. Finally, these two aspects together may encourage the observed behavior.

While not often incorporated until today, remain times and spatial distributions may be of great value for pedestrian simulation. Social distances and the distance to the platform edge could be modeled by push and pull factors. Additionally, we suggest to use heuristic decision making [19] to model waiting behavior and propose the following four rules as working hypothesis for future research: a) passengers get close to where the train arrives; b) they keep a safety distance to the platform edge; c) passengers keep a social distance to other passengers; d) they stay away from the escalators.

5 Conclusions

In this paper, we reported a study of pedestrian waiting behavior. First, we reviewed related concepts from social sciences. Second, we explored observational data from a train station platform and evaluated two simple working hypotheses. Finally, we proposed four heuristic rules that may be used in simulation models.

We argue that waiting behavior is an important aspect in pedestrian interactions. Although waiting is especially relevant in public transportation systems, pedestrian simulation models have put less focus on waiting behavior so far. Furthermore, quantitative data can also further the knowledge in social sciences. The measurement methodologies we used can be applied for other scenarios.

In the future, the proposed heuristics may be formalized, implemented, and studied in pedestrian simulations. The emergent effects can then be compared to empirical data, allowing for validating or rejecting the proposed decision making model. For empirical research, however, it is crucial to collect more data from heterogeneous scenarios with different contexts. This would enable, for instance, to disclose cultural similarities and differences, such as comparing European and Asian commuters' behavior.

This contribution can be seen as a basis for the investigation of waiting behaviors in pedestrian research – both for empirical research and mathematical modeling. We emphasized the need to approach waiting behavior in broader contexts, such as when taking into account the social environment (e.g. through social interactions) as well as the physical environment (e.g. spatial behavior). The presented study can be used for future empirical measurements, mathematical modeling, and further studies in social sciences.

References

1. A. Schadschneider, W. Klingsch, H. Klüpfel, T. Kretz, C. Rogsch, A. Seyfried, in *Encyclopedia of Complexity and Systems Science*, ed. by R.A. Meyers (Springer New York, 2009), pp. 3142–3176. DOI 10.1007/978-0-387-30440-3_187
2. S. Seer, N. Brändle, C. Ratti, Transportation Research Part C: Emerging Technologies **48**(0), 212 (2014). DOI 10.1016/j.trc.2014.08.012
3. M. Moussaïd, D. Helbing, S. Garnier, A. Johansson, M. Combe, G. Theraulaz, Proceedings of the Royal Society B: Biological Sciences **276**, 2755 (2009). DOI 10.1098/rspb.2009.0405
4. A. Seyfried, O. Passon, B. Steffen, M. Boltes, T. Rupprecht, W. Klingsch, Transportation Science **43**, 395 (2009). DOI 10.1287/trsc.1090.0263
5. M. Davidich, F. Geiss, H.G. Mayer, A. Pfaffinger, C. Royer, Transportation Research Part C: Emerging Technologies **37**, 210 (2013). DOI 10.1016/j.trc.2013.02.016
6. F. Johansson, A. Peterson, A. Tapani, Physica A: Statistical Mechanics and its Applications **419**, 95 (2015). DOI 10.1016/j.physa.2014.10.003
7. R. Ozaki, J.R. Lewis, Environment and Planning D: Society and Space **24**(1), 91 (2006). DOI 10.1068/d62j
8. J. Ruesch, W. Kees, *Nonverbal Communication: Notes on the Visual Perception of Human Relations* (University of California Press, Berkley and Los Angeles, 1956)
9. A. Rapoport, *Human Aspects of Urban Form: Towards a Man Environment Approach to Urban Form and Design* (Pergamon Press, Oxford, 1977)
10. I. Eibl-Eibesfeldt, *Non-verbal communication* (Cambridge University Press, Cambridge, 1972), chap. Similarities and differences between cultures in expressive movements, pp. 297–314
11. R. Kallus, Journal of Urban Design **6**(2), 129 (2001). DOI 10.1080/13574800120057818
12. D. Matsumoto, Acta de Investigación Psicológica **2**(2), 611 (2012)
13. I. Campari, in *Geographic objects with indeterminate boundaries*, ed. by P.A. Burrough, A. Frank (CRC Press, 1996)
14. H. Huang, S. Klettner, M. Schmidt, G. Gartner, S. Leitinger, A. Wagner, R. Steinmann, International Journal of Geographical Information Science **28**(12), 2456 (2014). DOI 10.1080/13658816.2014.931585
15. E.T. Hall, *The Hidden Dimension* (Doubleday, 1966)
16. R. Sommer, Sociometry **22**(3), 247 (1959)
17. T.C. Schelling, *Micromotives and macrobehavior*. FELS Lectures on Public Policy Analysis (WW Norton & Company, 1978)
18. G.W. Evans, R.E. Wener, Journal of Environmental Psychology **27**(1), 90 (2007). DOI 10.1016/j.jenvp.2006.10.002
19. G. Gigerenzer, P.M. Todd, A.B.C. Research Group, *Simple Heuristics That Make Us Smart* (Oxford University Press, Oxford, 1999)