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Doctoral Thesis

From Real Affective States towards Affective Agents Modeling

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Abstract

The modeling of agents involving emotions and affective states constitutes a relevant discussion topic in the research concerning multi-agent simulations, especially because of how the introduction of affective parameters inside the modeling process could effectively make the produced simulations more realistic.

In this research area, though, the modality in which parameters regulating the affective state of agents are introduced into models, so that the agents' behaviour and actions are influenced by them, is always based on emotional models found in literature, or on physics theories and models usually involved for the modeling of pedestrians and crowds.

The approach this work presents, then, aims at tackling this problem from the point of view of data, thus wanting to get to affective agent modeling starting from data coming from real people, acquired through ad-hoc experiments with the precise goal of observing reactions and behaviour to be later translated inside a model.

In particular, the focus of this work falls on the research on pedestrians and walkability, observing different types of interactions involving pedestrians through four different experiment through which gather data able to describe the participants' interactions to then implement them in the modeling step.

The proposed experiments are executed in-vivo, in-vitro and online, observing pedestrian interactions with vehicles, moving obstacles and other pedestrians, gathering data regarding these interactions through physiological data and questionnaires made for profiling purposes and in order to have more information regarding the subjects' behaviour and reactions.

The gathered data is then used for modeling, firstly from the point of view of cellular automata and then passing on to the multi-agent systems perspective, showing how the information obtained from the data is introduced inside the models to be parametrized in affective parameters that, depending on the assigned values, could influence in a certain way the behaviour of the agents.

After that, some simulation instances derived from the models are presented, as to observe how the affective parameters that were introduced in the models actively influence the behaviour of agents acting and moving in certain situations.

Abstract

La modellazione di agenti che tiene conto di emozioni e stati affettivi costituisce un argomento di discussione piuttosto importante nell'ambito della simulazione ad agenti, soprattutto per via di come introdurre parametri affettivi nella modellazione possa contribuire a rendere le simulazioni più realistiche.

In questo ambito di ricerca, però, il modo di introdurre nei modelli parametri in grado di regolare lo stato affettivo degli agenti per da influenzarne azioni e comportamenti è spesso basato sui modelli emozionali che si trovano in letteratura, oppure sulle teorie e i modelli fisici che vengono solitamente utilizzati per la modellazione di pedoni e folle.

L'approccio presentato in questo lavoro, quindi, mira ad approcciare il problema dal punto di vista dei dati, puntando ad arrivare alla modellazione di agenti affettivi partendo da dati provenienti da persone reali ed acquisiti tramite esperimenti creati ad hoc con il preciso obiettivo di studiare reazioni e comportamenti da poter poi tradurre in modellazione.

In particolare, in questo lavoro il problema viene affrontato concentrandosi in particolare sull'ambito pedonale, osservando diversi tipi di interazione coinvolgenti pedoni tramite quattro diversi esperimenti atti a raccogliere dati in grado di descrivere le interazioni operate dai soggetti per poi inserirle in un contesto di modellazione.

Gli esperimenti vengono effettuati in vivo, in vitro e online, osservando le interazioni di pedoni con veicoli, ostacoli in movimento ed altri pedoni, raccogliendo dati riguardo queste diverse interazioni tramite dati fisiologici e questionari atti a profilare i partecipanti e a fornire maggiori informazioni riguardo al comportamento e alle reazioni da loro dimostrate.

I dati raccolti vengono quindi utilizzati per la modellazione, prima in ambito di automi cellulari e poi, successivamente, nell'ambito dei sistemi multi-agente, mostrando come le informazioni ricavate dai dati vengano integrate all'interno dei modelli al fine di includere parametri affettivi che, in base ai valori assegnati, influenzino in un certo modo il comportamento degli agenti.

Vengono poi proposte alcune simulazioni derivanti dai modelli, ai fini di osservare come i parametri affettivi introdotti influenzino il comportamento degli agenti in azione in determinate situazioni.

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Introduction

The simulation of human agents displaying an increasingly more realistic behaviour is still an open topic in the agent-based simulation research, an interesting issue that nowadays is tackled by all kinds of approaches. There are many works in the literature, in fact, where researchers try to include new parameters inside the agents' design, parameters whose purpose is to influence the way they move around the environment and interact with each other [Pelechano et al., 2005, Adam et al., 2010, Gorrini et al., 2018].

Human behaviour, though, is incredibly complex: there are both internal and external factors guiding humans' behaviour and decisions regarding how to act in certain environments and situations, and it is particularly difficult to try and include such a complexity inside agent models. This becomes especially true when talking about the involvement of emotions and affects, which play a very important part in a person's reactions and interactions with surroundings and other people and which also tend to manifest differently for each person because of how everyone has different attitudes, experiences, physiology and so on. This can be easily seen, for example, when observing behaviours and physiological reactions in men and women [Bianchin and Angrilli, 2012], or when comparing younger and older people in their reactions to tasks [Shin and Lee, 2012, Gasparini et al., 2020c] highlighting how, even taking into consideration such large groups, it is possible to find meaningful variations in approaches to certain situations.

Most of the works done in this particular direction, with researchers exploring the idea of inserting emotions and affects as parameters influencing the agents' behaviour, tend to search for foundations in well-known emotional theories [Ekman, 1992, Ortony et al., 1990] and behavioural concepts already well-grounded in agent simulation [Nishinari et al., 2004], but do not actually try and tackle this matter directly starting from the people and the more realistic information that can be gathered by analysing their behaviour.

These considerations brought then to the pursue of the research line here presented, which involves studying people's behaviour and interaction through carefully planned experiment in order to acquire data on which to design an "affective agent model", namely an Affective Multi-agent System, utilizing more realistic inputs coming directly from observation and signal analysis. In particular, in this thesis, the matter of pedestrians movement and interactions is explored, starting from experiments designed as to investigate particular situations to then obtain relevant data to guide the design of models implementing affective parameters directly based on people's reactions.

In this first chapter, the motivations that brought to the pursue of the research here presented are illustrated, together with a first look regarding the main contributions brought by this thesis and the related publications that were submitted to journals and conferences as the work developed.

Motivation

The main aim of this thesis, as it is here presented, is focused on the presentation of a different approach to agent modeling, an approach that does not rely on psychological theories or on laws of physics to model and simulate people and their behaviour, but that rather relies on real data coming from experiments performed with real people. In the literature, as it will be later shown better in Chapter 1, many works started to try and tackle the issue of involving affective states into agents by starting from the numerous theories and formulas already present in the world of emotion and simulation, but very few have ventured towards implementing the information directly coming from real people into the models.

The study of real people behaviour in different situations, bringing information both from the simple observation of their conduct and from the analysis of data acquired through sensors and questionnaires, makes it possible to try and focus on real behaviour recorded in action rather than on formal rules and theories that sometimes do not find a correspondence in real life occurrences, or that may deliver a much simpler situation when the variety of people composing a crowd could make the simulated situations more nuanced. And given how the main focus lies on *realism*, it is of the utmost importance to get good quality data and to perform a sensible analysis on them in order to obtain useful information that correctly mirror the events recorded by the data.

Thus, what it is here presented is a proposal in terms of how to differently approach the modeling and simulation of agents with the inclusion of affective parameters, together with the demonstration of what kind of results can be reached by following the presented proposal. It will be shown how models including this kind of parameters, dictated by real data coming from real people, can effectively allow to observe agents behaving differently depending on their type, and how the simulations derived from these models can be regarded as more realistic because of how and why the agents' behaviour is influenced.

Thesis Contributions

In this thesis, aspects regarding the aforementioned introduction of realistically designed affective states insides multi-agent model design are investigated, starting from the data collection through different experiments to pass onto an example of modeling following the gathered data and end with some preliminary simulations of the designed model to show how the introduced parameters come into play when modeling certain situations. In particular, the work here presented focuses on three main points, which constitute the main contributions of this thesis:

- **Data collection process.** When working to gather data, it is important to understand what kind of data to acquire and how to properly acquire it in order to extract meaningful information that can give value to the models and simulations. Chapter 2 is then focused on presenting four experiments and their respective experimental protocols that show an approach to such a study when investigating pedestrian behaviour.

- **Modeling involving affective parameters.** After acquiring data, it is necessary to understand how to properly introduce the information gathered from the data analysis inside the models, in order to utilize the newly-found knowledge to make the designed agents more realistic. Chapters 3 and 4 both show how this issue can be tackled by taking into consideration the data from one of the experiments previously presented, approaching this matter both from a cellular automata and a multi-agent systems perspective.

- **Affective model simulation.** Once the models have been designed, then, it is interesting to start investigating the behaviour such models display in simulations, so as to evaluate the impact the information previously introduced have on the way the agents move and interact in an environment. Sections 3.1 and 3.2 and Chapter 5, then, show some preliminary simulations performed following the models previously described, showing the behaviour of cellular automata and agents instantiated after the aforementioned models in different situations.

Related Publications

The majority of the material that contributed building this thesis has been collected into papers throughout the entire PhD period, and published in peer-reviewed conference proceedings or sent for evaluation to peer-reviewed journals.

Because of this, all of the works in the context of this thesis that were presented to journals and conferences are listed hereafter, complete with references and citations. Moreover, for each following chapter of the thesis, the publications mainly related to the discussed matters will be reported.

- [Gasparini et al., 2020b] Gasparini, Francesca, Marta Giltri, and Stefania Bandini. "Experimental Approach to Study Pedestrian Dynamics Towards Affective Agents Modeling." *ATT@ ECAI.* 2020.

- [Gasparini et al., 2021b] Gasparini, Francesca, Marta Giltri, Daniela Briola, Alberto Dennunzio and Stefania Bandini. "Affectivity and Proxemic Distances: an Experimental Agent-based Modeling Approach." *AIxAS@ AI* IA.* 2021.

- [Gasparini et al., 2021a] Gasparini, Francesca, Marta Giltri, and Stefania Bandini. "Safety perception and pedestrian dynamics: Experimental results towards affective agents modeling." *AI Communications* 34.1 (2021): 5-19.

- [Gasparini et al., 2022] Gasparini, Francesca, Alessandra Grossi, Marta Giltri and Stefania Bandini. "Personalized PPG Normalization Based on Subject Heartbeat in Resting State Condition." *Signals* 3.2 (2022): 249-265.
- [Bandini et al., 2022b] Bandini, Stefania, Daniela Briola, Francesca Gasparini and Marta Giltri. "Furthering an agent-based modeling approach introducing affective states based on real data." *ATT@ IJCAI-ECAI* (2022).
- [Bandini et al., 2022a] Bandini, Stefania, Daniela Briola, Alberto Dennunzio, Francesca Gasparini, Marta Giltri and Giuseppe Vizzari. "Integrating the Implications of Distance-Based Affective States in Cellular Automata Pedestrian Simulation." *International Conference on Cellular Automata for Research and Industry.* Springer, Cham, 2022.

Supporting Project

This thesis work was partially developed under and supported by the Fondazione Cariplo "LONGEVICITY - Social Inclusion for the Elderly through Walkability" (Ref. 2017-0938), a project focused on population ageing, urbanization and walkability.

The LONGEVICITY project finds its place in as looking at how future cities will be characterized by the increasing presence of long-living citizens, brought by the increasing life expectancy that our societies allow with a better quality of life, and by the ever-growing automation in traffic dynamics, an important change that is already underway as vehicles start to implement more and more intelligent ways to move inside traffic without the driver's input. Fostering social inclusion and active ageing of the elderly in forthcoming urban scenarios thus becomes a question to be addressed.

To this end, LONGEVICITY has the objective to study walkability and pedestrian mobility considering the specific needs of senior citizens in a project that starts from Milan, Italy, to further the research to be done on these themes. It is based on methodological and computational tools aimed at assessing the level of walkability of a certain area and at achieving solutions to improve this aspect by considering the needs and perceptions of senior citizens, in particular taking into consideration infrastructures and mobility services in the City of Milan.

During the time period in which it was active the project involved many different activities, ranging from the analysis of socio-demographic data and elderly walkability indexes included in GIS (Geographic Information System) gathered in Milan to on site inspections of certain city areas, from questionnaires and interviews done with elderly people with the important partnership with the Auser association to in-vivo and in-vitro experiments to analyse people's behaviour with walking, crossing and collision avoidance tasks.

Thesis Outline

This thesis work is organized as follows. After the Introduction here presented, Chapter 1 presents the state of the art regarding the multiple aspects touched by this research, thus giving some pointers about walkability, about emotions and the research concerning it, to then pass onto cellular automata and agent systems, focusing in particular about the way affective parameters have been introduced into pedestrian modeling and the results obtained by these approaches.

Chapter 2 then presents the different experiments that were performed to observe and analyse pedestrians' behaviour in different situations, presenting their methods and scopes to properly understand what kind of information was sought after by performing the experimental trials.

Chapter 3 is then focused on how the Cellular Automata modeling was approached, illustrating both the 1D and the 2D model that were designed and the simulations that were done on the basis of the aforementioned models. Chapters 4 and 5 are concerned about the same modeling aspect but from the Agent systems perspective, thus presenting the modeling of a multi-agent system contemplating affective parameters and the developed simulations that were used to understand the impact of those same parameters on the pedestrians' behaviour and movement.

Lastly, conclusions about the presented thesis are drawn in the Conclusion section of the work, in order to sum up the research aspects addressed in the work, the presented approach to tackle them and the obtained results together with what insight can be gained from them.

1 Background

Given how there are different areas of interest involved in this thesis, ranging from the matter of affect recognition to agent modeling and simulation, this section aims to present some notions about the main research points this work touches on, in order to give a proper introduction to the concepts that will later be used throughout the presented chapters.

The Background chapter, as the investigation here presented involves the matter of pedestrian simulation, focuses on an introduction of the concept of walkability and what it brings with it when contemplated in research, to then shift over to an overview about emotion and affects, also illustrating how the usage of physiological signals has become a very popular way to study them in people in order to gather useful data to be involved in research for various purposes. Finally, both cellular automata and multi-agent modeling will be presented, with a particular focus on how the same emotions and affects previously illustrated are currently declined in order to design affective pedestrian models to further frame the work of this thesis inside this particular research direction.

1.1 Walkability

The concept of Walkability, which became widely known after the term was invented in the 1960s by Jane Jacobs' revolution in urban studies [Jacobs, 1961], is based on the idea that urban spaces, since they constitute the environment in which humans live, should be more than corridors that simply allow vehicles to pass through. Instead, they should be seen and conceived as *livable spaces* serving a variety of uses, people and modes of transportation that also reduces the need for travel by car.

The attention around the issue of walking in cities grew considerably at the end of the 1980s, with designers and urban planners starting to focus on strategies that could contribute to the development of pedestrian areas and, in general, on the promotion of walking as a preferable mean of transportation through urban environments. Also, in more recent years, walkability has gained wider popularity as an essential concept of sustainable urban design because of its envisioned benefits, ranging from health [Watts et al., 2015, McCormack et al., 2020, Frank et al., 2006] to economic growth [Gilderbloom et al., 2015, Litman, 2003] and environmental care [Rafiemanzelat et al., 2017, Azmi and Karim, 2012, Kato, 2020].

There are several factors [Dovey and Pafka, 2020] influencing the walkability of an environment that make it pedestrian-friendly, characteristics that are both taken into consideration in the design and in the evaluation of urban environments when walkability needs to be assessed. These factors include, for example, the items presented as follows:

- Level of urban density;
- Presence, absence and quality of footpaths for pedestrians (i.e., sidewalks, crossings etc.);

- Traffic and road conditions;
- Use patterns of the territory;
- Buildings accessibility;
- Size of neighborhoods;
- General safety.

Also, linking to these concepts what Jeff Speck proposed in his General Theory of Walkability [Speck, 2015], all of the aforementioned factors should aim at making walking throughout an environment a*favoured* experience. Despite taking the United States of America as the study case, in fact, the concepts Speck underlines in his book have a greater validity in regards of what concerns designing and building a more walkable environment in cities.

In particular, what the General Theory of Walkability says when referring to a walk is that, in order for it to be considered favoured, it must satisfy four main conditions: it should, in fact, be valued as useful, safe, comfortable and interesting all at once, since every condition is essential and one without the others cannot be sufficient.

Useful is connected to how most aspects of daily life should be located close at hand, so that they are organized in a way that makes them easily accessible by walking alone. *Safe* is related to how the street are designed, since they should be structured in order to avoid for pedestrians to avoid danger, which includes to be hit by cars and other vehicles. In particular, they should be designed not only to be safe, but also to feel safe, which is usually a much tougher requirement to satisfy. Then, *Comfortable* is linked to the way buildings and landscape should shape urban environments in a way that it maked it tailored for people, so that they succeed in attracting pedestrians. Finally, *Interesting* is connected to how buildings standing beside sidewalks are built, as friendly facades paired with lively traffic of people travelling in and out of the facilities are better at catching people's attention and interest as opposed to neglected and rundown areas.

In order to improve the urban environment in the way it is structured as to make it more people-friendly, there are different aspects that can be addressed by keeping into considerations the above mentioned factors. An example that can be brought to attention is the one regarding mobility, for instance: improving mobility with barrier-free buildings, punctual street maintenance, properly structured and maintained footpaths and space for outdoor activities can effectively intervene on how a certain urban area presents itself and how it is perceived by residents and visitors alike.

Also, such changes not only make the urban environments more accessible in general, but also make cities more age-friendly, towards elderly citizens in particular. And this is a very important point to take into consideration, especially given how the world population is slowly growing older and older as quality of life improves and life spans get longer.

1.1.1 Safety

When considering walkability and all the factors influencing a urban environment for the better, particular attention must be dedicated to the matter of safety and safety perception from the point of view of pedestrians.

Perceived safety is something that can concern various different aspects of people's life, but when focusing on the matter of urban planning, as the discussion on walkability requires, this perception becomes strongly conditioned by how the environment presents itself [Jansson, 2019, Hinkle, 2015, Jackson and Gray, 2010], but also by the emotional state of the person who roams around said environment, a dimension that is more difficult to research and define.

Especially because the emotional state is not influenced by the internal affects of the person, but also by the situation surrounding the pedestrian [Dosey and Meisels, 1969, Vine, 1982, Iachini et al., 2020] which bears an important impact on this state. As a direct consequence of this, different intensities of fear, anxiety and stress born from the outside inevitably condition perceived safety, and subsequently they also condition the interpersonal interactions and distances among people that directly stem from perceived safety.

An example of this can be found in how the diffusion of the COVID-19 pandemic dramatically influenced every aspect of human life, and the fear of infection induced by the spread of the virus can be considered as one important external factor conditioning the perceived safety of people. This becomes especially true when considering how risk perception is heavily influenced by information coming from media and by personal experiences [Iachini et al., 2020, Wise et al., 2020], and when considering how pervasive information about the rising pandemic was in papers, in social media or on television, it is reasonable to say the fear of contagion played an important part in people's perceived safety and interactions with one another.

1.1.2 Proxemics

When considering social interactions, and in particular the matter regarding interpersonal distances that became so important as the COVID-19 pandemic spread across the world, the study of proxemics becomes particularly relevant and informative.

Proxemics is a discipline that studies the human use of space and the effects of population density on behaviour, communication, and social interaction. Cultural anthropologist Edward Twitchell Hall in 1963 was the first one to coin the term [Hall, 1966] and, in his work, he tried to identify some basic characteristics common to all people when dealing with interpersonal distances. These characteristics were investigated because of the particular valence they could assume when focusing on behavioural aspects, since these features could help identifying and measuring more easily human behaviours linked to this form of communication.

The majority of studies on proxemic distances and human behaviour relate to the theory developed by Hall's research and, in particular, to the definition he gave of four distinct zones for interaction, each with its own scope and finality, when he followed on the research on interpersonal distances.

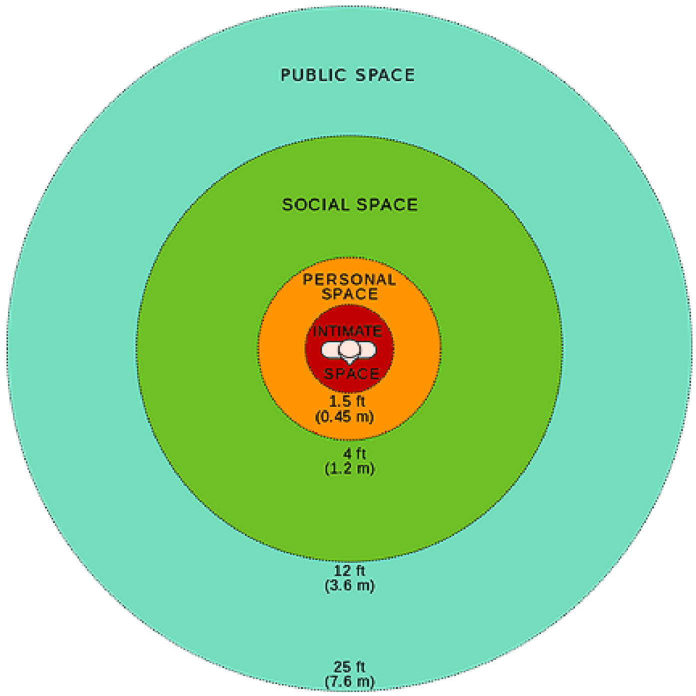


Figure 1: The four different spaces identified by Hall. As the figures clearly shows, every space described by Hall's theory has its upper and lower bounds, which characterize the space around a person up to 7.6 meters.

As shown in Figure 1, Hall identified four of what are here referred to as *Hall's spaces.* The *Intimate* space is the innermost of the group, defining the space immediately around the person up until a 45 centimeters distance, which is the one occupied for intimate interactions like embracing, touching or whispering. The *Personal* space, immediately following, is the one usually destined for interactions among good friends or family, and describes the space from 45 centimeters to 1.2 meters around the person. The *Social* space then, from 1.2 meters to 3.6 meters, is the one mainly used when interacting with acquaintances, and the *Public* one, the last one which is described from 3.6 meters to 7.7 meters, is the space related to public speaking.

Even with the definition provided by Hall, though, there are a variety of factors that influence how people approach interpersonal distances and the use of their personal space.

Gender, for example, proved to be one of these factors. Studies show, in fact, how women tend to show a lower tendency to engage in physical contact as opposed to men, especially if the considered situation contemplated an interaction with a person of the opposite sex [Shuter, 1977, Remland et al., 1995].

Age was also found to bear important influence on interpersonal distances, especially considering how proxemic behaviour seems to change with growth: children tend to interact with people at very close distances, distances that increase as the person grows and that reach their apex during adulthood only to grow smaller once again while nearing elderly age [Burgess, 1983, Heshka and Nelson, 1972]. This tendency of interpersonal distances growing shorter once again, in particular, seems to be connected to the elderly reduced social independence [Webb and Weber, 2003], which may lead them to grow closer to people since in need of help and assistance.

Also, as it was mentioned in the previous subsection, perceived safety is another factor affecting distances from others: depending on the environment and the situation in which people are interacting, in fact, these distances could approached in a different way. For example, people are more in favour of an eventual personal space invasion when it is justified by small or overcrowded spaces [Vine, 1982], even if such physical proximity is still regarded as psychologically disturbing and uncomfortable [Hall, 1966], while an unjustified invasion could cause discomfort and even fear [Tennis and Dabbs Jr, 1975]. In these cases, having a chance to escape could help in perceiving the uncomfortable situation as more bearable [Daves and Swaffer, 1971].

Nowadays, given the COVID-19 pandemic, perceived safety can also be linked to the fear of infection induced by the virus' presence and diffusion, these new and disorienting conditions changing people's approach to proxemic distances both because of the emotional impact of the event and because of the governmental regulations that had to be implemented in order to slow down the spread of the pandemic.

At the same time though, on another interesting note, it was also observed how proxemic behaviour could be influenced in the opposite way by the restriction imposed due to the outbreak [Mehta, 2020]. Given the distances to be respected in order to abide the newly imposed rules, new communications methods were found in order to keep in touch with acquaintances and interact with strangers. And it was also noticed how going outside frequently contributed to lower stress, anxiety and fear levels, as well as decrease interpersonal distances kept regarding others [Iachini et al., 2020], in a rather counter-intuitive way when considering the external factors that brought the adoption of new regulations in the first place.

1.2 Emotion and Affects

The investigation on emotion and affects has always been of particular interest in psychology, but in recent years many different fields started contributing into this same research topic, including medicine, history, sociology of emotions, and computer science. This, in particular, is evident in the works leaning towards the branch of Affective Computing [Picard, 1999], which aims at letting systems use information and data indicating the user's emotional state to create a more natural interaction with people.

This interest led to a rise in experiments focused on emotion and affects, stemming from the analysis of theories found in literature which were used as a base to build, over them, methods to use systems for the detection and recognition of such reactions in ways that could both advance what technology can do and improve people's relationship with said technology.

1.2.1 Theories and Models

Ever since psychologists started studying emotions, different definitions and ways to describe them have been presented in papers and research, marking the birth of various interpretations and models that could be used to describe this particular dimension of human psychology as, to this day, there is still no scientific consensus on a proper definition for emotions.

For example, the most basic distinction that can be described about the models being presented over the course of decades, starting from the late 1800s, is the one dividing emotion models in two distinct categories: discrete models and continuous models. Some examples for each category are reported in Table 1, highlighting some of the early and most known emotion models.

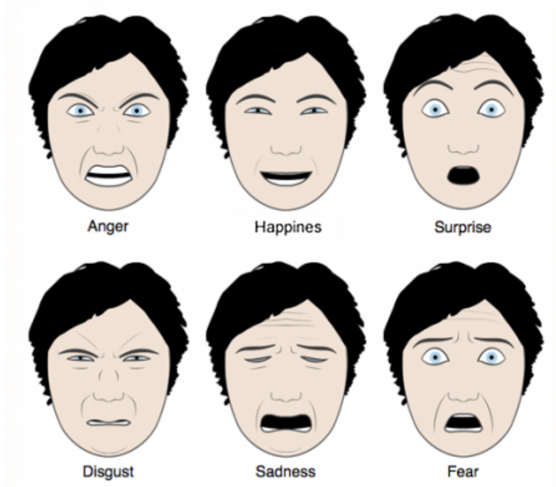
Discrete Models	**Continuous Models**
Ekman's Six Basic Emotions [Ekman, 1992]	Russell's Circumplex [Russell, 1980]
Plutchik's Wheel of Emotions [Plutchik, 1980]	PAD model [Mehrabian and Russell, 1974]
Clynes' Sentic Cycle Emotional Model [Clynes, 1977]	PANA model [Watson and Tellegen, 1985]

Table 1: Examples of emotional models for both the discrete and continuous categories.

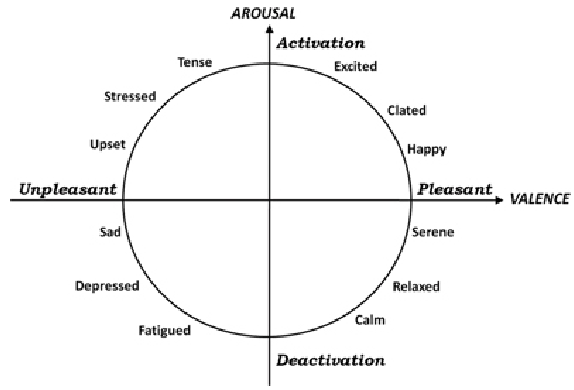
Ekman's and Russel's models, among the other ones listed in the table, are surely two of the most known in emotion and affect research, to which many works refer when contemplating how to classify and label emotional states, and can be used as useful examples of what discrete and continuous models entail.

Ekman's model [Ekman, 1992] describes the existence of emotions that agree with the view that sees emotions as discrete, measurable, and physiologically distinct, and it is the result of a facial-expression research which finds anger, disgust, fear, happiness, sadness and surprise to be the six basic emotions experienced by humans. On the other hand, Russel's model [Russell, 1980] describes a two-dimensional model in which emotions are described by certain levels of arousal (i.e., a state of activation or deactivation, found on the vertical axis) and valence (i.e., a state of pleasantness or unpleasantness, found on the horizontal axis) identified on a continuous space.

There are other models, though, that are not strictly included in the table above but whose presence is also quite frequent in the research works regarding emotions, utilizing different methods of definition which distinguish them from the most known ones.



(a) Image depicting Ekman's model and the six basic emotion he described.



(b) Image depicting Russel's model and the circumplex two-dimensional space.

Figure 2: Images showing the emotion models proposed by Ekman and Russel.

One, for example, is the Ortony, Clore and Collins's model of emotion (OCC) [Ortony et al., 1990], which states that the strength of a given emotion depends on the events, agents, or objects situated inside the environment of the agent exhibiting the emotion. The model specifies about 22 emotion categories and five processes composing the complete system that characters follow from the moment they encounter a particular event to the moment they display a certain behaviour in response. In particular, the five processes are the following: 1) classify the event, action or object encountered, 2) quantify the intensity of affected emotions, 3) let the newly generated emotion interact with the existing ones, 4) map the emotional state to a certain emotional expression and 5) express the resulting emotional state. For its structure and the way it is designed, the OCC is one of the most used models in agent modeling and simulation.

1.2.2 Emotion and Affect Recognition

The matter of emotion and affect recognition has grown to be one very important research area, given how different disciplines can benefit from results obtained pursuing this particular line of work. The ability of understanding how a person is feeling by looking at signals (e.g., physiological signals, video recordings, audio feedback) rather than relying on a user's direct feedback is highly sought after, for example in psychology, medicine and, as it was previously mentioned, in computer science, and this importance led a rise in experiments concerned with emotion elicitation and recognition.

The interest that different branches manifest in this research area manifests in many different approaches to the matter. And while this shows an appreciated variety in trying to investigate the issue from different points of view, this also leads to a very low comparability between experiments and data, even if coming from similar procedures. These diverse approaches, in fact, translate into works bearing many differences from one another, starting from the stimuli utilized in order to elicit a reaction from the subjects of the experiments: almost every experiment done in this area utilizes different stimuli, ranging from images to audios, from music videos to movie scenes, passing on to arithmetic computation, text reading and questionnaires when focusing on stress and cognitive load recognition tasks, which fall into the broader affection category rather than the emotion one.

There are dataset of stimuli specifically designed to be used in such instances, and they range from image sets (i.e., the IAPS [Lang et al., 1997], the NAPS [Marchewka et al., 2014] and the GAPED [Dan-Glauser and Scherer, 2011]), to video (i.e., the DEAP [Koelstra et al., 2011], the DECAF [Abadi et al., 2015] and the most recent ASCERTAIN [Subramanian et al., 2016]) and audio collections (i.e., the IADS [Bradley and Lang, 2007]). Unfortunately, though, the number of datasets publicly available is not very high, and the differences in the way the stimuli are recorded and labelled make things even more difficult: the emotional models adopted to label the stimuli with the emotions they are tested to evoke, in fact, are not consistent among all datasets because there is no a universal standard to follow when building such datasets.

Similarly, this same issue presents itself also in the experiments aiming at acquiring data for emotion recognition: since there is no emotional model regarded as standard, and since there is still no unified definition of what is an emotion, such experiments lead to data labelled in many different ways depending on the emotional model adopted by the researchers executing the experimentation. The most used emotional models were shown to be some slightly adapted versions of discrete classifications [Picard et al., 2001, Nasoz et al., 2004, Nardelli et al., 2015] followed by the Circumplex model used in its 2D instantiation, the Valence-Arousal model, with Valence being a scale from negative to positive affectivity and Arousal a scale measuring how calming or exciting a presented stimulus is [Wagner et al., 2005, Koelstra et al., 2011, Girardi et al., 2017, Chung and Vercoe, 2006].

Another factor that differentiates the emotion recognition experiments is the number of participants involved in the various studies. Looking at the works done in this field, in fact, a strong disparity in the subjects' numbers is noticed when comparing the papers published on this matter: some of them use a relatively high number of participants, with groups of 24 people or more [Koelstra et al., 2011, Alvarsson et al., 2010, Trochidis and Lui, 2015, Hönig et al., 2007], while others consider less than 10 people [Hernandez et al., 2011, Janssen et al., 2012] or even just 1 person only [Picard et al., 2001, Wagner et al., 2005]. Usually, large groups of subjects seem to be more involved when the ultimate goal of the experimentation is to build a dataset or to perform some kind of classification task on the acquired signals. Smaller groups, on the other hand, are mainly involved when the focus shifts on the specific person, especially when the research has just one participant: in this case the work is more concerned on recognizing the emotions induced to the subject and monitoring them in different moments during a certain period of time, thus gaining a better understanding of how that specific subject's emotions and affects vary and evolve over time and in different situations.

Lastly, this variety is also present both in experimental methods and in analysed signals, which nowadays can be acquired through a wide selection of sensors. Other than video and audio acquisitions during experiments, in fact, physiological signals have become known as a reliable source of information regarding the emotional and affective states of a person, and since there are many of such signals there are, similarly, many different sensors that can be considered for the experiments. The works done in this area, then, can not only be differentiated regarding the usage of video and audio recordings rather than physiological signals recording, but also regarding which physiological signals are actually considered in the experimentation.

1.2.3 Physiological Signals in Emotion Recognition

As previously mentioned, the diversification in approaches towards emotion and affect recognition matters is also particularly clear when investigating how physiological signals are involved in this particular branch of research, and how experiments contemplating the acquisition of such signals from participants vary greatly in terms of which devices to use and which signals to acquire. Moreover, this variety is underlined even more by the high number of devices currently available to measure and record a greater deal of physiological signals. Currently, the most popular and used signals are the following:

- **Electrocardiogram (ECG)**: signal recording the heart's electrical activity. Usually measured through electrodes placed on the chest, allows to record Heart Rate (HR) and Heart Rate Variability (HRV);

- **Photoplethysmogram (PPG)**: optically-obtained signal detecting blood volume changes in microvascular bed of tissue. Usually measured through sensors placed on fingers or on ear lobes, allows to record HR and HRV;

- **Electromyogram (EMG)**: signal recording the electrical activity produced by skeletal muscles, distinguished in Needle EMG and Surface EMG. Usually measured with electrodes places on the body part to be monitored, allows to record Respiration (RESP), Movement and Gestures;

- **Galvanic Skin Response (GSR)**: signal also known as Electrodermal Activity (EDA) and Skin Conductance Level (SCL) measuring how skin resistance varies through time and stimuli depending on sweat. Usually acquired through sensors placed on the fingers, allows to identify psychological or physiological Arousal;

- **Temperature (T)**: signal measuring the changes in human body temperature. Usually acquired through infrared digital thermometer and thermal energy transfer sensors placed on the body or on the hand;
- **Electroencephalogram (EEG)**: signal recording an electrogram of the macroscopical activity of the brain from the electrical activity perceived from the scalp. Usually acquired through electrodes caps and ad-hoc headsets following various electrodes positioning.

Most of the works involving physiological signals, for reasons ranging from the structure of the presented experiment to the goals of the experimentation itself, usually involve only a subset of these listed measures in different combinations: some works use GSR and PPG contemporarily [Alvarsson et al., 2010, Patrão et al., 2016], others include only GSR [Hernandez et al., 2011, Setz et al., 2009, Chung and Vercoe, 2006], some only consider measuring HRV [Nardelli et al., 2015, Chiu and Ko, 2017, Quiroz et al., 2018], while some others take advantage of a more extensive set of measures in order to have a more comprehensive view of the subject's state [Trochidis and Lui, 2015, Koelstra et al., 2011, Picard et al., 2001, Wagner et al., 2005, Hönig et al., 2007].

Interestingly enough, some of the studies also include some other kind of signal recorded from the participants just as, for example, the accelerometer data [Patrão et al., 2016, Quiroz et al., 2018], or take into account written information regarding the activity performed by the subjects provided by logs or questionnaires to further understand the recorded signals [Sano and Picard, 2013, Hernandez et al., 2011, Nasoz et al., 2004].

Other works' choices, on the other hand, fall on more complex signals, such as the Electroencephalogram (EEG) and the Electrocardiogram (ECG) [Hakimi and Setarehdan, 2018], which can be highly informative but that also are more difficult to obtain without utilizing invasive methods.

And given how restrictive some sensors for physiological signals are, binding the execution of the experiments the strict boundaries of laboratories, the growing research in this particular subject has also sparked interest in the creation and adoption of new sensors, in particular wearable sensors to be used both in and out experimental settings in order to bring the study regarding emotion and affect detection and recognition in more real-life situations [Zangróniz et al., 2017, Serrano et al., 2018]. With their small dimension, limited costs and the increased freedom of movement during activities they allow, wearable sensors enable for more types of experiments to be performed without losing significant accuracy in the acquired signals, thus representing a very valid option to adopt for this kind of research [Ragot et al., 2017, He et al., 2017].

1.3 Cellular Automata

Cellular automata (CA) are discrete model of computation studied in automata theory, which concept was originally discovered in the 1940s by Ulam and Von Neumann from their respective works on lattice networks and self-replicating systems. It was not until the 1970s, though, that the interest about cellular automata started growing out of academia and into new and diverse fields of research, when Conway's Game of Life [Conway et al., 1970], a two-dimensional automaton that achieves an impressive diversity of displayed behaviour, became quite popular, especially among the early computing community. Stephen Wolfram, also, contributed to bring the cellular automata concept to attention as he engaged in the study of one-dimensional cellular automata, what he called *elementary cellular automata*, which he found to exhibit an unexpected complexity in behaviour [Wolfram, 1983].

From them on, the increasing interest in cellular automata brought them to have many different applications in various research areas. In physics, for example, their application is utilized in the modeling and simulation of fluids, magnets and gas. In chemistry, chemical reactions can be modeled with cellular automata to observe the resulting mixtures and patterns produced by the afore mentioned reactions. In biology, cellular automata are widely used when investigating the patterns found in nature on shells, plants and animals.

But cellular automata are also considered of interest in the development of more social simulation, both concerning animals and humans, and they are still often employed for the modeling of traffic and crowds' dynamics, dealing with the behaviour of vehicles and pedestrians in urban traffic instances.

1.3.1 Pedestrian Simulation and Affects

Pedestrian dynamics have always been investigated from different points of view, and the cellular automata approach is surely one of the most widely used even at the present time, tackling different aspects of it.

The flow of pedestrians [Nowak and Schadschneider, 2012] has always been the main focus of this kind of research, with works investigating crowd dynamics [Sirakoulis, 2014, Lubaś et al., 2016, Feliciani and Nishinari, 2016] with cellular automata to study how pedestrians move, especially to study the high variety of collective phenomena that usually manifest when considering crowds [Schadschneider et al., 2002].

Multiple factors about this movement are usually considered when studying pedestrians, from the trajectories [Lovreglio et al., 2015] they adopt when moving around with a certain destination in mind to how group dynamics work [Bandini et al., 2011], since it very common for groups of pedestrians to be present inside a much larger crowd and the way these smaller groups behave and interact with the others as they move influence the behaviour of the entire crowd. There has also been interest in investigating particular situations, like the flow on bidirectional pedestrian walkways [Blue and Adler, 2001, Weifeng et al., 2003] or during evacuation events [Lu et al., 2017, Guo and Huang, 2008], in which the effects of conflicts for space between pedestrians have to be taken into high consideration for the effects that friction and clogging have on the evacuation itself [Kirchner et al., 2003].

When considering pedestrian behaviour, also, individual differences must be taken into account, such as the possibility of people moving at different speeds [Bandini et al., 2017], having particular interactions with vehicles [Li et al., 2012] and adopting different proxemic behaviour when dealing with personal space [Was et al., 2006, Bandini et al., 2020, Was et al., 2012, Ezaki et al., 2012]. But also emotions, nowadays, are starting to get more and more attention and consideration to be properly introduced into these kinds of models, since it is now recognized the important part emotions and affects play in people's behaviour and actions.

Some works concerning cellular automata and pedestrians show preliminary trials of the integration of emotion inside the models [Wang et al., 2022, Li et al., 2017, Saifi et al., 2016], mainly following the same theoretical approach already found in other aspects of cellular automata research regarding pedestrians. If works on pedestrians flow often find their base on fluid dynamics or on well-grounded cellular automata concepts [Burstedde et al., 2001] with changes in the pedestrians' behaviour dictated by ad-hoc formulas, for example, these works implementing emotions and affects in cellular automata stem from notorious emotion models and theories [Ekman, 1992, Ortony et al., 1990, De Raad, 2000] such as the ones that were previously introduced in Section 1.2.

1.4 Agent Modeling

Stemming from the work of Von Neumann, Ulam and Conway in the cellular automata field, agent modeling has roots that trace back to the early 1970s: the work of Schelling on segregation models [Schelling, 1969], in fact, embodied the basic concept of agent-based models as autonomous agents interacting in a shared environment with an emergent aggregate behaviour resulting from that interaction, while the work of Reynolds on flocking models [Reynolds, 1987] contributed to the design of some of the first biological agent-based models, one of the first example of lively biological agents which later became known as *artificial life*.

From that moment on, agent-based modeling has seen countless applications on many different research areas. For example, biology utilizes such models in many ways, simulating natural phenomena such as plant-animal interaction, vegetation ecology [Zhang and DeAngelis, 2020] and the spread of epidemics [Canzani and Lechner, 2015]. There are business models depicting the effects of marketing [North et al., 2010], team working and information spreading [Serrano et al., 2015], and in social sciences such an approach finds application on social phenomena like seasonal migrations, pollution [David and Don, 2012] and so on.

And, among the ones presented above, the one concerning traffic and pedestrian simulation is surely one of those research areas in which agent-based modeling is largely utilized, since there are many aspects of pedestrian behaviour, especially as far as interactions with other pedestrians, the environment and vehicles are concerned, that can be studied through this particular tool.

1.4.1 Pedestrian Simulation and Affects

During recent years, numerous studies have been developed in order to investigate different aspects of the pedestrian behaviour. The decision making of pedestrians in different situations, such as crossing [de Lavalette et al., 2009] and evacuation scenarios [Haghani and Sarvi, 2016], is often inquired, and particular attention is given to how people act, with research ranging from non-signalized pedestrian crossings [Feliciani et al., 2017], evasive behaviours in pedestrian interactions, flows and counter-flows in crowds [Liu et al., 2017] to pedestrian-vehicle interaction in proximity of an unsupervised crossing [Gorrini et al., 2018], crowd dynamics and grouping [Gorrini et al., 2015] and even the impact of proxemics [Was, 2010] in groups and crowd flow [Manenti et al., 2010, Dickinson et al., 2019]. As it is highlighted in different works [Gorrini et al., 2018, Feliciani et al., 2017], the heterogeneity of the system entities is relevant in order to properly identify the pedestrians' microscopic (i.e., individual) dynamics. And that is because aggregated dynamics can be of interest for who is regulating the system in its entirety.

In the case of agent-based crowd and pedestrian dynamics simulations, the modeling of a new generation of systems supporting crowd management that takes into account affective states represents a new research frontier, involving also many human disciplines [von Scheve and Salmella, 2014] which forward the investigation on how emotional aspects influence pedestrian and crowd dynamics [Saifi et al., 2013]. Numerous works have already started working towards the integration of emotion and affects in pedestrian agent simulation systems, ranging from simple flows to evacuation plans simulations, to reach the design of more plausible and realistic agent simulations.

One first example can be given by investigating the works presented in [Colombi and Scianna, 2017] and [Feliciani et al., 2017]. In the aforementioned papers, pedestrian agents with different behaviours were designed and modeled after observing people's behaviour in a real-live experimentation. Rather than concentrating on emotions, though, the agents in the simulations were modeled to reflect the subjects' behaviour by focusing on movement and speed, their designs being based on the information contained in the videos recorded during the in-vivo experimentation.

In the work done in [Pelechano et al., 2005], the agent simulation system was integrated with additional information about human behaviour, allowing each agent to perform according to a specific role, ability, stress level and emotion. This important integration of characteristics and communication was done in order to achieve individualistic behaviour and to obtain a realistic way to spread information across the environment.

The same importance to this integration is attributed by [Gorrini et al., 2018] which, in its analysis, underlines how pedestrian are heterogeneous and need to be treated as such in simulations, too. Moreover, in [Pelechano et al., 2007], the agents are given more characteristics in order to act more naturally and realistically, obtaining different psychological (e.g., impatience, panic, etc.) and physiological (e.g., locomotion, energy level) traits in order to display individual heterogeneous behaviour during the simulation.

In [Hollmann et al., 2011], recognizing how humans do not follow a strict list of goals but, instead, change and adapt their behaviour accordingly to emergent conditions and unexpected events, a prototype emotion model to be implemented in a pedestrian simulation system is presented. The *required time to perform a task* and the *available time* were introduced, presenting the agent with the concept of "time pressure" to influence their behaviour, alongside the *compulsory*, *time critical* and *elective tasks* which also provided the agents with the concept of "urgency".

Moreover, in [Xu et al., 2020] the impact of emotional contagion in high density crowds is investigated, focusing on both positive and negative emotions to evaluate how crowd dynamics are influenced when affects involving a large number of people are contemplated.

Shifting in particular to evacuation plans simulation, multiple works have tried implementing some sort of emotion or affect in their agents in order to obtain more realistic and informative simulations.

In [Thiel-Clemen et al., 2011], the WALK project is presented to address the need to build a reliable multi-agent model for human behaviour prediction in critical situations, including factors like emotional stress and complex interactions. The fundamental research brought onward regards the impact of emotions on crowd dynamics, and in this case a multidisciplinary approach and an effective simulation system are two of the fundamental steps needed to further the research.

The work presented in [Adam et al., 2010] finds its objective in studying the influence of emotions on human behaviour in crowds, and more precisely on the influence that their dynamics and propagation from an agent to another have. In the paper, it is clear that adding emotions to the agents provides huge benefits both to the agents behaviour and to the simulation quality, since emotions play a very important role in human beings' life by influencing their decision-making and reasoning processes just like also their interactions with others.

Another example is [Fu et al., 2016], where the pedestrian dynamics in counter flow integrated with the effect of panic propagation was explored. In this case the only emotion present in the simulation was panic, or fear, but it already provided interesting insights for managing a crowd during a stampede, in order to study the possible damages and to properly organize a safe mass evacuation.

In [Li et al., 2014] a similar issue is investigated, as the work research the impact of panic during evacuation. The difference between non-panic and panic evacuations is observed, with the utilization of the social force model to represent the former and the implementation of an evolution of that same model to represent the latter, thus introducing the effects of stress and fear on pedestrians.

In [Tsai et al., 2011], the ESCAPES system is presented, a multi-agent simulation tool that includes four features for simulation modeling in order to create more realistic outputs: different agent types, emotional interactions, informational interactions and behavioural interactions. The different agent types allow the system to create, for example, individuals, families, first time visitors or experienced agents, and the agent interactions allow to show the spread of knowledge, emotional contagion and social comparison throughout the crowd.

The work in [Zoumpoulaki et al., 2010] presents a system based on a multi-agent BDI architecture enhanced with the Five Factor model of personality, also called OCEAN model, and the OCC model of emotions. This simulation tool takes into account how every agent possesses *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness* and *Neuroticism* in varying degrees, and the concept of *Perception* that generates *Beliefs* and of *Decision making* that create *Desires* to be fulfilled through *Intention* are introduced. The involved OCC model also brought the modeling of five positive/negative emotion couples: Joy/Distress, Hope/Fear and Pride/Shame concerning the agent itself, while Admiration/Reproach and SorryFor/HappyFor concerning other agents. The interesting results of this approach is that the agent emotional state may influence its perception, affecting for example its ability to notice an exit sign or an obstacle, while relationships between agents like reproach or admiration can cause a communication message to be ignored or regarded respectively, providing a more realistic interaction between agents and a more reliable simulation.

In [Lin et al., 2022], then, the same OCEAN model is contemplated to study pedestrian-vehicle interaction and collision avoidance scenarios, with the personality model characterizing both the pedestrians crossing the street involved in the simulation and the drivers approaching the pedestrian crossing by car. In this case, the driver's personality traits directly influence the yielding strategy adopted when observing a pedestrian inside the driver's field of view, while the pedestrian's personality traits lead to changes in the pedestrian's behaviour towards the approaching car, thus accelerating or decelerating at the prospect of collision.

Another work utilizing both the OCEAN and the OCC models as reference for emotion modeling is the one presented in [Mao et al., 2019], which focuses on the emotional diversity of crowds and its influence during public emergencies. Together with the emotional models listed above, the paper also presents simulations observing agents behaviour under different stressors levels, utilizing the Yerkes–Dodson Law to depict agents performing differently in the chosen scenarios.

Finally, in [Colombi et al., 2017], the concept of pedestrian environmental awareness is introduced into a discrete Helbing-like approach, where each simulated walker is set to change his/her target destination according to new information learned from the surrounding environment and that different perceptions of the surroundings can lead walkers to react in a different way. This approach and the model developed in [Colombi and Scianna, 2017] support our proposal of including perceptual aspects in modeling pedestrian dynamics.

As it can be noticed, a good majority of the works focusing on introducing this kind of information mainly base themselves on well-known and established emotional models [Ekman, 1992, Ortony et al., 1990], utilizing them to as base on which to build the agents on [Bates et al., 1994], or mainly following emotional theory to craft functions to regulate the emotional aspects of the agents [Belhaj et al., 2014], while another important point in research dealing with agent simulation involving emotion resides in what kind of emotion is portrayed, which sometimes is even accompanied by parameters describing personality [Egges et al., 2003], and that is often *fear*. Especially in evacuation simulations, in fact, fear is widely used as a parameter apt to influence pedestrian behaviour, modeled in different ways and used differently depending on the types of agents involved in the simulations [Faroqi and Mesgari, 2015]. It is also one of the emotions usually investigated when studying emotion propagation, given its relevance in emergency situations [Minh et al., 2010].

What emerges from these works, then, is how emotion is usually dealt with on a rather theoretical plane, with information about the emotions to be modeled being usually gathered from literature and models used in psychology to then be parameterized into formulas for the agents to use. This leaves very few works which actually base themselves on data coming from an actual human population, making use of information gathered by observing the behaviour of real people in real life situations [Colombi and Scianna, 2017].

Given this panoramic view of the matter, it is understandable how the problem of introducing affects and emotions into agents modeling is still far from being approached in a unified matter and solved, and this validates even more how investigating this research area is relevant and vital to further the work done until now, in order to reach even more relevant and usable results.

2 Experiments for the gathering of Affective Data

As it was briefly mentioned as the Motivation of this thesis was presented, in order to try building an affective agent model on data coming from people, rather that on models of psychology and physics theory, it was first of all imperative to understand if there are some data features that can effectively allow to differentiate between different affective states in different types of people. Given the premises for this approach, in fact, data was to be one of the most important aspects to be investigated.

This is why it was important to properly tackle the substantial issues and challenges surrounding the design and the execution of experiments which could provide the data to be used in order to investigate subject-related features that could be utilized with the modeling task in mind. Learning how to structure an experiment, investigating which types of data could be acquired and which features could be extracted in order to try and evaluate people's affective states while looking for relevant differences between different populations were important stepping stones towards the ultimate goal of including real life information about human affects inside agents modeling.

In particular, with the focus on pedestrian behaviour and on modeling the realistic aspects of interaction between people and the environment around them and with what else populated it, three types of experiments were devised in order to study different aspects of the aforementioned interaction, which are illustrated as following.

- **Type 1 (T1)**: Outdoor experiments performed in-vivo in realistic situations to study the interaction between pedestrians and vehicles on road (Sections 2.1 and 2.2);
- **Type 2 (T2)**: Indoor experiments performed in controlled laboratory environments to study the interaction between pedestrians and moving obstacles (Section 2.3);
- **Type 3 (T3)**: Online experiment performed through a web portal purposefully built to study the interaction between pedestrian and pedestrian during the COVID-19 pandemic (Section 2.4).

The executed experiments all involved different populations, comparing in particular younger populations with elderly ones given by the focus brought by the LONGEVICITY project, and all of them followed the same research question here reported:

- **Is it possible to identify different affective states and behaviours between the considered populations when observing specific tasks?**

All of the experiments fell under this single research question because, if found, such differences could effectively allow for a more in-depth profiling of different types of people, promoting a more realistic modeling of such profiles that could lead the introduction in simulation of more diverse populations better reflecting realistic situations.

The aforementioned experiments are reported in the following chapter as listed, together with a full disclosure of their premises, their design and the analysis performed on the gathered data in order to give an answer to the research question under which the experiments were designed.

Contribution summary

The experiments presented in this chapter have been previously partially included into the following publications:

- [Gasparini et al., 2020b] Gasparini, Francesca, Marta Giltri, and Stefania Bandini. "Experimental Approach to Study Pedestrian Dynamics Towards Affective Agents Modeling." *ATT@ ECAI*. 2020.

- [Gasparini et al., 2021b] Gasparini, Francesca, Marta Giltri, Daniela Briola, Alberto Dennunzio and Stefania Bandini. "Affectivity and Proxemic Distances: an Experimental Agent-based Modeling Approach." *AIxAS@ AI* IA*. 2021.

- [Gasparini et al., 2021a] Gasparini, Francesca, Marta Giltri, and Stefania Bandini. "Safety perception and pedestrian dynamics: Experimental results towards affective agents modeling." *AI Communications* 34.1 (2021): 5-19.

- [Gasparini et al., 2022] Gasparini, Francesca, Alessandra Grossi, Marta Giltri and Stefania Bandini. "Personalized PPG Normalization Based on Subject Heartbeat in Resting State Condition." *Signals* 3.2 (2022): 249-265.

2.1 T1 - Crossing Experiment

The first experiment performed with the intention of studying pedestrian interaction with vehicles on road was executed near the University of Milano-Bicocca with a population of young university students.

This experiment was designed in order to observe pedestrians during road crossing and walking along an unsupervised crossroad, investigating the matter both from an observational point of view and a physiological perspective. It was performed in an uncontrolled urban scenario, following an experimental procedure that included both data collection through walking tasks and self-assessment questionnaires that were used to gather the participant's reports on the tasks they carried out.

Ethical Committee Approval: The experiment here presented was performed after an ethical committee approval, in compliance with the Ethical Committee of the University of Milano-Bicocca.

2.1.1 The Environment

Given how the experiment was designed to be executed in-vivo, and given what it was to be studied through it, the first step in designing it regarded choosing an environment that could satisfy the requirements of having subjects cross a road through an unsupervised and unregulated zebra crossing.

The chosen environment then contemplated an unsupervised crossroad on a two-way road, a busy street situated not too far away from the main buildings of the University of Milano-Bicocca and the U14 building, the one hosting the Department of Informatics, Systems and Communication. Figure 3 shows the selected experimental environment and, in particular, the zebra crossing at the centre of the experiment is highlighted with a red rectangle.

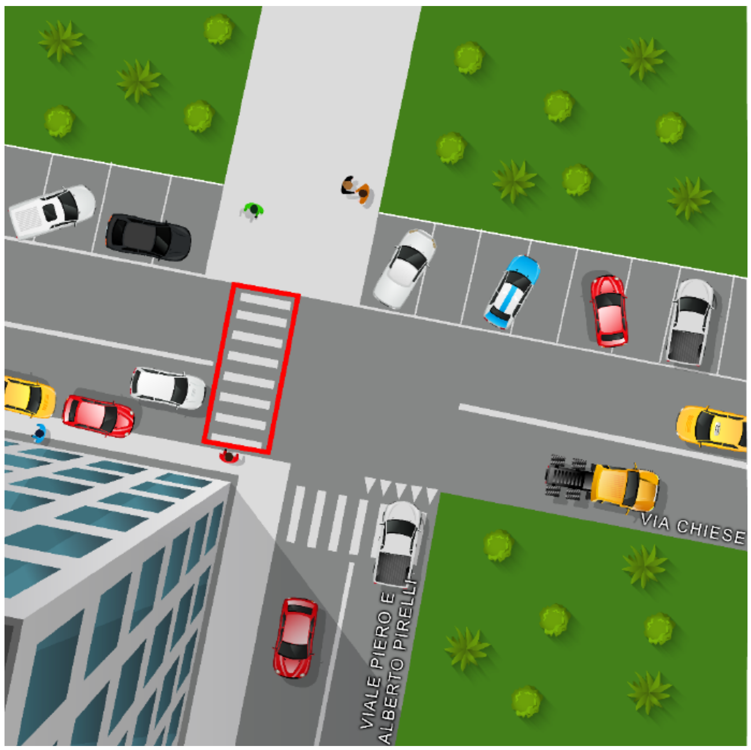


Figure 3: The intersection chosen for the experiment. The selected crossroads, main point of interest in the procedure, is highlighted in red.

This crossing is considered moderately dangerous for pedestrians for the following reasons:

- The crosswalk is located on a very busy road, given its location near offices, the university and a shopping mall;
- The crosswalk is unsupervised, with no traffic lights for neither the cars or the pedestrian;

- The numerous parking lots positioned alongside the intersection limit the view of the pedestrian before and while crossing the road;
- Different vehicles travel alongside this road, ranging from bicycles to cars, trucks and buses.

Since the subjects' safety perception was to be tested while they were traversing a stressing crosswalk, the one located at this crossroads presented some difficulties that could effectively elicit a stressful affective state. The only external indication that participants were given was related to the presence of vehicles on the road: in fact, subjects were asked to start the crossing task when there were vehicles approaching the zebra crossing, in order to make the experience more realistic than the one they could have had if they simply decided to cross with an empty road.

2.1.2 The Subjects

Given the nature of preliminary study of this experiment, set up as testing ground to then propose a more refined protocol with a view to a wider population involvement, the subjects involved in its execution were chosen from a same social and age group, focusing on young adults. A total of 14 participants were engaged in the matter, 7 males and 7 females aged between 20 and 26 years, with a mean of 24.42 years and a standard deviation of 1.65. All of them were university students enrolled in one of the scientific faculties at the University of Milano-Bicocca, something that brought them all to be quite familiar with the chosen intersection because of their usual attendance on campus for lessons. This was especially true for the Computer Science students involved in the experiment, since they usually found themselves crossing the street in that same location in order to reach the U14 building located nearby.

All of the subjects in this experiments were volunteers who provided informed consent before participating, to whom the experimental procedure was explained in all of its parts in order to let them know what their tasks consisted of, and to let them grow accustomed with the procedure. In particular, the participants were instructed on the procedure they had to follow for the data acquisition once the sensors had been placed, so that they could also start getting used to the sensors' presence.

2.1.3 Assessment

As it was addressed in Section 1.2, human affective states are influenced not only by environmental stimuli, but also by several subjective characteristics. In particular, personality traits strongly condition the affective responses of the person [Kehoe et al., 2012] and [Subramanian et al., 2016].

To profile an aspect of human personality that could be related to the defensive reaction to preserve safety while crossing a street, the Rosenberg Self-Esteem questionnaire [Rosenberg, 1962] was introduced into the experiment. This survey was selected in order to assess the person's self-esteem and to acquire data that could prove useful in understanding if people with different profiles react differently when faced with the crossing task.

Furthermore, to better correlate physiological responses to safety perception and different environmental conditions, an ad-hoc self-assessment custom questionnaire about the crossing task was also designed to be proposed after the crossing tasks.

Rosenberg Self-Esteem Questionnaire

This survey measures the appreciation and confidence that a person has towards him/herself. The subject needs to say how much he/she agrees with the presented sentences on a Likert scale, which goes from 1 (Absolutely not) to 4 (Absolutely yes). In particular, the items of this questionnaire are the following:

1. I feel that I'm a person of worth, at least on an equal plane with other.
2. I feel that I have a number of good qualities.
3. All in all, I am inclined to feel that I am a failure
4. I am able to do things as well as most other people.
5. I feel I do not have much to be proud of.
6. I take a positive attitude toward myself.
7. On the whole, I am satisfied with myself
8. I wish I could have more respect for myself.
9. I certainly feel useless at times.
10. At times I think I am no good at all.

Custom Crossing Task Questionnaire

This questionnaire is used to collect subjective perception about the crossing task, such as the stress level of the participant, his/her confidence in drivers, disturbing elements etc. The participant needs to classify every item of this survey as NULL, LOW or HIGH. The items of this questionnaire are the following:

1. Stress level during the crossing.
2. Confidence level towards the cars during the crossing.
3. Interference level brought by other means of transportation during the crossing.

4. Influence level brought by other pedestrians.

5. Confidence level in the crossing without traffic control or traffic lights.

6. Confidence level in the crossing with disturbing elements (parked cars, partially blocked view etc.).

2.1.4 Experimental Protocol

The experimental protocol designed for the experiment was composed of four main parts: the Rosenberg's questionnaire filling, the walking task, the crossing task and the assessment questionnaire filling. While the first questionnaire was compiled only at the beginning of the experiment, given its goal of recording aspects of the participants that were not going to change because of the tasks, the other three parts that composed the core of the experimental session were repeated four times by every subject, each task divided from the next by a 30 second baseline recording in which the participant had to remain standing still.

The entire experimental protocol, that was performed when already on the site of the trials, is extensively explained as follows:

- Questionnaire filling: Rosenberg Self-Esteem Scale
- Sensor placement on subject
- Sensor testing
- Experiment Core: repeated 4 times
  - Walking on sidewalk (non-stressing task), as depicted in Figure 4. The lengths covered by the subjects during the walking task was designed to equal the length covered while crossing up and down the street during the crossing task, so that the two could be comparable in terms of travelled distance.
  - 30 seconds baseline recording, where the subject had to stay straight up and still to record his/her physiological response in absence of tasks.
  - Crossing the road and coming back at the start point (stressing task), as depicted in Figure 5.
  - 30 seconds baseline, same as before, also intended to bring the subject back to a *neutral* state before the next crossing.
  - Crossing questionnaire filling.
- Sensor removal from subject

Figure 4: One of the involved subjects during one of her walking tasks on the selected sidewalk.

Figure 5: One of the involved subjects during one of her crossing tasks on the selected zebra crossing.

- End of trial

The experiment had a total duration of approximately 20 minutes, an understandable length since the subject, for their crossings, had to wait for cars to show up and approach the intersection.

In order to better understand the participant's behaviour, also, this experiment was filmed with a full HD camera in order to record the subjects' behaviour during the various tasks. Every participant gave consent to the recording of their crossings.

2.1.5 Physiological Data

In order to measure the participants' condition during the experiment, the sensors chosen for the task were selected aiming at recording the significant physiological responses of the participants. This brought to focus on three different signals in particular: the Galvanic Skin Response (GSR), also known as Skin Conductance (SC), which is often regarded as a reliable and widely used arousal indicator; the Photoplethysmography (PPG), which is also a widely used measure for arousal; and the Electromyography (EMG), measured in this case as surface electromyography, which can provide useful information about the subjects' muscle activity and walk.

As it was previously stated in Section 1.2, these physiological signals are some of the most used in the literature concerning affective recognition, and researchers have also started using them specifically for stress recognition given their reliability in this area [Setz et al., 2009], [Shi et al., 2010], [Sano and Picard, 2013], [Hernandez et al., 2011]. On the other hand, regarding the EMG signal, it can be effective in defining pace and speed of the pedestrians, and can be correlated to the affective categories of subjects obtained from the analysis of physiological signals (PPG and GSR).

In order to properly record these three signals, two different sensors from the Irish company Shimmer [shi, 2022] have been adopted: the Simmer3 GSR+ unit, tasked with recording both GSR and PPG data, and the Shimmer3 EMG unit. These low-cost wearable sensors were already utilized in different experiments concerning physiological signals analysis and affective state recognition with encouraging results [Burns et al., 2010].

Figures 6a and 6b show how the aforementioned sensors were worn by the subjects during the experimentation: the GSR electrodes were placed on two fingers of the non-dominant hand of the subject, the PPG light-emitting diode was placed on an earlobe, and the EMG electrodes were placed on the leg, measuring the muscle activity of the medial gastrocnemius muscle and of the anterior tibial muscle.

Because of how these kinds of sensor work, though, some restriction to the subjects' mobility had to be involved. During the experiment, in fact, the participants were asked to move their arms as little as possible, since movement noise can be of great disturbance in recording GSR and PPG data, especially with finger electrodes, both because of the movement itself and of the poor sensor adherence that such motion could facilitate.

As a last note on the matter, a problem emerged during the in-vivo data acquisition: because of the very low temperatures registered during the trial of three of the participants, the GSR+ sensor encountered some difficulties recording the GSR and PPG signals, thus rendering those three recordings unusable for the final analysis. This likely happened because the GSR+ sensor has an optimal temperature range of acquisition between 20°-28°C in order to function properly, while the registered temperatures during those days were around 8°-10°C.

2.1.6 Signal Preprocessing

The raw signals obtained during the experimentation needed to be preprocessed and cleaned, and proper features needed to be extracted from the signals, before performing the analysis. This, of course, since the original recordings performed during the experiment could contain noise and artifacts brought by the environment, the sensors and the subject, that could throw off the results.

The GSR and PPG signals were sampled with a frequency of 128Hz, while the EMG signal with

(a) One of the subjects wearing the GSR and PPG sensors.

(b) One of the subjects wearing the EMG sensor on the dominant leg.

Figure 6: Images showing the utilized sensors positioned on the arm and leg of the experiment participants. As it can be noticed from Subfigure 6a, the PPG sensor was not placed on the hand, but it was placed as a clip on the earlobe of the subjects.

a frequency of 512Hz. The preprocessing was then slightly different for the two types of data: for the GSR and the PPG filtering step, a zero-phase filter was used in order to properly remove the noise and the possible high-frequency artifacts that could be expected; for the EMG, on the other hand, a zero-lag Butterworth bandpass filter with a cut-off frequency of 20Hz was used. Examples of GSR and EMG raw and processed signals can be seen in Figures 7 and 8.

The filtered signals were then all normalized with a z-score function, so that all of the signals of all the participants could be properly compared in a same reference range, and were then split into different segments following the markers directions registered during the experimentation. This way, for every subject, a total of 21 segments coming from the initial recordings was obtained, divided into:

- 4 crossing segments

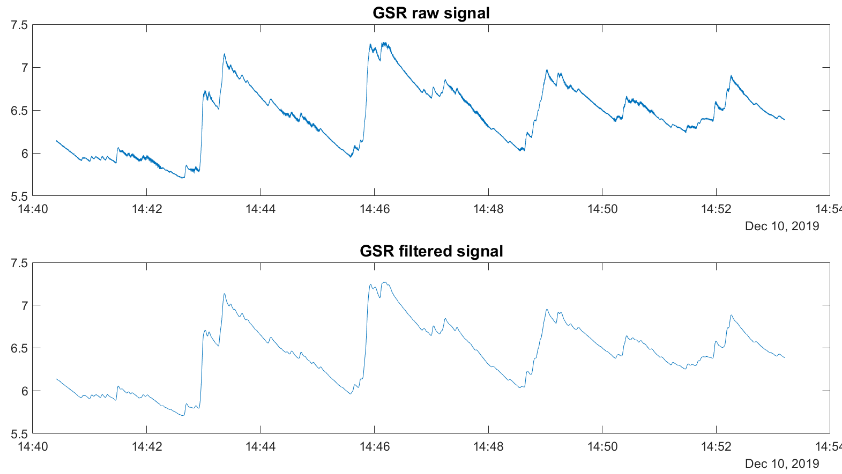


Figure 7: Example of raw (upper box) and filtered (lower box) GSR signal.

- 4 walking segments
- 8 (4 + 4) baseline segments
- 5 questionnaire segments

After this step, all of the signals were displayed overlapping with the markers that were placed during the sessions, obtaining for every of the remaining 11 participants a graphic similar to the one displayed in Figure 9 that could clearly depict the subject's physiological response for the entire duration of the experiment.

With such a visualization, every performed task can be easily distinguished along the physiological responses recorded through the task itself. It is already fairly clear how the muscle activity can be correctly acquired and differentiated by the EMG signal, given how periods of walking and crossing are very different from periods of standing and baseline, and the GSR peaks in skin conductivity and activation correspond to the crossing periods that could be expected from such a structure of the experimental procedure.

The event markers that were previously mentioned were created ad-hoc beforehand to be used during the experiment. Every marker correspond to a different phase of the experimentation, and they are differentiated by their heights. The height-marker correspondence, that can also be easily noticed in Figure 9, is the following:

- **Y = 2:** Questionnaire period (Q)
- **Y = 4:** Walking period (W)

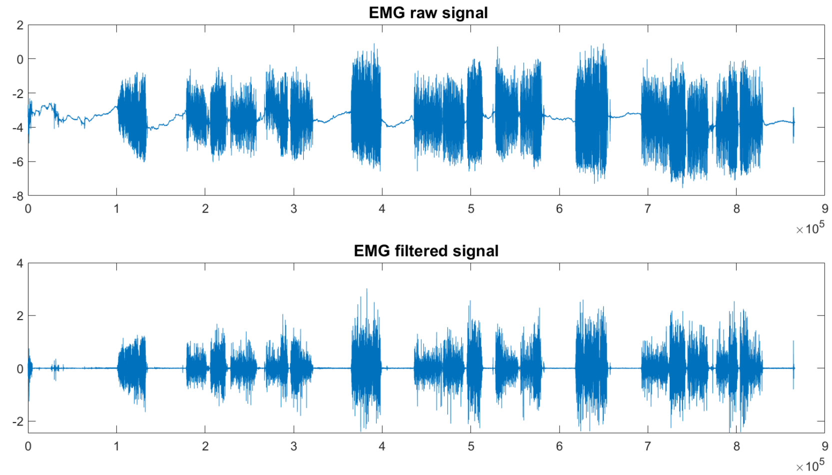


Figure 8: Example of raw (upper box) and filtered (lower box) EMG signal.

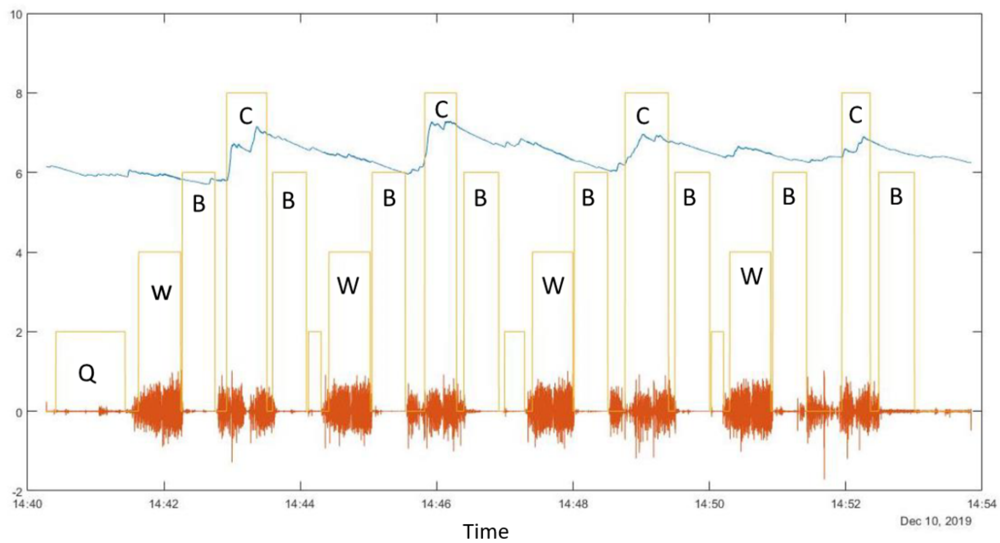


Figure 9: The graphic depicting the signals and the markers of a single participant. The orange track depicts the EMG signal and the blue one the GSR signal. Q indicates the Questionnaire periods (missing in the smallest windows), W the Walking periods, B the Baseline periods and C the Crossing periods.

- **Y = 6:** Baseline period (B)
- **Y = 8:** Crossing period (C)

Features	**GSR**	**PPG**	**EMG**
Max value	X	X	
Min value		X	
Mean	X	X	
Absolute Mean Value			X
Root Mean Square			X
Variance	X	X	
Mean Peak Height	X	X	
Peaks Area	X		
Peaks Rate	X	X	
Frequency Mean			X
Regression Coefficient	X		
IBI		X	
RMSSD		X	

Table 2: Table summarizing all of the selected features that were computed for the three analysed physiological signals.

2.1.7 Features Extraction

After some consideration regarding the analysed tasks and the physiological data recorded from the experiment, a total of 13 different features were listed to be calculated from the acquired data. Table 2 shows all of the selected features together with the signals they were computed for in order to perform the results analysis, since some of them were, for example, signal-specific: the IBI (Inter-Beat Interval) and the RMSSD (Root Mean Square of the Successive Differences) [Stein et al., 1994] are, in fact, specific features only applied to heartbeat measures.

The main thing that needs to be addressed is that, while the PPG and the EMG signals could be directly used for features extraction after the applied preprocessing, in order to correctly compute the features for the GSR it was necessary to separate the two different components of this signal: the Skin Conductance Level (SCL) and the Skin Conductance Response (SCR).

The SCL comprises all of the low frequencies of the GSR signal, thus giving the general trend of the signal, while the SCR includes all of the high frequencies and shows clearly all of the peaks that can be categorized as "natural peaks" or "elicitation peaks". In particular, these peaks are particularly relevant in the presented analysis, since they highlight the person's physiological response to external events and elicitations.

In order to do this, the SCL was derived from the processed GSR signal by using a low-pass filter at 0.05Hz, thus obtaining the *tonic part* of the GSR, and the SCR was then derived using a high-pass filter with the same frequency, thus generating the GSR *phasic part*. This distinction can be easily seen in Figure 10, presenting the initial signal and the result of the two different filtering processes.

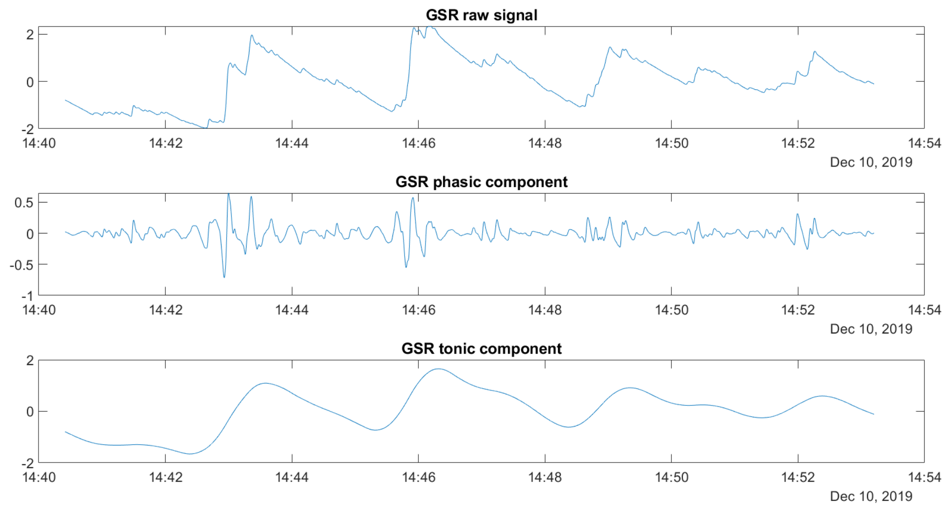


Figure 10: An example of GSR signal (upper box) with its phasic part (middle box) and its tonic part (lower box).

All of the GSR features were calculated from the phasic part of the various GSR signals whit the exception of the Regression Coefficient, which was obtained from the tonic part since it contained the necessary information about the signal slope.

2.1.8 Rosenberg's Questionnaire Analysis

The first step to be taken, after processing the data that the experiment allowed to gather, was to observe the results obtained from the Rosenberg's Questionnaire that was presented to the participants before they approached the walking tasks. This was done in order to understand if the obtained results would need to be addressed by taking into consideration differences inside the population that weren't previously taken into account.

Looking at the results obtained from the Rosenberg's Self-Esteem Scale, though, what was understood about our subject sampling was that all of the participants had a very good self-perception, tending to approach in a serene way new tasks given them. This was to be expected since, as it was said before, the subjects that were taken into consideration were young students in good health. Other than putting them all at the same level in approaching the designed experiment, the results also confirm the homogeneity of the population considered in the experimentation, thus reducing the variables to be considered when investigating the physiological results.

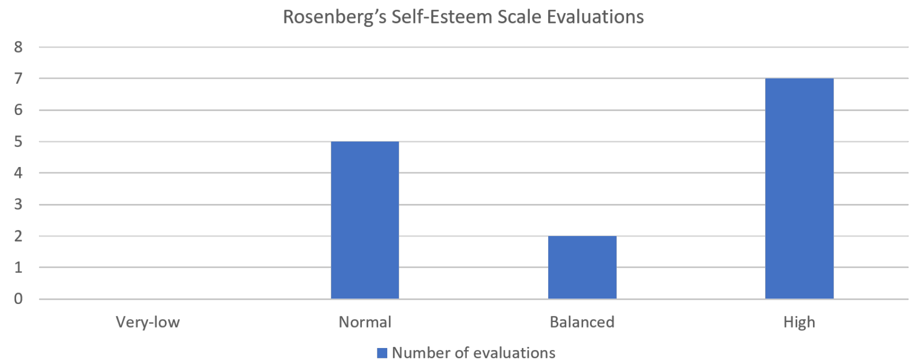


Figure 11: The results obtained from the Rosenberg's Questionnaire analysis.

2.1.9 Data Comparison Analysis

After observing the Rosenberg's questionnaire results, one of the first analysis performed on the obtained features was a Kruskal-Wallis test, a non-parametric method to assess the equality or the diversity of two groups medians. In this case, in fact, the goal was not to interpret the gathered signals and measures to understand what tasks a person was experiencing, which would have been a much difficult object to study because of how people are intrinsically different and because of how the interpretation of physiological signals can also lead to erroneous conclusions, but the test was performed in order to understand if the physiological feature distributions coming from different tasks recorded during our experimentation were statistically different. The testing then involved distributions belonging to the baseline, walking and crossing phase of the experiment to check their present or absent statistical difference, thus corroborating or dismissing the hypothesis that the physiological response of a subject can differentiate between different affective states of the person.

The Kruskal-Wallis test was chosen after verifying that the obtained data did not belong to a normal distribution, thus rendering the utilization of other tests, such as the ANOVA (ANalysis Of VAriance), not suitable for the analysis.

In particular, the Kruskal-Wallis test provides a null hypothesis, for which two distributions provided as input are similar enough to be considered as coming from the same initial distribution. If the returned result of the test, the *p-value*, is lower than a certain significance level, the null hypothesis is rejected and the two input distributions are deemed as statistically different and thus diversifiable. In this specific analysis, then, the goal was to obtain low p-values, particularly falling below the threshold that was put at $\alpha = 0.05$, in order to confirm that physiological features differed while in different states.

The first test that was performed was about comparing the features distributions of the Walking tasks with the ones from the Crossing tasks, and table 3 shows the obtained results.

Kruskal-Wallis p-values: Walking-Crossing Comparison			
Features	**GSR**	**PPG**	**EMG**
Max value	0.0016	0.4945	//
Min value	//	0.1629	//
Mean	0.0012	0.3812	//
Absolute Mean Value	//	//	<0.001
Root Mean Square	//	//	<0.001
Variance	<0.001	0.3359	//
Mean Peak Height	<0.001	0.7655	//
Peaks Area	0.0011	//	//
Peaks Rate	0.0026	0.3918	//
Frequency Mean	//	//	0.4414
Regression Coefficient	<0.001	//	//
IBI	//	0.376	//
RMSSD	//	0.6373	//

Table 3: Table showing the results of the Kruskal-Wallis test comparing the feature values of the walking tasks with the ones from the crossing tasks.

The green values highlighted in the table are the ones that were lower than the significance level previously selected. In this case, almost half of the performed tests comparing feature distributions from different activities were found to be statistically diverse, and these results corroborate the hypothesis that different walking conditions such as crossing in the presence of vehicles or walking on the sidewalk, related to different safety perception, induce different uncontrolled physiological reactions in pedestrians.

A similarly evident result, albeit maybe more predictable, was also achieved as the comparisons between Crossing and Baseline and between Walking and Baseline were carried out, whose Kruskal-Wallis test results are reported in Tables 4 and 5.

The low p-values obtained from these comparisons highlight even more how the selected physiological signals recorded very different reactions coming from the participants during the different tasks of the experiment, showing even clearer statistical differences between the data obtained during the resting phases as opposed to the data recorded during movement.

Another thing that emerges from the analysis of the above mentioned tables is that the PPG and the EMG signals do not seem to be really correlated to an affective state, but rather they seem to be more connected to movement in general: comparing Table 3 with Tables 4 and 5, in fact, it is clear that the distributions coming from the walking and crossing tasks for these two signals, for the PPG in particular, seem more similar than in the other two cases, thus not passing the Kruskal-Wallis test for more than one feature.

Kruskal-Wallis p-values: Crossing-Baseline Comparison			
Features	**GSR**	**PPG**	**EMG**
Max value	<0.001	0.0232	//
Min value	//	0.0157	//
Mean	<0.001	0.1333	//
Absolute Mean Value	//	//	<0.001
Root Mean Square	//	//	<0.001
Variance	<0.001	0.0017	//
Mean Peak Height	<0.001	0.1358	//
Peaks Area	<0.001	//	//
Peaks Rate	0.0026	0.0833	//
Frequency Mean	//	//	0.0031
Regression Coefficient	<0.001	//	//
IBI	//	0.1039	//
RMSSD	//	0.2942	//

Table 4: Table showing the results of the Kruskal-Wallis test comparing the feature values of the crossing tasks with the ones from their related baseline.

Kruskal-Wallis p-values: Walking-Baseline Comparison			
Features	**GSR**	**PPG**	**EMG**
Max value	0.0181	0.1237	//
Min value	//	0.8024	//
Mean	0.0162	0.7876	//
Absolute Mean Value	//	//	<0.001
Root Mean Square	//	//	<0.001
Variance	0.0123	0.2769	//
Mean Peak Height	0.0207	0.1039	//
Peaks Area	0.0041	//	//
Peaks Rate	0.2209	<0.001	//
Frequency Mean	//	//	<0.001
Regression Coefficient	0.0127	//	//
IBI	//	<0.001	//
RMSSD	//	0.8099	//

Table 5: Table showing the results of the Kruskal-Wallis test comparing the feature values of the walking tasks with the ones from their related baseline.

2.1.10 Assessment Questionnaire Analysis

After the signal analysis, it was also decided to perform a sample checking analysis in order to better understand what impression of the crossing task the participants had. Therefore, the first thing that was done was to gather all of the custom questionnaire answers for all of the subjects and all of their crossing tasks, thus obtaining a total of 56 answers to every question. From this set the percentages of NULL, LOW and HIGH answers given by the participants were then computed, obtaining the graphic that can be seen in Figure 12.

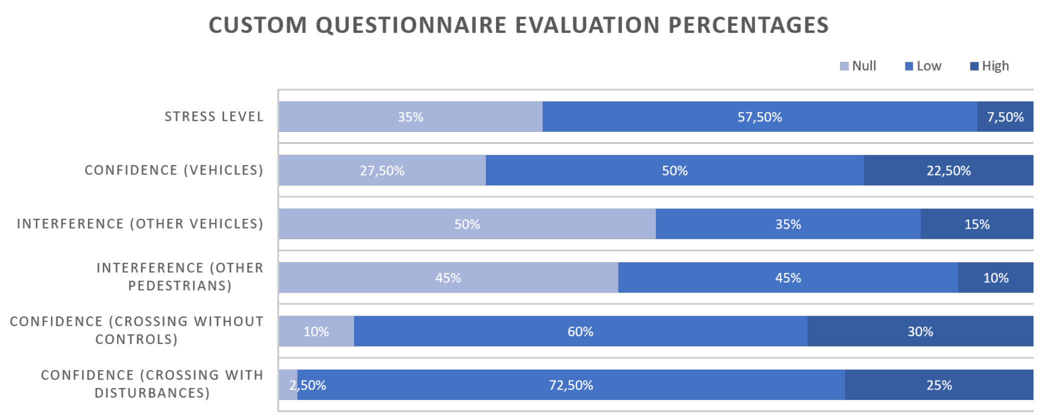


Figure 12: Answer percentages for every evaluation category obtained for the custom questionnaires about the crossing experience of our subjects.

As it can be noticed, the majority of the crossings delivered low to null stress to the subjects, and only a few high stress levels were reported through the custom questionnaires after the task. This data is not unexpected since, as it was previously highlighted as the experimental population was introduced, the subject sample for this experiment was narrowed down to healthy and young students who are also accustomed to crossing this particular intersection while walking through the university campus. Having to face a challenge that was already familiar to them may have let them perceive the task as not as dangerous as it could have been for someone who never saw or walked through that intersection before.

Figure 13, on the other hand, shows the correlation matrix obtained by checking the relations between the answers, a test performed using Pearson correlation index. From left to right, and from low to high, these categories are considered: Stress Level, Confidence (Vehicles), Interference (Other Vehicles), Interference (Other Pedestrians), Confidence (Crossing without Controls), Confidence (Crossing with Disturbances).

The highest Pearson correlation coefficient (0.4574) is between Confidence (Crossing without Controls) and Confidence (Crossing with Disturbances): this can mean that many participants were

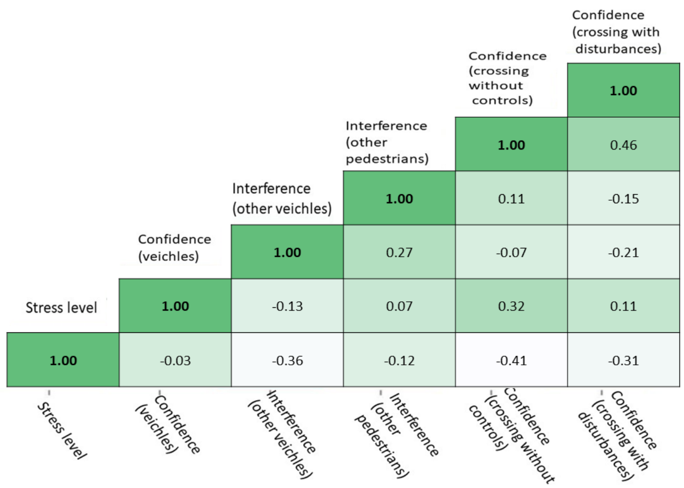


Figure 13: Pearson correlation matrix between the answers of the self-assessment questionnaire.

less confident in crossing the street for both these factors. The lowest Pearson correlation coefficient (-0.4089), on the other hand, is between Stress Level and Confidence (Crossing without Controls).

Even if from the self-assessment questionnaires emerges that the subjects involved in the experiment were not particularly stressed by the crossing tasks, the physiological data clearly shows different patterns with respect to the different activities as well as differences in the feature distributions that are statistically significant, constituting important hints towards the uncontrolled affective reactions of subjects in the pedestrians-vehicles interaction.

2.2 T1 - Cantù Experiment

Following what was done in the crossing experiment described in Section 2.1, in order to have the possibility to compare the young-adults behaviour regarding vehicles with a different population, a similar experiment was conducted with an elderly population was conducted in the city of Cantù [can, 2022], a Lombard town of about 40,000 inhabitants located at the foot of the Como pre-Alps with a conformation following the one of a medieval town, with numerous and narrow uphill streets. The same experimental core involving walking and crossing tasks was maintained, in order to recreate as close as possible the situation previously observed with university students.

Ethical Committee Approval: The experiment here presented was performed after an ethical committee approval, in compliance with the Ethical Committee of the University of Milano-Bicocca.

Collaboration: The experiment here presented was performed with the assistance and collaboration of the local branch of the Auser association [aus, 2022], an italian voluntary organization that promotes active and healthy ageing in the elderly population and which concerns itself with initiatives and services targeted at caring for and promoting the experiences and values the elderly can bring to others.

Auser provided a thorough consultation regarding the spaces to be used, helped with the recruitment of the experimental population and made spaces available to perform the initial questionnaires and sensors check.

2.2.1 The Environment

Given the premises under which this experiment was designed, it was first and foremost important to choose an environment that could be comparable to the one selected for the Bicocca crossing experiment. Auser Cantù then helped in identifying a location, not too far away from its offices, that could present conditions similar to the one already identified for the first experiment.

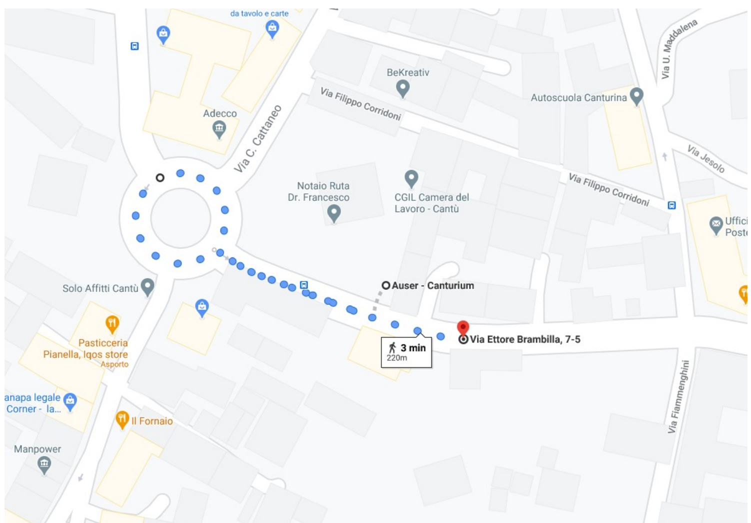


Figure 14: The map showing the distance of the selected crossing from the Auser offices that were utilized as base for the participants and the static part of the experiment.

The chosen environment contemplated an unsupervised crossroad right after a roundabout on a two-way road, a busy street situated at a couple minutes walk from the Auser offices (Figure 14). Similarly as the zebra crossing for the Bicocca experiment, this crossing too was unsupervised and experienced heavy traffic during the day by all types of vehicles (Figure 15). This, the restricted visibility given by parked cars and buildings around the road and the complete absence of regulations for both vehicles and pedestrians rendered the chosen crossing perfectly suitable for the experiment.

The environment also presented a long enough sidewalk to be used for the walking part of the

Figure 15: Images showing the usual traffic on the street chosen for the experiment. Heavy and large vehicles often use that road and roundabout despite the limited space and visibility which characterize the spot.

experiment (Figure 16), thus allowing enough space to perform every task in the experimental procedure without moving too far away from Auser offices and the selected crossing.

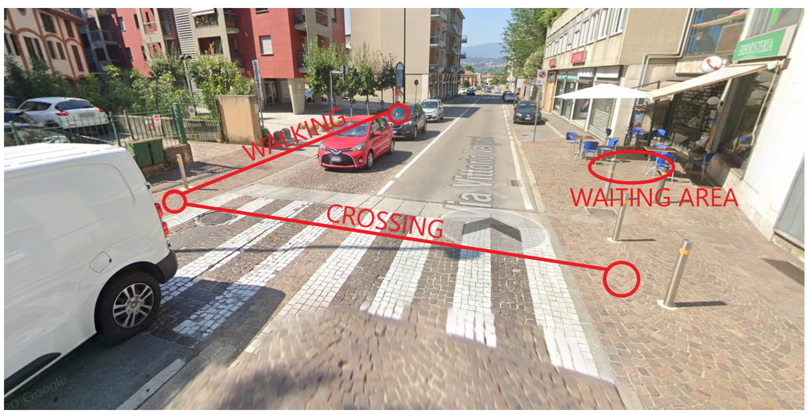


Figure 16: The intersection chosen for the experiment, with highlighted the path the participants would have walked on for both the walking and the crossing tasks.

2.2.2 The Subjects

As previously mentioned, the subjects participating in this experiments were volunteers recruited with the help of Auser Cantù among its volunteers and regular visitors. A total of 22 elderly participants were recruited for the trials, divided between 10 males and 12 females aged between 60 and 82 years (average age = 70.23 years). All of them were regular visitors of the Auser structure, both for courses offered by the association or for trips and other initiatives brought by the volunteers.

At the same time they were also all accustomed to Cantù, as all of them lived in the city, and knew well the chosen intersection given its vicinity to the Auser offices.

The subjects all previously participated to a preliminary presentation of the experiments, as to understand how it was to be structured and the finality of it, and all provided informed consent before participating. The entire procedure was then explained them again the day of the experiment, together with the usage of the sensors that were going to be implemented in the trials.

Moreover, in order to guarantee anonymity, a unique ID was assigned to every participant so that the questionnaires and data could not be traced back to a precise name but could still be properly associated when analysed.

2.2.3 Assessment

Since the tasks scheduled for the experiment were the same involved in the Bicocca crossing experiment, the Rosenberg Self-Esteem Questionnaire and the custom crossing questionnaire were proposed to the elderly participants in the same way.

In addition to the Rosenberg scale, though, other two questionnaires were proposed to the subjects at the beginning of their experimental sessions: the STAI-Y, a questionnaire regarding the measurement of anxiety, and the BIG5, which is a questionnaire measuring the personality traits following the OCEAN five factors (Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism).

These two questionnaires were added to the procedure, after they were not contemplated into the procedure of the first iteration of the crossing experiment, in order to gather more information regarding the psychology of every subject to later try and correlate those information with the acquired physiological responses.

2.2.4 Experimental Protocol

In order to follow as close as possible the experimental procedure already implemented in the Bicocca crossing experiment, the protocol designed for the Cantù experiment strongly resembles the one presented in Section 2.1, together with the presence of the four main parts previously highlighted. In this case, also, the parts concerning the walking, crossing and assessment questionnaire tasks that composed the core of the experimental session were repeated four times by every subject, in order to have the same amount of data for the young-adult population and for the elderly one.

The only differences from the original procedures regard the navigation steps from and to the Auser offices, since the preparation phase for the participants could not be performed directly at the site of the experiment, and the longer baseline recordings, that were extended from the previously set 30 seconds in order not to have the elderly participants rush from a task to the other.

Also, given how the experiment was performed when COVID-19 regulations were still active in all of Italy, the experiment was performed with all the personnel involved wearing masks and following safety instructions regarding distances and hygiene, conditions that the first experiment did not need complying to.

The experimental procedure is extensively presented as follows:

- Preparation phase: done at Auser Cantù offices
  - Questionnaire filling: BIG5, STAI-Y and Rosenberg Self-Esteem Questionnaire
  - Sensor placement on subject
  - Sensor testing with 60 seconds baseline recording, where the subject had to stay straight up and still to record his/her physiological response in absence of tasks.
- Navigation to experimental environment
- Experiment Core: done at the selected intersection, repeated 4 times
  - Walking on sidewalk (non-stressing task).
  - 60 seconds baseline recording, same as the one recorded during preparation.
  - Crossing the road and coming back at the start point (stressing task).
  - 60 seconds baseline, same as before, also intended to bring the subject back to a *neutral* state before the next crossing.
  - Crossing questionnaire filling.
- Navigation back to Auser offices
- Sensor removal from subject
- End of trial

2.2.5 Physiological Data

As it had already been the case for the Tokyo experiment described in Section 2.3, the physiological signals that were chosen to record the participants' conditions were the same already used for the Bicocca crossing experiment, even more so since the experiment was purposefully designed to mimic the one already performed with the younger population. The selected signals for this experiment, then, were still the Galvanic Skin Response (GSR), the Photoplethysmography (PPG) and the surface Electromyography (EMG).

(a) Image depicting how participants wore the GSR+ Shimmer sensor during the experiment.

(b) Image depicting how participants wore the EMG Shimmer sensor during the experiment.

Figure 17: Images showing the utilized sensors positioned on the arm and leg of the experiment participants. As it can be noticed from Subfigure 17a, the PPG sensor was not placed on the hand, but it was placed as a clip on the earlobe of the subjects.

2.2.6 Results

Given the need to carefully process the data obtained from the experiment, strongly influenced by the environmental noise and by the poor reception of the signals (the high temperature registered during the day chosen for the experimentation caused the sensors to adhere inadequately to the participants skin), and the high volume of questionnaires to be logged and processed in order for the questions' results to be correlated with the physiological information of the subjects, the data coming from this experiment still need to be properly analysed and compared to the data previously gathered through the Bicocca crossing experiment.

2.3 T2 -Tokyo Experiment

Aimed at investigating the interactions between pedestrians and moving obstacles, a laboratory experiment was designed and executed at the Research Center for Advanced Science and Technology laboratory of the University of Tokyo.

The experiment was performed in two different sessions, one involving a young adult population of university student and the other involving elderly people. Both the sessions were performed into the same environment and following the same procedure, thus allowing to acquire comparable data on the way pedestrians belonging to the two populations approached obstacles while walking.

Ethical Committee Approval: The experiment here presented was performed after an ethical committee approval, in compliance with the Research Ethics Committee at The University of Tokyo, Japan (No. 19-283 and 19-376).

2.3.1 The Environment

A controlled laboratory belonging to RCAST was the chosen environment for the execution of the experiment, with its space properly organized in order to accommodate all the tasks envisioned by the designed procedure.

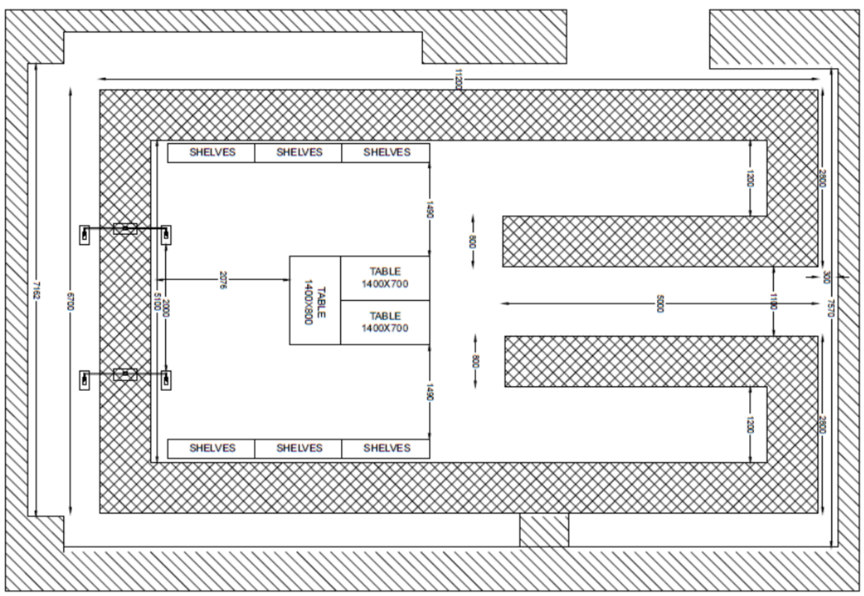


Figure 18: The experimental setup of the room utilized for the experiment. It was organized with the valuable contribution of Architect Matteo Belfiore, who helped design the "heart path" the subject were to walk on during the experiment.

The desks located in the middle part of the environmental setting accommodated the researcher station with the system to which the sensors used by the participants were connected, while the path drawn along the room was the trail used to carry out the walking tasks planned in the experimental procedure. The map displayed in Figure 18 highlights both the lanes the participants had to follow, with the available space and the number of sensors allowing for two participants to perform the experiment at the same time, and the position of the obstacles they had to deal with during one of their tasks.

2.3.2 The Subjects

As it was briefly mentioned in the section introduction, two different groups of subjects were involved in the experiment: a population of young adults, composed of 16 Japanese master and PhD students (average age = 24.7 years, standard deviation = 3.3, 4 women), and a population of Japanese elderly people, composed of a total of 20 participants (average age of 65.15, standard deviation = 2.7, 10 women). All the subjects were healthy, with no reports of diseases or mental illnesses that could have made them unsuited for the experiment.

The two populations participated in the experiment in two different moments in time, following sessions purposely aimed at observing one group at a time: the first session involving the university students was executed in November 2019, while the second one with the elderly group was performed in February 2020. Despite being performed in two different moments in time, though, the experiment remained the same for both the populations, and all the participants performed the same tasks defined by a previously designed experimental protocol.

2.3.3 Assessment

Given the simplicity of the walking tasks envisioned for the experiment, and given how the entire procedure was to be executed in a controlled laboratory environment, there were no assessment questionnaires planned for the participants to answer after their trials.

At the beginning of the experimental session, though, they were asked to fill out a STAI-Y questionnaire, the same previously presented in Section 2.2, in order to have further information about them as they approached the experiment.

2.3.4 Experimental Protocol

The designed procedure for this experiment contemplated four main parts, each of them focused with a different task the participants had to perform before passing onto the next: the STAI questionnaire's filling, a collision avoidance task, a forced speed walk task and a free walk task. Given the structure of the walking tasks presented to the participants and the fact that the sequence including the active tasks is repeated three times per subject, the experiment had a variable duration, usually around 30 minutes considering every step followed by the subjects.

The experimental procedure is extensively illustrated as follows:

- **Subject's profiling** carried out filling the STAI questionnaires [Spielberger, 1983] lasting 3 minutes.

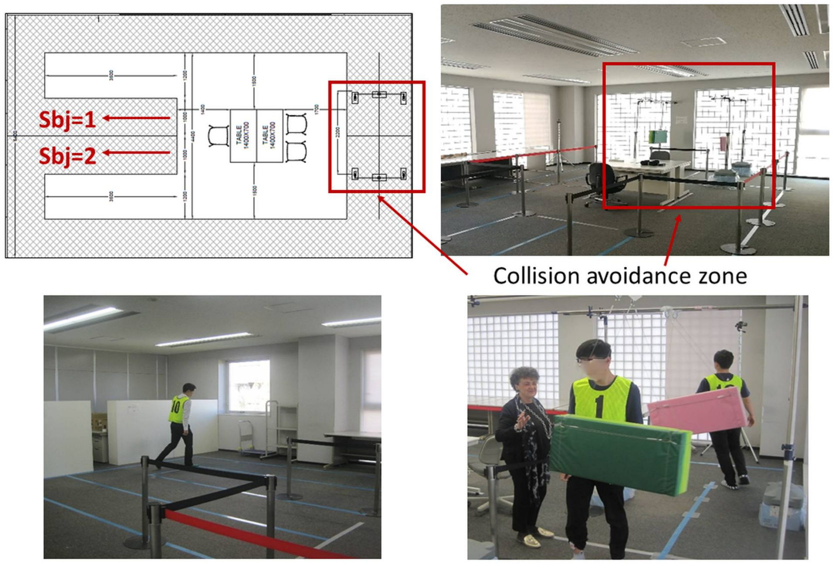


Figure 19: Figure showing participants performing the walking tasks of the second half of the experiment.

- **Collision avoidance**: two subjects, at the same time, walk with their own pace along the U path (Figure 19 top left). At about half of the path, they reach the collision avoidance zone where they have to avoid the collisions with both the obstacles (**Obs**), represented by two pendulums, and the other subject (Figure 19 top and bottom right). Then they complete the U path, with their natural pace (**WO**) and go back in the opposite direction repeating the same actions.
- **Baseline acquisition $\mathbf{B}_W$**, a 1 minute period of time in which the participants rest between a task and the other.
- **Forced speed walk**: the participants walk with a forced speed based on the metronome ticking. Three speeds in total are considered: 70 bpm (**F1**), 85 bpm (**F2**) and 100 bpm (**F3**).
- **Baseline acquisition $\mathbf{B}_W$**, a 1 minute period of time in which the participants rest between a task and the other.
- **Free walk (FW)**: the participants walk freely along the course, without constraints and following their own pace to complete the route. This particular task was only executed during the February session, with the elderly population.

2.3.5 Physiological Data

The physiological signals that were chosen to be acquired throughout the experiment in order to record the participants' conditions are the same that were already utilized for the crossing experiment previously presented. The selected signals for this experiment, in fact, are the Galvanic Skin Response (GSR), the Photoplethysmography (PPG) and the surface Electromyography (EMG), which was always positioned in order to obtain the muscle activity of the medial gastrocnemius muscle and the anterior tibial muscle.

Figure 20: Figure showing the sensors used throughout the experiment. The two images to the left show the GSR and PPG sensor (up) and the EMG sensor (down), while the central image and the right one show how the participants wore those same sensors during the experimental sessions.

During the whole experiment, as it was already done, the physiological signals were collected using wearable sensors from the Irish company Shimmer [shi, 2022]. In this experiment too, both the Simmer3 GSR+ unit and the Shimmer3 EMG unit were adopted, with Figure 20 showing how the experiment subjects wore them during the tasks. The PPG and GSR signals were collected using a sampling frequency of 128 Hz, while the EMG signals were acquired using a sampling frequency of 512 Hz.

2.3.6 Signal Preprocessing

After both sessions of the experiment were completed, the data was ready to be processed and prepared for the subsequent analysis. This passage was in fact vital to remove noise and artifacts from the signals that were recorded throughout the sessions, especially since the data was coming from two different populations: in order to properly assess possible differences between signals coming from university students and from elderly people, it was necessary to have the data as clean as possible, since anomalies and outliers could contribute in leading the investigation astray.

The first step in the preprocessing involved signal denoising. Each signal can be affected by different types of noise and artifacts, for example related to the characteristics of the environment (e.g., temperature of the room, electromagnetic interference), the experimental conditions adopted for the study (e.g., uncontrolled movements of the subjects, poor sensor contact against the subjects' skin) or even the influence of other physiological processes (e.g., the activity of neighboring muscles in the case of the EMG analysis [Sweeney et al., 2012]), and the raw signals collected during the experiment made no exception to this and appeared corrupted by noise and artifacts that could make them unusable or difficult to analyze.

In order to remove these artifacts, the PPG raw signals were pre-processed using a Multiresolution Wavelet Denoising Strategy described in [Gasparini et al., 2020c] and in [Biswas et al., 2019]. A similar denoising strategy based on Multiresolution Wavelet Decomposition was then adopted in pre-processing GSR signals, following the positive results achieved in [Chen et al., 2015], and given how in literature it is reported how the use of Multiresolution Wavelet Denoising Strategy appears promising in removing noise also from EMG signals [Phinyomark et al., 2009a, Wei et al., 2012] this same process was used for the obtained EMG data coming from the experiment (Figure 21.

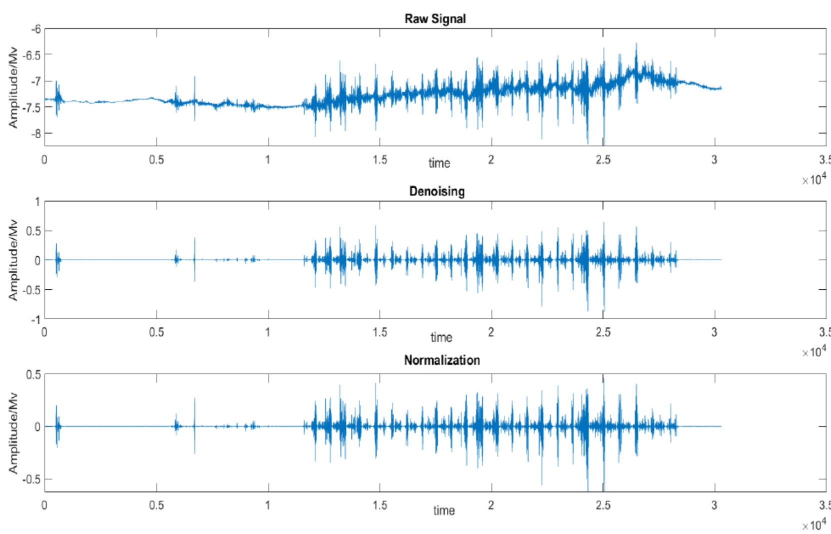


Figure 21: Figure showing a sample of an EMG signal before and after preprocessing. The upper image depicts the raw signal, the middle one shows the signal after denoising and, finally, the lower one shows the signal after normalization.

Signal denoising was then followed by a process of subject normalization: physiological signals, in fact, not only depend on the induced stimulus, but also on the subject's own characteristics. A proper normalization process is needed in order to reduce both inter and intra subjects heterogeneity, and every strategy was applied considering the signals related to each session separately.

Concerning the PPG, the amplitude of the whole subject's signal for each session was standardized by the application of the Z-score operation. Likewise, following the work in [Ganapathy et al., 2020], the GSR signal of each subject was also normalized in amplitude using the z-score function. For what concerned the EMG signals, on the other hand, the amplitude normalization was carried out dividing each channel of the denoised signal by the maximum peak activation value obtained from the signal itself. This strategy, described in [Halaki and Ginn, 2012], has been selected after an empirical analysis, as it appeared as the most effective method to reduce the inter-subjects variability.

Proceeding to the signal segmentation was the next step in the preprocessing pipeline. The data were acquired continuously during the experimental sessions, and thus it was necessary to apply a proper segmentation of the recordings in order to be able to identify and analyze each task performed by the participants. This segmentation was performed by adopting the markers that were introduced during the acquisitions through Consensys Pro, the proprietary software of the Shimmer devices. In particular, for each participant, the markers, which were manually recorded during the data acquisition phase, were used to determine the beginning and end of each task performed by the subject and, thus, used to cut the signals in shorter segments.

After the signal segmentation, another problem appeared regarding the normalization applied so far to the PPG signals. The process that was applied, in fact, allowed to uniform the signals concerning amplitude but it did not take into account the differences in the subjects' heartbeat that are more related to frequency. In [Avram et al., 2019], for example, it is reported how the heart rate frequency of a resting adult can vary in a range between 60 and 100 beats per minute depending on many different factors, both personal (e.g., age, sex, ethnicity, sports ability, diet, illnesses, prescribed medications, etc.) and environmental (e.g., humidity, temperature, etc.).

Because of this, only for PPG signals, the segmentation phase is followed by a frequency normalization phase in order to take into account frequency differences in subjects' heartbeat and reduce the heterogeneity in signals that these heartbeat differences introduce. The normalization is carried out using a new subjective resampling frequency calculated started from each subject's baseline heartbeat. Then each PPG signal, originally defined in a Discrete Time Domain (DTD), is mapped into a new Subject Normalized discrete Domain (SND) where all the subjects are normalized with respect to their heartbeat measure obtained in a resting state condition, as explained in [Gasparini et al., 2022].

2.3.7 Features Extraction

After the preprocessing step was concluded, it was possible to proceed with the features extraction phase. For each analyzed signal, several features were extracted in order to highlight significant characteristics that could describe the subject's physiological behavior during the different tasks that the experiment proposed them. In particular, for every recorded signal a certain set of features was selected, including statistical ones and signal-specific ones.

Considering the PPG signals, seven time-domain features were calculated:

- Four statistical features: Minimum, Maximum, Mean and Variance of the signal;
- Three peak related features:
  - Peak Rate, representing the mean number of peaks each 128 Subject Normalized Samples;
  - Inter Beat Interval (IBI), representing the mean distance between two peaks in a row;
  - Root Mean Square of Successive Distance (RMSSD), representing the variance of the distance between two peaks [Stein et al., 1994].

As it was already done for the crossing experiment, both Phasic and Tonic component time domain features were considered in handling the GSR features extraction. This time, though, the work of [Greco et al., 2015] was followed for the signal decomposition, obtaining from the GSR signal three different parts: the Phasic component, the Tonic component and the additive white Gaussian noise term incorporating errors and artifact. Disregarding the last extracted part containing only noise, then, several features were computed for the Phasic and Tonic components:

- For the Phasic component, eight statistical and peak related features were computed:
  - Maximum, Mean and Variance;
  - Peak Rate, representing the mean number of peaks per second;
  - Peak Area and Peak Area per Second, representing respectively the mean area under the peaks and the mean area under peaks evaluated per second;
  - Peak Height, representing the mean height of the peak detected on the Phasic component;
  - Rise Time (or also Onset-to-Peak Time) defined as the mean number of samples from the onset of the skin conductance response to the top of the peak ([Braithwaite et al., 2013, Boucsein, 2012]).
- For the Tonic component, only one feature was computed:
  - Regression Coefficient, representing the signal slope.

Regarding the GSR phasic features, it is necessary to bring forward some considerations about the detected peaks, since not all of them could be related to significant skin responses. Small changes in the signals, in fact, can also be due to negligible changes, sensor's movement, noise in the equipment or other experimental conditions. Thus, in order to keep only the most significant peaks into consideration, a fixed threshold of 0.02 μs has been set to filter the Peak Amplitude. This value was calculated as $0.005 * 2 * 2$ were the 0.005 was the selected threshold indicated in [Aqajari et al., 2020] while the others two terms *(2*2)* were connected to the use of z-scoring signal normalization whereas of the the min-max signal's normalization employed in [Aqajari et al., 2020]. Moreover, as an additional method of peak selection, a minimum peak distance threshold of 128 samples has been also considered, thus considering only the tallest peak in case of recorded distances shorter than the imposed value.

Finally, for EMG signals, two features were considered for the analysis:

- The mean power of the signal, calculated by the Root Mean Square [Phinyomark et al., 2009b]

  $$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{1}$$

  where x_n is the amplitude of the $n-th$ sample of the EMG signal, and N is the total number of samples;

- The walking frequency, known as Stride Frequency, evaluated in terms of number of steps per second and extracted as described in [Gasparini et al., 2020d].

Many of the data analyses here reported, consist in classification tasks aimed at recognizing the age of the subjects or the levels of arousal induced by the different tasks performed. In these analyses only the features related to PPG and GSR signals are considered. In particular, three different feature sets are taken into account during the classification tasks: features extracted considering only PPG signals, features extracted considering only GSR signals and the joining of PPG and GSR features. It is important to underline that all the features are standardized using z-score before using them as input to the different classifiers. For each experiment, this standardization is applied to the whole set of analyzed instances before splitting it into training and test set.

2.3.8 Walking Session Analysis

Given the data recorded during the experimental sessions, particular attention was given to all the physiological signals collected, especially given the different features to be analysed for all of them.

Walking behavior studying EMG data

The first physiological signal analysed was the EMG, starting with the data coming from the Forced Speed Walk task indicated in the experimental protocol.

During this task, participants were forced to walk at three specific speeds, dictated by a metronome played to a side. The subjects had then to repeat these forced speed walks three times in order to acquire more data for each of them.

In particular, the three metronome speeds selected were F1 = 70, F2 = 85 and F3 = 100 bpm (i.e., beat per minute), which corresponded respectively to 1.167, 1.417 and 1.667 step/second. But given how these values refer to the stride frequency made moving both the legs, and the EMG sensor used only measured the activity of one leg per participant, these frequency values needed to be halved to be compared with the values extracted by the proposed feature. The new frequencies used as ground truth were then 0.583 step/second for 70 bpm, 0.708 step/second for 85 bpm and 0.833 step/second for 100 bpm.

Regarding the analysed signals, on the other hand, a premise must be made: of the processed EMG signals, four of them related to the first channel of the sensor and two related to the second channel had to be removed due to low quality and absence of important information, thus leaving to compute the analysis on the remaining channels.

The metronome frequencies, together with the estimated Stride Frequencies for both populations, are reported in Table 6.

	Young	**Elderly**
Metronome	EMG	EMG
F1 = 0.58	0.59	0.66
F2 = 0.70	0.72	0.76
F3 = 0.83	0.85	0.85

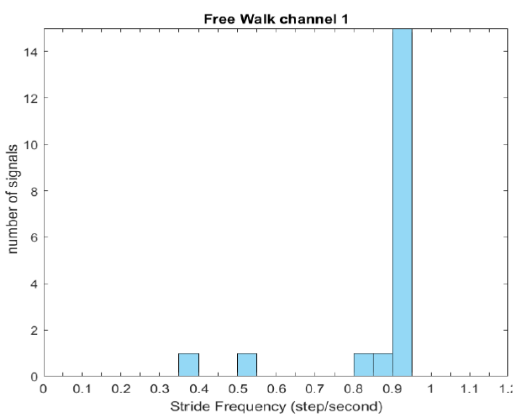
Table 6: The estimated Strides Frequency for both subject groups are reported and compared with the metronome frequencies (F1, F2 and F3)

Looking at the Strides Frequency values estimated from the EMG recorded during the forced speed tasks, elderly people seem to struggle more than young adults in order the metronome forced speeds. In particular, this behavior is observed mainly in the two lower speeds, F1 and F2 where the Strides Frequency values detected on the elderly signals appear usually higher than the metronome ticking.

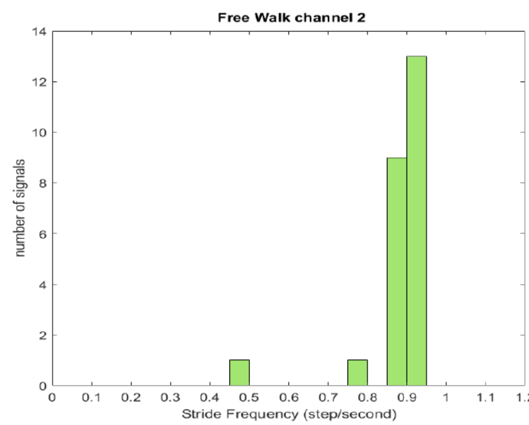
The same information can be drawn by looking at Table 7, where the number of times subjects were identified as matching the proposed frequencies are reported in percentages. Even looking at these values, it is clear to see how elderly participants found themselves out of rhythm more often than the young students of the first sessions: given the low values associated with their accordance to the walking frequency set by the metronome and the strides frequency showed before, it seems like the elderly subjects did not really manage to maintain the lower speeds in favour of frequencies more similar to their habitual walking speed.

	Gastrocnemius Muscle				*Tibial Muscle*			
	F1	**F2**	**F3**	**Total**	**F1**	**F2**	**F3**	**Total**
Young Adult	95%	90%	90%	*92%*	95%	90%	85%	*90%*
Elderly	57%	52%	89%	*66%*	68%	58%	92%	*72%*

Table 7: Percentage of times where subjects respected the metronome frequency, comparing both the populations and the different frequencies adopted. The first four columns are about signals acquired on the first EMG channel while the last four columns regard the signals acquired on the second channel.



(a) Stride Frequencies recorded on channel 1 (gastrocnemius muscle).



(b) Stride Frequencies recorded on channel 2 (tibial muscle).

Figure 22: Histograms of the stride frequencies calculated on the free walk task for both populations.

These findings find ground in what emerges from the analysis of the stride frequencies performed on the Free Walk task. The mean Stride Frequency detected, as it can be seen in Figure 22, is usually around 0.90 steps/second, a measure that is in complete agreement with the metronome frequency F3, with which the participants found themselves more in accordance in comparison to F1 and F2, and with the normal pace speed reported in the literature, which is usually between 0.90 and 1 steps/second as reported in [Ji and Pachi, 2005].

Passing onto the Collision Avoidance task, for its analysis a Stride Frequency evaluation and a signal energy analysis were performed.

To analyse changes in EMG signals during the stressful walking task related to collision avoidance, the signal was firstly divided into five segments using non overlapped windows. Segments 1, 3 and 5 refer to the free walking phases that preceded or followed the obstacle zone crossing, while segments 2 and 4 refer to the walking performed along the pendulum avoidance zone.

For both populations, when analyzing the obtained Stride Frequency values in the portions of the path away from the collision zone (i.e., segments 1, 3 and 5), values in the range [0.80 - 1] steps/second were obtained, which were similar to both the values reported by the literature in case of free pace and also to the ones detected during the free walk task of our experiment. However, when compared with these latter values, a greater variance was observed. These results, in any case, seem to imply that the pace of walking is not significantly influenced by the presence of an obstacle at another position along the path.

On the other hand, when evaluating Stride Frequencies in the portions of path corresponding to the obstacle areas (i.e., segments 2 and 4), changes of pace were identified, with values falling near to 0.37 step/second indicating a real deceleration or stop in the subject's walking.

To better understand how does the walking pace change within the collision avoidance zone, an analysis based on signal energy was then performed. This analysis, in particular, focused on the muscle power changes detected on the EMG signals through the RMS feature previously described.

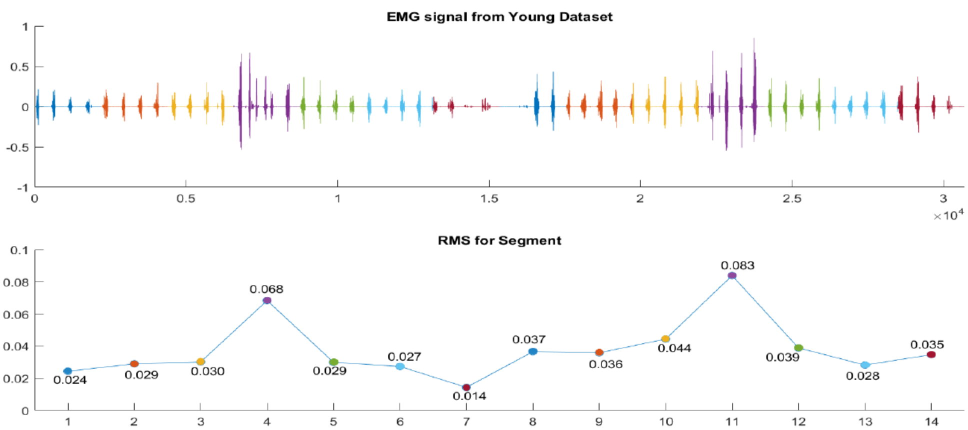


Figure 23: Analysis on a trial of collision avoidance task for one young subject. The signal has been divided into fourteen uniform windows (top row). Purple windows correspond to the collision avoidance events. Bottom row reports the trend of the energy values in different segments.

Analysing changes during the two phases that compose the task, namely the free walking phase before and after the collision avoidance zone and the crossing itself, allowed to identify a different behavior between young and elderly during the crossing.

When young adults were involved, in fact, it was usually noticed an increase of the signal power in correspondence to the collision avoiding events. This growth seemed due to a strong muscle activation, which was probably caused by the effort of the subject to accelerate in front of the obstacle and safely pass it without stopping to let it make space (Figure 23). Only in few cases (5 out of 42), participants decided to stop in front of the obstacle, and only one subject seemed to be able to pass the obstacle without changing its speed. The obtained results were then coherent with

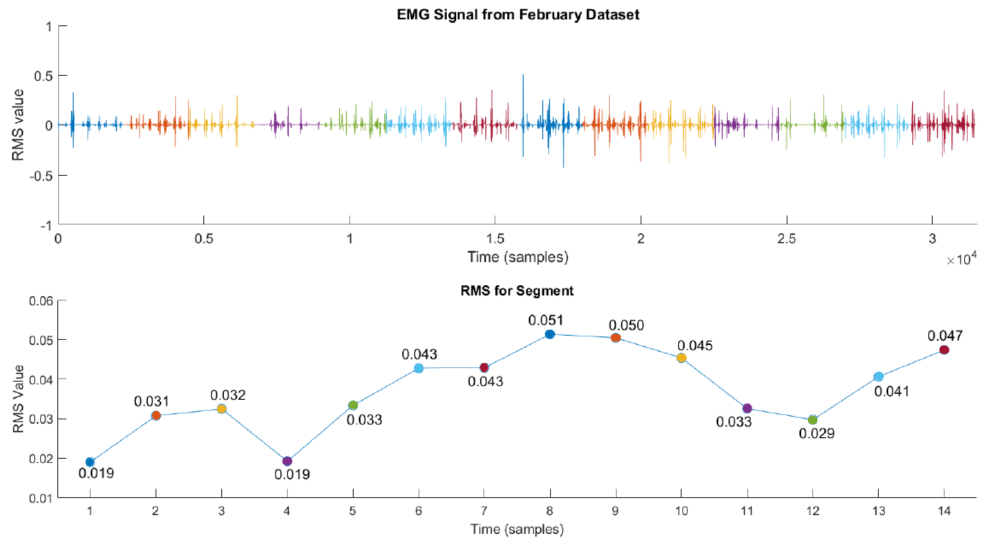


Figure 24: Analysis on a trial of collision avoidance task for one elderly subject. The signal has been divided into fourteen uniform windows (Top row). Purple windows correspond to the collision avoidance events. Bottom row reports the trend of the energy values in the different segments.

what was observed during the experiment, in which the young adults seemed less inclined to stop than the elderly.

Analyzing the power of the EMG signals for the elderly, on the other hand, in many cases (29 out of 37) led to observe a decreasing signal power during collision avoiding events (Figure 24). Such findings could be considered related to the observed evidence mentioned before, regarding participants decelerating or even stopping in correspondence of the obstacle area in order to wait for the pendulum to pass. This behaviour led to a reduction in the electrical discharge produced by the muscle, which was effectively measured by the sensors, proving how the elderly population approached in a more careful manner the presented obstacles.

Walking behavior studying PPG data

Despite the denoising pre-processing, the signals of five young subjects and six elderly were to be removed due to low quality of the signal itself and absence of valuable information. The remaining signals, however, appeared heterogeneous and still representative of the two analysed populations. To compare the different walking tasks and to evaluate the effect of walking pace on heartbeat, then, a statistical similarity analysis was performed. In the case of this experiment too, in fact, the main goal was to check if the chosen signals could be utilized to discriminate between different tasks and states of the person, rather than to interpret the data on its own.

To this aim, the non-parametric Kruskal Wallis test [Kruskal and Wallis, 1952] was applied to the obtained data. This test is based on the null hypothesis which sees the two distributions provided as input as similar if their medians are found equal. On the other hand, if the two distributions are statistically different, the p-value returned by the test appears lower than a certain significance level, which usually set to $\alpha = 0.05$, and the null hypothesis is rejected. In this analysis, in particular, the Kruskal Wallis test is used to compare the feature distributions of different walking tasks in order to investigate if such statistical differences are present.

The analysis was performed using the signals that were pre-processed using the methods described above. Furthermore, it is necessary to recall that the Free Walk task (FW) was performed only in the experiment involving elderly population, and thus it is analyzed only for these subjects' group.

Moreover, to separate the free walking tasks that anticipate and follow the crossing from the obstacle crossing itself in young adults experimental group, the signals were divided in a total of 14 segments. Of them, segments 4 and 11 refer to the free walking phases that precede or follow the collision zone, while segments 1, 2, 5, 6, 9, 10, 13 and 14 refer to the effective pendulum avoidance zone. Segments 7 and 8 refer, on the other hand, to the phase in which the participant ends the path walking and prepares to go back. This task falls outside the target of this analysis intentions and has been, for this reason, removed.

First task	**Second task**	**Max.**	**Min.**	**Mean**	**Variance**	**Peak Rate**	**IBI**	**RMSSD**
B_W	F1	<0.001	<0.001	0.29	<0.001	<0.001	<0.001	<0.001
B_W	F2	<0.001	<0.001	0.21	<0.001	0.24	0.45	<0.001
B_W	F3	<0.001	<0.001	0.03	<0.001	<0.001	<0.001	<0.001
B_W	WO + Obs	<0.001	<0.001	0.01	<0.001	<0.001	<0.001	<0.001
F1	F2	0.58	0.66	0.80	0.64	<0.001	<0.001	0.14
F1	F3	0.77	0.64	0.28	0.14	<0.001	<0.001	0.70
F1	WO + Obs	<0.001	<0.001	0.18	<0.001	<0.001	<0.001	<0.001
F2	F3	0.51	0.91	0.42	0.37	<0.001	<0.001	0.08
F2	WO + Obs	<0.001	<0.001	0.20	0.01	<0.001	<0.001	0.08
F3	WO + Obs	<0.001	<0.001	0.71	0.17	0.10	0.24	<0.001

Table 8: Kruskal Wallis p-values derived from the comparison between tasks in the Young Adult population. The values highlighted in red refer to p-value found lower than the significance level chosen, which corresponded to $\alpha = 0.05$. The analyzed tasks are: B_W = baseline task acquired in walking session, F1 = Metronome Forced Speed task (70 bpm), F2 = Metronome Forced Speed task (85 bpm), F3 = Metronome Forced Speed task (100 bpm), WO + Obs = single signal for the whole task of collision avoidance (Free walk and obstacle crossing).

Tables 8 and 9 show the p-values obtained when comparing the feature distributions for all the couple of tasks shows in the first columns and considering young adults and elderly, respectively.

First of all, in both the experimental groups considered and in most of the features analyzed, the walking tasks appear significantly different from the recorded baseline $\mathbf{B}_W$, with p-value usually lower than the significance level. In particular, the RMSSD seems to be the most significant feature in discriminating between walking and resting tasks.

On the other hand, this feature presents p-values usually greater then $\alpha = 0.05$ when comparing different walking tasks, which make it appear as less significant in further analyses. It is important to remember, though, that during the baseline acquisition the subjects were still and standing and thus the acquired signals were not affected by the subject movement, which may have compromised enough the signals during the walking tasks as to not gather significant information from the RMSSD feature. Thus, this difference in heartbeat between walking tasks and no-movement tasks proves the necessity to further and deeper analysis for the topic.

Looking at the other obtained values, then, the IBI measure and the Peak Rate feature also seem to be quite discriminant between tasks, and not only between resting and walking tasks but also between different walking tasks. The Peak Rate, in particular, shows many p-values under the 0.05 threshold that was established for the analysis, marking its case as especially relevant.

First task	Second task	Max.	Min.	Mean	Variance	Peak Rate	IBI	RMSSD
B_W	F1	<0.001	<0.001	<0.001	<0.001	0.18	0.15	<0.001
B_W	F2	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
B_W	F3	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
B_W	FW	<0.001	<0.001	0.20	<0.001	<0.001	<0.001	<0.001
B_W	Obs	0.19	<0.001	0.01	<0.001	<0.001	<0.001	<0.001
B_W	WO	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
F1	F2	0.78	0.89	0.98	0.66	0.03	0.03	0.56
F1	F3	0.90	0.60	0.73	0.49	<0.001	<0.001	0.30
F1	FW	0.28	<0.001	0.01	0.78	<0.001	<0.001	0.13
F1	Obs	0.07	0.49	0.88	0.10	<0.001	<0.001	0.13
F1	WO	0.38	0.74	0.01	0.08	<0.001	<0.001	0.31
F2	F3	0.90	0.64	0.82	0.73	0.16	0.18	0.58
F2	FW	0.38	0.01	0.01	0.82	0.38	0.27	0.30
F2	Obs	0.04	0.32	0.99	0.19	<0.001	0.02	0.41
F2	WO	0.30	0.85	0.02	0.15	<0.001	0.02	0.77
F3	FW	0.25	0.02	<0.001	0.60	0.67	0.84	0.73
F3	Obs	0.07	0.19	0.92	0.35	<0.001	0.23	0.91
F3	WO	0.36	0.82	0.04	0.33	0.03	0.36	0.66
FW	Obs	0.01	<0.001	0.05	0.14	<0.001	0.14	0.77
FW	WO	0.06	<0.001	<0.001	0.09	0.01	0.20	0.35
Obs	WO	0.18	0.18	0.05	0.94	0.01	0.72	0.51

Table 9: Kruskal Wallis p-values derived from the comparison between tasks in the Elderly population. The values highlighted in red refer to p-value found lower than the significance level chosen, which corresponded to $\alpha = 0.05$. The analyzed tasks are: B_W = baseline collected during walking session, F1 = Metronome Forced Speed task (70 bpm), F2 = Metronome Forced Speed task (85 bpm), F3 = Metronome Forced Speed task (100 bpm), FW = Pure Free Walk task, WO = Free Walk in the collision avoidance task, Obs = obstacle crossing.

Figure 25 reports the boxplots coming from the Peak Rate values from the young adult population and the elderly population. From these boxplots, it emerges that the subjects' speed directly affects their heartbeat, as it could be expected. In fact, considering the three different forced speed tasks that are here indicated as F1, F2 and F3, as the frequency speed increases so does the heartbeat of the participants. And this is particularly true when considering the results obtained from young adults. These differences are also noticeable in the p-values produced by the Kruskal Wallis test, that are often lower than 0.001 and displaying a statistically relevant difference. Even in the elderly population it is possible to observe a general heartbeat increase related to the speed increase, shown by the median values reported in the right boxplot of figure 25. This trend, as it happens for the young adult population, is also visible from the p-values generated by the Kruskal Wallis test, even if the obtained values appear as slightly greater than the ones reported for the young adults. This results may be due to the elder participants attitude, already described before, which saw them walk at a faster pace with respect of the metronome forced speeds and thus rendering all of their trials more similar in speed, a behaviour that is clearly reflected in the data.

Besides, from the analysis of the p-values in case of the elderly, it is not possible to exclude the null hypothesis when comparing the Free Walking task and the faster of the forced speed tasks, F3. In this case, in fact, the p-value generated by the test with reference to the peak rate appears rather high (0.91), in accordance with what has already been observed in the EMG analysis.

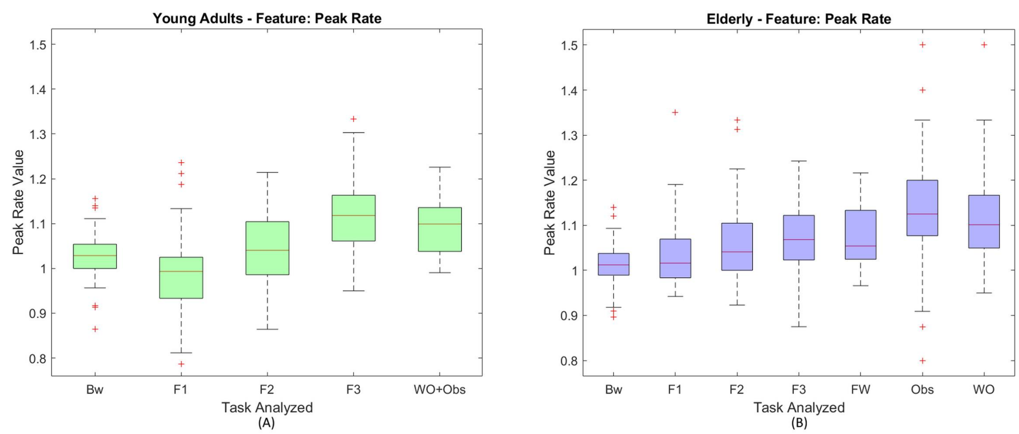


Figure 25: Boxplots of the Peak Rate for the different tasks. The left boxplot of the figure regards the Young Adult population, while the right boxplot regards the Elderly population.

It is worth of notice what emerges from the comparison of the F3 task and the WO task, keeping in mind how a similar stride frequency has already been observed in both of these tasks as the the EMG analysis was performed. This similarity previously detected, in fact, is also confirmed by the high p-values obtained for both young adults and elderly in most of the PPG features here. An interesting exception is observed in the Peak Rate, while comparing F3 and WO in the case of elderly population. In this occurrence, in fact, the p-value appears lower than $\alpha = 0.05$, and the null hypothesis can be rejected, thus highlighting statistically relevant differences between the data coming from the two tasks. From the boxplots analysis of the Peak Rate, also, it is possible to observe that the median value of the dedicated WO box appears higher than the one of the F3 one. This difference may prove that, when approaching an obstacle, the upcoming encounter elicits variations in the current affective state of the elderly, who probably perceive this type of walking as more stressful than the speed-constrained one precisely because of the obstacle presence.

Likewise, it is not possible to reject the null hypothesis between the two tasks of crossing indicated as Obs and the free walking during the collision avoidance task, which is always WO. In both the populations and in most of the features analysed, in fact, the p-values generated by the Kruskal Wallis test are greater than the level of significance considered, with the only exception again referring to the Peak Rate in case of the elderly people, where the p-value appears lower than 0.001. In the Elderly boxplot of Figure 25, also, it is possible to notice that, in general, the heartbeat values observed on task Obs appear higher than the ones of task WO, suggesting that the elderly perceive crossing the zone of the collision avoidance task as potentially more stressful than walking along the path sections preceding the encounter.

The positive results achieved from the analysis of data acquired through the walking sessions shows how physiological signals managed to record differences that allow both to discriminate between the proposed tasks and between the two different populations involved in the iterations of the experiment. The recorded reactions, in fact, underline how people of different ages react differently to similar stimuli, both from an emotional and a behavioral point of view.

Regarding GSR data and STAI questionnaires

As GSR data started being analysed, the obtained results immediately appeared as not particularly relevant or significant when trying to address the research question this experiment was aimed at. In fact, no particular differences were found when investigating the two different populations or comparing the different tasks involved in the procedure, probably due to the fact that keeping the participants on the move and active had their perspiration act up more because of the movements themselves rather than their increased arousal.

Regarding the questionnaires that were filled out by the participants, on the other hand, it was quickly realised how a much larger data cardinality would be needed in order to carry out more significant analyses. With only the present data, in fact, the information gathered from the participants cannot be considered significant for an eventual more precise profiling.

2.4 T3 - Proxemics Virtual Experiment

After the results obtained through the investigation regarding the interaction of different populations with vehicles and moving obstacles, there was one last aspect of pedestrian behaviour to approach, one that got particularly interesting and important with the COVID-19 pandemic spreading through the world at the beginning of 2020. It was the aspect regarding interpersonal interactions, concerning the concept of proxemics, as they involved interpersonal distances kept by people when interacting with each other in different environments and different situations. It was an aspect of interaction that the advent of the epidemic brought to important changes because of how people started distancing themselves from others both out of fear of contagion and because of governmental regulations introduced in order to slow down the virus spreading.

Given the state of emergency brought by the fast diffusion of the COVID-19 virus both in Italy and in the rest of the world, though, it was not possible to perform an *in-vivo* experiment regarding the changes in proxemic distances due to the pandemic. Because of this, the experiment was designed and modeled utilizing an ad-hoc digital platform which could allow to answer the research requirements for the experiment while remaining as faithful as possible to the situations that was originally to be proposed in a real-life environment.

The main goal of the virtual experiment was to understand how people approached interpersonal distanced with the influence of the pandemic, collecting both subject-related information through a questionnaires and data regarding distances perceived as comfortable by the participants in different environments when facing different situations.

The experiment was implemented by creating a website, thus allowing complete flexibility in terms of what to include and how to structure every element, using *WordPress* as the preferred content management system. The experiment, despite the data collection phase being officially closed, can be found at the following domain: `www.distanziamentovirale.altervista.org`.

Ethical Committee Approval: The experiment here presented was performed after an ethical committee approval, in compliance with the Ethical Committee of the University of Milano-Bicocca.

2.4.1 The Subjects

Since the experiment was launched online, this allowed it to reach a vaster population than the one that could have been involved with the performance of an in-vivo experiment, especially since there virtually were no particular limitations regarding the participants' suitability to the study. The experiment was made public between 27/12/2020 and 18/01/2021, an important information given how the perception of COVID-related risk greatly changed according to the trend in the number of infections and the media coverage of the pandemic, and during that period of time 84 compilations in total were gathered. Excluding from the analysis the ones where the subjects declared to already have contracted the COVID-19 virus, since it was taken into consideration how the perception of people that had been infected could significantly vary from the one of people that had kept healthy, a total of 80 compilations were eventually aggregated, 36 done by men and 44 by women. Participants were aged between 16 and 92 years old, with 25 of them belonging to the elderly age group (i.e., aged 65 and older).

2.4.2 Experimental Protocol

The experimental protocol for the experiment was designed to have it divided into two main phases, each of them concerned with a different aspect: the first one presented a questionnaire to the participants, allowing to perform an initial information gathering on the subjects; the second one presented a number of tasks following the typology of virtual *figure-stop activity*, that was devised and developed as inspired by previous studies regarding this methodology [Dosey and Meisels, 1969, Roger, 1982, Webb and Weber, 2003].

First phase: Questionnaire

The first phase of the experiment involved the administration of a questionnaire, introduced by a policy statement to better present the experiment and its finality to the subjects who approached the study. The participants were promptly informed of this, together with the anonymous nature of the questionnaire, as soon as they landed on the web page, so that they could promptly decide whether to continue or to leave the experiment.

The questionnaire was divided into three parts, in order to gather different types of information. They were presented separately, as not to appear confusing to the subjects:

- *Generic Information Section*: in this part, questions about age, sex, sociability level, population density of their municipality and living conditions (with or without others) were asked;
- *Required Aid Section*: part only administered to those participants who signed themselves as elderly. The questions were focused on the physical aids the subject used on a regular basis, such as glasses, an hearing aid or a walking cane;
- *COVID-19 Section*: this section was focused on gaining information about the subject's fear of being infected by the COVID-19 virus, and about the perception of safety during different daily-life activities as influenced by the pandemic.

Second phase: Figure-stop activities

In the second part of the experiment, some virtual figure-stop activities were then proposed to the participants, which can be described as follows:

- Subjects were presented an avatar (Figure 26), chosen in respect of their indicated gender and age group, positioned in an outdoor (park) or indoor (restaurant) environment;
- While their avatar was on the left side, there was another figure of opposite gender and age group, positioned on the right side of the environment (Figure27, right);
- Participants were then instructed to move their avatar towards the other figure through a slider operating under the picture, stopping when they felt that the distances between them and the figure could get uncomfortable if shortened further. Distances were properly indicated on the slider so that the subjects could have a better perception of the distance they were choosing.

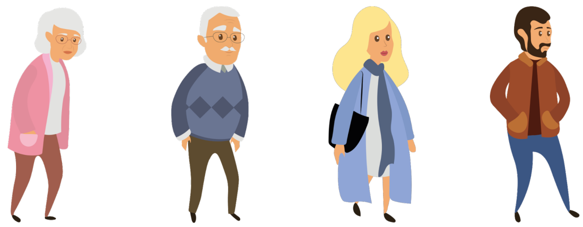


Figure 26: The four avatar used in the experiment, differentiated by age group and gender.

A total of eight tasks were presented to the participants, using both of the environments previously mentioned and four different mask configurations (Figure 27 left) for the figurines in each of the environments: (1) both the subject's avatar and the other avatar had a mask on, (2) only the subject's avatar had a mask on, (3) only the other avatar had a mask on and (4) no avatar had a mask on.

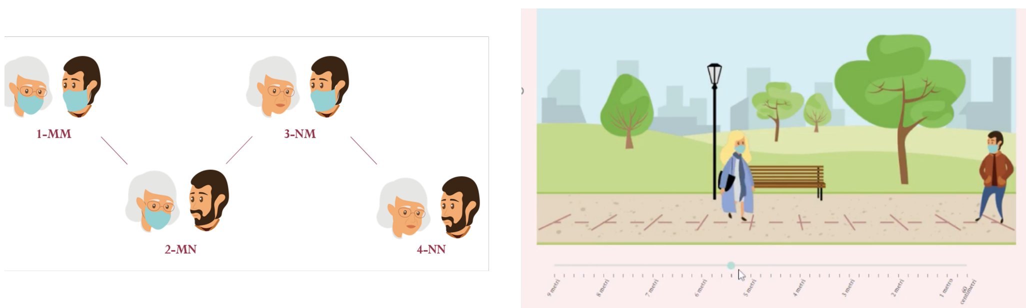


Figure 27: Left: The four mask configurations, right: the figure-stop activity in the outdoor environment.

2.4.3 Results

After gathering all the data coming from the online experiment, the subsequent performed analysis was aimed at investigating the participants' entries in order to understand which parameters identified by the questionnaire seemed to bear a certain influence on the way the subjects chose their proxemic distances throughout the proposed activities.

In particular, the factors that proved to influence the most the distances adopted by the participants are a subset of the ones that were actually included in the design of the experiment. The parameters included in the set, then, are the following:

- Gender;
- Age;

- Mask conditions;
- Fear of contagion;
- Sociability levels.

The factor for which the most clear differences were found is surely the gender of the participant, which proved to be one of the most relevant aspects concerning how proxemic distances were selected by the experiment participants.

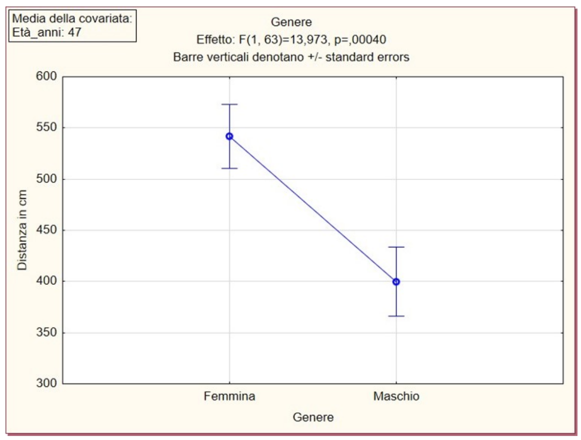


Figure 28: Distances differences between females (left point) and males (right point).

Figure 28 shows the differences found aggregating the selected distances chosen by females and males by dividing the entire population in two groups depending on their gender. As the graphic clearly shows, females tended to leave their character farther away from the other figure presented in the experiment, with distances mainly around 5.5 meters, as opposed to males who, on the other hand, see their distances gather around 4 meters. This result is consistent with what is found in the literature, which indicates how females appear to maintain wider distances from others when compared with males.

Age, albeit in minor measure, was another factor that showed relevant differences in the approach to distances: elderly people, in fact, appeared to have chosen slightly larger distances in comparison to the younger population involved in the experiment, but even more interesting was the correlation found between age and fear of contagion: Table 10, in fact, shows a good value of correlation between these two factors, that shows how, progressing with age, fear of contagion reached higher values.

Another factor bearing important influence on the selected distance was then the mask configuration.

Figure 29 shows the distances that entire population showed in each and every mask configuration that was presented before. While it was expected to record similar distances for the second and

Variable	Mean	Standard Deviation	Age of subject	Fear of contagion
Age of subject	47.11250	24.06531	1.00000	0.22379
Fear of contagion	3.63750	1.96323	0.22379	1.00000

Table 10: Table depicting the correlation between the age and fear of contagion factors.

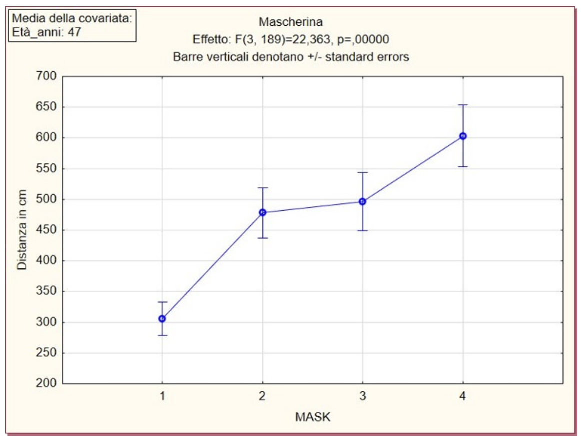


Figure 29: Distances differences between different mask configurations. The numbers are related to the presence-absence of mask configurations that were involved in the experiment: 1 indicates that both people had the mask on, 2 that only the figurine for the participant had the mask, 3 that only the other figurine had the mask on and 4 that neither of them hat a mask.

third condition, where only one of the figures had the mask, the most evident difference is between the first and the fourth condition: people generally deemed safe being closer to the other figure in the environment when both of them had a mask on, with distances around 3 meters, while the complete absence of masks compelled them to stop way farther in order to remain comfortable, reaching much larger distances around 6 meters.

Figure 30 better shows the dynamic presented above, as well as highlighting the differences between males and females persisting among different mask configurations and environment. In the presented plots, in fact, it is clear how the presence or absence of masks influenced people to adopt wider and wider distances when in potentially more dangerous situation, and also how the slopes depicting data coming from the female population present a steeper growth.

Moreover, the picture allow for a consideration about the role of the environment in the distances choice. As it can be seen comparing the two graphs in Figure 30, in fact, the recorded distances do not seem so different between the two environments, thus hinting at how the indication of an outdoor

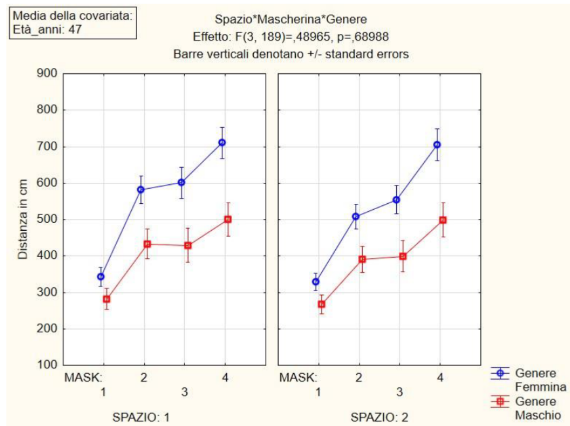


Figure 30: Distances differences between males (red lines) and females (blue lines) found for the outdoor environment (left) and the indoor one (right) in different mask conditions.

or indoor setting did not have much influence on how people chose to maintain their proxemic distances.

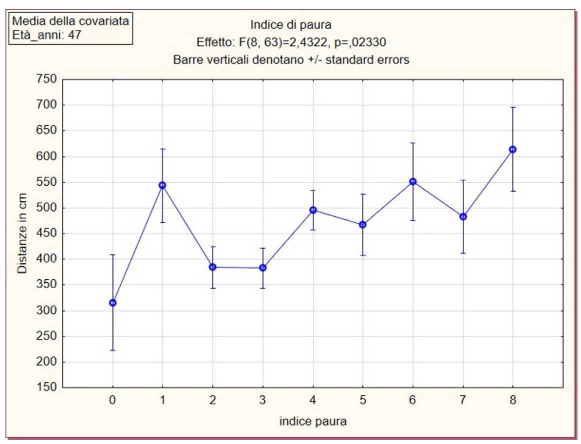


Figure 31: Distances differences between different fear levels.

Fear of contagion was also a factor to influence the distances selected by the participants. Figure 31 shows the different distances maintained by people with different levels of contagion fear. A total of 9 fear levels were involved (from 0 to 8), and the graphic shows the different distances adopted by the participants that indicated one of those levels. Even if not perfectly continuous, the tendency for people with lower fear levels is to generally adopt shorter distances, while people who fear contagion much more tend to stay farther from the other figures they might come across.

Lastly, the sociality levels indicated by the participant also seemed to play their part in influencing

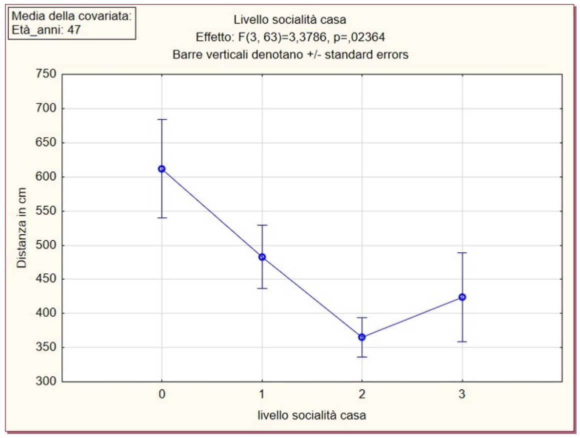


Figure 32: Distances differences between different sociality levels.

the choice of proxemic distances. Figure 32 shows here the different distances adopted by people with different sociability levels, here focusing in particular on sociability levels at home. A total of four different levels were considered, with 0 corresponding to people living alone, 1 to people having only another person living with them, 2 to people with two or three others living with them and 4 to people with four or more people living in the same house. From the presented pictures, it is noticeable how people who do not usually interact with people at home tended to choose wider distances, while shorter distances were selected from those who also interacted with other people in their own household.

Variable	**Mean**	**Standard Deviation**	**Internal Sociality**	**Fear of contagion**
Internal Sociality	1.65000	0.76473	1.00000	-0.26264
Fear of contagion	3.63750	1.96323	-0.26264	1.00000

Table 11: Table depicting the correlation between the internal sociality and fear of contagion factors.

Another important information regarding sociality is also its correlation, this time negative, with fear of contagion. The obtained results, in fact, indicate how people are more scared the less they interact with others, which also corroborates the results obtained by the correlation between age and fear since elderly people were find to be the ones living alone for the most part.

2.4.4 Extension to another population: experimentation in Brazil

After concluding the data analysis on the experiment, interest arose in proposing the same procedure to another population, in order to investigate if participants with a cultural background different from the one of the population considered for the first iteration were going to display different behaviour through questionnaires and tasks.

Thanks to the six-month collaboration with professor Flavio Soares Correa da Silva of the University of São Paulo, done as an abroad internship performed online because of the limitations and issues caused by the pandemic, the experiment was once again opened to the public and proposed to a population residing in the city of São Paulo, Brazil, through academic contacts.

Given the fact that the data gathering was performed between 01/06/2022 and 31/07/2022, though, the data is still yet to be analysed in order to understand if relevant information regarding population behaviour can be acquired from this new iteration.

3 Cellular Automata Modeling and Simulations

As the prospect of modeling with the introduction of data coming from people was approached, the first attempt in this direction contemplated including the data and results obtained from the experiments previously executed inside a cellular automata model. This line of work was followed in order to learn a formal framework in which to operate, working to include the gathered information inside a *state* that could then be transferred to agents.

In particular, in order to start dealing with data simple enough to discretize and include inside the model, the work on a first attempt at Cellular Automata modeling was done by utilizing the information that were extracted from the online proxemic experiment presented in Section 2.4. This was also done because of the increasing relevance of the topic handled by the experiment, given the rise of the COVID-19 pandemic and the impact that both the epidemic and the rules derived from the fight against the highly contagious virus brought on society and on the way humans interact with each others [Haghani, 2022].

Contribution summary

The models here shown were both presented in the following publication:

- [Bandini et al., 2022a] Bandini, Stefania, Daniela Briola, Alberto Dennunzio, Francesca Gasparini, Marta Giltri and Giuseppe Vizzari. "Integrating the Implications of Distance-Based Affective States in Cellular Automata Pedestrian Simulation." *International Conference on Cellular Automata for Research and Industry.* Springer, Cham, 2022.

3.1 1D CA Model

The first model design that was attempted after defining the experiment to focus on and the data to take into consideration was set to describe the simplest CA that could be used to model the experimental scenario described in Section 2.4 in the most natural way possible. The goal, in this case, was to translate the behaviour seen inside the experiment into a CA model.

In order to keep the model as simple as possible, then, the affectivity has been embedded into the local rule of the automaton. As a matter of fact, introducing it inside the CA state set would have produced a much too complex design with respect to the considered scenario, which only contemplated two different people at a time moving in a basic one-dimensional space.

Following such an approach for the writing of the local rule led us to have a family of different cellular automata: since the local rule depends on the value m, which is the minimum distance the moving person can have from the non-moving person in the environment, it means that every single value of m leads to a different CA, all sharing a local rule written in the same way but depending on different values.

In particular, this happens because the m value is derived from the affective states of the two people involved in the situation described by the CA, which bring the variation of the parameter. The moving person's information derived from the experiment (i.e., gender, age, sociality levels, fear of contagion, mask) and the other person's mask condition are used to select a Hall's space with a certain probability. It's the chosen Hall's space, then, which gives the upper and lower bound of the interval in which the m value is to be randomly selected, thus resulting in the distance the moving person needs to maintain from the other when walking closer.

The scale of discretization implemented in the model is also, of course, important: traditionally, CA based pedestrian models employ 40 cm sided cells [Burstedde et al., 2001], so in this case too it was considered as a baseline value for the model. This, together with a time step duration fixed at 0.33 seconds, allowed to have a walking speed of about 1.2 metres per second, which is in line with typically observed values [Gorrini et al., 2016]. These measurements were decided considering that a person fully occupies a cell of the environment.

3.1.1 The Model

With the premises just presented, the involved one-dimensional CA are then triples (S, r, f) where there are set of states $S = \{0, 1, 2\}$, the radius $r \in \mathbb{N}$ and the local rule $f : S^{2r+1} \to S$ which defines the way the automaton evolves through time.

Regarding the states belonging in S, as far as any cell of the one-dimensional lattice is concerned, $0, 1, 2$ correspond to an empty cell of the lattice, a cell containing a moving person and a cell containing a resting person, respectively.

The radius r of the CA then assumes the value of the ceiling of the m value, the minimum distance that was described above. This, together with leading the creation of a family of CA rather than a single defined system, also brings the distinction of two different CA classes contained within this same family.

When m is an integer, in fact, the CA radius is $r = m$ and the local rule f is defined for any $(a_{-r}, ..., a_0, ..., a_r) \in S^{2r+1}$ as follows:

– if $a_0 = 2$,

$$f(a_{-r}, ..., a_0, ..., a_r) = a_0 \quad ,$$

– if $a_0 = 1$,

$$f(a_{-r}, ..., a_0, ..., a_r) = \begin{cases} 0 & \text{if } a_1 = ... = a_r = 0 \\ 0 & \text{if } \exists\ 0 < i < r \text{ s.t. } (a_i = 1 \lor a_i = 2) \land a_{-1} = 0 \\ a_0 & \text{if } (a_r = 1 \lor a_r = 2) \land a_1 = ... = a_{r-1} = 0 \\ a_0 & \text{if } \exists\ 0 < i < r \text{ s.t. } (a_i = 1 \lor a_i = 2) \land (a_{-1} = 1 \lor a_{-1} = 2) \end{cases} \quad ,$$

– if $a_0 = 0$,

$$f(a_{-r}, ..., a_0, ..., a_r) = \begin{cases} a_0 & \text{if } a_{-1} = a_1 = 0 \\ a_0 & \text{if } a_1 = 1 \wedge a_2 = ... = a_r = 0 \\ a_0 & \text{if } a_{-1} = 1 \wedge \text{ if } \exists\, 0 < i < r \text{ s.t. } (a_i = 1 \vee a_i = 2) \\ 1 & \text{if } a_{-1} = 1 \wedge a_1 = ... = a_{r-1} = 0 \\ 1 & \text{if } \exists\, 1 < i < r \text{ s.t. } (a_i = 1 \vee a_i = 2) \wedge a_1 = 1 \end{cases} .$$

When m is not an integer, on the other hand, the CA radius is $r = \lceil m \rceil$. The local rule f is defined for any $(a_{-r}, ..., a_0, ..., a_r) \in S^{2r+1}$ as specified before, except for the following case:

– if $a_0 = 1$,

$$f(a_{-r}, ..., a_0, ..., a_r) = 0 \quad \text{if } (a_r = 1 \vee a_r = 2) \wedge a_1 = ... = a_{r-1} = 0 \ .$$

The lattice considered for this family of automata is a one-dimensional array of squared cells where every cell is associated with a certain state from S. Also, the state of each cell is updated at every discreet time step by the local rule f on the basis of its own current state and the ones of its r-neighbouring cells found both on its left and on its right.

Moreover, there's a clarification that needs to be made regarding the inevitable consequences that the discretization of the space, in the passage from the experiment to the cellular automaton, brings with it. The second CA class that was described, the one in which $r > m$ because of this discretization, causes an oscillatory movement in the CA dynamics which is completely absent when considering the experiment the model comes from. This happens since the moving person finds himself/herself switching from a position where it is still far enough from the other to a position where it is already too close to the other. For example, with an m value of 6.5, the pedestrian would continuously jump from the cell at distance 7 to the cell at distance 6 from the non-moving person present in the environment, because none of the positions actually satisfy the conditions under which the moving person can be comfortable in the presence of others because of how space is handled in the CA model. Such an occurrence is of course absent when the CA with $r = m$ are considered since, in that case, integers that are not affected by the discretization are involved.

3.1.2 Implementation and Results

Following the formalization of the 1D CA, the next step was to proceeded to formalize its transition function inside a virtual simulation in order to observe how the CA behaved with the rules that were set. NetLogo [Wilensky, 1999] was the tool chosen for the implementation of the simulation, it being simple but powerful enough to let us build a model able to reproduce the behaviour described by the CA, and the resulting interface is shown in Figure 33.

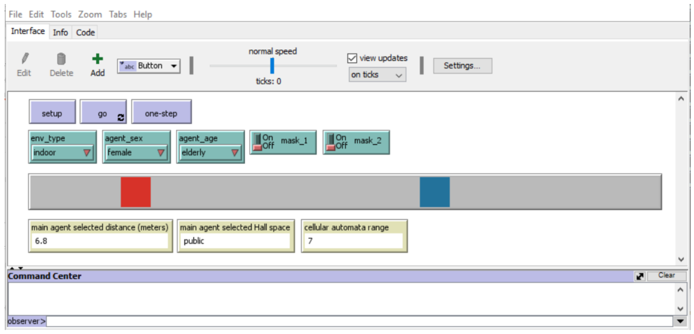


Figure 33: The user interface of the NetLogo model used for the 1D CA simulation.

Given the parameters that were introduced inside the CA, the simulation allows the user to choose different options for the settings in order to reproduce the different instances described by the designed family of CA. The options firstly allow to set the environment, choosing from the two options that were available in the experiment, to then pass on to the characteristics of the moving and of the non-moving person: there are parameters allowing to select the gender and age of the main moving person, together with others for the mask configuration for both the moving and the still person, thus following the specification of the online experiment in order to embed those same conditions in the in-vitro simulation. All of these parameters are then used in an internal function that firstly determines the adopted Hall's space following a weighted probability distribution extracted from the data, and secondly the precise distance adopted inside the Hall's space.

As it can be noticed, though, in the first simulation of the model here presented there are some parameters coming from the online experiment that are not contemplated. The sociality levels, both internal and external, and the fear of contagion, in fact, have not been included in this preliminary trial, wanting to focus on the simplest affective aspects to implement inside the simulation.

Since every parameter is easily set with the help of GUI elements and remain visible throughout the entire execution of the simulation, differences in cell colour along the lattice are only used to distinguish the two types of pedestrian involved in the simulation: a cell highlighted in *red* signals the presence of the moving person on that cell, while one coloured in *blue* shows the cell where the still person is. Just as it was proposed in the online experiment, the moving person is always setup to be on the left of the other person on screen. The only modification applied to the simulation design, as compared to its original source, regards the specific place in which the two pedestrians get set up as starting condition for the CA: the positions of both people are, in fact, randomly selected before the simulation can be started, with each of them being placed in one specific half of the environment in order to comply with the experimental setup that was proposed during the online trials. This means that, given the positions each person starts in at the beginning of the simulation, there could be cases in which the moving person walks away from the other rather than walking closer, in order to put between itself and the non-moving person the distance dictated by m.

Given how the simulation is built, the data and the information gathered from the online experiment being directly feeded to it, this 1D CA actually manages to reproduce the same situations proposed during the figure-stop activities performed by the human participants after the questionnaire. In this case, because of its intrinsic design, the CA behaviour mirrors the one already observed in the subjects. In fact, as it was stated before, the conditions regulating both the moving and the still person are the same that were implemented in the experiment, with the specific goal to verify if the transition function of the automaton worked to correctly show what it was expected after analysing those results. Moreover, the initial conditions always contemplate a single moving person and a single non-moving person, thus rendering the proposed scenarios as instances to observe in order to understand if the defined set of rules works to describe the situations meant to be portrayed by the model.

There are only two main differences from the online experiment, as it was previously said when presenting the two CA classes brought by m being an integer or not and when describing the way the simulations are initialized: the first lies in the fact that the moving person could be moving both backwards and forwards, depending on its initial position in respect of the non-moving person in the environment; the second, on the other hand, lies in how the moving agent behaves in the case where $m < r$, a case well described in the formalization of the CA transition function as it takes into consideration how the lattice is built differently from the continuous space the human participants experienced in their trials. The latter is surely the most notable difference from what it was observed in the experiment. When encountering such a situation, in fact, the main pedestrian starts an oscillatory movement between two cells of the lattice, one being still far from the non-moving person and the other being too close to it. Because of this, the moving person cannot actually stop on one of them, because neither of the two cells satisfy its requirements in terms of comfortable distance. This particular behaviour leads the CA presenting m as an integer value to reach stability after a certain number of time steps, while all the other CA in which m is not an integer keep permanently oscillating.

3.2 2D CA Model

Moving on from the 1D CA Model presented in Section 3.1, the modeling efforts were then shifted towards introducing the same affective parameters mentioned before inside a larger model, contemplating a two-dimensional environment rather than a one-dimensional one in order to observe pedestrian behaviour on a larger scale and less specific premises. Expanding to a two-dimensional environment, in fact, would allow the observation of the behaviour of a crowd of pedestrians rather than the one of a single person, also shifting the focus on the possible emerging dynamics between pedestrians that, by construction, couldn't have been investigated with the one-dimensional example.

3.2.1 The Model

The introduced two-dimensional CA is based on a rectangular lattice $L = \{0, ..., M-1\} \times \{0, ..., N-1\}$ composed of squared cells, representing the discretization of the real space, where M and N are the horizontal and vertical sizes of the lattice respectively. Periodic boundary conditions are applied to L so that it can be viewed as a two-dimensional discrete torus, which allows every cell of the lattice to always have the required neighborhood to check in order to proceed with the evolution of the automaton.

Regarding the neighborhood to be considered for the dynamical evolution of the CA, given that there are now more than two directions to check, for any cell $x \in L$ and any h the h-radius Moore neighborhood of x is defined as:

$$N_h(x) = \{y \in L : ||x - y||_\infty \leq h\}$$

where $|| \cdot ||_\infty$ is the usual infinity (or maximum) norm.

Then, the set of states of the CA is described as $S = \mathit{DIR} \times MD \times G \times \mathit{AG} \times M \cup \{\oslash\}$, where $\oslash$ is the state assigned to empty cells (i.e., in which there is no person) while a tuple from the cartesian product is the state assigned to cells containing a person. The sets involved in the cartesian product are defined as follows:

- $\mathit{DIR} = \{0, 1, ..., 8\}$ is the set of the possible moving directions for a person. Namely, numbers from DIR refer to the following direction vectors: $v_0 = (0, 0), v_1 = (1, 0), v_2 = (1, 1), v_3 = (0, 1), v_4 = (-1, 1), v_5 = (-1, 0), v_6 = (-1, -1), v_7 = (0, -1), v_8 = (1, -1)$. In this way, 0 concerns a resting person, while every other value $j \in \mathit{DIR}$ with $j \neq 0$ refers to a person at a certain position $x \in L$ with a moving direction v_j;

- $MD = \{\mathit{relaxed}, \mathit{worried}, \mathit{scared}\}$ is the set of so-called moods a person could be in. Each value from AS is obtained by combining data about sociality and fear previously obtained through the experiment and structured into three different levels;

- $G = \{\mathit{male}, \mathit{female}\}$ is the set of the genders of a person. Given the data that were collected, only the *male* and *female* options were involved, without including other genders;

- $\mathit{AG} = \{y, ya, a, e\}$ is the set of age groups a person could belong to (y = young, ya = young-adult, a = adult, e = elderly);

- $M = \{\mathit{on}, \mathit{off}\}$ is the set of the possible settings for a person as far as a mask is concerned, i.e., the values specifying if the person wears a mask or not.

It is important to say that, unlike the case of the 1D CA model presented before, here the affectivity details are now included inside the set of states of the CA. This jump into complexity is now applicable, since the goal is to model more complex situations contemplating people with different characteristics moving together inside a two-dimensional environment. Also, with an abuse of notation, for any state $s \in S$ and any $i \in \{1, ..., 5\}$, the writing s_i will denote the i-th component of s whenever $s \neq \oslash$.

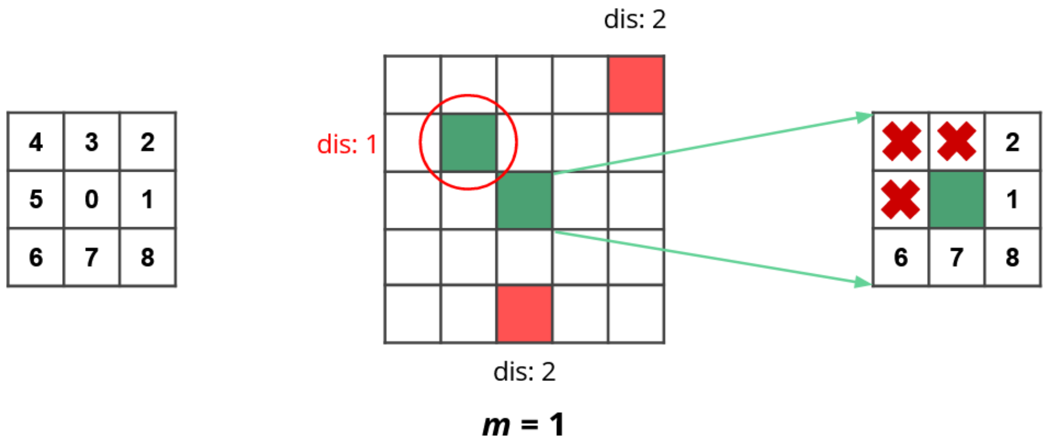
Following how the state of the lattice cells is structured, the CA configuration is then a map $c : L \to S$ associating every cell $x \in L$ with a state $c(x) \in S$. Thereafter, regarding the dynamical evolution of the CA, for every $t \in \mathbb{N}$, any $x \in L$ and every $i \in \{1, ..., 5\}$, c^t, $c^t(x)$ and $c^t_i(x)$ will denote the CA configuration at time t, the state of the cell x inside c^t, and the $(c^t(x))_i$, i.e., the i-th component of $c^t(x)$, respectively. The radius of the CA, on the other hand, is the value $r \in \mathbb{N}$ defining the largest set $N_r(x)$ that every cell looks at as its neighborhood. In other words, the value r and the set $N_r(x)$ respectively identify the perception radius of a person located in any cell $x \in L$ and the cells that same person is able to detect and observe around himself/herself.

Moreover, in our 2D model also, one time step corresponds to 0.33 seconds, the considered lattice cells are 40 cm sided cells and, consequently, this numbers lead to a walking speed of about 1.2 metres per second. It was in fact decided to keep the same parameters utilized for the one-dimensional CA to comply with the literature investigated in this regard.

Going back to how the evolution of the CA works, it needs to be pointed out that the defined CA is non deterministic. Because of this, in order to describe its dynamical evolution $\{c^t\}_{t \in \mathbb{N}}$ starting from any initial configuration $c^0 \in S^L$, it is necessary to illustrate how the configuration c^t at time t is transformed by the CA into the configuration c^{t+1} at time $t+1$. In particular, each time step sees the succession of three different stages composing the entirety of the evolution of the automaton.

During the first one, for any time $t \in \mathbb{N}$ the configuration c^t is transformed into the intermediate configuration d^t in such a way that $\forall x \in L$, $\forall i \neq 1$, $d^t_i(x) = c^t_i(x)$. In other words, only the direction of every cell x containing a person may change during this stage, since empty cells, during this first part of the automaton evolution, simply maintain their empty status.

For any cell $x \in L$ with $c^t(x) \neq \oslash$, the value $d^t_1(x)$, which identifies the passage to the intermediate configuration, is computed as follows. Firstly, the cells in the neighborhood $y \in N_r(x)$ s.t. $c^t(y) \neq \oslash$, i.e., containing a moving or resting person, are identified. Then, according to the values $c^t_i(y)$ with $i \in \{2, ..., 5\}$ (i.e., the components of the state of the neighboring people previously detected), the minimum possible distances between the person at cell x and each of them is determined through an appropriate function. Such distances are computed taking into account the affective information of the person in cell x and the mask condition for the person in cell y. These information are used to designate a probabilistic distribution weighting the selection of a certain Hall's space, then proceeding to randomly select an m distance between the upper and lower bound of the drafted space. This part, in fact, follows what has already been established for the 1D CA.



(a) Square showing the numbered directions a person could adopt for its next movement.

(b) Image showing the process of identifying the people deemed as too close to the person inside the cell currently under observation, with subsequent direction exclusion from the $D(x)$ subset. In this configuration, with $m = 1$, there is only one other person that can restrict the movement of the person at x, resulting in $D(x) = \{1, 2, 6, 7, 8\}$.

Figure 34: Illustration of the process regarding the evolution of a certain x cell's direction during the first substep of the dynamical evolution of the model.

The aforementioned process results in a subset $D(x) \subseteq \{1, ..., 8\}$ of possible directions the person located at cell x could adopt for their next movement (Figure 34). Namely, $j \in D(x)$ if and only if the person, moving alongside the direction v_j, is not going to get nearer to the other people in cells $y \in N_r(x)$ that are already at a smaller distance than or on the edge of the distance m computed between them and the person at x. Once $D(x)$ has been computed, two different cases can be contemplated depending on the obtained results: the first one sees $D(x) = \emptyset$ which brings the direction for the person's next movement to be fixed as $d_1^t(x) = 0$, corresponding to the person at cell x not moving as the configuration evolves; the second one, on the other hand, sees $D(x) \neq \emptyset$ which leads $d_1^t(x)$ to get randomly chosen from $D(x)$, corresponding to the person standing at x eventually moving towards one of the directions allowed by the current states of its neighbouring cells. In this way, $d^t(x)$ has been defined.

Then, the second stage of the dynamical evolution manages possible conflicts (Figure 35). In fact, it may happen that, referring to the configuration d^t, for a certain empty cell x there exist at least two non-empty cells y^1 and y^2 belonging to its neighborhood $N_1(x)$ where there are non-null $d_1^t(y^1) = k^1$ and $d_1^t(y^2) = k^2$ with $k^1, k^2 \in DIR$ such that $x = y^1 + v_{k^1} = y^2 + v_{k^2}$. In other words, there are two people in two distinct cells whose directions $d_1^t(y^1)$ and $d_1^t(y^2)$, if followed, would move them into the same empty cell x, thus resulting into a conflict for space. Since the model is based on

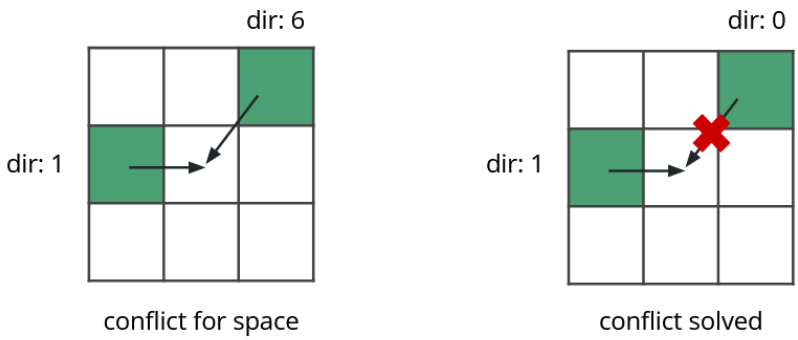


Figure 35: Illustration of the process regarding the resolution of conflicts for space. As seen in the example, with two pedestrian potentially moving to the same cell, one of them gets blocked, its direction set to 0 in order not to have both move as the configuration evolves.

an experiment on proxemic distances in which maintaining a proper distance from others is seen as vital for comfort and safety, such situations need to be properly handled in order not to let multiple people try and take the same spot. This is why the configuration d^t is then transformed into another intermediate configuration e^t, which aims at taking care of them. When a conflict is found, every person involved in it, with the exception of a randomly chosen one, has their direction set to 0, thus blocking their movement and only allowing one person to proceed on their selected destination.

Finally, the third stage of the CA evolution allows to get c^{t+1} from e^t. Namely, this step describes the movement of each moving person from a cell x towards the adjacent one identified by the moving direction of the person in $e_1^t(x)$. This behaviour is formally expressed with the following rules:

- if $e^t(x) = \emptyset$,

$$c^{t+1}(x) = \begin{cases} e^t(y) & \text{if } \exists\ y \in N_1(x) \text{ s.t. } x = y + v_k \text{ with } k = e_1^t(y) \\ e^t(x) & \text{otherwise} \end{cases},$$

- if $e^t(x) \neq \emptyset$,

$$c^{t+1}(x) = \begin{cases} \emptyset & \text{if } e_1^t(x) \neq 0 \\ e^t(x) & \text{otherwise} \end{cases}.$$

3.2.2 Implementation

As it was done for the simulation of the 1D CA presented before, the 2D CA model was also promptly translated into a NetLogo simulation to check the transition rule functioning, and Figure 36 presents the interface designed for the model as it was implemented into the tool.

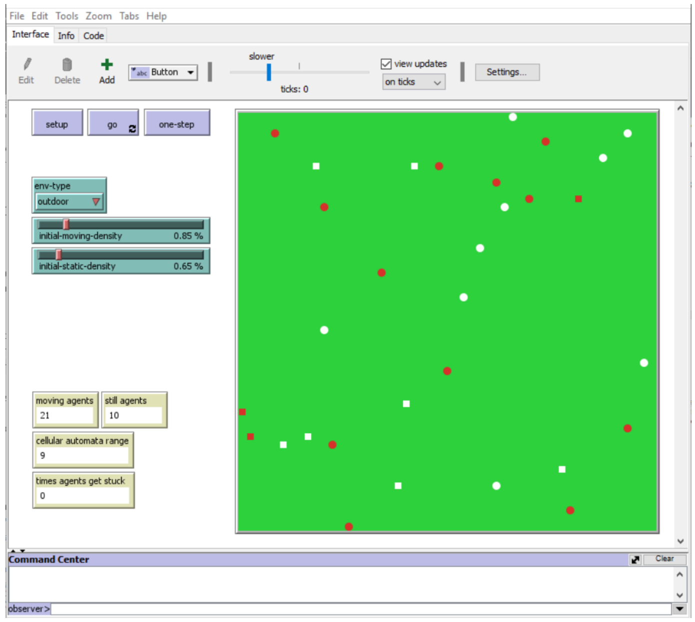


Figure 36: The user interface of the NetLogo model used for the 2D CA simulation.

The model allows the user to set the preferred environment to observe during the simulation, just as it was done for the 1D model, and to set the initial density for both the moving people and the non-moving ones that are going to constitute the population of the simulation. The maximum density that can be set for both type of people is 10%, so that the total population density present inside the environment will never exceed the percentage of 20%. These values were selected in order to be aligned with the intention of observing the behaviour of the CA at low densities, in order to better see how proxemic distances impact the pedestrians' movement throughout the environment. In this case, the user doesn't directly set the parameters for every single person inside the simulation, but the gender, age and mask condition of every instantiated person are randomly selected from the respective sets in order to have a diverse population which could cover the wide variety of combinations the parameters allow.

The moving pedestrians inside the simulation have been modeled to roam inside the environment by *random walk*, thus moving without a clear goal to follow or a specific reward to chase, using a built-in NetLogo function to randomly select one of their allowed directions to plan their next step. Also, given how in this two-dimensional case a pedestrian could find both masked and non-masked people as it moves around, every pedestrian computes not one but two different preferred distances: one to be maintained from masked people, and the other to be maintained from non-masked people.

The monitors placed on the GUI of the simulation are set up for keeping under control the numbers of the pedestrians on screen, together with the indication of the currently adopted CA range (resulting as the maximum distance computed by the people) and of how many times a moving person found itself unable to move around due to it being surrounded too closely by others. For an easier visualization, the moving people are here represented by *circles* and the non-moving ones by *squares*, and, with the same purpose, masked pedestrians are identified by the color *white* while the non-masked pedestrians are shown with the color *red*.

Regarding possible conflicts and collisions that could occur amongst pedestrians, given how this too is an often studied dynamic in the context of pedestrian simulation, a clarification needs to be made. In our specific case, as this is only a preliminary simulation of a CA model, it is not contemplated that two moving people could find themselves walking to and standing on the same cell of the lattice. Such situations are avoided, as it was mentioned before, because of the intention of working with low crowd density inside the environment and, moreover, because of the behavioural rules that were implemented implemented, as it was showed before how the conflicts are solved in order to actively keep the pedestrians away from each other. The moving people roam the environment but, given how the model is built, with them avoiding moving in certain directions if encountering others in order to remain comfortable, their main tendency is to avoid whoever comes too close to them. The combination of these two factors lead the pedestrians to stay at a distance from others and never actually occupy the same space out of necessity, for example, remaining still if movement is not doable.

A generalization of the model here proposed, without the limitations specifically introduced for our case regarding crowd density and pedestrians' behaviour, should then be able to properly address conflicts for space and avoid collisions, especially if supported by data coming from experiments. Some approaches that could be adopted in order to deal with this issue have already been introduced in the literature, like the one presented in [Kirchner et al., 2003] regarding friction.

3.2.3 Simulation and Results

Tables 12 and 13 show some preliminary results obtained by making the 2D simulation run for 500 timesteps at a time, each time with different pedestrian densities as initial configurations, and observing the simulation running both utilizing the indoor and the outdoor environment. For every combination of density and environment type, 50 run of the simulation were executed, in order to extract mean values for every parameter of interest.

As it can be noticed from the data, as the pedestrian density inside the environment grows, the number of events recording how a moving person find itself stuck grows rather quickly, and that is clearly visible looking at the percentage indicating the mean of moving people recorded as still per timestep. The percentage reached even with a density of only 20%, which is not considered a high density in terms of crowding, indicates how, despite the environment not being too crowded for people to move around into, the distances set by the affective state of every person are held in high regard and prevent the pedestrians from moving around when others are perceived too close to

Outdoor Environment			
Population density (%)	**Moving**	**Still**	**Pedestrians stuck per timestep (mean)**
1%	12.58	12.56	0.11 (0.88%)
5%	63.14	63.86	18.77 (29.73%)
10%	121.72	129.58	71.28 (58.56%)
15%	180.58	196.42	132.37 (73.30%)
20%	233.4	261.86	190.25 (81.51%)

Table 12: Table showing the percentage of pedestrians remaining stuck for each timestep in simulation performed with different initial densities in the outdoor environment.

Indoor Environment			
Population density (%)	**Moving**	**Still**	**Pedestrians stuck per timestep (mean)**
1%	13.6	12.42	0.07 (0.51%)
5%	63.28	64.26	19.95 (31.53%)
10%	123.5	128.54	73.82 (59.77%)
15%	181.82	194.9	133.71 (73.54%)
20%	232.86	259.98	189.88 (81.54%)

Table 13: Table showing the percentage of pedestrians remaining stuck for each timestep in simulation performed with different initial densities in the indoor environment.

allow movement.

An interesting thing that can be noticed from the obtained results, also, is how the percentages of pedestrians that found themselves stuck per timestep during the progression of the simulation do not differ consistently between the outdoor environment and the indoor one. It could have been expected, in fact, that in an outdoor environment and in the open air, people would have adopted shorter distances, thus allowing for an ease of movement superior to the one that an indoor environment would have allowed, especially given how it is known how the risk of contagion is higher in closed spaces. This does not seem to have happened, though, despite the delta values presented in Table 14 show how, with the single exception regarding the values recorded for a population density of 1%, the percentages are always a bit higher when speaking about the indoor environment. This could be the result of people participating in the online trials always acting careful regardless of the differences in environment, thus always gravitating towards similar Hall's spaces and distances because of the effect of the other variables contemplated in the experiment (their sociality, fear of contagion, the presence or absence of masks etc.).

Population density (%)	Outdoor percentage of pedestrians stuck per ts.	Indoor percentage of pedestrians stuck per ts.	Percentage delta (Δ)
1%	0.88%	0.51%	- 0.37%
5%	29.73%	31.53%	+ 1.80%
10%	58.56%	59.77%	+ 1.20%
15%	73.30%	73.54%	+ 0.24%
20%	81.51%	81.54%	+ 0.03%

Table 14: Table showing the delta difference between the percentages of pedestrians stuck for each timestep in the outdoor environment and in the indoor one.

Despite being gathered from a preliminary trial based on data coming from an experiment in a 1D environment, the results reported here are already quite promising in terms of how affective states modify pedestrian behaviour. The affective state modeled in the CA effectively influences the pedestrians' choices, driving them to get farther from people too close to them and making them stop the moment every choice regarding direction they could take would only make them uncomfortable.

4 Agent Modeling

After investigating the integration of affective parameters into cellular automata models, bringing to the design and the implementation of the two models presented before, the attention was shifted towards the multi-agent domain. This change of focus was brought in order to take advantage of the higher freedom and flexibility of multi-agent models, that allowed to leave behind the issues regarding strict requirements and computational explosion the CA models would have inevitably faced with the addition of more parameters to the state.

The shift towards agents, in fact, allowed for a less restrictive and more realistic environment to work with, eliminating the limits imposed by the discretization of space and the difficulties given by the increasing computational complexity. Because of the gained freedom, trying to design and simulate other situations around the model was also easier, thus allowing to explore further how pedestrian behaviour influenced by a strict application of proxemic distances could appear.

Contribution summary
The multi-agent modeling topic presented in this chapter was previously introduced with the following publications:

- [Gasparini et al., 2021a] Gasparini, Francesca, Marta Giltri, and Stefania Bandini. "Safety perception and pedestrian dynamics: Experimental results towards affective agents modeling." *AI Communications* 34.1 (2021): 5-19.
- [Gasparini et al., 2021b] Gasparini, Francesca, Marta Giltri, Daniela Briola, Alberto Dennunzio and Stefania Bandini. "Affectivity and Proxemic Distances: an Experimental Agent-based Modeling Approach." *AIxAS@ AI* IA*. 2021.
- [Bandini et al., 2022b] Bandini, Stefania, Daniela Briola, Francesca Gasparini and Marta Giltri. "Furthering an agent-based modeling approach introducing affective states based on real data." *ATT@ IJCAI-ECAI* (2022).

4.1 Multi-Agent Systems and Agent-Based Simulations

To better understand the framework that was followed to develop the agent model that is going to be presented in the next subsection, it is firstly necessary to explain what a multi-agent system is, what it entangles and what does a multi-agent simulation involve.

Multi-Agent Systems (MAS) are well-known models for modeling and studying and complex systems of various nature. Formally, a MAS is a collection of a certain number n of individuals or entities, called *agents*, each of them identified by an index $i \in \{1, \dots, n\}$ and taking, in each timestep of the simulation, a state from a set S, which is the system's *set of states*. The state of each agent includes the known details about the agent itself, such as the position of the agent inside the common d-dimensional space $X \subseteq \mathbb{R}^d$ where all the agents are situated.

A *configuration* of a MAS is a snapshot of all the states of the agents, namely a vector $c = (c_1, \ldots, c_n) \in S^n$ where, for every $i \in \{1, \ldots, n\}$, the element $c_i \in S$ is the state of the agent numbered as i. For each $i \in \{1, \ldots, n\}$, the i-th agent updates its own state according to a certain map $f_i : S^n \to S$ on the basis of its own state and the states of, if possible, all the other agents present in the system.

All the agents update their own state synchronously at each discrete time step. In this way, the overall update of the states of all agents at any time step is described by the *transition function* $F : S^n \to S^n$, which is defined as:

$$\forall c \in S^n, \quad F(c) = (f_1(c), \ldots, f_n(c)) \ .$$

Hence, the sequence $\{F^t(c)\}_{t \in \mathbb{N}}$, is nothing but the *dynamical evolution*, or *orbit*, of a given MAS starting from its initial configuration $c \in S^n$, where for every $t \in \mathbb{N}$ the element $F^t(c)$ of that sequence is the configuration of the MAS at time $t \in \mathbb{N}$. It is important to underline that the set $\{f_1, \ldots, f_n\}$ completely determines the transition function F of a MAS and that, therefore, a MAS can be concisely described as a triple defined as $\langle n, S, \{f_1, \ldots, f_n\} \rangle$.

Following this definition, an Agent-Based Simulation (ABS) is a MAS as described before together with all the information needed to perform a simulation, which includes the description or reproduction of a specific dynamical evolution of the given MAS. In other terms, these details may include, for instance, the data for setting up the initial configuration of the MAS, the total number of time steps corresponding to the duration of the phenomenon the MAS models and so on.

4.2 Affective Multi-Agent model

Now that the concepts of Multi-Agent Systems and Agent-Based Simulations have been described, it is possible to introduce the multi-agent model developed after the CA models described in Chapter 3 and designed to integrate affective aspects into agents.

In particular, as it happened for the 1D and the 2D cellular automata models previously presented, the multi-agent model here described was also designed following the online experiment shown in Section 2.4. Therefore, the affective parameters here included directly relate to the data acquired during the experiment.

The designed Affective Multi-Agent System (AMAS) is then a MAS $\langle n, S, \{f_1, \ldots, f_n\} \rangle$ with a certain set of states defined as the Cartesian product $S = X \times G \times M \times R \times A \times IS \times ES \times CF \times MD \times H \times D$, where:

- $X \subseteq \mathbb{R}^d$ is the d-dimensional space, the environment, that contains all the possible spatial positions the agents can be in;

- G, M, and R are the sets of the binary values g, m, and r, respectively, that when associated with any agent i indicate if i is male ($g = 1$) or female ($g = 0$), if i has a mask on ($m = 1$) or not ($m = 0$), and if i can move around the environment ($r = 1$) or not ($r = 0$), respectively;

- $A = \{y, ya, a, e\}$ is the set of age groups an agent can belong to with the different labels indicating the age groups y = young, ya = young-adult, a = adult, and e = elderly respectively;

- IS and ES are two sets of four values each which indicate the agent levels of *internal* and *external* sociality respectively, ranging from 0, which indicates low sociability, to 3, which corresponds to high sociability;

- $CF = \{0, 1, ..., 8\}$ is the set of the levels of contagion fear the agent could have, which ranges from 0, indicating absent fear, to 8, corresponding to severe fear;

- $MD = \{neutral, scared\}$ is the set containing the two possible moods a person could be in, and the value of the parameter md assumed in an agent's status is derived from combining the agent's parameters about sociality and fear previously introduced;

- $H = \{in, pr, sc, pb\}$ is the set of zones coming from Hall's interpersonal distances an agent can embrace, the labels indicating the in = intimate, pr = private, sc = social, and pb = public space respectively. The agent's Hall space is determined by all the factors listed above and, given how every Hall space has its upper and lower bounds defining it, the value assumed by this parameter influences the d value that follows;

- $D \subseteq \mathbb{R}^+$ is the set of values for the **minimum** distance an agent can have from any other agent. This minimum distance, as it was previously mentioned, it is influenced by the h value described above.

Following this definition, for any state $s \in S$ and for each $j = 1, \ldots, 7$, the j-th component of s will be denoted by s^j. In other words, the writing $s = (s^1, s^2, s^3, s^4, s^5, s^6, s^7, s^8)$, involves $s^1 \in X$, $s^2 \in G$, $s^3 \in M$, $s^4 \in R$, $s^5 \in A$, $s^6 \in P$, $s^7 \in H$, and $s^8 \in D$.

4.3 Parameter initialization

Given how the parameters of the model interact with each other in order to define the complete state of an agent, it is necessary to briefly talk about how those parameters are initialized once the designed model is translated into a simulation.

As it can be easily noticed by how the affective parameters have been introduced into the model, the majority of the parameters perfectly correspond to the ones that were identified in the experiment. In particular, this is referred to those parameters that were personally specified by the participants in the online questionnaire (i.e., age group, gender, sociality levels, fear of contagion) and to the parameters regarding the presence of a mask, the position in the environment and the ability to move.

Because of this, these are the parameters that can be more easily initialized in the simulations, either by making the user directly intervene on them to set them as needed or by randomly setting them when, for example, there is a whole crowd of agents to be initialized.

This is particularly true for the position of the agent, which has to be given an initial value, and for the agent's ability to move, which is always initialized as true.

There are, though, other parameters that are not simply selected at the instantiating of the simulation, but that are strictly correlated to others, having some previously mentioned dependencies that need to be taken into account. Three of those parameters, in fact, cannot be instantiated following the same logic explained above, because they are derived from a number of the other parameters which values heavily influence the resulting ones. These parameters, in particular, are the mood of the agent, its selected Hall's space and the distance to be maintained from other agents, and every single one of them has different requirements in order to be selected.

4.3.1 Mood parameter

As it was previously mentioned, the mood parameter is derived from a combination of other parameters and, to define the two levels of MD, the procedure explained below was followed.

Firstly, a mood measure that was a linear combination of the three measures IS, ES and CF was proposed and defined as:

$$moodMeasure = \alpha * IS + \beta * ES + \gamma * CF \tag{2}$$

To obtain the proper coefficients of this combination, then, a Particle Swarm Optimization (PSO) technique [Kennedy and Eberhart, 1995] was applied on the data coming from the online experiment.

The chosen fitness function was the Pearson Correlation Coefficient (PCC) between the distances chosen by the subjects and the $moodMeasure$ defined by Equation 2, previously transformed using a polynomial monotonic function to take into account the eventual non-linear mapping between distances, fear and sociality. A threshold was then applied to binarize the $moodMeasure$ in order to obtain the two levels for the mood, *neutral* and *scared*.

This process was executed two times, in order to address males and females separately given how the online experiment results highlighted the clear differences in chosen distances that men and women had when performing the figure-stop activity tasks.

4.3.2 Hall's Space and Distance parameters

Starting from the selection of a Hall's space, the applied process is the one explained as follows.

As it was mentioned when the parameter was introduced, the Hall's Space for a certain agent is determined by looking at all the *personal* parameters of the agent, such as gender, age, mask condition and mood. Sociality levels and fear of contagion are not explicitly included in the process because they are already present in the selection process, since the mood maintains information about all three parameters that were used to calculate it.

Every combination of the four aforementioned parameters leads to a different set of weights influencing the probability of each Hall's space being picked. The results analysis of the online experiment, in fact, led to discover how people seemed to choose every space with different tendencies as those parameters were kept into consideration. and thus such information was to be taken into account when selecting a value for the selected Hall's space of the agent. Once these weights have been identified, then, one of the Hall's spaces is selected by weighted choice.

As the Hall's space is picked, then, another information is obtained. Because every Hall's space has a certain lower and upper bound, in fact, choosing a certain space also binds to a certain set of possible distances to be adopted. In this particular case, the agent's distance is chosen at random between the upper and lower bound of the selected Hall's space.

5 Agent Simulations

In the following chapter, the simulations designed and executed on the basis of the proposed agent model are presented, showing how agents having their behaviour influenced by the introduced affective parameters would act in different situations. It was important, in fact, to understand how dealing with such parameters could influence the individual behaviour of every agent, but also how their application could impact the collective behaviour of entire crowds.

It is important to note that, in this case, the virtual simulations here reported cannot be properly validated by looking directly at the data collected through the experiments, since the situations here tested haven't yet been reproduced in an in-vivo or online experiment. Moreover, given how this is a first attempt at approaching the modeling of affective agents following the aforementioned design choices, the simulations here presented are approached under some limitations and assumptions appropriate for a preliminary work such as this, but that will need to be properly addressed with future works on the matter.

Nevertheless, virtual simulations are a useful tool to start theorizing how agents modeled with this kind of affective parameters could move around in different environment, how they could interact with other agents and with the environment itself with their behaviour influenced like so. Because of this, the simulations presented in the following are mainly going to provide information about possible agent behaviour to be later checked in other experiments, getting properly modified to more realistically reflect people's reactions if evidence indicating other types of behaviour is gathered.

As a last note, a few details need to be specified.

The first one is that the presented simulations, just how it happened for the simulations performed with the CA models, were executed through the NetLogo environment. This tool was once again utilized because of its ease of use and because, given the present but moderate complexity of the involved model and scenarios, it could still be used to simulate the envisioned instances without the need to turn to more sophisticated simulation environments. Moreover, given how the simulations were programmed inside the Netlogo environment, their approximate computational complexity is of $O(n)$.

The second one is that the models here presented follow the same regulations previously established for the CA models: one time step corresponds to 0.33 seconds and cells are considered as having a side 40 centimeters long, thus obtaining once more a speed of 1.2 metres per second for the agents that move inside the simulations.

The third one is that, following the limited availability of data coming from the online proxemic experiment, finding a sensible amount of data for every combination of affective parameters introduced in the model proved to be impossible given how only 80 subjects participated. For this reason, rather than utilizing measures biased by the small group for every combination of parameters, the simulation here presented take into consideration the parameters of gender, mask, sociality and fear but do not include the parameter of age into the computation.

5.1 First simulation model: Multiple agents free roaming

The first model here presented is very similar to the one already described for the 2D cellular automaton, since it is based on the very same premise. It regards, in fact, the simulation of multiple agents moving around in a two-dimensional environment, their behaviour and their chosen proxemic distances influenced by the factors composing their affective state.

The model is structured in order to allow the user to set a small set of parameters controlling different aspects of the simulation, and also to observe the agents' behaviour given different initial conditions using monitors.

There are four main parameters the user can set for the simulations, other than basic settings that allow to decide to use a certain seed for the simulation and to activate or deactivate the observance of proxemic distances.

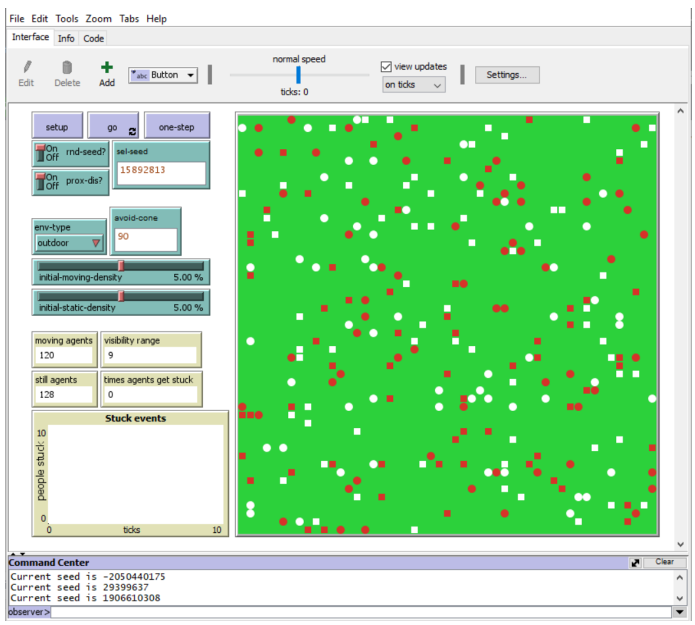


Figure 37: The user interface of the first model used for *multiple agents free roaming* simulations. The interface shown here displays one of the possible initial configuration the environment could assume with 5% moving and 5% non-moving population density.

The first parameter shown regards the selecion of the *environment* to be used and observed during the simulation, for which there are two option: an indoor one and an outdoor one, representing the restaurant and the park of the online experiment. This choice also influences the colour of the patches in the displayed environment, making them grey for the indoor and green for the outdoor.

The second and third parameters that can be set are then the initial densities for two different agent populations, with the first one composed of agents that are going to be able to move around the environment, thus acting as *pedestrians* or moving people, and the second one identifying the agents that are not going to move, thus acting as *obstacles* or non-moving people. The maximum density that can be set for both type of agents is 10% and, because of this, the total population density in the environment can never exceed 20%. In particular, this limit was set with the intention of maintaining a low total population density for the simulation trials, in order to better observe the agents' behaviour regarding the preservation of safe distances.

Finally, the fourth parameter the model allows the user to set is the angle of what is here called an *avoidance cone*. This measure is used to decide how much to restrict the agent's movement directions when finding another agent that is deemed too close, thus removing all the values in that cone from the agent's set of possible directions for movement.

The pedestrians inside the simulation, an example of which is shown in Figure 37, have been designed to freely walk inside the given environment, modeled with periodic boundary condition as to follow the shape of a two-dimensional discrete torus, by *random walk*: this is done by exploiting a built-in NetLogo function that randomically select one of their allowed direction as to plan their next step. Also, given that the online experiment highlighted how the distances selected by the participants were not only influenced by their own personal parameters but also by the use or non-use of a mask on behalf of the other figure contemplated in the activities, every pedestrian computes two different preferred distances to be referred to when interacting with others: one to be maintained from people who are wearing a mask, and the other to be maintained from people who are not wearing a mask.

The monitors positioned on the interface allow the user to keep an eye on the quantities of people on screen, together with a number indicating the visibility range adopted by the agents and a counter showing how many times a pedestrian found himself/herself unable to move around due to the excessive vicinity of both other pedestrians and obstacles. This same data is shown inside the underlying plot, which illustrates the trend the value assumes while the simulation runs. Moreover, for an easier visualization of the different populations in the environment, the pedestrians are represented by *circles* and the obstacles by *squares*. Following the same purpose, masked and non-masked people are differentiated by colour: people coloured in *white* have a mask on, while people coloured in *red* do not.

Just as it was previously mentioned for the 2D simulation performed for the 2D CA model presented in Section 3.2, in this simulation too conflicts and collisions between agents are not contemplated or bound to happen, both because of the limited density and the behaviour of the agents' themselves. The strict maintenance of the proxemic distances from others, in fact, keep them from ever occupying the same space of someone else, remaining on their already occupied spot rather than risk bumping into others voluntarily.

5.1.1 Trials and Achieved Results

Table 15 shows some preliminary results obtained by making this first model simulation run 50 times for 250 timesteps at a time, in different combination of environments, visibility ranges and total crowd density.

It was previously showed how the densities of moving people and non-moving people can be set separately, in order to set them differently for different trials, but for the trials here presented they had been set as equal so that, summed up, they could reach the population densities that are reported into Table 15 in terms of $\frac{pedestrians}{m^2}$. The different numbers of people, despite the same percentages used for the parameters instantiation, are derived from the way the environment is set up: since every empty patch randomly chooses a number than, if smaller than the density set through the slider, allows them to spawn an agent representing a person, the differences in agent creation numbers lie in the random selection of those numbers.

Other than differences in environment and population density, it was also decided to perform the trials with different avoidance angles for the pedestrians. This was done given how there could be differences in how people anticipate the others' movements [Suma et al., 2012], to simulate and see if varying this particular parameter too could bring interesting differences in the obtained results.

As the results presented in Table 15 show, as the pedestrian density inside the environment grows, the number of events recording the moments a pedestrian agent finds itself stuck grows rather quickly, and this is clearly visible when observing the percentages indicating the mean of pedestrians recorded as stuck per timestep.

		Outdoor Environment			*Indoor Environment*		
Avoidance Angle	**Total Density** ($\frac{pedestrians}{m^2}$)	**Moving (mean)**	**Still (mean)**	**Pedestrian stuck per timestep (mean)**	**Moving (mean)**	**Still (mean)**	**Pedestrian stuck per timestep (mean)**
90°	0.31 (5%)	64	65.86	9.60 (15.01%)	62.86	63.64	8.32 (13.24%)
	0.61 (10%)	120.28	130.14	52.74 (43.84%)	121.58	126.94	52.14 (42.88%)
	0.90 (15%)	179.5	194.54	105.59 (58.82%)	177.62	197	102.53 (57.72%)
	1.20 (20%)	232.34	258.24	153.15 (65.92%)	233.34	259.16	153.40 (65.74%)
180°	0.31 (5%)	64.24	66.02	33.66 (52.40%)	63.94	66.1	33.74 (52.77%)
	0.61 (10%)	124.96	133.9	92.03 (73.65%)	124.58	128.64	90.50 (72.64%)
	0.90 (15%)	179.82	193.1	148.64 (82.66%)	181.88	194.16	151.15 (83.11%)
	1.20 (20%)	234.78	259.38	206.70 (88.04%)	234.24	256.02	206.70 (88.24%)

Table 15: Table showing the percentage of pedestrians remaining stuck for each timestep performed with different initial densities and avoidance angles in the two contemplated environments.

The percentages reached even with a total density of only $1.20\frac{ped}{m^2}$, which corresponds to a selected 20% density, indicates how, despite the environment not being too crowded for people to move around into, the distances set by the affective states of every person prevent them from moving around when others are perceived as too close to allow a comfortable movement. Also, the avoidance angle adopted appear to have a visible impact regarding pedestrian behaviour in this sense.

Avoidance Angle	**Total Density** $(\frac{pedestrians}{m^2})$	**Outdoor Pedestrians stuck per timestep (%)**	**Indoor Pedestrians stuck per timestep (%)**	**Percentage delta (Δ)**
90°	0.31	15.01%	13.24%	- 1.77%
	0.61	43.84%	42.88%	- 0.96%
	0.90	58.82%	57.72%	- 1.10%
	1.20	65.92%	65.74%	- 0.18%
180°	0.31	52.40%	52.77%	+ 0.37%
	0.61	73.65%	72.64%	- 1.01%
	0.90	82.66%	83.11%	+ 0.45%
	1.20	88.04%	88.24%	+ 0.20%

Table 16: Table showing the differences when considering percentages of pedestrians that remained stuck in the outdoor environment in comparison to the indoor environment. The red values show a decrement in stuck pedestrian percentages in the passage from outdoor to indoor, while the green shows an increment.

An interesting result, similar to the one already observed with the simulations done for the 2D CA model, regards the differences between the results in the indoor and outdoor environments. Looking at the percentages of pedestrians stuck per timestep reported in Table 16, and focusing in particular on the percentage deltas reported in the last column of the table, it is clear how the differences in agents' mobility between the two environment are not very accentuated. And, in an even more peculiar detail, the percentages regarding the indoor environment are, in 5 out of 8 analysed instances, actually lower than the ones for the outdoor environment. This shows how people in the indoor environment tended to be less prevented from movement, albeit for minor changes in percentages that never surpass a 2% difference.

Given how small the deltas are, then, this result could be a simple exception to the behaviour that can be observed by looking at the rows of the table showing an increment in stuck events with the environment change, and that can also be traced back to the considerations that were outlined in Section 3.2 regarding people's approach to the activities presented during the online experiment.

The same table can also be observed from the perspective of the avoidance angle, which allow for more considerations.

As it was explained during the presentation of the simulation model, the avoidance angle was

Environment	Total Density ($\frac{pedestrians}{m^2}$)	Pedestrians stuck per timestep with 90° angle (%)	Pedestrians stuck per timestep with 180° angle (%)	Percentage delta (Δ)
Outdoor	0.31	15.01%	52.40%	+ 37.39%
	0.61	43.84%	73.65%	+ 29.81%
	0.90	58.82%	82.66%	+ 23.84%
	1.20	65.92%	88.04%	+ 22.12%
Indoor	0.31	13.24%	52.77%	+ 39.53%
	0.61	42.88%	72.64%	+ 29.76%
	0.90	52.72%	83.11%	+ 30.39%
	1.20	65.74%	88.24%	+ 22.50%

Table 17: Table showing the differences when considering percentages of pedestrians that remained stuck with an avoidance angle of 90° in comparison to an avoidance angle of 180°. The green values show a increment in stuck pedestrian percentages in the passage from the smaller to the wider avoidance angle.

used to regulate how agents decided to approach the matter of maintaining distance from others, influencing how much their available directions were to be limited because of other agents' presence. The wider the angle, the more directions were excluded were contemplating the agent's next step, thus restricting its movement in different degrees depending on the selected angle.

The trials here performed contemplated angles of both 90 and 180 degrees, and Table 17 shows the different percentages of pedestrians stuck per timestep in different environment compared for these two avoidance angles, with the computed deltas highlighting how much those percentages differ.

This time, the trend underlined by the percentage deltas provide a very clear view on how, at the doubling the angle considered for the elimination of possible directions, the pedestrians found themselves to be stuck more often, with increments over 20% in all of the cases presented in the table. The most evident one regards the indoor environment, in the comparison between the percentages at the 0.31 density: the increment in the percentage of pedestrian stuck per timestep identified for that line, in fact, equals a high +39.53%. A similar case, reaching a result close to the one just presented, regards the outdoor environment at the same density: there, in fact, the percentage delta shows an increment of +37.39%.

These results show just how much different approaches in terms of anticipating others' movements can impact the simulation, thus highlighting how this too could be a parameter to be properly investigated in people in the future.

5.2 Second simulation model: Single agent goal oriented

The second model here presented aims at simulating one single agent having the goal of traversing a room full of people in order to reach the other side of a certain environment, observing then how the agent moves throughout the crowd to reach its objective given the affective component influencing its behaviour.

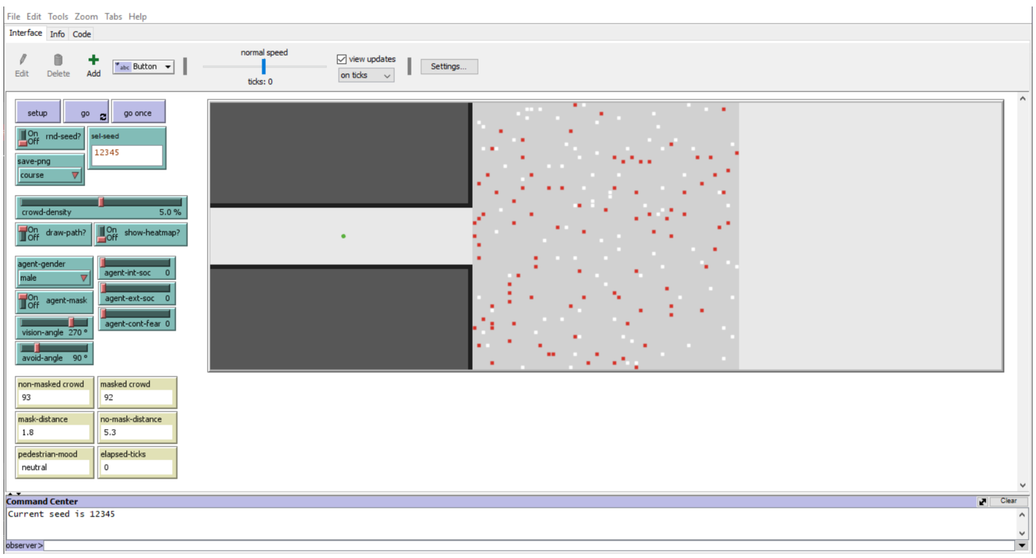


Figure 38: The user interface of the second model used for *single agent goal oriented* simulations. The agent that is going to traverse the environment towards the right side of the screen is presented on the left of the hall where the crowd moves.

This time, the model presents an environment with a specific structure, rather than the borderless open space that was utilized in the previous simulation. In particular, the environment is here divided in three different sections: the first one, on the left side, is a corridor where the *main moving agent* is going to be instantiated; the second one, occupying the middle of the environment, is a big room in which the agents composing a *crowd* move by *random walk* inside its limits; the third and last one, situated on the right side of the space, is the empty room the main moving agent intend to reach. As it was mentioned, in fact, this agent moves with a goal, and in this case the goal is to arrive on the far right side of the empty room.

For the sake of an easier visualization, following what was done with the previous simulation, the different agents can be distinguished by shape and colour: the main agent, in fact, has the shape of a circle, while the agents composing the crowd have the shape of a square. White and red, once again, highlight pedestrians with or without a mask on, but, in order to make the main agent clearly visible among the crowd, two more colours were introduced: the main agent, in fact, is painted green if it has a mask on, and is painted orange otherwise.

The model allows to set different parameters regarding the main moving agent, in order to observe different types of agents tackle the same task. It is in fact possible to decide the gender, mask usage, sociality levels and fear of contagion for the agent, and to also set a *visibility angle*, which is a parameter that dictates how much the agent looks around itself, and an *avoidance angle*, the avoidance cone implemented into the previous simulation, which influences the agent's capability of moving and thus its decisions on how to correct its course to reach its goal.

Other than the parameters for the main agent, it is also possible to set the density for the *crowd* occupying the middle section of the environment which, in this case, is capped at 10% to observe the simulated situation with limited population density.

As the monitors on screen allow to keep track of the distances the agent is going to maintain from both masked and non-masked people, there is also a counter tasked with keeping track of the *time* the agent takes to reach the edge of the room on the right, and two options allowing the agent to draw his course as it goes and to show the heat-map of its movements once the simulation has ended.

5.2.1 Trials and Achieved Results

Table 18 shows some preliminary results obtained from the second model simulation runs. In this case, the simulation was run 50 times for different combination of parameters regarding the main agent and different crowd densities. Trials were performed with different combinations of gender, mood and mask for the main agent, and the tested crowd densities were 2% and 7%, corresponding respectively to densities of 0.12 and 0.43 in terms of $\frac{pedestrians}{m^2}$.

The parameters regarding visibility and avoidance angles, on the other hand, were pre-selected and kept the same throughout the entirety of the trials: in particular, a 270° visibility angle was selected in order for the main agent to disregard people behind its back as it proceeded towards its goal, while an avoidance angle of 90° was adopted.

Only one limit was posed to the simulations, in order to avoid them for running indefinitely, and that was in the maximum number of timesteps to occur before the simulation stopped: every trial, in fact, could run for a maximum of 5000 timesteps, which gave agents a time of approximately 28 minutes to reach the other side of the environment and meet their goal.

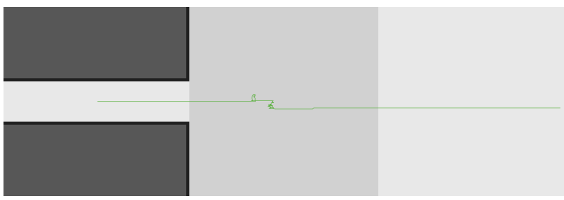
Gender	Mood	Mask	Crowd Density ($\frac{pedestrians}{m^2}$)	Distance from masked crowd (mean)	Distance from unmasked crowd (mean)	Elapsed time (mean)	Unreached goal events (%)
Male	Scared	Yes	0.12 (2%)	3.17 m	3.85 m	170.39 s	0%
			0.43 (7%)	2.80 m	4.22 m	676.54 s	28%
		No	0.12 (2%)	4.16 m	5.15 m	287.36 s	0%
			0.43 (7%)	4.33 m	4.82 m	1134.69 s	44%
	Neutral	Yes	0.12 (2%)	2.34 m	2.62 m	158.16 s	0%
			0.43 (7%)	2.44 m	3.16 m	507.72 s	16%
		No	0.12 (2%)	3.87 m	3.74 m	233.03 s	2%
			0.43 (7%)	3.02 m	3.38 m	504.97 s	16%
Female	Scared	Yes	0.12 (2%)	4.36 m	6.27 m	453.14 s	10%
			0.43 (7%)	4.48 m	4.67 m	1089.69 s	52%
		No	0.12 (2%)	5.70 m	6.02 m	472.73 s	6%
			0.43 (7%)	6.03 m	6.37 m	1572.61 s	92%
	Neutral	Yes	0.12 (2%)	2.56 m	3.62 m	170.66 s	0%
			0.43 (7%)	2.91 m	4.58 m	874.31 s	42%
		No	0.12 (2%)	4.95 m	4.99 m	337.84 s	4%
			0.43 (7%)	5.04 m	5.51 m	1339.71 s	72%

Table 18: Table showing an example of how much time agents with different parameters and with facing different crowd densities use in order to reach the other side of the environment.

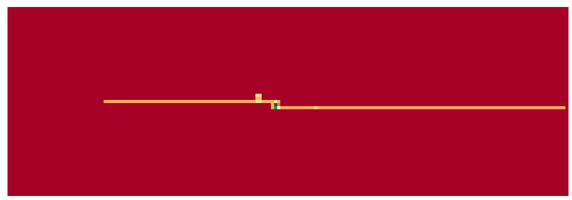
Numerous considerations can be drawn from the data presented in Table 18 given the information extracted from the data coming from the simulations.

One of the first considerations that can be made regards the correlation existing between the crowd density in the room at the center of the environment and the elapsed time which, as it was previously said, measures how long it took the agent to reach its goal at the other side of the environment. As the population density increased, in fact, the used time rose with it, the elapsed time mean doubling or even tripling with the passage from a 2% to a 7% density. A particularly noticeable case is the one contemplating the mean values for the combination of a female masked agent in a neutral mood, in which the time measured with a 7% density is 5.1 times the one recorded with a 2% density.

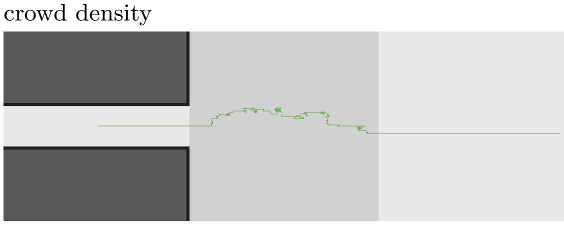
To take a better look in a trial executed following these parameters, figures 39 and 40 investigate one of the runs recorded for a female masked agent, showing the path to destination traversed by the agent both as a drawn path on the environment and as a heat map.



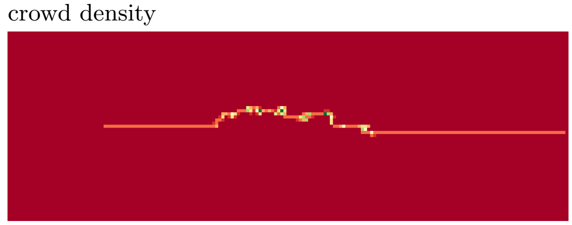
(a) Path for the neutral female masked agent, 2% crowd density



(b) Heatmap for the neutral female masked agent, 2% crowd density



(c) Path for the neutral female masked agent, 7% crowd density

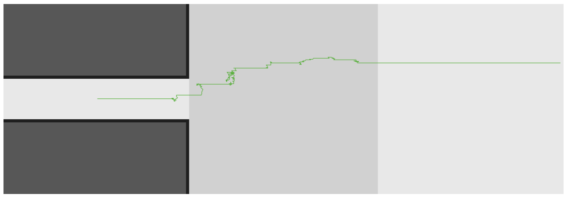


(d) Heatmap for the neutral female masked agent, 7% crowd density

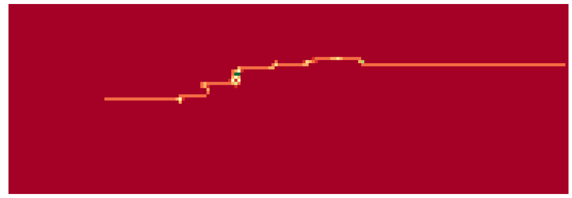
Figure 39: Paths and heatmaps recorded for a female masked agent in a neutral mood. In both cases, the agent succeeded in reaching the other edge of the environment after traversing the crowd in the room at the center.

While the displayed example does not show the path of the neutral agent growing too complicated or long to justify such an increment in the travel time, it shows how the agent's path becomes less linear as the crowd density rises. The heatmap, in particular, highlights how the agent found itself to step onto the same patches more than once, showing the areas in which the crowd swarming around it prevented its movement towards its goal.

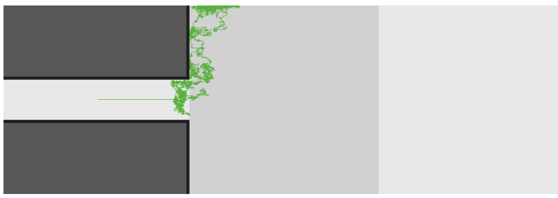
The difficulties brought by the higher density are particularly evident when analysing a simulation



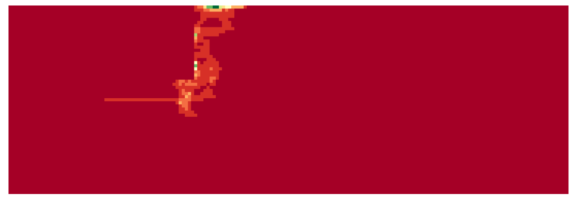
(a) Path for the scared female masked agent, 2% crowd density



(b) Heatmap for the scared female masked agent, 2% crowd density



(c) Path for the scared female masked agent, 7% crowd density



(d) Heatmap for the scared female masked agent, 7% crowd density

Figure 40: Paths and heatmaps recorded for a female masked agent in a scared mood. While the agent succeeded in reaching the other edge of the environment in the first case, with 2% crowd density, it remained stuck in the crowded room when facing a 7% crowd density.

with a scared female masked agent. Not only the figures in Figure 40 show how the agent did not manage to follow a linear path to its destination, following a route highlighting the same impediments mentioned before, but also how the combination of high crowd density and scared mood brought the agent not to succeed in reaching its goal before the 5000 timesteps run out.

These examples show, then, how pedestrians naturally moved more easily in a less crowded space, encountering more difficulties as they found more people around to block their path. And this is particularly evident when observing the percentage of unreached goal events recorded during the trials performed for every combination of parameters, an information that needs to be taken into consideration together with time since the simulations weren't made to run indefinitely given the risk of agents not reaching the destination. The higher percentages recorded always pertain to situation of high density, and other important considerations that can be drawn regard how these percentages are higher for scared agents in comparison to neutral ones, for unmasked agents in comparison to masked ones and for female agents in comparison to male ones.

This result highlights how all the identified parameters strongly influence the way the agent is going to behave in the simulation, and the same influence can be noticed in the way distances and times are distributed for the different parameters combination that were tested during the trials. Tables 19 and 20 summarize the acquired information, better showcasing the detected differences.

Crowd Mask configuration	Mood	Mask	Crowd Density	Male Distances from crowd (mean)	Female Distances from crowd (mean)	Distance delta from crowd (meters)
Masked	Neutral	Yes	0.12 (2%)	2.34 m	2.56 m	+ 0.22 m
			0.43 (7%)	2.44 m	2.91 m	+ 0.47 m
		No	0.12 (2%)	3.87 m	4.95 m	+ 1.08 m
			0.43 (7%)	3.02 m	5.04 m	+ 2.02 m
	Scared	Yes	0.12 (2%)	3.17 m	4.36 m	+ 1.19 m
			0.43 (7%)	2.80 m	4.48 m	+ 1.68 m
		No	0.12 (2%)	4.16 m	5.70 m	+ 1.54 m
			0.43 (7%)	4.33 m	6.03 m	+ 1.70 m
Unmasked	Neutral	Yes	0.12 (2%)	2.62 m	3.62 m	+ 1.00 m
			0.43 (7%)	3.16 m	4.58 m	+ 1.42 m
		No	0.12 (2%)	3.74 m	4.99 m	+ 1.25 m
			0.43 (7%)	3.38 m	5.51 m	+ 2.13 m
	Scared	Yes	0.12 (2%)	3.85 m	6.27 m	+ 2.42 m
			0.43 (7%)	4.22 m	4.67 m	+ 0.45 m
		No	0.12 (2%)	5.15 m	6.02 m	+ 0.87 m
			0.43 (7%)	4.82 m	6.37 m	+ 1.55 m

Table 19: Table showing the mean distances adopted by the agents during the simulations, with the comparison aimed at the differences detected in male and female agents. The green values show an increment in the recorded distances for different combinations of mood and mask configuration.

As it can be noticed by looking at Table 19, the distances adopted by males and females when in the same mood and in the same mask configuration only slightly differ from one another depending on the crowd configuration and density, given how that is not a parameter that influences how agents decide to approach. On the other hand, the distances clearly get longer when the agent is scared rather than neutral, and when it is unmasked rather than masked, increasing for both genders.

However, what the data confirm rather clearly is how females tended to adopt longer distances in comparison to males, a behaviour that was already observed during the result analysis of the online experiment and that is here correctly represented by the simulations. The increments reported in the table vary between 0.2 and 2.5 meters with no particular pattern, but the important information resides in the fact that the mean of the distances selected by female agents are consistently higher than the one reported for male agents, highlighting once more the higher tendency that females have to stay at farther distances from others in comparison to males.

This tendency of female agents and scared agents to select longer distances in comparison to males and neutral agents is additionally reflected in the elapsed times recorded during the trials. In particular, Table 20 presents the differences in time recorded between agents in neutral mood and agents in scared mood, while Table 21 presents the differences in time recorded between male and female agents, showing the aforementioned table from a different perspective.

Gender	**Mask**	**Crowd Density** ($\frac{pedestrians}{m^2}$)	**Neutral Elapsed time (mean)**	**Scared Elapsed time (mean)**	**Time delta (seconds)**
Male	Yes	0.12 (2%)	158.16 s	170.39 s	+ 12.23 s
		0.43 (7%)	507.72 s	676.54 s	+ 168.82 s
	No	0.12 (2%)	233.03 s	287.36 s	+ 54.33 s
		0.43 (7%)	504.97 s	1134.69 s	+ 629.72 s
Female	Yes	0.12 (2%)	170.66 s	453.14 s	+ 282.48 s
		0.43 (7%)	874.31 s	1089.69 s	+ 215.38 s
	No	0.12 (2%)	337.84 s	472.73 s	+ 134.89 s
		0.43 (7%)	1339.71 s	1572.61 s	+ 232.90 s

Table 20: Table showing the time-to-exit means recorded for neutral agents in comparison to the one recorded for scared agents, highlighting the differences in said times. The green values show an increment in the times.

The obtained results, showing higher elapsed time means for scared agents of both genders and for female agents of both moods, could, in fact, be a direct reflection of how such agents usually choose larger distances than their direct counterparts: larger distances bring to intercept the crowd found in the middle room earlier, to keep further away from it, thus taking more time in getting around those people and reaching the far end of the environment.

Mood	Mask	Crowd Density ($\frac{pedestrians}{m^2}$)	Male Elapsed time (mean)	Female Elapsed time (mean)	Time delta (seconds)
Neutral	Yes	0.12 (2%)	158.16 s	170.66 s	+ 12.50 s
		0.43 (7%)	507.72 s	874.31 s	+ 366.59 s
	No	0.12 (2%)	233.03 s	337.84 s	+ 104.81 s
		0.43 (7%)	504.97 s	1339.71 s	+ 834.74 s
Scared	Yes	0.12 (2%)	170.39 s	453.14 s	+ 282.75 s
		0.43 (7%)	676.54 s	1089.69 s	+ 413.15 s
	No	0.12 (2%)	287.36 s	472.73 s	+ 185.37 s
		0.43 (7%)	1134.69 s	1572.61 s	+ 437.92 s

Table 21: Table showing the time-to-exit means recorded for male agents in comparison to the one recorded for female agents, highlighting the differences in said times. The green values show an increment in the times.

5.3 Third simulation model: Room clearing

The third and final model presented in this section stems to the same structure previously presented for the first simulation model, and it involves a scenario of room clearing in which a crowd has to exit a room.

The structure of this simulation is very similar to the one already presented in Section 5.1, given the common root involving a 2-dimensional space and a crowd moving inside said environment, but with a few notable differences that are going to be explained hereafter.

The first change done in respect to the first simulation model is the structure of the environment: this time in fact, while maintaining both the indoor and outdoor options, the borders of the environment also outlined the limits of an enclosure that the crowd had to respect, thus introducing the boundary conditions that were avoided for the free roaming simulations.

Also, given how the environment now depicted an outdoor enclosure or an indoor room, it was necessary to introduce a way for the agents to exit the space. Two new parameters were then included in the GUI for this purpose: the *exit position* selector, which allowed to position an exit on one of the four cardinal points, and an *exit width* slider, which allowed to differently scale the positioned exit.

Another change, and probably the most noticeable one, one regards the presence of only one type of agent inside the simulation, namely the one identifying moving people: given the situation of room clearing that was to be depicted, in fact, only a moving crowd was included in the model. The density parameter on the interface regulating the moving population density inside the environment maintained the same limit, though, of a maximum population density of 10%. Moreover, the *random walk* movement was substituted with a *goal oriented* movement: since the agents were to clear the

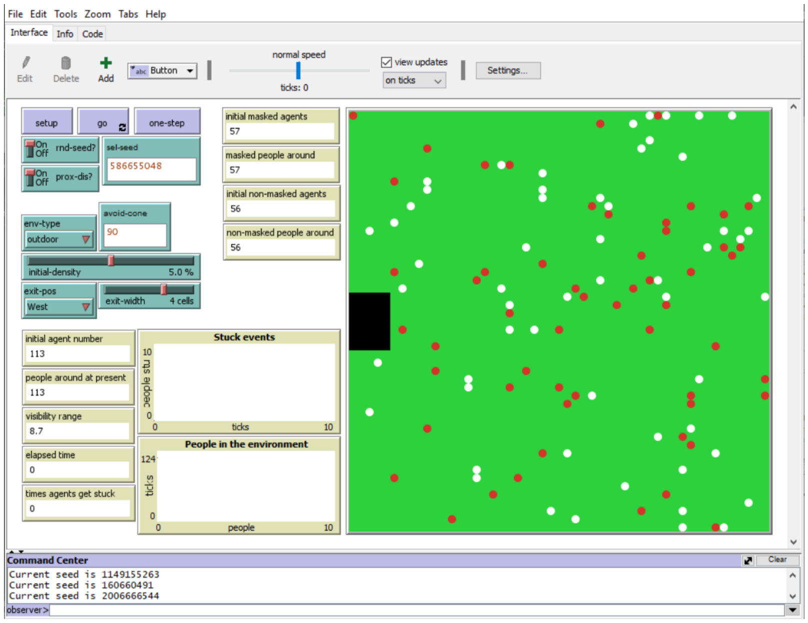


Figure 41: The user interface of the third model used for *room clearing* simulations. The interface shown here displays one of the possible initial configuration the environment could assume with an initial crowd density of 5% and the exit positioned to the West.

room, in fact, their movements tended to bring them closer to the appointed exit whenever possible, adopting directions that brought them farther from their destination only when the direction leading them for the exit appeared blocked by the presence of other agents.

Finally, the monitor and plots on the interface allow to keep a better eye on how the launched simulation evolves over time. In particular, there are monitors that keep track of how many people are still inside the room at any given timestep, counting both masked and non-masked pedestrians and comparing the actual population with the one recorded at the initialization of the system, together with monitors showing the current visibility range, the elapsed time in timesteps since the simulation started and the number of stuck events recorded in total. The two plots accompanying those monitors, then, allow a better visualisation of the crowd evacuation and of the number of stuck events over time.

Other parameters and mechanisms, such as the avoidance cone and the way conflicts for space were handled, kept their functionality and procedures as they were introduced in Section 5.1.

5.3.1 Trials and Achieved Results

Environment	Exit Location	Population density ($\frac{pedestrians}{m^2}$)	Pedestrians with mask (mean)	Pedestrians without mask (mean)	Pedestrians stuck per timestep (mean)	Time to clear room (mean)
Indoor	West	0.13 (2%)	24.92	26.06	0 (0%)	16.13 s
		0.30 (5%)	65.30	64.98	0 (0%)	16.73 s
		0.45 (7%)	90.64	90.84	0.0004 (0.0002%)	17.15 s
		0.61 (10%)	130.84	127.42	0.0007 (0.0003%)	18.10 s
	East	0.13 (2%)	24.88	26.74	0 (0%)	16.17 s
		0.30 (5%)	65.52	63.34	0 (0%)	16.67 s
		0.45 (7%)	90.12	88.24	0.0004 (0.0002%)	17.09 s
		0.61 (10%)	128.86	128.10	0.0004 (0.0001%)	17.94 s
Outdoor	West	0.13 (2%)	26.12	26.42	0 (0%)	16.02 s
		0.30 (5%)	63.16	63.54	0 (0%)	16.70 s
		0.45 (7%)	89.44	91.68	0 (0%)	17.18 s
		0.61 (10%)	128.02	126.08	0.0007 (0.0003%)	17.99 s
	East	0.13 (2%)	26.54	25.88	0 (0%)	16.14 s
		0.30 (5%)	63.58	64.42	0 (0%)	16.90 s
		0.45 (7%)	89.92	89.80	0.0008 (0.0004%)	17.15 s
		0.61 (10%)	130.46	128.08	0 (0%)	17.97 s

Table 22: Table showing, for the trials performed with a *population disregarding proxemic distances*, the percentages of pedestrian stuck events and the times used for clearing the room for different environment, exit placements and population densities.

Environment	Exit Location	Population density ($\frac{pedestrians}{m^2}$)	Pedestrians with mask (mean)	Pedestrians without mask (mean)	Pedestrians stuck per timestep (mean)	Time to clear room (mean)
Indoor	West	0.13 (2%)	26.08	26.66	0.13 (0.25%)	27.15 s
		0.30 (5%)	63.80	65.60	1.89 (1.46%)	47.35 s
		0.45 (7%)	93.10	91.44	4.94 (2.67%)	61.11 s
		0.61 (10%)	128.44	126.68	11.93 (4.68%)	79.48 s
	East	0.13 (2%)	25.86	25.60	0.12 (0.23%)	26.43 s
		0.30 (5%)	63.22	67.22	1.98 (1.52%)	47.92 s
		0.45 (7%)	91.24	90.88	4.70 (2.58%)	60.13 s
		0.61 (10%)	131.88	128.64	12.38 (4.75%)	80.88 s
Outdoor	West	0.13 (2%)	25.42	25.74	0.11 (0.21%)	26.50 s
		0.30 (5%)	63.66	61.90	1.70 (1.35%)	45.48 s
		0.45 (7%)	89.78	90.72	4.89 (2.71%)	61.00 s
		0.61 (10%)	127.34	128.70	12.14 (4.74%)	80.73 s
	East	0.13 (2%)	25.04	24.54	0.14 (0.29%)	25.68 s
		0.30 (5%)	64.16	64.50	2.01 (1.56%)	47.58 s
		0.45 (7%)	89.96	87.60	4.12 (2.32%)	59.58 s
		0.61 (10%)	129.76	131.00	12.66 (4.86%)	83.11 s

Table 23: Table showing, for the trials performed with a *population taking into consideration proxemic distances*, the percentages of pedestrian stuck events and the times used for clearing the room for different environment, exit placements and population densities.

Tables 22 and 23 show the preliminary results obtained from the third model simulation runs. In this case, too, the simulation was run 50 times. with different combinations of parameters. Four different population densities were taken into account: trials were performed for 2%, 5%, 7% and 10% densities, which corresponded respectively to values of 0.13, 0.30, 0.45 and 0.61 in terms of $\frac{pedestrians}{m^2}$. Also, tests were performed by taking into consideration two different exits, placed at West and East points, and by observing the behaviour of populations both respecting and disregarding proxemic distances. This was done to later compare the observed behaviour, in order to better understand what kind of impact the respect of distances had on the observed situations.

Other parameters, on the other hand, were maintained the same throughout the entirety of the trials: for example, an avoidance angle of 90° was adopted in line with the other executed simulations, and the exit dimensions were always fixed at 4x8 cells.

Finally, for this simulation too, in order to avoid the trials running indefinitely, a maximum number of timesteps was decided: the upper bound was placed at 2000 timesteps, which gave the agents a time of approximately 11 minutes to clear the room.

Looking at both Table 22 and Table 23, it is easily noticeable that the environmental parameters involved in the analysis do not generate highly differentiable results. Both considering the two different environment and the two different exits used in the trials, in fact, the recorded stuck events and the times to clear are quite similar in each case.

Checking the entries at specific population densities, in fact, the results obtained comparing the environments or comparing the exits are very close. In particular, looking at Table 22, the differences in pedestrians stuck per timestep are negligible, and the ones in the times to clear room are usually around 0.1 seconds or less. Looking at Table 23, then, the differences in pedestrians stuck per timestep do not ever surpass 0.2 percentage points, and the ones in the times to clear room are mainly around and lower 1.5 seconds.

However, these slight difference were expected: it was already noticed how the results obtained in Section 5.1 regarding the change in environment did not report any significant difference in terms of how pedestrians approached proxemic distances, and since placing different exits in the environment did not imply any major changes regarding obstacles and similar impediments similar results were to be expected. This reasoning, of course, is not valid for the case in which pedestrians did not have proxemic distances to keep into consideration, but the fact that a similar population was involved in the trials is reason and explanation enough for the obtained data.

More evident differences, on the other hand, can be found when analysing back to back the results coming from the two different slices of trials, namely comparing the data obtained from the simulations with pedestrians not considering proxemic distances (NO-PR) and from the ones with pedestrians considering those same distances (PR).

Env.	Exit Location	Population density ($\frac{pedestrians}{m^2}$)	NO-PR Ped. stuck per ts (mean)	PR Ped. stuck per ts (mean)	NO-PR Time to clear room (mean)	PR Time to clear room (mean)	Time delta (seconds)
Indoor	West	0.13 (2%)	0 (0%)	0.13 (0.25%)	16.13 s	27.15 s	+ 11.02 s
		0.30 (5%)	0 (0%)	1.89 (1.46%)	16.73 s	47.35 s	+ 30.62 s
		0.45 (7%)	0.0004 (0.0002%)	4.94 (2.67%)	17.15 s	61.11 s	+ 43.96 s
		0.61 (10%)	0.0007 (0.0003%)	11.93 (4.68%)	18.10 s	79.48 s	+ 61.38 s
	East	0.13 (2%)	0 (0%)	0.12 (0.23%)	16.17 s	26.43 s	+ 10.26 s
		0.30 (5%)	0 (0%)	1.98 (1.52%)	16.67 s	47.92 s	+ 31.25 s
		0.45 (7%)	0.0004 (0.0002%)	4.70 (2.58%)	17.09 s	60.13 s	+ 43.04 s
		0.61 (10%)	0.0004 (0.0001%)	12.38 (4.75%)	17.94 s	80.88 s	+ 62.94 s
Outdoor	West	0.13 (2%)	0 (0%)	0.11 (0.21%)	16.02 s	26.50 s	+ 10.48 s
		0.30 (5%)	0 (0%)	1.70 (1.35%)	16.70 s	45.48 s	+ 28.78 s
		0.45 (7%)	0 (0%)	4.89 (2.71%)	17.18 s	61.00 s	+ 43.82 s
		0.61 (10%)	0.0007 (0.0003%)	12.14 (4.74%)	17.99 s	80.73 s	+ 62.74 s
	East	0.13 (2%)	0 (0%)	0.14 (0.29%)	16.14 s	25.68 s	+ 9.54 s
		0.30 (5%)	0 (0%)	2.01 (1.56%)	16.90 s	47.58 s	+ 30.68 s
		0.45 (7%)	0.0008 (0.0004%)	4.12 (2.32%)	17.15 s	59.58 s	+ 42.43 s
		0.61 (10%)	0 (0%)	12.66 (4.86%)	17.97 s	83.11 s	+ 65.14 s

Table 24: Table showing the comparison of the pedestrian stuck events recorded and of the time to clear coming from the trials with the population not following proxemic distances (**NO-PR**) and with the population following them (**PR**), highlighting the time differences in the last column of the table. The green values show an increment in the elapsed time.

Table 24 shows a summary of the aforementioned comparison between the results coming from the trials with the two different populations, highlighting both the data regarding pedestrians stuck per timestep and time to clear.

The differences in both columns are immediately visible, especially regarding the number of recorded events in which pedestrians found themselves stuck and unable to move: while it is an almost non-existing occurrence for the NO-PR population, the PR population still records some of these events, with percentages of stuck pedestrians ranging from low values around 0.10% to higher values around 4.90%. Those percentages, as predictable, increase with the increasing density of the population that has to exit the environment, the higher concentration of pedestrians leading to less space to move and more people to keep into consideration when deciding where to move next.

Similar considerations can be drawn by looking at the recorded times to clear, whose differences are further highlighted by the time deltas reported in the last column of Table 24. While for the NO-PR population the times to clear always gravitate towards similar values, which only slightly increase with the increasing population density, the times reported for the PR population are generally much higher, presenting clear growth both when comparing lower to higher densities and when comparing the recorded times with the ones for the NO-PR population.

Such prominent difference probably mainly reside in the way the two populations behave differently in order to accomplish the room clearing task: where the NO-PR population does not pay attention at the distance to be maintained from others, immediately walking towards the exit and not caring if standing too close to other people, the PR population expresses a more cautious approach, in which every pedestrians takes its own preferences in proxemic distances into consideration and moves accordingly.

As the NO-PR population finds the easiest and fastest way towards the exit, then, the PR population cannot actually make the same choice, because every pedestrian has not only to keep into consideration where the exit is, but also where the others surrounding it are and how far from it they are. Their movement is also influenced by the fact that they have to work around others and to keep a proper distance from them as they do, and this is what makes them encounter more frequently situations in which it is impossible to move without compromising their proxemic distances.

Given how they have to actively keep others into consideration, thus following longer paths towards the exits, and how they stumble more frequently into being stuck among others, it is reasonable how the pedestrians composing the PR population take more time to clear the room and accomplish the task.

Such a consideration obtains particular relevance if considered in the context of simulation which aim at depicting real evacuation scenarios. The observance of proxemic distances for whatever reason or occurrence, in fact, could have a considerable impact on the progress of the evacuation, as demonstated by this simple example.

Conclusion

In this thesis, the open issue of integrating affective parameters inside agent models is approached, following the route starting from data directly coming from people rather than emotion theories found in the literature to parameterize and include affective information into the models.

The proposed approach involves the investigation of pedestrian behaviour through experiments designed to observe different facets of pedestrian interaction with others and with the environment in which they move, experiments that have been extensively presented in Chapter 2 and that have brought with them results highlighting relevant differences in the observed populations.

Considering those highlighted differences, and focusing in particular on the online proxemic experiment shown in 2.4, cellular automata and multi-agent models have then been designed and reported in Sections 3.1, 3.2 and 4, implementing the affective parameters identified in the experiment and found to be influencing people's behaviour and interactions starting from the acquired data.

Lastly, some preliminary simulations based on the presented models have been presented, with Section 5 in particular showing the impact of the previously identified affective parameters on population behaviour through three different simulations where the agents' design followed the affective multi-agent model introduced before.

In this last chapter, a summary on the main contributions brought by this thesis is brought, together with a contemplation regarding limitations encountered as the work proceeded and a look towards what could be the future in forwarding the research that has been here presented.

Contribution Summary

The following section reports some final remarks regarding the contributions of this thesis, firstly highlighted in the Introduction, summarizing the performed work and the obtained results for each of the points previously introduced.

Data Collection Process

Chapter 2 showed the design and execution of multiple experiments aimed at investigating the behaviour of different pedestrian population, focusing each time on a different aspect of pedestrian interaction to try and study this particular matter in a comprehensive way.

The obtained results, both in the form of categorical data and physiological signals acquired through wearable sensors, proved the existence of differences in approaches and reactions among different populations that could be effectively recorded through the selected means, making the data useful to be then utilized in agent modeling as reference for the introduction of affective parameters.

In particular, the Bicocca crossing experiment presented in Section 2.1 allowed to observe and record the behaviour of young adults while approaching an unsupervised crossing situation that brought them to interact with multiple vehicles, behaviour that is to be later compared with the one observed with the elderly population involved in the Cantù crossing experiment of Section 2.2.

Then, the experiment performed in Tokyo regarding walking and obstacle avoidance tasks (Section 2.3) highlighted how differently young adults and elderly people react and behaved in similar walking situations, differences that are especially clear when contemplating the obstacle avoidance task. Other than normally adopting different stride frequencies, in fact, the experiment allowed to observe how young adults tend to approach moving obstacles faster, as to pass them as quickly as possible, while the elderly population tended to adopt a much cautious approach, slowing down and even stopping before the obstacle to wait for it to pass before crossing.

Lastly, the online experiment done on proxemic distances during COVID-19 times (Section 2.4) allowed to identify many factors influencing people's choices regarding the interpersonal distances to adopt in certain situations. It showed differences in approaching these distances in regard of gender and age, as it was already found in the literature, but it also pointed out at other parameters as, for example, sociality and fear.

Modeling involving affective parameters

Chapters 3 and 4 showed how cellular automata and multi-agent models introducing affective parameters can be designed, together with explanations regarding how those parameters have been introduced, how the data acquired from the experiment illustrated in Section 2.4 has been used to embed the affective factors into the models.

Every model had their different specifics regarding how to implement the introduced proxemic behaviour, but all of them were enriched with the implementation of affective parameters coming from the factors previously highlighted in the experiment which then guided the performed modeling.

Affective models simulation

Sections 3.1 and 3.2 and Chapter 5, then, presented a few simulations implemented as to follow the models previously designed and observe in action crowds of pedestrians moving and interacting in an environment while keeping into high consideration the affective parameters that were introduced.

The most interesting observations came from the situations modeled and simulated in Chapter 5, where the impact of proxemic interpersonal behaviour of agents wass not only tested in a free roaming example (Section 5.1) but also in situations in which one (Section 5.2) or more agents (Section 5.3) had a specific goal to follow that led their movement inside the environment.

The strict application of proxemic distances proved to be strongly influencing the three described simulation, and this with a crowd strongly varied in its composition because of the way the agents' parameters were initialized as to follow the previously designed model.

The first proposed simulation, for example, showed how much affectively influenced proxemic distances could impact crowds at population density increased, making the majority of pedestrians inside the environment frequently stand still rather than follow random walk movements because of the movement restriction the observance of those distances involved. And this was particularly evident even with the low population densities involved.

The second simulation, then, showed the impact of the affective parameters on the movement of a single agent moving towards a goal, with the different choices in terms of distance and movement tracing back to the combination of affective parameters decided during the initialization of the simulation. In particular, differences between male and female agents appeared correctly consistent with the experimental findings.

Lastly, the third simulation compared room clearing results of a population affected by affective parameters and observing proxemic distances with the ones of a population that, on the other hand, didn't consider the distances to be maintained. The differences in behaviour between the two populations were clearly visible, both in the events recording people remaining still because of others' uncomfortable vicinity and in the total time utilized to clear the environment of their presence, thus highlighting even more the importance of taking into consideration affective aspects in pedestrian simulation.

Limitations and Future Works

The work presented in this thesis, despite it being a step in the direction of including more realistic and significant affective parameters inside agent modeling and simulations, still represents a rather introductory work in what is a much wider research area that has considerable scope for improvement and many different directions that can be considered for further, interesting developments.

Focusing in particular on the work that has been presented here, a first important improvement that could be done to the models introduced in Chapters 3 and 4 regards the integration with parameters and data coming from the other experiments that were illustrated, thus not focusing in including information only concerning one type of interaction, but also enriching their design by modeling together other facets of pedestrian behaviour regarding the interplay between them, the environment and what can be found inside it.

In the instance described in this work, in fact, only the experiment presented in Section 2.4 was used as a base to expand a multi-agent system as to include affective information extracted from people's behaviour, but the other experiments illustrated in Chapter 2 led to observe different behaviour of different populations that could certainly be included in the models to further bring them towards a more realistic depiction of pedestrian behaviour. The data coming from the Bicocca crossing experiment and the Cantù crossing experiment (Sections 2.1 and 2.2), for example, could provide valuable insight on how different populations approach vehicles whenever in an unsupervised context, while the Tokyo experiment (Section 2.3) could provide interesting information regarding how different kinds of people tend to approach moving obstacles, changing their walking behaviour as to match the situation they encounter. A proper way to parameterize the results obtained from the physiological signals coming from those experiments is needed, then, in order to proceed in this direction and effectively utilize the knowledge acquired through them.

This point also brings to another important factor regarding the results obtained through the experiments. As it was previously said, in fact, the information acquired from the participants through questionnaires have not been extensively analysed yet, thus leaving out other data for profiling different types of pedestrians. Investigating the relation between psychological characteristics and the behaviours shown by physiological signals could help in parameterise new factors to include in the model, further developing the agents to display realistic behaviour. Also, concerning this topic, several factors like different cultural aspects could be taken into account in future experiments to create systems able to depict even more heterogeneous agents, especially since there already are works underlining how cultural differences may show themselves also in pedestrian behaviour [Solmazer et al., 2020, Chattaraj et al., 2009].

Lastly, the pursuit regarding the design and execution of new experiments is another point to take into high consideration. As they were presented here, the experiments illustrated in this work all allowed to gather data from restricted samples of populations, with the only exception being the online proxemic experience (Section 2.4) which had the undeniable advantage of allowing an asynchronous performance to a potentially unrestricted number of subjects. Even then, though, the gathered data delineate a rather small population with similar characteristics, as the participants all came from the same country and within the same region. This is the main reason a similar trial was proposed to be performed with a Brazilian population, both for the acquisition of more data to be utilized and for the concept of involving a different population which could display a different behaviour in comparison to the one already tested.

As it was already mentioned multiple times before, data is a cardinal point in this kind of research, given how much weight it holds in allowing to insert new but realistically calibrated parameters inside agent models, so it is of the utmost importance to gather enough data in order not to fall into biased representations of the involved populations. Thus, it is necessary to properly follow up with experiments in order to gather data from more people and, especially, from more diverse people that could further help in enriching the models to be designed by following the ones here presented.

A Other Research Works

Other than the work presented here in this thesis, during the course of the PhD other research directions have been followed, investigating areas adjacent to the ones that were explored more in depth as the focus of the main PhD work got more refined.

In this appendix, then, the work performed while following those other directions is presented, giving a brief description and explanation for every subsection and presenting the publications that were prepared on the results following those investigations.

A.1 Investigation on Affective States induced by Audio Stimuli

Concerning the work performed on physiological signals for the differentiation and recognition of human affective states, one of the first applications that were investigated regarded the utilization of physiological responses coming from a person to guide the proposition of audio stimuli to that same person in order to help them maintain or change their affective state.

In order to work towards the goal of developing a system able to continuously create music playlists taking into consideration physiological responses and eventual external inputs from a user, then, it was necessary to face the issue of affect recognition through physiological signals, in order to understand if the people's physiological response recorded through accessible sensors would be enough to properly differentiate between different affective states.

This investigation was furthered by the execution of ad-hoc experiments, performed in a controlled laboratory setting with different populations, audio stimuli and audio players, whose results were then gathered and published through the following papers:

- [Bandini et al., 2019] Bandini, Stefania, Francesca Gasparini, and Marta Giltri. "Personalized music experience for the wellbeing of elderly people." *International Conference on Internet Science*. Springer, Cham, 2019.

- [Gasparini et al., 2020a] Gasparini, Francesca, Marta Giltri, and Stefania Bandini. "Discriminating affective state intensity using physiological responses." *Multimedia Tools and Applications* 79.47 (2020): 35845-35865.

In the first entry shown above, the concept of a cyber physical system devoted to the creation of the aforementioned music playlist is described, together with a high-level design of its functioning and of the elements what would compose it. It is in that same short paper that the concept of experiments performed to gather data about how physiological data relate to different human affects.

In the second paper, on the other hand, shows the execution of a real-life experiment executed *in-vitro*, namely the controlled laboratory environment previously mentioned, aimed at recording physiological signals from participants. The signals were recorded as the subjects listened to natural audios and were performing mathematical operations, in order to then analyse the obtained signals to identify if physiological signals could effectively distinguish between the different affective states induced by the two types of task.

The work done in the instances here presented produced an experimental procedure that was then refined and restructured in another experimental trial, then published in [Gasparini et al., 2022].

A.2 Investigation on the addressing of Digital Divide for Healthy Ageing

Participating in the LONGEVICITY project presented in the Introduction, there was a particular focus on the issues regarding ageing and elderly health in multiple instances, given how the goal of the project revolved around the elderly population. This interest brought then the exploration of how elderly people approach technology and, more in particular, how they approach those medical systems that nowadays are being developed to provide a more accurate and careful home care after patients are discharged from the hospital.

Working along this line of research, where the issue of digital divide is probably the most felt as elderly try interfacing with new technologies and systems, the following work was produced:

- [Saibene et al., 2020] Saibene, Aurora, Michela Assale, and Marta Giltri. "Addressing Digital Divide and Elderly Acceptance of Medical Expert Systems for Healthy Ageing." *AIxAS@ AI* IA*. 2020.

The work here presented had the main purpose of surveying the existing solutions for telemedicine, which is seen as the most promising approach to adopt in order to give continuous care to elderly people that may need it without having them go to a hospital or another structure even for simple check-ups. A matter that grew especially important since the quick spread of the COVID-19 pandemic brought to light the shortcomings to the current system, in need of proper solutions that could lighten the strain on traditional health care by helping people getting the treatment they need and only going to the hospital if required.

And, as it was previously mentioned, the matter of Digital Divide was taken into consideration: given how elderly people could be one of the largest slices of the global population to use this kind of medical solutions on a daily basis, having the correct approach in designing these technologies in order to make them as intuitive and usable as possible for them is just as important as delivering a system that works and correctly provides a valuable service.

A.3 Survey on Medical Expert Systems

Stemming from the investigation previously presented, the line of work regarding the state of medical expert systems currently present in the literature brought to write another paper that was the natural extension of the survey mentioned in the previous subsection.

- [Saibene et al., 2021] Saibene, Aurora, Michela Assale, and Marta Giltri. ”Expert systems: Definitions, advantages and issues in medical field applications.” *Expert Systems with Applications* 177 (2021): 114900.

With this work, the aim was to present a broad overview regarding the state of the art of expert systems applied in the medical domain, looking at the systems and technologies introduced by researcher during the last 10 years.

In the paper, the heterogeneity of the solutions proposed by the literature is shown, and the investigation allowed to identify how the reviewed approaches are bounded to the specific needs a medical expert system is called to answer, how the lack of a proper system validation seems to be very common and how these systems application could provide benefits if applied and used in synergy with the more traditional techniques currently utilized.

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