A Survey on Socially Aware Robot Navigation: Taxonomy and Future Challenges

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Abstract
Socially aware robot navigation is gaining popularity with the increase in delivery and assistive robots. The research is further fueled by a need for socially aware navigation skills in autonomous vehicles to move safely and appropriately in spaces shared with humans. Although most of these are ground robots, drones are also entering the field. In this paper, we present a literature survey of the works on socially aware robot navigation in the past 10 years. We propose four different faceted taxonomies to navigate the literature and examine the field from four different perspectives. Through the taxonomic review, we discuss the current research directions and the extending scope of applications in various domains. Further, we put forward a list of current research opportunities and present a discussion on possible future challenges that are likely to emerge in the field.

Keywords
Socially Aware Robot Navigation, Human-aware Navigation, Literature Survey, Taxonomy, Challenges

1 Introduction

Socially aware robot navigation has steadily gained interest in recent years, becoming a research field of its own. With the increase in the number of service robots and autonomous vehicles, it is crucial for them to be able to carry out their tasks around humans efficiently and seamlessly. This applies not only to their ultimate goals but also to all skills that these build on top of, including navigation. Socially appropriate behavior is key for a robot to gain acceptance from humans and prevent causing any discomfort. In addition to mobile robots, drones and autonomous vehicles have also entered this field in recent years, taking inspiration from existing research on socially aware mobile robot navigation. In this paper, we conduct a survey and analyze the literature based on different aspects of socially aware robot navigation, with special emphasis on how the navigation is currently implemented in different types of robots and how these differences affect human perception of comfort and safety (Fig. 1).

Figure 1. An autonomous ground robot figuring its way among humans.

While existing surveys have provided valuable insights, there is a need for a new comprehensive survey that addresses a broader range of robots and contributes with a more inclusive definition of socially aware robot navigation. Furthermore, our survey analyzes various research areas required to support and advance the field. These include studies, tools, methods of evaluation, and human trajectory and intention prediction techniques. Most importantly, we present multi-faceted taxonomy-based classifications for socially aware robot navigation and examine the problem from different angles. Our aim in proposing taxonomies is to help the reader navigate the vast number of contributions and select those that are most relevant to their discipline and objectives. We hope that this classification will not only be pertinent to robot developers but also to application designers and evaluators and act as a basis for interdisciplinary cooperation on the topic.

The remaining of this section introduces essential definitions and presents a preliminary analysis of the literature, including previous surveys in the field. In section 2, we propose a taxonomy that is used to refine the analysis in section 3 (Types of robots), section 4 (Planning

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and Decision-Making), section 5 (Situation Awareness and Assessment), and section 6 (Evaluation methods and tools). Section 7 puts forward a set of recommendations to enhance socially aware robot navigation. Finally, section 8 covers prospective challenges in the field.

1.1 Socially Aware Robot Navigation

Navigation is the activity whereby an embodied agent (a robot or a person) changes its position in an environment to reach a goal. While navigating, the agent may encounter other agents who are sharing the same environment. This subject has received different names in the robotics community, being the frequently used ones '*human-aware navigation*', '*social navigation*', and '*socially aware navigation*'. '*Human-aware*' is used in the sense that the design and the algorithm need to take into account specifically the presence of the human in the proximity of the robot, their activity, and preferences. No assumption is made in the wording on the fact that the robot acts naturally or socially. '*Social navigation*' means navigation that integrates social rules, protocols, and roles that are generally used by humans when they act or interact with other humans. The risk here is the inability to distinguish, at least in the wording, between human social behavior and robot social behavior and capabilities. '*Socially aware navigation*', while insisting on the social aspect of navigation in the proximity of humans, does not, in the wording, enforce the need for the robot social navigation to be identical to human social navigation. Therefore, we choose to use the term ***socially aware robot navigation*** in the rest of the paper and call the agents involved in such navigation as ***social (navigation) agents***.

To move toward specific definitions, we propose a set of properties for social (robotic) agents. Thus, a robot can be called **socially aware** if:

1. It detects human agents and treats them as special entities, with their safety as the utmost priority.
2. Its behavior is designed to minimize disturbance and discomfort to human agents and cause little to no confusion to them.
3. It exhibits its navigation intentions, explicitly or implicitly.
4. In case of a conflict, it assesses the situation and takes the action that it expects will resolve the conflict in a social manner, potentially compromising its own task.

In the above, the term **human agent** is used to refer not only to individual humans but also to vehicles and robots controlled by them. To satisfy the last property (4, above), the robot requires an understanding of human intentions and negotiation capabilities. However, human intentions are hard to predict as they are often context dependent. Therefore, most of the existing research in socially aware navigation systems focuses on the first three aspects. Although, to the best of our knowledge, there is no explicit consensus, in our opinion, for a robot navigation algorithm to be called socially aware it should at least satisfy the first two properties, which can be seen as the minimal requirements.

1.2 Article Collection and Preliminary Analysis

Although socially aware robot navigation has been a topic of research for over 20 years (Tadokoro et al. 1995; Wilkes et al. 1998), there has been an increasing number of publications over the past 6 years. This can be observed in Fig. 2, where the yearly trend of the number of papers on socially aware navigation in IEEE Xplore is shown as a blue line. This trend is approximately exponential, showing a fast-growing interest in the field. The slight decrease in 2020 could be attributed to COVID-19. We have collected articles from different sources like IEEE Xplore, ACM digital library, and Google Scholar that match the search query, ('social' OR 'human-aware') AND 'navigation' AND ('robot' OR 'autonomous vehicle' OR 'drone'). More than 200 articles have been used to write this survey, which are either directly associated with socially aware robot navigation or the supportive literature that is required by the field. To keep the length of this survey within reasonable limits, a comprehensive review of the collected papers was conducted to select distinctive proposals that would form a representative subset of what has been done in socially aware robot navigation. For this selection, we have restricted ourselves to the past 10 years since there are previously existing surveys like Kruse et al. (2013) that cover most of the papers until 2012. The papers in the survey at hand and their distribution by year are presented in Fig. 2. Although there are papers addressing socially aware navigation in autonomous vehicles and drones, a large portion of papers correspond to mobile robots, as it has generally been the core area of focus. Since our main goal is taxonomic analysis, we do not think that it suffers from this limitation.

1.3 Previous Surveys

The rise of research in socially aware robot navigation has led to an increase in surveys in the field. In one of the early surveys, Kruse et al. (2013) presented diverse approaches used to tackle socially aware robot navigation and the accompanying challenges.

It also briefly covered evaluation methodologies. The survey in (Rios-Martinez et al. 2015) focused on how proxemics has been adapted to perform socially aware robot navigation around individuals and groups of people while taking affordance spaces into account. The review presented in (Pol and Murugan 2015) covered different strategies employed for planning, Chik et al. (2016) reviewed literature based on different navigation frameworks and their components. A literature survey on the required level of robot perception, mapping, and awareness to properly navigate human environments was provided in (Charalampous et al. 2017). It further provided an integrated framework for analyzing pedestrian behavior in shared spaces and described the limitations of the approaches at the time. Recent works like Ridel et al. (2018) and Rudenko et al. (2020) present detailed literature reviews on pedestrian behavior and human motion prediction methodologies. Honig et al. (2018) presented a comprehensive review of person-following robots and the different elements involved in their design and evaluation. In recent years, research on the social aspects of autonomous vehicles (AVs) has started to exploit the vast literature available on

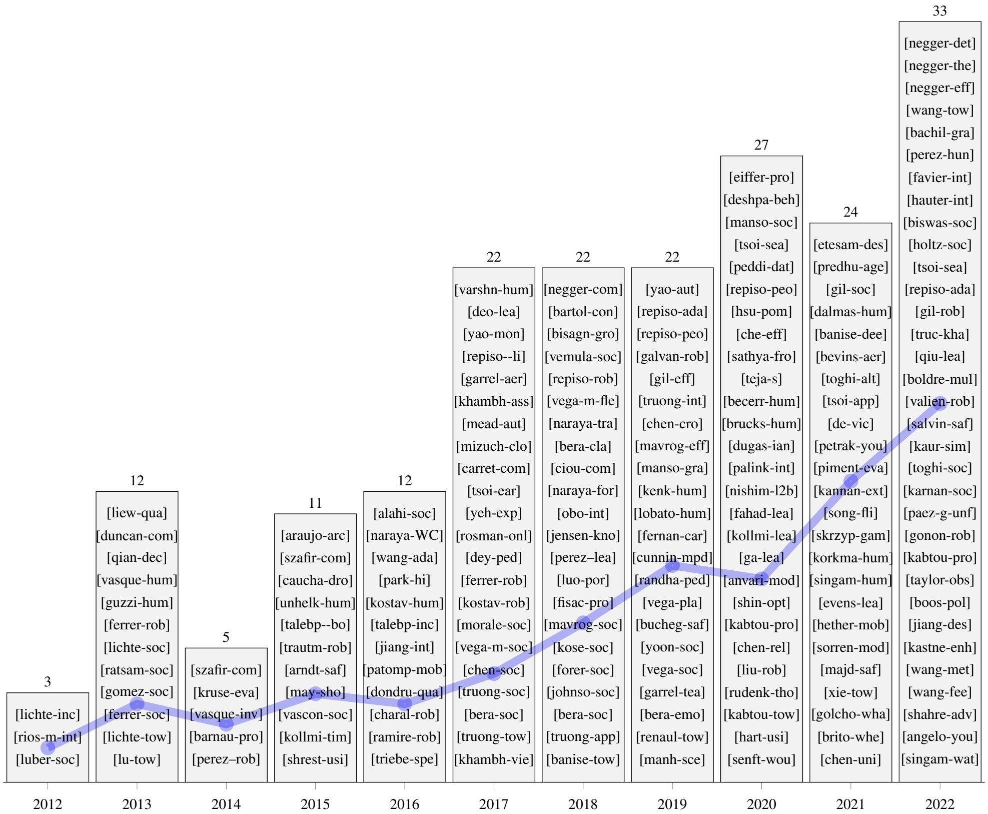

Figure 2. Distribution of papers in this survey by year. Yearly trend of publications in IEEE XPlore is shown in blue.

vehicle-pedestrian interactions. For example, the survey in (Rasouli and Tsotsos 2019) addresses pedestrian behaviors, communication modalities, and strategies for AVs. More recent works like Prédhumeau et al. (2021) study human-robot-vehicle interactions in shared spaces and propose an integrated framework to systematically analyze studies in the field.

The survey in (Mavrogiannis et al. 2023) divides the problem into three types of challenges (planning, behavioral, and evaluation) and explains how they are approached in the literature, along with open questions. The work in (Möller et al. 2021) views the problem from the perspective of visual understanding and planning to provide a deeper understanding of different aspects of socially aware robot navigation and the available datasets. A list of works in the field is provided in (Ngo 2021). There are also more focussed surveys like Gao and Huang (2022) that present different types of evaluation strategies employed in the field. The work in (Mirsky et al. 2021) defines conflicts in socially aware navigation settings and proposes a taxonomy around them to organize the literature. It presents the possible future extensions of the taxonomy and provides a checklist to verify while contributing to the field.

In this context, we extend the boundaries of existing surveys by providing a comprehensive multi-faceted classification system. Although Mirsky et al. (2021) also provide a taxonomy in their recent survey, our classification covers multiple dimensions of socially aware robot navigation, taking into account the type of robot, planning and decision-making aspects, situation awareness and assessment, as well as evaluation methods and tools. By adopting this multi-dimensional approach, we aim to offer a holistic view of the field and address the complex interplay of the different factors taking place in socially aware robot navigation. For example, while surveys that focus on particular types of robots exist (*e.g.*, autonomous vehicles in (Rasouli and Tsotsos 2019)), ours is the first explicitly considering the different types of robots and how their specific features influence navigation.

Furthermore, we incorporate topics that have not received much attention in previous surveys. This is the case of contextual information that can be obtained from the environment, the task, and pedestrian intention detection. Environmental and task contexts are included as part of the planning open problems in (Mavrogiannis et al. 2023), however, we provide a deeper analysis of the related works. In our review, we extend the literature analysis of these topics through specific branches of the proposed taxonomy. While Möller et al. (2021) address different contexts and tasks, they emphasize human-robot interaction rather than socially aware navigation. Our primary focus is socially aware navigation. Additionally, although intentions are analyzed in (Mavrogiannis et al. 2023), the discussion pertains to how robots should communicate their intentions. In our survey, we include the detection of human intentions as a specific topic in our situation awareness and assessment taxonomy. The communication of robot intentions is also analyzed in the proposed planning and decision-making taxonomy.

Regarding evaluation, most recent surveys analyze in depth the tools used for evaluating socially aware robot navigation proposals (Gao and Huang 2022; Mavrogiannis et al. 2023; Möller et al. 2021). These tools encompass studies, datasets, simulators, and metrics. We extend the analysis of socially aware navigation evaluation provided in other reviews by classifying the evaluation methods into qualitative and quantitative. This classification aims to offer an additional perspective on the existing evaluation methodologies, providing deeper insight into the limitations and challenges in evaluating socially aware navigation.

In summary, our survey stands out by offering a multi-dimensional perspective on socially aware navigation, covering aspects often discussed in less depth, and providing an inclusive classification system. This inclusive approach fosters a more holistic understanding of the field, offering a comprehensive overview of the state of the art in socially aware robot navigation. We believe these unique features distinguish our work and establish its significance in complementing existing surveys in the domain.

2 Proposed Taxonomies

We propose multi-faceted taxonomies for classifying and arranging the literature into four distinct aspects related to socially aware navigation. For the classification, we conducted a deductive thematic analysis (Clarke et al. 2015), where a predefined set of themes (taxonomy trees) are defined from the start and the articles fit into them. This section presents the review process and the final taxonomies.

2.1 Review Process

The review procedure started with multiple discussions on arranging the articles into a unified classification that can reflect different aspects of socially aware robot navigation. Four different multi-faceted taxonomies were selected, as combining multiple non-overlapping perspectives into a single taxonomy is not ideal.

Once the taxonomies were decided and the nodes were defined, we used a *tag* to represent each node. The *tags* can be seen as the *codes*, and the taxonomies can be seen as the *themes* in thematic analysis. Using these node definitions and *tags*, we reviewed every article collected and made a summary for each. Some articles were discarded during this process, and the remaining ones were assigned multiple *tags* corresponding to one or more of the four taxonomies. The exclusion criteria used were: a) the paper refers to socially aware navigation but it is not the core topic, and b) the paper provides only a small incremental contribution over those already covered in the survey (frequently by the same authors). We did multiple passes on these reviews, which resulted in improved taxonomies and definitions. There were major revisions in some of these taxonomies, which required revisiting the literature and reassigning *tags* according to the new classification.

At the end of this process, we were left with 193 articles with multiple *tags* that were utilized to classify them across different perspectives. For each article, along with a summary, we included descriptions of the aspects of the work associated with each assigned *tag* to facilitate analysis.

2.2 Taxonomies Description

This section provides a detailed description of the proposed taxonomies and their associated taxa: robot type, planning and decision-making, situation awareness and assessment, and evaluation and tools.

2.2.1 Taxonomy for Robot type: With the advancements in delivery, logistics, automation, and service sectors, various types of robots are being deployed in human environments. Although there are common norms that apply to each type

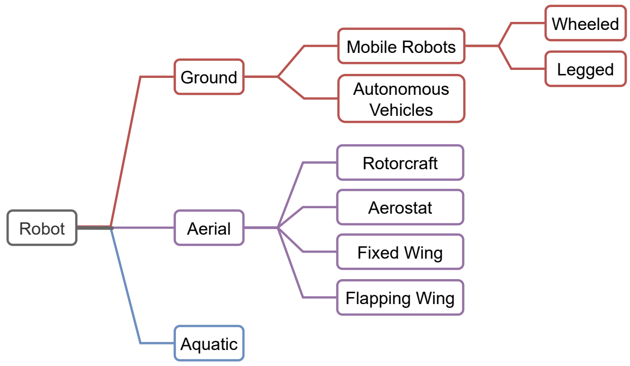

Figure 3. Taxonomy based on robot type.

of robot, there are also specific norms that differentiate them. These specificities affect the design of their socially aware navigation strategies. Therefore, we propose our first classification of socially aware navigation papers based on the robot type as shown in Fig. 3. In this taxonomy, the facets in the leaf nodes are mutually exclusive for most works.

Definitions

1. ***Ground***: This taxon contains all the articles with robots that maintain contact with ground while they move.
   (a) ***Mobile Robots***: A robot that has the capabilities to sense and move in an environment autonomously. They do not carry any human passengers while they move.
      i. ***Wheeled Robots***: Any kind of mobile robot with wheels (differential, omni, Ackermann, etc.).
      ii. ***Legged Robots***: Any kind of legged robot (bi-ped, tri-ped, quadra-ped, etc.).
   (b) ***Autonomous Vehicles***: Autonomous systems that can sense and move among human environments while carrying or transporting human passengers. It includes personal mobility vehicles (PMVs) as well.
2. ***Aerial***: This taxon consists of the articles with robots that can move or fly in the air without any physical support from the ground. This classification is based on the type of mechanism used to generate the flight (Hassanalian and Abdelkefi 2017).
   (a) ***Rotorcraft***: The rotors are used to generate the thrust in this of robots. It consists of single rotor systems like helicopters and multi-rotor drones.
   (b) ***Aerostat***: The lighter-than-air flying robots that float in the air and use small propelling systems to move around. It contains systems like blimps and hot-air balloons.
   (c) ***Fixed Wing***: All the fixed wing drones like airplanes and gliders.
   (d) ***Flapping Wing***: All the ‘ornithopter’ drones that use bird or insect type wing flapping mechanisms.

3. ***Aquatic***: This taxon contains all the articles that deal with socially aware navigation in the robots that move on or under the surface of the water. For now, we have not included any further classification as this taxon of robots does not have any works on socially aware navigation yet.

2.2.2 Taxonomy for Planning and Decision-Making: This classification includes planning and motion decision-making, which are core topics in robot navigation. Other characteristics related to different types of decision-making have also been included in this classification, namely types of tasks, communication, and negotiation strategies. Fig. 4 shows this classification and its sub-divisions. Here, the facets are not mutually exclusive.

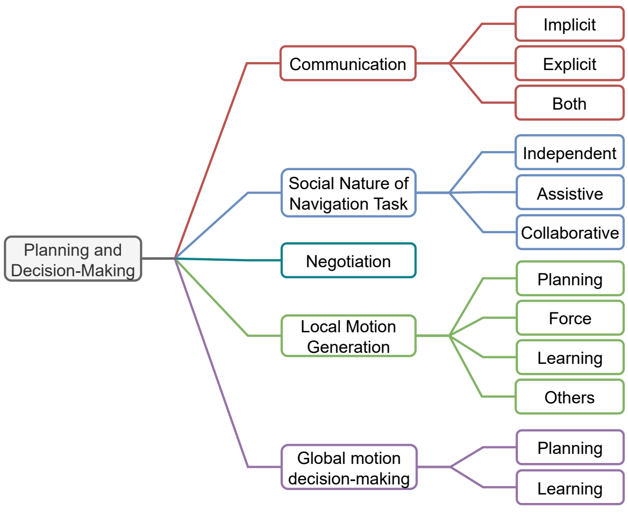

Figure 4. Taxonomy based on planning and decision making.

Definitions

1. ***Communication***: This taxon considers articles that use some form of intentional communication where the robot communicates or responds to humans' signals.
   (a) ***Implicit***: The form of communication where the recipient is expected to infer the message from implicit signals like body motion or posture, force, or gaze.
   (b) ***Explicit***: The form of communication is through speech, video, or gestures, where agents explicitly convey their intentions.
   (c) ***Both***: Strategies that use a mixture of implicit and explicit communication forms.
2. ***Types of Navigation Task***: This taxon classifies the works based on robots' and humans' roles in the navigation task.
   (a) ***Independent***: Tasks where the robot performs socially aware navigation and is not tightly bound to any human (e.g., crowd navigation, delivery). The pedestrians are treated as social dynamic obstacles, but no interaction occurs.
   (b) ***Assistive***: The navigation task where a robot or a vehicle provides assistance or support to one or more people. Assistance can be provided in several ways, like following or accompanying a person, or taking the shape of transportation services (e.g., pushing a wheelchair or running a shuttle).
   (c) ***Collaborative***: A robot and human agent working together to coordinate and successfully navigate through complex environments, such as narrow hallways or doorways, where cooperative effort and coordination are needed to reach the desired destination.
3. ***Negotiation***: This taxon considers articles that adapt the robot's navigation based on some form of dynamic information exchange (e.g., asking for permission to pass, different forms of inducement).
4. ***Local Motion Generation***: This taxon includes articles that present methodologies or improvements for lower-level motion generation like trajectory or velocity commands.
   (a) ***Planning***: Methodologies that rely on trajectory generation or forward simulations for getting the robot's command velocity (e.g., DWA, MPC, Elastic Bands).
   (b) ***Force***: Methodologies that rely on potential fields and object forces to generate velocity command for the robot (e.g., Social Force Model, Artificial Potential Fields).
   (c) ***Learning***: Methodologies that use data and/or learn models to generate the velocity command directly from the observations (or input).
   (d) ***Others***: Any other methodology that cannot be fit into the above strategies.
5. ***Global Motion Decision-Making***: This taxon includes the articles that use a global representation to generate a decision and/or path to assist motion generation.
   (a) ***Planning***: Methodologies that use geometric or formal planning approaches.
   (b) ***Learning***: Methodologies that are data-driven and/or use learned models.

2.2.3 Taxonomy for Situation Awareness and Assessment: This classification covers situation awareness following the definition by Ensley (1995): "*the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*". Because the meaning of the term 'comprehension' is debatable when it comes to robots, this classification will mainly focus on the representation and prediction of the state of *agents* and other items that are modeled for the purpose of socially aware navigation. This includes other aspects related to physical elements of the *environment* and non-tangible elements involved in socially aware navigation that may affect decision-making, like the *social norms*. Fig. 5 shows the main taxa and the different branches that arise from them.

Definitions

1. ***Environment***: This taxon considers aspects related to the physical space in which the robot navigates. Collective issues such as the density of humans are also considered within this.
   (a) ***Semantics***: Approaches that consider information related to the type or purpose of the area where socially aware navigation takes place.

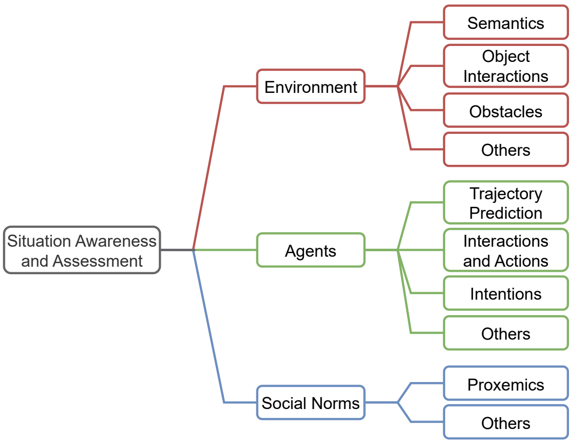

Figure 5. Taxonomy based on situation awareness and assessment.

(b) ***Object Interactions***: Approaches that consider human-object or robot-object relations.

(c) ***Obstacles***: The approaches that represent the area of the space that is not available for navigation, regardless of whether the representation is purely metric (*e.g.*, occupancy grids), symbolic, or hybrid.

(d) ***Others***: Any other aspect of the environment apart from those mentioned above.

2. ***Agents***: This taxon describes how are agents represented in the articles, if any. Although the definition does not explicitly restrict the concept of agents to humans, in practice, they are the only external agents found in the literature, except for the case of autonomous vehicles.

   (a) ***Trajectory Prediction***: Approaches using future human pose estimations.
   (b) *Interactions and Actions*: Approaches considering representation and usage of actions, as well as human-human and human-robot interactions.
   (c) ***Intentions***: Approaches that use or detect agent's intention for socially aware navigation.
   (d) ***Others***: For other aspects of the agents that may be exploited for the navigation.

3. ***Social Norms***: This taxon includes the articles that discuss the aspects related to the comfort, safety and humans' preferences.

   (a) ***Proxemics***: Approaches considering social distances rather than just collision avoidance.
   (b) ***Others***: Approaches including other frequently used conventions during human navigation (*e.g.*, walking on the right or left-hand side).

2.2.4 Taxonomy for Evaluation and Tools: This classification considers the strategies employed for the evaluation of the socially aware navigation schemes. Various types of evaluation methodologies that are employed to assess the robot's behavior and the tools that support or are required for the evaluation are included in this classification. The taxa of this classification are shown in Fig. 6.

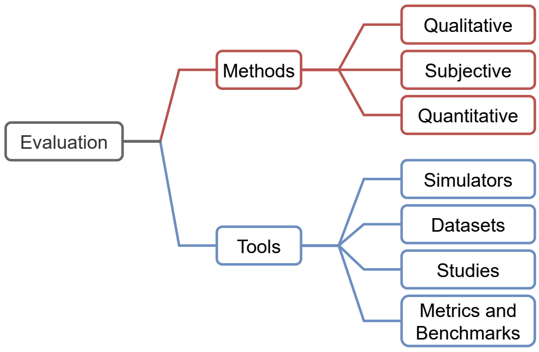

Figure 6. Taxonomy for tools and evaluation methods.

Definitions

1. ***Methods***: This taxon contains the articles that have some form of evaluation of socially aware navigation.
   (a) ***Qualitative***: Methods that use numerical/non-numerical data and use subjective or comparative analysis for evaluation.
   (b) ***Quantitative***: Methods that use numerical data and objective analysis (based on metrics or benchmarks) for evaluation.

2. ***Tools***: This taxon contains the articles that provide or propose tools for advancement and evaluation of socially aware navigation.
   (a) ***Simulators***: Articles that propose new simulators or strategies to improve the human-robot navigational interaction in simulation.
   (b) ***Datasets***: Articles that propose new datasets that can advance socially aware navigation. This could be in the form of human-robot navigational data or rich human-human interaction data.
   (c) ***Studies***: Articles containing user studies in wild or controlled spaces that analyze human-robot interaction which could be employed to improve socially aware navigation.
   (d) ***Metrics and Benchmarks***: Articles that propose new metrics or benchmarks.

3 Types of robots

More than 80% of the articles in this survey use some kind of robot either physically or in simulation to implement or test a socially aware navigation scheme, study the interactions or collect data. Based on the proposed classification, 156 papers are distributed among various types of robots. As it can be seen from Fig. 7, a large portion of papers (116) fall under the *mobile robots* taxon, and the rest are distributed between *autonomous vehicles* (22) and *aerial robots* (18). Only one paper by Cunningham et al. (2019) applies their navigation scheme to a mobile robot and an autonomous car. Aerial robots and autonomous vehicles recently started exploring the idea of socially aware navigation and there are preliminary works that use the term **'social'** or **'human-aware'** or '**socially aware**'. The navigation of autonomous wheelchairs has been a research topic for quite some time, but the field has not been as active in recent years (Sivakanthan et al. 2022). We have not found in the literature any paper dealing with socially aware navigation for sea or underwater robots. Thus, this section focuses only on ground and aerial robots.

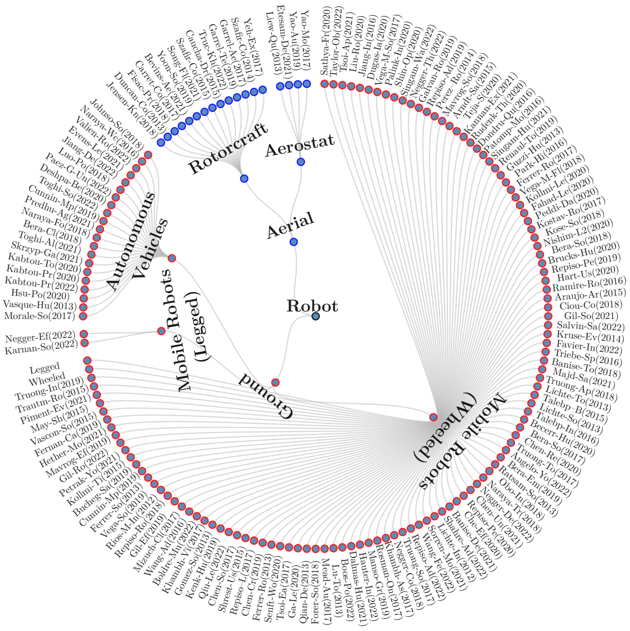

Figure 7. Distribution of papers by Robot type. The figure is best viewed zoomed in using a digital version.

Figure 8. Mobile Robots: (a) Spencer (Triebel et al. 2016), (b) PR2 (Singamaneni et al. 2021), (c) Pepper (Angelopoulos et al. 2022), (d) Ivo (Gil et al. 2021), (e) Tiago (Hauterville et al. 2022) and (f) Tibi (Ferrer et al. 2013).

3.1 *Ground Robots*

Ground robots taxon encompasses a wide variety of platforms like mobile humanoid robots, simple mobile bases, wheelchairs, autonomous cars, delivery pods, legged robots, etc., that majorly operate on the ground. Although most of the works presented in this survey are based on wheeled robots (or vehicles), this taxon does not discard the possibility of having socially aware navigation using legged robots. For instance, Karnan et al. (2022) uses Boston Dynamics' Spot to build the dataset for socially-aware navigation. Neggers et al. (2022) uses bi-pedal NAO robot for a user study. Robots like Spot and Cheetah already have good controllers for mobility (Di Carlo et al. 2018; Zimmermann et al. 2021) and we expect to see more works dealing with socially aware navigation using these robots or other kinds like bi-peds.

socially aware robot navigation originated as a part of human-robot interaction (HRI) research (Singamaneni 2022). Architectures were developed to deploy an interactive robot among humans and navigation remained a challenging task from the very beginning. The initial works on socially aware navigation always consisted of a higher-order task to accomplish like guidance or assistance. Due to this, many of the works on socially aware navigation use **mobile humanoid robots** (Singamaneni et al. 2021; Teja S. and Alami 2020; Hauterville et al. 2022; Ferrer et al. 2013) that have the appearance of a humanoid but use wheels instead of legs to move. As time progressed, socially aware navigation became a field on its own rather than a mere requirement for other tasks.

Some of the mobile humanoid robots that are used by the research community are shown in Fig. 8. Although the PR2 robot is relatively old, it is still being used by many researchers (Khambhaita and Alami 2017; Mead and Matarić 2017; Kruse et al. 2014; Teja S. and Alami 2020; Singamaneni et al. 2021; Ramirez et al. 2016; Lu and Smart 2013; Khambhaita and Alami 2017; Forer et al. 2018; Singamaneni et al. 2022) because of its robust hardware, multiple high fidelity sensors for perception and open source support of the platform. The other frequently used humanoid robot for socially aware navigation is Pepper, which is commercially available and closer to human in appearance (Teja S. and Alami 2020; Singamaneni et al. 2021; Dugas et al. 2020; Bera et al. 2019; Randhavane et al. 2019; Bera et al. 2018; Angelopoulos et al. 2022). Pepper has tactile sensors and multiple language support for human-robot interaction and is often used to investigate short-range navigation tasks near humans. Tiago is a more recent commercial humanoid robot that is being used by the robot navigation community (Macenski et al. 2020). This robot is built on an open-source platform which allows the user to make modifications to the packages as required. Hauterville et al. (2022) uses this robot to test a socially aware navigation stack in Gazebo. From time to time, specialized robots like Tibi (Ferrer et al. 2013), IVO (Gil et al. 2021), Robovie (Anvari and Wurdemann 2020; Senft et al. 2020) or SPENCER (Triebel et al. 2016) are built to have more customizability and to address specific needs of the researchers. These robots allow the user to modify the components or the software stacks easier in comparison to commercial robots.

Given that arms are not strictly necessary to perform socially aware navigation, most works just use **mobile bases** (Boldrer et al. 2022; Vasconcelos et al. 2015; Truong et al. 2017; Liu et al. 2020; Chen et al. 2017; Charalampous et al. 2016; Guldenring et al. 2020; Chen et al. 2020; Banisetty et al. 2021; Sathyamoorthy et al. 2020; Jiang et al. 2016; Chen and Lou 2022; Wang et al. 2022). They are typically fitted with proximity sensors and/or LiDARs to detect and avoid obstacles, which are used by socially aware navigation researchers to detect humans using leg detection. Some of the commonly used mobile bases are shown in Fig. 9. Among the articles collected in this survey, we found that the Pioneer 3-DX is used by many works (Chen et al. 2020; Buchegger et al. 2019; Trautman et al. 2015; Banisetty et al. 2021;

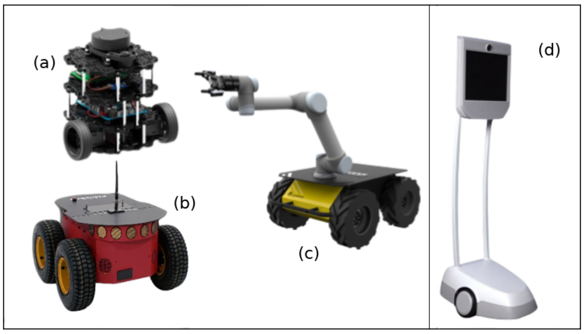

Figure 9. Mobile Bases: (a) Turtlebot (Kollmitz et al. 2015), (b) Pioneer 3-DX (Chen et al. 2020) , (c) Husky (Hart et al. 2020), and (d) Beam Pro Robot (Mavrogiannis et al. 2019).

Ciou et al. 2018; Fahad et al. 2020; Rösmann et al. 2017; Shahrezaie et al. 2022) followed by different versions of Turtlebot (Che et al. 2020; Sathyamoorthy et al. 2020; Jiang et al. 2016; Qiu et al. 2022; Kostavelis et al. 2017; Kollmitz et al. 2015). There are also other commercial platforms like ClearPath Jackal and MiR100 that are used in crowd navigation (Liu et al. 2020; Chen et al. 2017; Hart et al. 2020; Karnan et al. 2022) and warehouse navigation (Guldenring et al. 2020) respectively. Custom-built robot bases always offer more personalization compared to commercial robots and some works in this survey like Lichtenthäler and Kirsch (2013); Charalampous et al. (2016); Arndt and Berns (2015); Truong and Ngo (2018) and Shrestha et al. (2015) use these personalized robots to test their frameworks.

Sometimes the mobile bases are accompanied by screens to display signs or emulate expressions (Mavrogiannis et al. 2019; Sorrentino et al. 2021; Hart et al. 2020). These robots are either custom-built (Hart et al. 2020; Araujo et al. 2015; Pimentel and Aquino-Jr 2021; Truong and Ngo 2018) or chosen from the available ones in the market (Qian et al. 2013; Mavrogiannis et al. 2019). The idea behind the extra screen is to make the robot more human-friendly by displaying faces and communicating intentions. For instance, Hart et al. (2020) use the additional screen to display a face to study the communication strategies using gaze, whereas Mavrogiannis et al. (2019) uses it to just display a smiley face while studying different navigation algorithms. In general, simple mobile bases are used in works that do not include any kind of explicit communication strategies and rely only on implicit cues (Che et al. 2020; Kannan et al. 2021; Hetherington et al. 2021; Palinko et al. 2020) whereas screens or signal lights (or LEDs) are attached for explicit conveyance in some cases (May et al. 2015; Mavrogiannis et al. 2019; Hart et al. 2020; Palinko et al. 2020). When mobile robots are equipped with moving heads, it is also possible to use head movements to communicate intention and attention (Khambhaita et al. 2016). Wearable communication devices are a new addition and Che et al. (2020) use a haptic device along with vision and audio for explicit communication. Urban **delivery robots** are the best examples where socially aware navigation and good communication strategies are essential. These are discussed in the works by Kannan et al. (2021); Boos et al. (2022) and one such robot is shown in Fig. 10 (d).

socially aware **autonomous vehicle** navigation (Fig. 10 (b)) is a relatively new topic. When autonomous vehicles

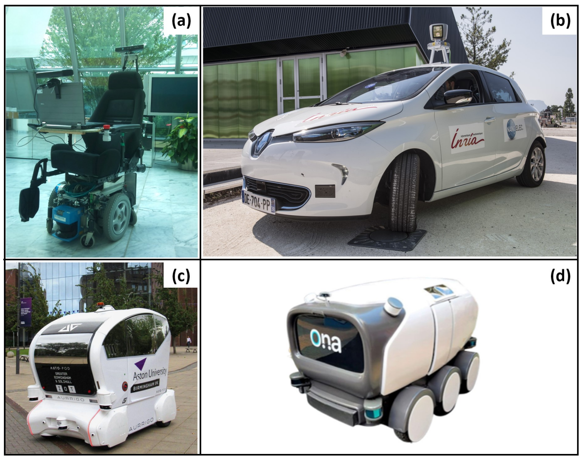

Figure 10. Autonomous vehicles and Wheelchairs: (a) Wheelchair from (Rios-Martinez et al. 2012) (b) Autonomous Car at INRIA (c) Aurrigo Auto-Pod* (d) CARNET Ona Robot (Puig-Pey et al. 2023).

such as **cars and shuttles** share their environment with pedestrians, the interaction between them needs to be understood and modeled. This requires additional hardware, new designs, and protocols that are different from those of mobile robots. Recently, there has been a growing interest in pedestrian trajectory or crowd behavior modeling when they are close to an autonomous vehicle (Prédhumeau et al. 2021; Prédhumeau et al. 2021; Song et al. 2018; Kabtoul et al. 2020; Hsu et al. 2020; Deo and Trivedi 2017). Some works have explored this in pedestrian-aware navigation (Luo et al. 2018; Cunningham et al. 2019; Randhavane et al. 2019; Kabtoul et al. 2020; Hsu et al. 2020; Kabtoul et al. 2022). Autonomous cars can also cooperate with other human drivers in traffic, and this is yet another research area that came into existence recently, and can be considered as a part of socially aware navigation. The works by Evens et al. (2022); Toghi et al. (2021); Valiente et al. (2022) focus on this issue particularly. **Personal mobility vehicles (PMVs)** is an umbrella term for a wide range of devices including cars, shuttles, wheelchairs, Segways, scooters, etc., that can carry one or more persons and usually move at lower speeds among shared human spaces. Fig. 10 (a, c) shows some pictures of PMVs used by the researchers. Although autonomous **wheelchair** navigation research has slowed down gradually (Sivakanthan et al. 2022), there are relevant papers that study autonomous or semi-autonomous navigation in wheelchairs taking social norms into account (Rios-Martinez et al. 2012; Vasquez et al. 2013; Narayanan et al. 2016; Morales et al. 2017; Johnson and Kuipers 2018; Skrzypczyk 2021). Other kinds of PMVs like **Segways and scooters** were also used for developing socially aware navigation strategies to move among the pedestrians (Luo et al. 2018; Chen et al. 2019; Paez-Granados et al. 2022).

3.2 Aerial Robots

This taxon considers various kinds of **unmanned aerial robots or vehicles** that can be used for deliveries, construction, signaling, etc. A majority of the works in this

*https://aurrigo.com/autopod/

survey fall under the *rotorcraft* taxon, specifically, **multi-rotor** drones. The vast availability, the ease of use and the precise control of these systems might be a reason for this. Although the drones in the other taxa like *aerostat* were explored in socially aware navigation from time-to-time, *winged drones* (fixed and flapping) were not explored much.

Drones are a recent addition to the field of socially aware navigation and pose a contrasting set of challenges compared to mobile robots. This sparked a several studies using drones to investigate proxemics (Duncan and Murphy 2013; Yeh et al. 2017) and communication strategies (Bevins and Duncan 2021; Szafir et al. 2015, 2014; Cauchard et al. 2015; Jensen et al. 2018; Yao et al. 2019) to enable their deployment in the real world. Regarding communication, some of these works include additional hardware like LEDs (Szafir et al. 2015) to mimic traffic signals while some others study gestures and flight paths. The noise and wind generated by multi-rotor drones (Cauchard et al. 2015) coupled with the lack of familiarity often affect the humans' perception of safety, comfort, and reliability - compelling new designs, studies, and ways to integrate drones in a better way around humans. The study by Liew and Yairi (2013) suggested that a blimp might be better for socially aware navigation compared to a multi-rotor drone as they are quieter. Recently, Etesami et al. (2021) investigated the design of a social blimp and found that people felt safer and comfortable around the blimp.

The current socially aware navigation planning for drones tries to transfer knowledge from the mobile robot and make suitable adjustments. For instance, Truc et al. (2022) utilizes the cost functions from the social mobile robot navigation for planning socially compliant trajectories for flying robots. A series of works on the aerial social force model by Garrell et al. (2017); Carretero (2017); Garrell et al. (2019) modified the classical social force model to define a 3D social force and applied it to quad-rotors in simulation and the physical world. Unlike these, the approach by Yoon et al. (2019) proposes a hidden Markov model-based social trajectory generation using a learned model of the human. The works by Yao et al. (2017, 2019) used a blimp drone to follow humans indoors while reacting to human gestures. We expect to see more works on socially aware navigation in drones and other kinds of aerial robots in the near future that will populate this taxon.

4 Planning and Decision-Making

In this section, we have included not only classical planning and decision-making techniques, local motion generation, and global motion techniques, but also other aspects that affect planning and decision-making: communication, negotiation, and the type of navigation task (collaborative, assistive, or independent). Local motion generation uses sensing and perception to create trajectory or velocity commands that guide the robot. The global motion process requires employing an extensive spatial representation to provide a command (or decision) that directs the robot's motion.

While a robot performs socially aware navigation, it may move through crowded pedestrian regions autonomously or take on the role of guiding or escorting one or more people. All of these situations demand planning and decision-making techniques that appropriately take into account the existence of bystanders and/or those in need of aid. In the field of HRI, the development of two-way communication between humans and robots is essential for both cooperative and autonomous robot navigation in a pedestrian environment with varying motion patterns. Additionally, bidirectional negotiation is a crucial part of the built-in planning and decision-making processes. It is worth mentioning that differentiating papers based on the type of task provides a useful framework for understanding the current state and the challenges that remain in socially aware navigation research.

Based on this classification, all the methodological papers specific to socially aware navigation (149) matched some of the planning and decision-making criteria. The distribution is illustrated in Figure 11.

4.1 Communication

The study of effective human-robot **communication** is a fast-expanding topic in HRI in general, as well as in socially aware navigation specifically. For their seamless integration, robots or humans – for example, pedestrians or accompanied people – must understand and respond to the communication signals of the other agent. In the case of robots, they have to grasp pedestrians' intentions and let others know about their own. Humans also have to understand the robot's intentions and tell about their intentions. It will be always a bidirectional communication that will help to improve safety, efficiency, and comfort. Although research in this area is especially important to navigate in complex and crowded environments, communication can enhance the overall user experience even in less challenging environments (Senft et al. 2020; Hetherington et al. 2021).

On the one hand, **explicit communication** between robots and humans is critical to facilitate successful decision-making in socially aware navigation. Robots must be able to comprehend and react to the explicit communication of humans, such as spoken language and written instructions. Simultaneously, robots should be able to communicate their own goals and choices to humans in a way that is simple to understand. Explicit robot communication strategies employed by roboticists include *verbal* (speech) and *visual* (display or video, gestures) communications. For instance, Yeh et al. (2017) present a visual approach using a custom-designed social drone with a social shape, face, and voice for human interaction. The work by Kannan et al. (2021) studies visual robot communication using words, symbols, and lights while Palinko et al. (2020) use lights along with gestures to convey the robot's intention. The work in (Rios-Martinez et al. 2012) studies gestures in the context of a robotic wheelchair, and integrates a technique to interpret user intentions using head movements into a socially aware motion policy. Further, in (Jensen et al. 2018), three studies on drones' gestures to acknowledge human presence and clarify suitable acknowledging distances are presented. Yao et al. (2019) use the human gestures to understand their intentions and provide feedback through LED display. In the case of mobile robots as well, gestures are explored to show the robot's intentions while crossing corridors (Hart et al. 2020; Senft et al. 2020; Angelopoulos et al. 2022) or taking turns (May et al. 2015; Palinko et al. 2020). Lastly, verbal communication is used by Dugas et al. (2020) and Boos et al. (2022) to study the effectiveness of robot's speech in clearing its way while Repiso et al. (2022) use it for interaction.

Explicit communication is especially important in decision-making situations, where clear and accurate communication is necessary for both parties to make informed choices (Nishimura and Yonetani 2020; Vega et al. 2019; May et al. 2015; Kollmitz et al. 2020). Research in this area has the potential to significantly advance the capabilities of robots in a variety of settings, including aerial and ground robots. Enhancing robots' comprehension and use of explicit communication to increase their effectiveness when engaging with people has also been studied. For instance, External Human-Machine Interfaces (eHMI) (Kannan et al. 2021) were enhanced to convey intents to humans; Szafir et al. (2015) explored the design space regarding explicit robot communication of flight intentions to nearby viewers; and Dalmasso et al. (2021) created a new interface where robots and humans can communicate to perform collaborative tasks.

On the other hand, **implicit communication** is frequently considered a more natural exchange of information (Winkle and Dautenhahn 2016; Huang et al. 2016). Implementing implicit communication in HRI, however, can also present some difficulties because it might be more challenging for robots to correctly decipher and react to complex cues and context. This may result in misinterpretations or communication mistakes that may reduce the effectiveness of the encounter. Teja S. and Alami (2020) proposed a new framework combining decision-making and planning in the human-robot co-navigation scenario to address such misinterpretations and exhibit pro-actively a proposed solution for a navigation conflict. This is done by introducing different modalities of planning and shifting between them based on the situation at hand. However, the study of implicit communication in this field is still an underdeveloped area of research, with relatively few papers addressing the subject like (Singamaneni et al. 2021; Mavrogiannis et al. 2018; Hsu et al. 2020; Khambhaita and Alami 2017) and (Hetherington et al. 2021). Further, it can be difficult to use implicit communication for complex human-robot interactions involving decision-making (Repiso et al. 2020).

Despite these challenges, the study of implicit communication between robots and humans in the context of decision-making in socially aware navigation is a valuable and important area of research. Repiso et al. (2020, 2018) presented some work where robots became more ubiquitous in society, and they were increasingly being used in HRI scenarios, concretely, in socially aware navigation. The works by Khambhaita and Alami (2017) and Singamaneni et al. (2021) use early intention-show of robot as implicit communication in corridor crossing. Hetherington et al. (2021) study different implicit communication strategies to convey robot's yielding intentions in a door-crossing setting.

While both implicit and explicit communication between robots and humans play important roles in facilitating successful decision-making in socially aware navigation, the study of both forms of communication in this context is limited, for instance (Dey and Terken 2017; Petrak et al. 2021) and (Che et al. 2020). Instead of looking at how implicit and explicit communication interact, many academics have concentrated on one of the two. Robots might also not be able to express nonverbal signs in the same manner that people can, such as showing empathy or worry through body language and facial expressions. Establishing trust and rapport between the robot and the human might be challenging as a result, adding to the complexity of decision-making. This underlines how crucial it is to create efficient communication plans that consider the special capabilities and constraints of robots to promote successful interactions.

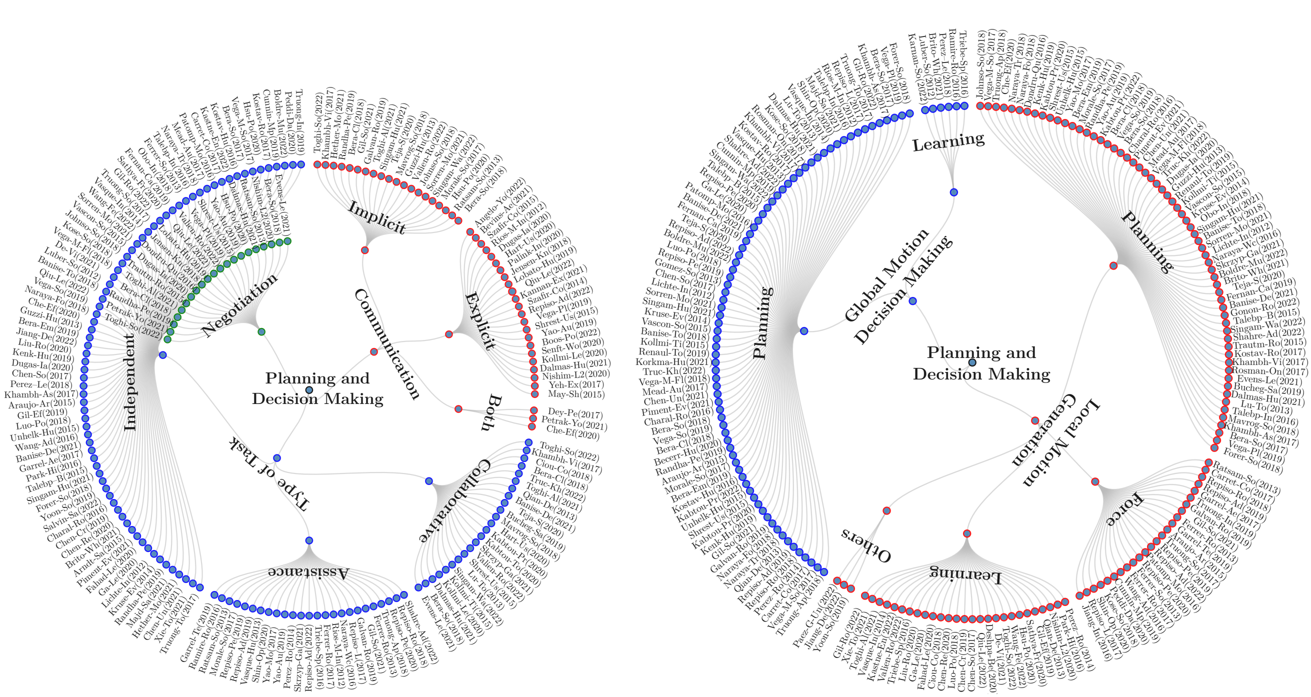

Figure 11. Distribution of papers by planning and decision making. The figures are best viewed zoomed in using a digital version.

4.2 Types of Navigation Task

socially aware navigation tasks can be broadly classified into three types: *independent*, *assistive*, and *collaborative*, based on the interaction between people and the robot while the navigation task is being accomplished. It has to be noted that human environments are highly dynamic. Depending on the context and the evolution of a situation, navigation tasks may change. For instance, in narrow passages or corridors, it may happen that an independent navigation task may call for a collaborative solution.

Collaborative socially aware robot navigation is especially difficult since the robot and humans must share the same goal and they aim to navigate along. This means that robots must be able to model other agents in the environment (Kollmitz et al. 2015), to include their intentions (Kabtoul et al. 2020), and to adapt their behavior (Shrestha et al. 2015; Ciou et al. 2018). In such tasks, robots need to communicate and cooperate with humans to accomplish a specific navigation task (Luber et al. 2012). For example, the works by (Khambhaita and Alami 2017; Truong and Ngo 2018; Bera et al. 2018; Singamaneni et al. 2021; Kollmitz et al. 2020) address the challenge of humans and robots navigating together sharing the same plan.

Collaborative robot navigation can be effectively categorized into two major approaches: *rule-based methods* (Parhi and Singh 2010; Bayazit et al. 2004) and *learning methods* (Wang et al. 2018; Marge et al. 2017). Rule-based methods involve the formulation of a predefined set of guidelines and regulations that the robot rigorously follows to execute its intended navigation behavior. These rules are often crafted based on a priori knowledge and established norms, providing a structured framework for the robot's interactions with its environment and other agents. For instance, in scenarios where robots are deployed in manufacturing facilities, rule-based navigation can be tailored to ensure safe and efficient movement, adhering to spatial boundaries and predefined routes (Kabtoul et al. 2020). While rule-based methods offer a high degree of predictability and safety, they may lack adaptability in dynamic and unstructured environments, where situations can change rapidly (Teja S. and Alami 2020; Galvan et al. 2019).

On the other hand, learning methods in collaborative robot navigation rely on machine learning algorithms to enable robots to acquire knowledge and adapt their navigation strategies over time (Gil et al. 2021; Toghi et al. 2021). These approaches leverage data-driven techniques to make informed decisions based on the robot's interactions with its surroundings and other agents (Garrell et al. 2017, 2019). For example, reinforcement learning algorithms can enable robots to learn optimal paths and navigation behaviors through trial and error, while deep learning models can be used to recognize and respond to various environmental cues (Yen and Hickey 2004). Learning methods excel in scenarios where the environment is constantly changing, and adaptability is essential. However, they may require significant amounts of training data and computational resources to develop robust navigation capabilities, which can be a challenge in some applications (Toghi et al. 2021; Kabtoul 2021; Kabtoul et al. 2022; Toghi et al. 2022). The choice between rule-based and learning methods often depends on the specific requirements of the collaborative robot navigation task and the level of adaptability and autonomy desired.

Assistive socially aware navigation is an important domain in the field of robotics that seeks to create robotic systems that can help people with navigation tasks without requiring either explicit or active cooperation (Rios-Martinez et al. 2012; Morales et al. 2017; Shin and Yoon 2020; Yao et al. 2019; Repiso et al. 2019, 2020). This discipline has been through a huge transition in recent years, mostly due to rapid advancements in artificial intelligence and machine learning. These developments in technology have made it possible to create complex algorithms with context-aware and sophisticated assistance while navigating (Garrell et al. 2017; Vasquez et al. 2013; Triebel et al. 2016; Yao et al. 2017; Shin and Yoon 2020).

One significant avenue of development in assistive socially aware navigation is the integration of deep learning-based techniques (Garrell et al. 2019). These techniques have demonstrated great potential, especially in urban environments where robots can produce natural language instructions specific to the individual's position and destination (Chen et al. 2017; Ye et al. 2020). Robots can interpret user intent, examine the environment, and communicate instructions in a manner that is human-friendly by employing deep learning. This method has the potential to completely transform urban navigation by increasing its efficiency and accessibility, particularly in complex and crowded urban settings (Zhu and Zhang 2021; Liang et al. 2018).

Reinforcement learning-based methods are another important area in this field, as they allow to factor in variables that are frequently difficult to handcraft. These methods allow robots to observe humans and modify their behavior and actions accordingly (Hua et al. 2021). They have also shown to be quite beneficial for assisting with transportation-related activities (Toghi et al. 2022). These methods allow robots to observe humans and modify their behavior and actions accordingly. The robot can adapt and adjust its actions to the dynamic and frequently unexpected traits of real-world surroundings, such as small-scale public spaces thanks to reinforcement learning. This flexibility guarantees that the robot will be able to efficiently address the numerous and changing demands of those who need help in a navigation task (Li et al. 2019).

In summary, machine learning and artificial intelligence are enabling assistive socially aware navigation, which is rapidly developing intelligent, adaptive, and supportive robotic systems that can help people navigate challenging and constantly changing environments. These developments have the potential to significantly improve people's mobility and quality of life in a variety of settings.

Independent socially aware navigation is an important area where robots autonomously move without direct human interaction (Peddi et al. 2020; Narayanan et al. 2018; Park et al. 2016). This paradigm is especially applicable to situations where robots are working autonomously and need to navigate through crowded environments (Vasquez et al. 2014; Chen et al. 2020). The use of these techniques is necessary when navigating through crowded areas in order to guarantee safe and efficient motion.

Crowd navigation employs a diverse set of strategies. For instance, Narayanan et al. (2018) and Brito et al. (2021) predict sub-goals to move towards the goal while (Nishimura and Yonetani 2020) learns how to efficiently move through the crowd without freezing or timing out. A similar approach focused on avoiding robot freezing among human groups was proposed by Sathyamoorthy et al. (2020). Dugas et al. (2020) use different communication modalities to assist in passing through dense spaces. A number of advanced obstacle avoidance policies are also proposed to pass through crowds like (Chen et al. 2017, 2019; Bera et al. 2019; Cunningham et al. 2019; Qiu et al. 2022; Gonon et al. 2022; Kästner et al. 2022; Wang et al. 2022).

Furthermore, robots moving in warehouses (Fernandez Carmona et al. 2019; Kenk et al. 2019; Guldenring et al. 2020) and approaching people for interaction (Truong and Ngo 2018; Ramirez et al. 2016) could be included into both independent and assistive socially aware navigation category.

Despite significant progress in independent socially aware navigation, several challenges remain. For instance, the development of algorithms that can handle a wide range of social environments and cultural contexts, the integration of multiple modalities for perception and sensing, and the improvement of safety and privacy in socially aware navigation (Qiu et al. 2022; Salvini et al. 2022; Narayanan et al. 2018; Shrestha et al. 2015; Bera et al. 2019).

4.3 Negotiation

Negotiation, in the context of robotics, and particularly in the domain of robot navigation, refers to the dynamic interaction and communication between robots and other entities, including humans and other robots, in order to accomplish efficient and successful movements. It involves a process where robots actively exchange information to coordinate their actions and resolve potential conflicts. Thus, negotiation strategies, in robot navigation, encompass a wide spectrum, from simple actions like requesting passage through a congested area, to more complex decision-making processes that balance different objectives, eventually helping in the beneficial interaction of humans and robots in shared areas.

Therefore, this section explores research that includes explicit negotiation, which comprises elements such as requesting permission to move forward or clearly expressing intentions, and implicit negotiations like dynamic behavior adaptation by detecting intentions. Agents (human or robotic) can come to agreements or solve issues through the process of negotiation.

Negotiation in robot navigation requires the robot to be able to interpret and respond to the needs and motivations of pedestrians with whom it is negotiating, as well as to effectively communicate its own goals and constraints. In (Dalmasso et al. 2021), the robot computes a multi-agent plan for both itself and the human which is then communicated to the human for review; this planner is based on a decentralized variant of Monte Carlo Tree Search (MCTS) with one robot and one human as agents. In (Hsu et al. 2020) researchers contribute with a minimal model to manage ambiguity and produce actions that are expressive and encode aspects of humans' intents. Furthermore, Lobato et al. (2019) present a socially aware navigation system that allows to establish a negotiation framework to improve the socially aware navigation system.

The ability to effectively negotiate in robot navigation can be a key factor in enabling robots to interact and cooperate with humans and their environment in a natural and intuitive manner (Jensen et al. 2018). Vega et al. (2019) focus on planning algorithms that facilitate negotiation between robots and humans in dynamic environments. Kabtoul et al. (2020) propose a proactive negotiation approach to enhance human-robot collaboration. Dondrup and Hanheide (2016) explore qualitative spatial reasoning techniques for negotiating spatial relations in human-robot interaction scenarios. Furthermore, (Chen et al. 2020) investigate graph strategies that enable robots to establish relations among agents and maintain advanced predictions of humans to negotiate their plan better during navigation tasks. Nishimura and Yonetani (2020) explore the robot beeping mechanism to negotiate with the humans to clear the way. These works contribute valuable insights into the field of negotiation in socially aware robot navigation, paving the way for the development of more efficient and interactive robotic systems.

Another important aspect of negotiation is the ability to adapt to changing circumstances. The negotiation process may involve a number of back-and-forth exchanges as the agents work to reach an agreement, and the robot must be able to adjust its negotiation strategy as needed to reach a mutually acceptable solution. Trautman et al. (2015) explore the use of adaptive negotiation strategies in the context of human-robot collaboration, emphasizing the importance of dynamically adjusting negotiation behaviors based on situational cues. Bera et al. (2018) propose a socially adaptive negotiation framework that enables robots to learn and modify their negotiation strategies based on user preferences and interaction history. Shrestha et al. (2015) investigate the use of contact-based inducement to negotiate in a congested scenario. Finally, Ratsamee et al. (2013) focus on the role of adaptability in negotiation, demonstrating the need for robots to continuously learn and adapt their negotiation behaviors to foster successful human-robot interactions. All these works highlight the significance of adaptive negotiation strategies in enabling robots to effectively navigate and interact with humans in dynamic environments.

In addition to these aspects, negotiation in socially aware robot navigation may also involve resolving conflicts or obstacles that arise during task execution (Toghi et al. 2021), as well as coordinating actions and sharing resources with other robots or autonomous systems. By effectively negotiating with these parties, the robot can facilitate cooperation and coordination, enabling it to achieve its goals and to complete tasks more effectively (Evens et al. 2022).

4.4 Local Motion Generation

Local motion generation, which often involves local sensing and perception, is the creation of a trajectory or velocity commands for guiding the robot's motion at a lower level (Boldrer et al. 2022). Local motion generation can be divided into several categories, including *planning-based approaches* (Unhelkar et al. 2015; Bera et al. 2017; Singamaneni et al. 2021; Banisetty et al. 2021; Chen and

Lou 2022; Gonon et al. 2022), *force-based approaches* (like potential fields and social forces) (Patompak et al. 2016; Cunningham et al. 2019; Repiso et al. 2020; Kivrak et al. 2018; Jiang et al. 2016), *learning-based approaches* (Liu et al. 2020; Chen et al. 2017; Sathyamoorthy et al. 2020), and *others*, which are not included in the previous categories (Paez-Granados et al. 2022).

Planning-based approaches involve generating a trajectory for a robot to follow and, then, converting it to velocity commands. These approaches are often used in complex environments where obstacles and other dynamic elements need to be taken into account. Different planning methodologies can be used to generate trajectories, such as Model Predictive Control (MPC), dynamic windows (Truong and Ngo 2018; Kabtoul et al. 2022), elastic bands (Rösmann et al. 2017; Vega et al. 2019; Singamaneni et al. 2021; Khambhaita and Alami 2017; Singamaneni et al. 2022), and obstacle avoidance techniques (Jiang et al. 2022; Gonon et al. 2022; Bera et al. 2017).

MPC-based approaches use a predictive model of the robot's motion to generate an optimal trajectory over a finite time horizon. The trajectory is generated by solving an optimization problem that takes into account the robot's kinematics, dynamics, and environmental constraints. For instance, Che et al. (2020) propose a planning framework, based on MPC, that generates explicit communication (finite number of discrete signals) and robot motions. In (Brito et al. 2021), the robot combines a sub-goal prediction mechanism with an MPC controller to navigate the environment efficiently. Evens et al. (2022) propose an MPC-based scheme to handle general traffic situations for PMVs.

Dynamic window approaches (DWA) involve generating a set of reachable velocities based on the robot's kinematics and dynamics (Truong and Ngo 2018). The set of reachable velocities is used to select the best velocity command that will take the robot closer to the goal while avoiding obstacles. A similar approach presented in (Kabtoul et al. 2022) uses a dynamic channel to maneuver around pedestrians while anticipating their cooperation. Dondrup and Hanheide (2016) propose some modifications to DWA to generate safe and efficient trajectories to reach the goal while trying to ensure human acceptance. Due to its conceptual simplicity, DWA is one of the widely used approaches and can be easily employed to test new ideas (Truong and Ngo 2018; Dugas et al. 2020).

Elastic band approaches, on the other hand, require a slightly more complex implementation. They involve generating a path for the robot to follow and simulating an elastic band to smooth the path while stretching (or compressing) it around obstacles and generate velocity commands (Khambhaita and Alami 2017; Vega et al. 2019; Pimentel and Aquino-Jr 2021). Traditional elastic bands could include only kinematics constraints (Vega-Magro et al. 2018; Vega et al. 2019) whereas the timed elastic bands proposed by Rösmann et al. (2017) can handle kinodynamic constraints. Khambhaita and Alami (2017) and Singamaneni et al. (2021) use these timed elastic bands for proactive planning to solve complex human-robot navigation settings.

Finally, the dynamic obstacle avoidance techniques that are prevalent in the motion planning community have also been modified to accommodate humans and navigate safely in social environments. The works of Bera et al. (2018, 2019) rely on the generalized velocity obstacles approach. Very recent work by Gonon et al. (2022) proposes acceleration obstacles to handle the case of crowd robot navigation specifically. Lastly, Sathyamoorthy et al. (2020) proposes a hybrid approach to avoid freezing by switching between planned and learned controls.

Force-based approaches like potential fields and social forces, involve generating velocity commands based on the potential or force fields in the robot's environment and the interaction forces generated by the way people move. They are widely used in robot navigation to generate velocity commands based on attractive and repulsive forces. The first group uses virtual potential fields to generate attractive forces towards the goal and repulsive forces away from obstacles (Araujo et al. 2015). The robot's motion is then controlled based on the gradient of the potential field. On the other hand, the social force model (SFM) uses the concept of social forces, where the forces result from interactions between individuals or groups and the robot. The forces to avoid collisions with humans are generated using the relative velocities between the robot and the pedestrians, and they are combined with the forces from the other obstacles (Repiso et al. 2020; Alahi et al. 2017). Finally, these combined forces are used to generate velocity commands for the robot.

One popular potential field approach is the Artificial Potential Field (APF) method (Jiang et al. 2016). The APF method has been widely used in robot navigation and extended to dynamic environments by incorporating time-varying potentials and obstacle-avoidance strategies (Ferrara and Rubagotti 2007). The simplicity of implementation and computational efficiency of APF makes it ideal for real-time applications. Considering the adaptive nature of potential fields, some researchers used it to address both simple (Wang et al. 2016) and complex socially aware navigation tasks in dynamic environments like offices (Araujo et al. 2015) or sparse crowds (Cunningham et al. 2019).

Social force approaches were first proposed by Helbing and Molnar (1995) to model pedestrian behavior in crowds. This idea was later adapted to control the robot's motion based on the sum of attractive and repulsive forces generated by the social forces from various kinds of interactions (Ferrer et al. 2013,; Patompak et al. 2016; Repiso et al. 2017). Since its inception, social force-based robot control has been modified and extended to address different kinds of problems in social robot navigation. Ferrer et al. (2013) used it to navigate the robot in crowded environments and later proposed an extension for proactive kinodynamic planning (Ferrer and Sanfeliu 2014). Building on this extended SFM, a set of works (Repiso et al. 2018, 2019, 2020, 2022) were proposed to approach and accompany individual as well as a group of people. This online adaptive planning in dynamic environments is achieved by incorporating time-varying social forces (Repiso et al. 2020,). In the works presented in (Truong et al. 2017) and (Truong and Ngo 2017), the SFM is extended to include human-object interactions and group interactions to address dynamic crowds. SFM has been adapted to aerial robots as well and the works by Garrell et al. (2017, 2019) show these extensions called aerial social force models designed to accompany humans. Some recent approaches combine policy learning (Cunningham et al. 2019; Gil and Sanfeliu 2019) and machine learning (Gil et al. 2021) with SFM to achieve better socially aware robot navigation policies.

In **learning-based approaches** velocity commands are frequently generated directly, without the need to construct a precise trajectory, through the application of machine learning algorithms. These approaches typically involve either reinforcement learning (Chen et al. 2017; Guldenring et al. 2020; Gil and Sanfeliu 2022), deep learning (Gil et al. 2021; Xie et al. 2021), imitation learning (Garrell et al. 2019; Fahad et al. 2020; Liu et al. 2020) or inverse reinforcement learning (Vasquez et al. 2014; Ramirez et al. 2016).

Reinforcement learning (RL) or deep reinforcement learning (DRL) in general is used by several articles in this survey to teach socially aware navigation to a robot. For instance, the works by Chen et al. (2017, 2019, 2020) use different kinds of networks architectures to capture the relations and interactions in the crowd and teach a robot to move socially. They use the deep V-learning where the neural network is initialized with regression and then trained using reinforcement learning. In (Qiu et al. 2022) researchers also propose a hybrid learning approach combining supervised learning with DRL. The authors learn the interactions among pedestrians using supervised learning, and this interaction policy is used within DRL navigation policy training to learn when to alarm the surrounding pedestrians to clear the path. This alerting mechanism for path clearing was inspired by (Nishimura and Yonetani 2020), where the authors learn the balance between human safety and navigation efficiency in a similar manner.

As mentioned previously, the works by Gil and Sanfeliu (2019, 2022) combine DRL with SFM, in order to study the effects of SFM rewards and human motion prediction strategies on the navigation policy. The work in (Guldenring et al. 2020) presents a DRL-based ROS local planner that is trained to avoid humans in warehouses using 2D LiDAR data as input. DRL is also explored for learning the navigation policies for autonomous vehicles (AVs). The work by Deshpande et al. (2020) uses deep recurrent Q-network to handle high-level behavioral decision-making while the AV is navigating among pedestrians. In other works (Toghi et al. 2021, 2022), different policy learning mechanisms like A2C and multi-agent RL are used to learn social behaviors in traffic with emphasis on coordination and altruism.

Among the other kinds of learning approaches, deep learning is generally employed for robot perception. However, there are works like (Xie et al. 2021) that use deep learning to navigate through crowded environments. Imitation learning is employed to clone the behavior of humans in (Fahad et al. 2020) while it is used to assist robot navigation policy learning in (Liu et al. 2020). Garrell et al. (2019) use imitation learning to make a neural network learn to mimic the expert flying a drone. The work in (Ramirez et al. 2016) uses inverse reinforcement learning to train a robot to approach humans appropriately while Pérez-Higueras et al. (2014) use it to navigate robot in public spaces.

One key advantage of learning-based approaches is that they can capture the nuances of social interaction, such as motion dynamics (Chen et al. 2020), social norms, and respond appropriately to human feedback (Kollmitz et al. 2020). Hence, learning-based approaches have the potential to significantly improve the field of socially aware robot navigation, enabling robots to navigate and interact with humans in a more natural and intuitive way (Toghi et al. 2021). These approaches typically require a model trained on a dataset of sensor inputs and corresponding command velocities, using a suitable loss function and optimization algorithm (Triebel et al. 2016; Liu et al. 2020; Toghi et al. 2022). Researchers are also focusing on more innovative approaches and applications of socially aware robot navigation for more complex social environments (Park et al. 2016; Ciou et al. 2018; Evens et al. 2022; Qiu et al. 2022).

Last but not least, there exist papers that do not fall under any of the above groups but deal with low-level motion generation. They have been classified as **others** in our taxonomy. In (Yoon et al. 2019) authors introduce a novel framework for path planning that considers the safety perception of humans when a flying robot is present. With this, they aim to ensure safe and socially acceptable interactions between humans and flying robots. Researchers in (Bera et al. 2017) published an approach to mathematically model social cues in order to predict both human trajectories and personal/social distances, which are key components of socially aware navigation planning. To accomplish this, a Bayesian-based model of personality traits is used, with video data serving as the source for observing and quantifying these traits. By leveraging these models of human behavior, the aim is to enhance the ability of robots to interact with humans in a safe and socially acceptable manner. A novel methodology to unfreeze the robot from unintended collisions with pedestrians is proposed in (Paez-Granados et al. 2022). They design a special controller that modulates the velocity upon detection of contact to mitigate the risks. In the work presented by Jiang et al. (2022), a pedestrian-aware controller for an autonomous car was proposed that modulates the speed depending on the estimated pedestrian density.

4.5 Global Motion Decision-Making

Global motion decision-making, in the context of socially aware robot navigation is the process of computing a valid robot trajectory at a coarse level, taking into account the requirements of socially aware navigation. It often utilizes a representation of the environment to guide the process, and considers aspects like collision avoidance and the needs of bystanders. This differs from local decision-making, which relies on sensors and the immediate surroundings to guide motion. The approaches for global motion decision-making mainly consist of *planning-based* approaches (search and sampling) (Korkmaz 2021; Forer et al. 2018; Singamaneni et al. 2021; Kollmitz et al. 2015; Talebpour et al. 2016; Vega-Magro et al. 2017; Chen et al. 2017) and *learning-based* approaches (Luber et al. 2012; Pérez-Higueras et al. 2018; Karnan et al. 2022; Brito et al. 2021).

Planning-based approaches are very frequently used to make global-level decisions and plan the initial path for the robot to follow. The articles in this survey include *search-based approaches*, like A* methods (Luo et al. 2018;

Banisetty and Feil-Seifer 2018), D* methods (Charalampous et al. 2016), diffusion maps (Chen et al. 2017), Dijkstra (Pérez-Higueras et al. 2014; Truong and Ngo 2018), etc.; and **sampling approaches** like PRM (Korkmaz 2021), RRT (Becerra et al. 2020; Shrestha et al. 2015), Risk-RRT (Narayanan et al. 2018), PRM-RRT (Vega-Magro et al. 2017), Fast Marching methods (Talebpour et al. 2016), etc.

One of the main challenges in this area has been the ability of the robot to adapt to changing environments or unexpected obstacles (Repiso et al. 2020). To address this challenge, some researchers have developed methods that incorporate real-time feedback or sensory data into the global planning process (Peddi et al. 2020; Vega-Magro et al. 2018; Randhavane et al. 2019). Other approaches use a combination of global and local maps to generate a decision or plan a better path (Dondrup and Hanheide 2016; Fernandez Carmona et al. 2019; Singamaneni et al. 2022). The global map provides a high-level view of the environment, while the local map represents the robot's immediate surroundings in more detail. By combining these two types of maps, the robot can generate a path that is both efficient and able to adapt to local environmental changes (Teja S. and Alami 2020; Singamaneni et al. 2022; Kollmitz et al. 2015). Continuous re-planning is also used in some cases (Korkmaz 2021).

The papers that use **learning-based** methods involve training a model on data to make predictions about future states or decisions. These methods can leverage large amounts of data to learn patterns and adapt to new situations but may require significant training time and may not generalize well to novel situations. These methods make use of deep reinforcement learning (Brito et al. 2021; Valiente et al. 2022), deep learning architectures like CNNs (Pérez-Higueras et al. 2018), and inverse reinforcement learning (Vasquez et al. 2014). Even with the limitations, these approaches can help provide a good initial estimate that assists in better planning (Pérez-Higueras et al. 2018). Further, they can be used to select sub-goals for guiding a local planner (Brito et al. 2021). In PMVs as well, they can be used to make high-level decisions (Valiente et al. 2022).

There are also papers that do not explicitly focus on either of these approaches, but instead consider additional aspects of global motion decision-making, such as the representation of the environment (Arndt and Berns 2015), the incorporation of social cues, the integration of multiple modalities of sensing and communication (Che et al. 2020), or Wizard-of-Oz studies (Lichtenthäler et al. 2013). In general, the choice of a global motion decision-making strategy depends on specific demands and features that characterize the concerned task.

5 Situation Awareness and Assessment

Fig. 12 shows the distribution of the papers according to the taxonomic aspects of situation awareness and assessment. Most works exploit elements of the three main branches, although none of the reviewed proposals considers all of them. By a large margin, the most frequent aspects considered in the literature for situation awareness are *obstacles* in the *environment*, *trajectory prediction* of the *agents*, and *proxemics* constraints as the main *social norm*. The remainder of the section presents a detailed analysis of the different taxa.

5.1 Environment

This taxon considers papers representing aspects related to the physical space in which the robot navigates other than the agents in the environment, which are considered in the next section. Collective issues such as the density of humans in the area are also considered.

The **semantics of the environment** is a topic that has received limited attention in the literature. Some proposals assume a specific type of space for navigation, such as the office-like environment in (Araujo et al. 2015) or the wheelchair navigation system in (Morales et al. 2017) that estimates corridor width. In (Banisetty et al. 2021), the navigation system includes a context classification module that distinguishes between four contexts and is used to guide the robot in selecting social objectives. Other approaches, such as the socially aware variant of a NAMO algorithm in (Renault et al. 2019), use a semantic map with taboo zones for movable obstacle placement, while Kostavelis et al. (2016) combine a metric map with a structured map containing relevant objects and standing positions for humans that are used to improve future predictions of the occupancy of different areas. In a similar way, in (Kostavelis et al. 2017) predefined locations of frequently visited areas of the environment are used for human presence anticipation. The work presented by Singamaneni et al. (2022) also proposes a geometric approach to anticipate the emergence of humans from occluded locations.

An alternative application of the semantics of the environment can be found in (Hsu et al. 2020). Their proposed system provides estimates for the intentions of pedestrians and nearby pedestrian crossings using semantics information as input. Other proposals consider environment information, although not of semantic type (e.g. size, structure), for navigation (Vega-Magro et al. 2018; Manso et al. 2019).

In relation to **object interaction**, most of the proposals considering this element, model the interaction area using predefined functions to prevent the robot from traversing those zones. For instance, Lobato et al. (2019) and Vega et al. (2019) model the interaction zone as a symmetric trapezoidal area, while others (Truong and Ngo 2018) use Gaussian functions. Likewise, Truong and Ngo (2017) and Truong et al. (2017) consider detected object interaction, creating a circular object interaction space to avoid. Differently, in Manso et al. (2019) object interactions are included in the representation of a scene, but the interaction areas are not explicitly modeled.

A different perspective on applying human-object interactions for socially aware navigation can be found in Bruckschen et al. (2020) and Vega et al. (2019). In particular, Bruckschen et al. (2020) use observed human-object interactions along with prior knowledge about typical human transitions to predict the most likely navigation goal of the human. On the other hand, Vega et al. (2019) consider only one type of interaction with one type of object, namely doors, and focuses on the relationship where one or more humans are blocking the door, which is used in the proposal to ask for permission to pass.

Other than agents, **obstacles** constitute the most important type of physical elements of the environment in the vast majority of socially aware navigation works. Navigation algorithms not considering obstacles work on simple scenarios where humans (or agents in general) are the only entity robots may collide with (Nishimura and Yonetani 2020). This is particularly common in simulated environments. Some of the obstacle-aware approaches to socially aware navigation do not use a representation that integrates information over time. Instead, they use the instantaneous information perceived through the robot's sensors (de Vicente and Soto 2021; Guzzi et al. 2013; Sathyamoorthy et al. 2020; Paez-Granados et al. 2022).

Papers representing obstacles have been classified according to three types of representation: dense, sparse, and hybrid. Fig. 13 shows the distribution of a representative subset of the reviewed papers into these three different types of representations.

Dense representations consist of a metric map of the environment where the obstacles are located. In this case, obstacles cannot be identified as individual entities, but the representation still allows disregarding areas of the environment that the robot cannot cross during navigation. The commonly used dense representations are occupancy grids and cost maps. This type of obstacle representation is the most widely used in the literature.

Sparse representations, where each obstacle is an independent element with its own properties, are found on the other side of the spectrum. Frequently, works using this kind of representation consider position and size as the only properties of the obstacles, assuming circular shapes for them (Ferrer et al. 2013; Bera et al. 2018).

The third obstacle representation category corresponds to hybrid approaches, which combines dense and sparse models for different purposes. Examples of hybrid representations can be found in (Lobato et al. 2019), (Renault et al. 2019), and (Vega-Magro et al. 2018). The proposal by Lobato et al. (2019) uses a sparse obstacle representation, where detected objects are nodes of a symbolic graph of the environment and a dense one for modeling the occupied space. In (Renault et al. 2019) a 2D metric map is built to compute a first plan. Then, the plan is refined iterating over movable obstacles. The work in (Vega-Magro et al. 2018) represents the obstacles of the environment by means of a cost map, but also incorporates wall descriptors that are later used by the control system.

Even though most of the environment-related elements considered for socially aware navigation can be included in the three already mentioned taxa (semantics of the environment, object interactions, and obstacles), some works take into account other aspects of the area where the navigation takes place. All these aspects are included in a fourth branch labeled as ***others***. After our review, only four papers have been found that can be included in this branch. Specifically, Pérez-Higueras et al. (2018); Ciou et al. (2018) and Jiang et al. (2022) consider people's density as an additional property of the environment. Besides, Johnson and Kuipers (2018) represent gateways along with other elements of the area where the robot navigates.

5.2 Agents

This taxon describes how the agents are represented. We use the term *agent* instead of *human* to encompass all active entities involving humans that may be present in the environment (*e.g.*, other vehicles in the case of autonomous driving).

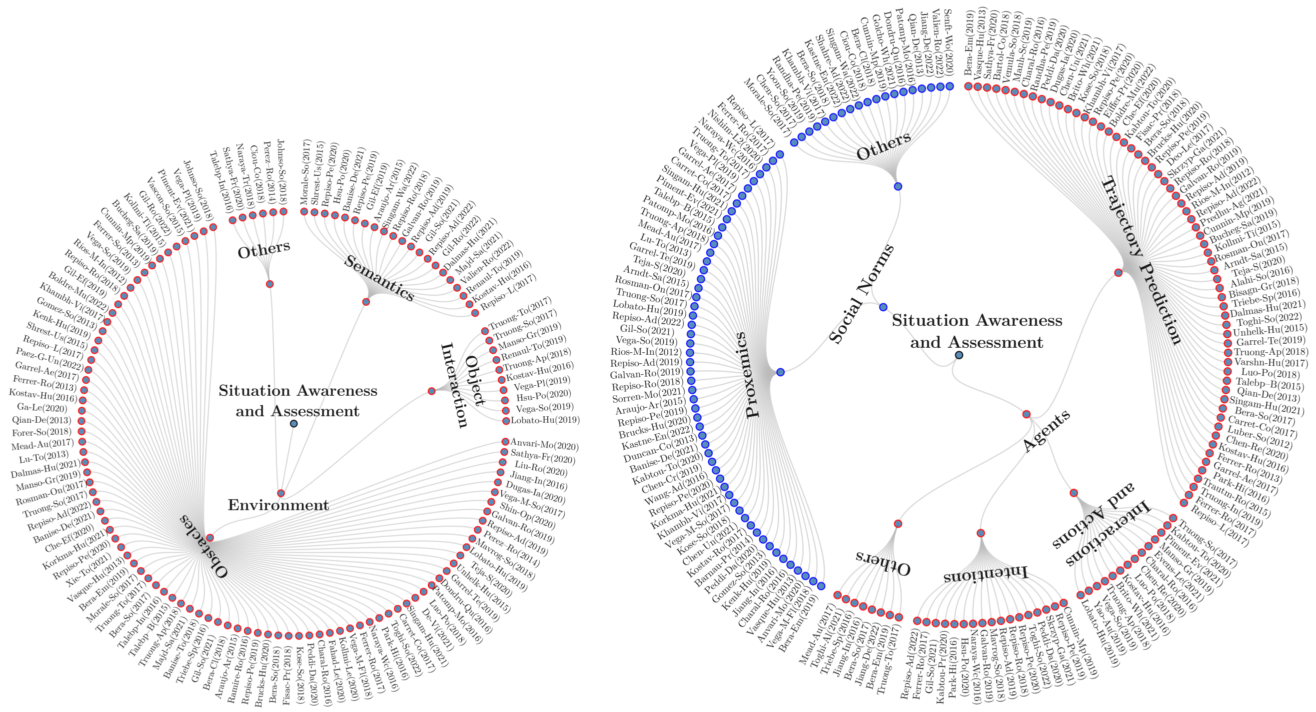

Figure 12. Distribution of papers by situation awareness and assessment. The figures are best viewed zoomed in using a digital version.

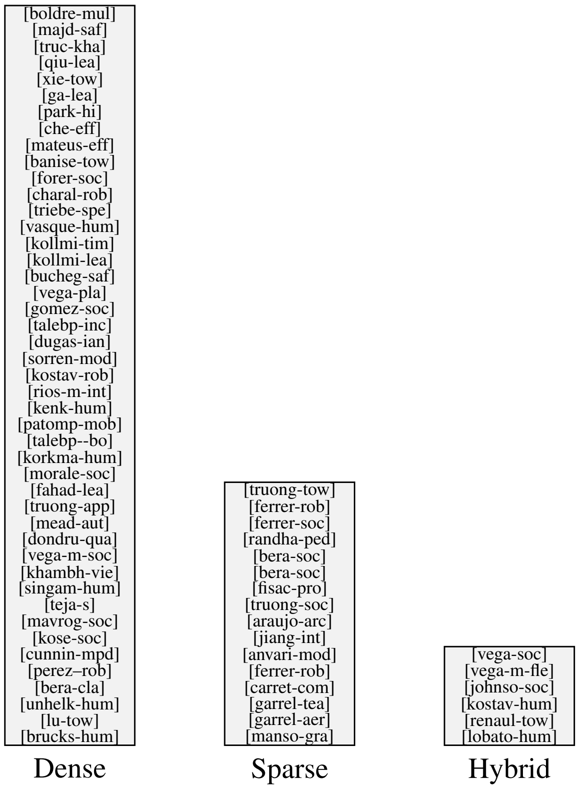

Figure 13. Classification of papers according to how obstacles are represented.

All works dealing with socially aware robot navigation consider a common set of attributes that provide, in the simplest case, a minimal representation through which an agent can be treated as a "special obstacle". Strictly speaking, this common set consists of the 2D position of the agents, although the orientation of the agents is frequently considered as well. Therefore, our taxonomy ignores these pose-related attributes in the proposed classification and focuses on other aspects of the agents for which a more diverse treatment can be found in the existing literature, starting with **trajectory prediction**.

Predicting the trajectory of an agent involves estimating the agent's future positions based on its past positions and, potentially, information about the environment and other agents. Pedestrian trajectory prediction is a research field in itself. Numerous works have been proposed on this topic, although they are not necessarily framed within a robot navigation proposal. We will begin by focusing on trajectory prediction proposals that can be directly applied to robot navigation. Next, we will analyze works that use trajectory prediction within the context of socially aware robot navigation.

Given the recurrent nature of trajectory prediction and the surge in machine learning in recent years, recurrent neural networks (RNN) have a special role in recent trajectory prediction approaches. One of these learning-based approaches is Social-LSTM (Alahi et al. 2016), which proposes an LSTM-based model that can jointly estimate the future trajectory of all the people in a scene, using one LSTM per individual and a pooling layer to share the information between them. Based on this idea, some variants have been proposed. For instance, Bisagno et al. (2018) first cluster people into coherent groups before using Social-LSTM to predict their trajectories. Varshneya and Srinivasaraghavan (2017) propose a variant of Social-LSTM that considers several factors such as the dynamic of neighboring subjects and the spatial context in which the subject is. In (Bartoli et al. 2018), human-human and human-space interactions are incorporated into the Social-LSTM model. Other proposals applying RNNs to trajectory prediction are the one by Vemula et al. (2018), which uses RNNs to model the spatial and temporal dynamics of trajectories in human crowds, and the work by Manh and Alaghband (2018), an LSTM-based approach that combines scene information into the human trajectory prediction. Likewise, Eiffert et al. (2020) combine Recurrent Neural Networks with Mixture Density Networks for pedestrians' trajectory prediction with the goal of enabling autonomous vehicles to navigate through crowds.

In the context of autonomous driving, other approaches for trajectory prediction can be found. Kabtoul et al. (2020) present a model that estimates the pedestrian's cooperation with the vehicle and uses this estimation to predict the trajectory of the pedestrian by a cooperation-based trajectory planning model. Also, in (Prédhumeau et al. 2021) a pedestrian trajectory prediction model is proposed for autonomous vehicles, combining SFM and a decision model for conflicting pedestrian-vehicle interactions. Another example is the approach in (Deo and Trivedi 2017), which proposes an extension of the Variational Gaussian Mixture Model-based probabilistic trajectory prediction framework for on-road pedestrians. The aforementioned proposals constitute a limited subset of the existing trajectory prediction approaches. Many others can be found. For a more comprehensive overview of the topic, readers may refer to specific surveys (Ridel et al. 2018).

Despite advances and new techniques in trajectory prediction, many works in socially aware navigation propose their own approach to the problem. Some papers employ uncomplicated solutions to predict the trajectory of agents, using no other information than the last positions/velocities of the agent. Thus, in the works by Guzzi et al. (2013) and Chen and Lou (2022), all agents are assumed to keep their current heading and speed. Carretero (2017) estimates the new velocity of a human as the average of the last 10 velocities. Kivrak et al. (2018) do not predict trajectories as such, but estimate the time to collision according to the current positions and velocities of the humans.

More elaborate solutions have also been proposed using only the past trajectory of the agents. Garrell et al. (2017) use a prediction module based on online linear regression. In (Garrell et al. 2019) a neural network takes the last 10 known positions of a human to predict the new position one second into the future. Truong and Ngo (2018) and Talebpour et al. (2015) apply Kalman filters for predicting the future state of pedestrians. Probabilistic approaches (Bera et al. 2017, 2019; Arndt and Berns 2015; Fisac et al. 2018; Trautman et al. 2015; Randhavane et al. 2019; Dugas et al. 2020; Luber et al. 2012; Ferrer et al. 2013; Sathyamoorthy et al. 2020; Park et al. 2016), Hidden Markov Models (Vasquez et al. 2013; Peddi et al. 2020), and social force models (Ratsamee et al. 2013; Boldrer et al. 2022) have also been applied for trajectory forecasting.

Other approaches use additional information for trajectory prediction. For instance, Unhelkar et al. (2015) use turn indicators as features in the prediction of human motion trajectories. In (Park et al. 2016) human intentions are classified and used to predict their motions. Chen et al. (2020) use a neural model (MLP) for predicting the next states of humans using the relations between agents predicted by a relational graph model.

A subset of proposals predict the goal positions of humans instead of their trajectories (Bruckschen et al. 2020; Ferrer et al. 2017) or along with them (Teja S. and Alami 2020; Singamaneni et al. 2021; Vemula et al. 2018; Kostavelis et al. 2017). Khambhaita and Alami (2017) use the goal positions of humans to predict their paths by means of elastic bands, but the goals are assumed. Finally, it is worth mentioning that there is a group of proposals that, although they have not been classified in this taxon since they do not make predictions, use the past trajectories of pedestrians for different purposes (Bera et al. 2018).

Interactions and **actions** constitute the next aspect of agents taken into account in our classification. The term interaction can be found frequently in the literature, but, in some cases, it is used with a different meaning than the one we want to reflect here. For instance, proposals related to SFM use the term interaction to refer to the influence of other agents on the dynamics of an agent. Similarly, in the field of autonomous driving, the word interaction is commonly used to specify the mutual influence of two or more road users in their actions and reactions Wang et al. (2022). In this review, we adopt a more intuitive interpretation of the term **interaction**: an intentional combined action between two or more agents, implying a collective behavior.

We make a distinction between interactions that involve the robot (human-robot interactions) and those that are performed among other agents (human-human interactions). Regarding the last group, in (Manso et al. 2019), although no specific detection technique is used, the proposed model considers interactions between two people standing facing each other. Vega-Magro et al. (2017) cluster individuals into groups according to their social interactions. In (Truong et al. 2017) and (Truong and Ngo 2018) human group interactions are detected using a variant of the Graph Cuts of F-formations. Other approaches detect and use human-robot interactions. An example is the work in Park et al. (2016), which detects when a human is likely to interact with or obstruct the robot. In other proposals, both human-human and human-robot interactions are considered. Thus, Lobato et al. (2019) consider human-human interactions, but also includes actions for human-robot interactions through a dialogue module. Also, Chen et al. (2020) propose a relational graph learning approach that uses GCNs to compute interaction features between humans and between humans and the robot.

The context provided by current activities and actions is also exploited in a subset of the works reviewed. Some of the planning-based approaches modify the robot's path based on the human actions like in (Mateus et al. 2019) that consider activities like sitting/standing, and in (Charalampous et al. 2016) which selects a different set of actions: talking, walking, and working.

The detection of **intentions** of the agents is certainly an important feature in a socially aware navigation approach. The ability to understand the intentions of the agents allows the robot to anticipate and timely adjust its behavior to the agents' preferences and actions. We consider two different types of intentions: ***expected*** and ***unexpected***. Expected intentions are those that occur regularly in the context in which the navigation takes place. A pedestrian's intent to cross the street is an example of expected intention. On the contrary, unexpected intentions are linked to unusual attitudes/actions of the agents, but which could have a significant impact on navigation, such as for example, the intention to hinder any movement of the robot.

All the papers detecting intentions included in our taxonomy can be classified into the first group (*expected intentions*). In addition, the intentions considered in some cases are closely related to trajectory prediction (Ferrer et al. 2017; Kostavelis et al. 2017), interaction predisposition (Ratsamee et al. 2013; Park et al. 2016) and interaction detection (Park et al. 2016). Specifically, in the domain of autonomous vehicles, a variety of works targeting different kinds of intentions can be found. That is the case of works estimating vehicles' predisposition to cooperate (Kabtoul et al. 2020; Evens et al. 2022), forecasting changes in vehicles' speeds and trajectories (Chandra et al. 2020), or predicting pedestrians intentions to cross (Chandra et al. 2020).

Differently, although linked to trajectory prediction, in (Mavrogiannis et al. 2018) the proposed system reads signals of intentions or preferences over avoidance strategies. Also, Skrzypczyk (2021) detects and uses signals of intentions to cooperate with the robot. Another differentiated approach to detecting agents' intentions for socially aware navigation is the one by Cunningham et al. (2019). In this proposal, the system simulates forward the robot and the other agents under their assigned policies to obtain sequences of predicted states and observations.

Besides these aspects of the agents, some papers consider **other attributes**. For instance, Bera et al. (2017) aim at estimating personality traits, Bera et al. (2019) and Jiang et al. (2016) estimate the emotional states of the humans sharing the navigation area with the robot and make the robot act according to the detected emotions. Another interesting factor proposed in the context of autonomous driving is *altruism* (Toghi et al. 2021), which considers the performance of other vehicles. Similarly, Toghi et al. (2022) use the concepts of sympathy and cooperation. Specifically, sympathy is defined as the autonomous agent's altruism toward a human and cooperation is the altruistic behavior among autonomous agents.

Other works working with other geometrical information have been classified within *other attributes*. This is the case of works that consider gestures (Truong and Ngo 2017), or the orientation of the humans, which is a proxy to their field of view (Ratsamee et al. 2013; Truong and Ngo 2017; Truc et al. 2022).

5.3 Social norms

The last main taxon for situation awareness and assessment deals with **social norms**, making a distinction between proxemics and other social rules. **Proxemics** is one of the main elements considered in the vast majority of socially aware navigation proposals to make a robot behave more suitably when navigating around humans than it would do if using a more general navigation approach.

To integrate the idea of proxemics into the robot's navigation system, some proposals consider a uniform circular area around humans that the robot must avoid traversing (Bruckschen et al. 2020; Anvari and Wurdemann 2020; Araujo et al. 2015; Wang et al. 2016; Peddi et al. 2020; Korkmaz 2021; Nishimura and Yonetani 2020; Kenk et al. 2019; Chen et al. 2019; Qiu et al. 2022). Other approaches model the space around humans using Gaussian functions to represent different degrees of discomfort based on proximity (Lobato et al. 2019; Singamaneni et al. 2021; Vega-Magro et al. 2017; Chen et al. 2020; Patompak et al. 2016; Rios-Martinez et al. 2012; Kostavelis et al. 2017; Sorrentino et al. 2021; Truong et al. 2017; Truong and Ngo 2018; Kostavelis et al. 2016; Charalampous et al. 2016; Vega-Magro et al. 2018; Vega et al. 2019; Mateus et al. 2019; Ratsamee et al. 2013). In some cases, additional factors are considered when modelling personal spaces. For instance, Chen et al. (2020) consider a Gaussian variance proportional to the relative velocity of the person. Also, in (Patompak et al. 2016), the space around humans is modeled as a 2D Gaussian function considering the gender, the social distance (familiar/strange), and the physical distance. Other examples are the approaches in (Truong and Ngo 2018; Mateus et al. 2019) that take into consideration the status of a human (e.g. sitting, standing, moving) as well as their potential interactions with objects to represent their personal space. Although not using a Gaussian modeling approach, other proposals build personal space around humans considering other factors as well, such as the person's emotion (Bera et al. 2019; Jiang et al. 2016) or the specific area where the person is located (Lu and Smart 2013). In addition to being a frequently used tool for modeling people's personal space, Gaussian modeling has also been applied to estimate the interaction space of groups of people (Lobato et al. 2019; Vega-Magro et al. 2017; Truong et al. 2017; Truong and Ngo 2018; Rios-Martinez et al. 2012).

The inclusion of proxemics in many proposals on socially aware navigation focuses on defining forbidden or inappropriate areas for navigation that the robot must avoid crossing. Nevertheless, there are approaches in the current literature in which proxemics is used to perform kinodynamic control. Specifically, the speed of the robot is limited or modulated depending on the distance to people (Garrell et al. 2017; Carretero 2017; Ferrer et al. 2017; Teja S. and Alami 2020; Singamaneni et al. 2021), alleviating this way the freezing robot problem in complex situations.

Besides proxemics, some proposals consider **other social norms** during navigation. These additional social norms include walking on a specific side of the navigation area (Cunningham et al. 2019; Mateus et al. 2019) or passing a human from their conventionally preferred side (Dondrup and Hanheide 2016; Ciou et al. 2018; Chen et al. 2017). In the work by Morales et al. (2017), along with navigating on a particular side, the proposed system is designed to avoid zigzag motion effects in order to improve the predictability of the autonomous vehicle. Khambhaita and Alami (2017) propose a planning technique based on a graph optimization approach that considers additional constraints along with proxemics such as directional constraints that penalize motions where humans and the robot are moving straight forward to each other. The planning method proposed by Bera et al. (2018,) integrates the concept of entitativity to enhance social invisibility in multi-robot systems. The norms to communicate crossing intention are considered in (Hsu et al. 2020). In addition, the proposal by Patompak et al. (2016) considers the gender, the relative distance the robot percepts from the human, and the social distance, distinguishing between familiar humans and strangers, to assign an acceptable physical distance. Similarly, in (Kästner et al. 2022), social norms are modified to suit three different age groups (child, adult and elder) and the robot is trained to handle such variations. Finally, in a work by Shahrezaie et al. (2022), the authors proposed different kinds of social interaction rules based on the subjective analysis of the data collected through interviews. These rules are then used to define different social behaviors for the robot.

6 Evaluation

This section discusses the analysis of the papers according to the taxonomy of evaluation. The distribution of the articles as per this taxonomy is shown in Fig. 14. For the evaluation, researchers employ either of the *qualitative* or *quantitative* methodology. In some cases both these methodologies are applied to gain deeper insights. Among the papers in this survey, a major portion of *tools* taxon is dedicated to *studies* rather than *datasets*, *simulators*, and *benchmarks*.

6.1 Methods

The subjective and multifaceted nature makes evaluating socially aware navigation challenging. As a result, different kinds of methodologies are frequently applied to understand the full picture. Based on the type of methodology employed, they can be broadly divided into two types, (i) *qualitative* and (ii) *quantitative*. The *qualitative* method uses the non-numerical data to explain the behavior and the social-awareness of the robot, while the *quantitative* method tries to provide more objective analysis based on numbers.

The **qualitative approach** of evaluating robot's socially aware behavior provides some initial cues about navigational performance. This mode of evaluation is used by many researchers irrespective of whether it is a *mobile robot* (Qian et al. 2013; Araujo et al. 2015; Jiang et al. 2016; Khambhaita and Alami 2017; Kenk et al. 2019; Guldenring et al. 2020; Repiso et al. 2020; Chen et al. 2019; Banisetty et al. 2021; Singamaneni et al. 2021; Gil et al. 2021; Qiu et al. 2022), *wheelchair* (Rios-Martinez et al. 2012; Vasquez et al. 2013; Johnson and Kuipers 2018; Skrzypczyk 2021), *PMV* (Hsu et al. 2020; Kabtoul et al. 2020; Evens et al. 2022; Paez-Granados et al. 2022) or a *drone* (Yoon et al. 2019; Truc et al. 2022). Due to the diverse nature of data and techniques it deals with, qualitative methodology is mostly subjective and we haven't found any articles in this survey that does objective analysis. Typically, the path, trajectory and/or the velocity profiles of the robot and the human(s) are analyzed systematically and logical inferences are drawn (Qian et al. 2013; Vasquez et al. 2014; Patompak et al. 2016; Khambhaita and Alami 2017; Repiso et al. 2017; Banisetty and Feil-Seifer 2018; Guldenring et al. 2020; Teja S. and Alami

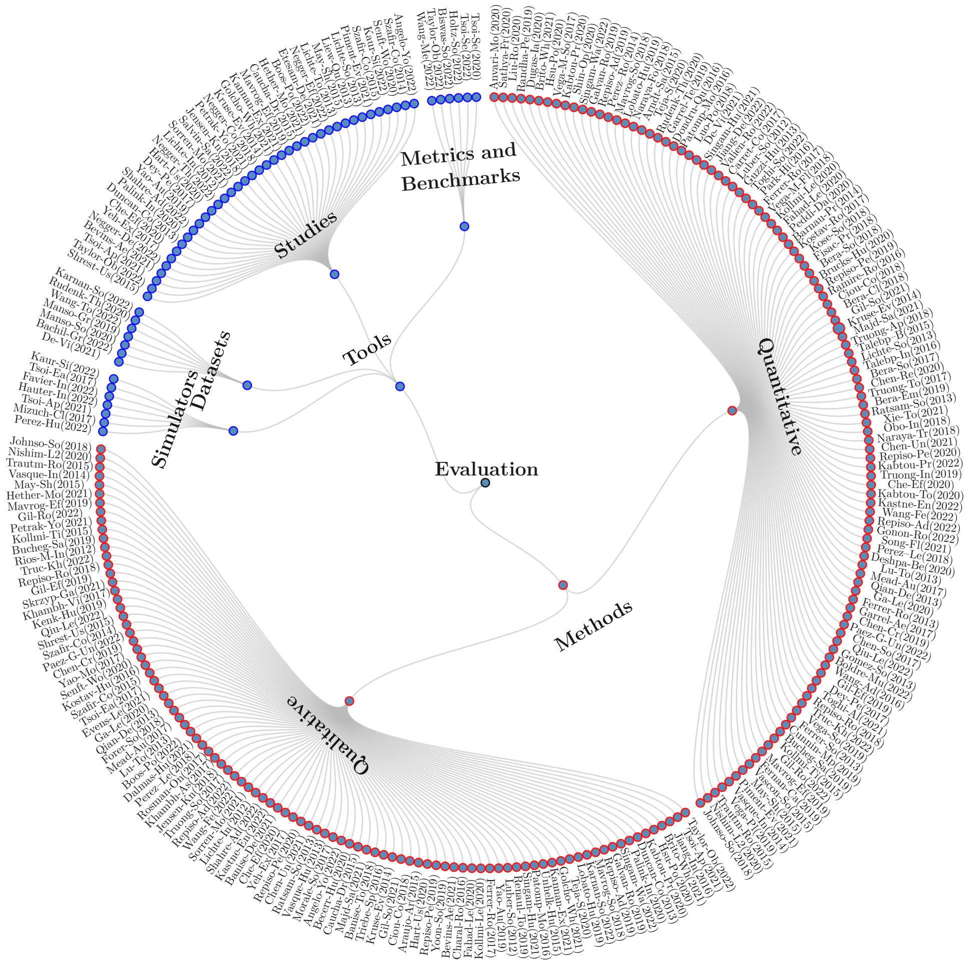

Figure 14. Distribution of papers by evaluation and tools. The figure is best viewed zoomed in using a digital version.

2020; Nishimura and Yonetani 2020). They are sometimes accompanied by step-by-step analysis of a situation using screenshots of simulated (Qian et al. 2013; Khambhaita and Alami 2017; Repiso et al. 2019; Teja S. and Alami 2020; Guldenring et al. 2020) and/or real world experiments (Qian et al. 2013; Ratsamee et al. 2013; Araujo et al. 2015; Hsu et al. 2020; Teja S. and Alami 2020; Singamaneni et al. 2021; Paez-Granados et al. 2022; Repiso et al. 2022; Singamaneni et al. 2022). This kind of analysis focuses on minute aspects that affect human-robot interaction during navigation. Sometimes, it can also include comparisons of the given navigation planner with some other planners (Qian et al. 2013; Khambhaita and Alami 2017; Chen et al. 2019; Teja S. and Alami 2020; Nishimura and Yonetani 2020; Kabtoul et al. 2020; Qiu et al. 2022) followed by the explanations about the improvements or deteriorations. For example, Khambhaita and Alami (2017) qualitatively compare their socially aware planning system with two other systems in various simulated scenarios with sets of screenshots and discusses the advantages of the proposed system. Qualitative methodology is highly useful during the initial stages of development and when standards are not defined, which is the case of socially aware navigation.

The robot navigating and interacting with humans in the environment needs to have legible motion and acceptable behavior. These criteria are subjective to humans' experiences and cannot be analyzed comparatively as above. Thus, *user studies* are conducted to collect data through questionnaires (Lichtenthäler et al. 2012; Kruse et al. 2014; Szafir et al. 2015; Morales et al. 2017; Jensen et al. 2018; Repiso et al. 2020; Mavrogiannis et al. 2019; Petrak et al. 2021; Bevins and Duncan 2021; Dalmasso et al. 2021; Repiso et al. 2022) or interviews (Duncan and Murphy 2013; Szafir et al. 2015; Cauchard et al. 2015; Mead and Matarić 2017; Senft et al. 2020; Sorrentino et al. 2021; Shahrezaie et al. 2022) to analyze the humans' experiences, expectations and perceptions. The data is then used to subjectively evaluate a specific system or the behavior of the robot. Some of the commonly used methods for this employ the Godspeed Questionnaire with Likert Scale (Weiss and Bartneck 2015; Carpinella et al. 2017) followed by the analysis of variance (ANOVA). This kind of analysis is also used in *behavior studies* (Lichtenthäler et al. 2012; Kruse et al. 2014; Szafir et al. 2014; May et al. 2015; Morales et al. 2017; Jensen et al. 2018; Hart et al. 2020; Hetherington et al. 2021; Senft et al. 2020) that provide useful insights while designing new socially aware navigation strategies and behaviors for a robot, car or a drone. Despite their remarkable usefulness, user studies require experiments with real humans followed by statistical analysis and are often not easy to replicate and organize. In our survey, roughly half of the papers employ some kind of qualitative methodology during the evaluation and around 33 of them perform user studies.

Table 1. Different types of Quantitative metrics. Each metric in the table is for one complete trajectory executed (until an abort or end) to reach a goal.

Metric Type	Metrics
Navigation	success, efficiency, collisions, time to reach the goal (or completion time), distance traveled (or path length), velocity and acceleration (Chen et al. 2017, 2019; Bera et al. 2018, 2019; Sathyamoorthy et al. 2020)
Discomfort	human-robot distance, number of social space intrusions (personal and interaction spaces), time spent in social spaces (personal and interaction spaces), human safety and comfort indices (SII, SGI, RMI), performance metrics (Vega et al. 2019; Kollmitz et al. 2020; Truong and Ngo 2017; Kostavelis et al. 2017; Ferrer et al. 2013; Talebpour et al. 2016; Singamaneni et al. 2021; Manso et al. 2019; Bachiller et al. 2022)
Naturalness	average displacement error, final displacement error, non-linear displacement error, cumulative Heading changes (Vega et al. 2019; Alahi et al. 2017)

Quantitative methods try to measure the effects (Dugas et al. 2020; Toghi et al. 2021; Mavrogiannis et al. 2018; Peddi et al. 2020; Hsu et al. 2020) or the performance (Guldenring et al. 2020; Repiso et al. 2020; Singamaneni et al. 2021; Teja S. and Alami 2020; Nishimura and Yonetani 2020; Shin and Yoon 2020; Boldrer et al. 2022; Chen and Lou 2022) of the robot navigation strategies numerically and provide good objective means for evaluation. Since socially aware robot navigation will always have to satisfy the **navigation metrics**, a large number of works (Sathyamoorthy et al. 2020; Chen et al. 2020, 2019; Brito et al. 2021; Fernandez Carmona et al. 2019; Guzzi et al. 2013; Johnson and Kuipers 2018; Kollmitz et al. 2015; Vega-Magro et al. 2018; Vega et al. 2019; Singamaneni et al. 2022) involve such objective analysis while assessing their system and comparing it to other state-of-art systems. Such navigational metrics include success rate, path length, number of collisions, etc. Some of the commonly used navigation metrics are listed in the first row of Table 1.

The socially aware part, however, requires a different set of metrics that could quantify the *social* quality of navigation and the humans' discomfort. In this article, we call such a set of metrics **discomfort metrics** and they try to estimate how acceptable the robot's motion around humans is. The commonly used metrics in this group and some variations are listed in the second row of Table 1. Even after being an active field for over 20 years, most of these are still based on Hall's Proxemics Theory. There are some metrics like time-to-collision (*ttc*) (Biswas et al. 2022) that are recently gaining more attention. From time to time, some researchers define specialized metrics combining various criteria. For example, the works of Repiso et al. (Repiso et al. 2018, 2020,, 2022) define performance metrics that combine various discomfort measures to form a single metric. These performance metrics in each setting are then utilized to evaluate simulated as well as real-world experiments. Similar performance metrics are used in (Ferrer et al. 2013, 2017; Garrell et al. 2017, 2019) as well. The works in (Truong and Ngo 2018, 2017) define a set of metrics to measure socially aware navigation at various interaction levels. The Social Individual Index (SII) is defined based on the proxemics theory to measure the comfort at the individual level of the human, while the Social Group Index (SGI) is defined to deal with human groups and human-object interactions that occur during the navigation of the robot. They use something similar to *ttc*, called Relative Motion Index (RMI) to measure the relative motion between the human and the robot and state that a lower RMI value results in more acceptable robot navigation. Another comfort index called the Social Direction Index (SDI) is defined to evaluate the direction of approach when the robot approaches humans. The robot's behavior is evaluated based on how close the calculated SDI is to the defined maximum in the situation. It has to be noted that the maximum desired value of SDI changes from one situation to another and also depends on the number of humans. Learning-based discomfort metrics have also appeared recently in (Manso et al. 2019; Bachiller et al. 2022).

Another set of metrics that are commonly used in human trajectory prediction (Alahi et al. 2016; Bisagno et al. 2018; Manh and Alaghband 2018; Vemula et al. 2018; Song et al. 2018) and sometimes in socially aware navigation planning are the similarity metrics. The similarity metrics are applied to the socially aware navigation systems when the robot tries to mimic or follow a human's trajectory (or behavior) like in the case of (de Vicente and Soto 2021; Fahad et al. 2020; Luber et al. 2012). Some of the works in socially aware robot navigation also measure the path irregularity by employing measures like counting the unnecessary heading or orientation changes (Vega et al. 2019,). The **similarity metrics** together with the **irregularity measures** are grouped together as **naturalness metrics** (like in (Gao and Huang 2022)) in our work and are presented in the last row of Table 1. All these metrics (navigation, discomfort, and naturalness) are usually well-defined with some analytical formulation. They could be calculated automatically in a large number of scenarios to determine the robustness, advantages, and limitations of the defined socially aware navigation scheme. The objective nature of this methodology also makes the comparisons between different systems simpler. Hence, quantitative methods are often used when a new socially aware navigational system is proposed. As seen from Fig. 14, more than 100 articles in this survey were found to include some form of quantitative evaluation. Table 1 shows only some of the commonly used metrics. However, researchers define their own set of metrics from time to time like in (Cunningham et al. 2019; Repiso et al. 2022; Ferrer et al. 2017; Paez-Granados et al. 2022; Teja S. and Alami 2020; Kabtoul et al. 2020).

In Table 1, we present the metrics just for one trajectory to make the presentation homogeneous, but in reality, this may not be the only way they are used. For example, it is a common practice to define the rate of success, efficiency, and performance over a set of trajectories or goals (Ferrer et al. 2013; Ratsamee et al. 2013; Fisac et al. 2018; Bera et al. 2018; Mavrogiannis et al. 2019; Repiso et al. 2020; Chen et al. 2020; Xie et al. 2021; Valiente et al. 2022). Sometimes, it is applied to collisions as well and the collision rates are compared (Luo et al. 2018; Chen et al. 2019, 2020; Guldenring et al. 2020; Liu et al. 2020). Even among the metrics that are calculated per trajectory, the metrics like velocity, acceleration, and human safety and comfort indices present evolution over time for better explanation (Gómez et al. 2013; Kruse et al. 2014; Truong et al. 2017; Luo et al. 2018; Truong and Ngo 2018; Mavrogiannis et al. 2019; Anvari and Wurdemann 2020; Singamaneni et al. 2021; Truc et al. 2022).

Although not very common, there are papers that use subjective analysis in quantitative evaluation. The works by Manso et al. (2019, 2020) use subjective scores provided by human users to create general metrics that allow different types of navigation strategies in robots to be compared. Finally, it should also be noted that the researchers need not have to employ only one kind of analysis. For instance, the works in (Qian et al. 2013; Patompak et al. 2016; Repiso et al. 2020; Wang et al. 2022; Kästner et al. 2022; Mavrogiannis et al. 2019; Gil et al. 2021) use both quantitative and qualitative evaluation while some works like (Deshpande et al. 2020; Gonon et al. 2022; Kabtoul 2021) employ only quantitative evaluation.

6.2 *Tools*

Tools that assist the development and evaluation of a socially aware navigation system fall under this taxon. Although there is no restriction what can be considered a tool, we have identified that *studies, simulators, datasets, benchmarks* and *new metrics* are generally used by researchers in socially aware robot navigation.

Studies can be seen as one of the powerful tools that help the field progress by providing deeper understanding and useful information. For example, the papers studying communication strategies (Szafir et al. 2014; May et al. 2015; Morales et al. 2017; Che et al. 2020; Hart et al. 2020; Bevins and Duncan 2021; Kannan et al. 2021; Senft et al. 2020; Boos et al. 2022; Angelopoulos et al. 2022) show different ways of expressing intention and how they are perceived by humans. The studies and surveys on pedestrian-vehicle interactions (Ridel et al. 2018; Rasouli and Tsotsos 2019; Prédhumeau et al. 2021) provide necessary information to design or improvise interaction strategies for autonomous vehicles and robots, while the studies on legibility (Lichtenthäler et al. 2012; Kruse et al. 2014; Hart et al. 2020; Hetherington et al. 2021; Taylor et al. 2022; Neggers et al. 2022) show how the designed strategies are assessed by humans. These studies on human-robot interaction and navigation (Lichtenthäler et al. 2012; May et al. 2015; Morales et al. 2017; Yeh et al. 2017; Hetherington et al. 2021; Senft et al. 2020; Salvini et al. 2022; Palinko et al. 2020) are great tools to design human complaint behaviors of the robot while it's navigating or interacting. For example, the work in (Shahrezaie et al. 2022) uses the user study to design different social behaviors for the robots. Neggers et al. (2018, 2022,) through a series of studies provided details on comfortable passing distances and speeds for different type of robots around humans.

Simulators are the other tools that greatly aid the development process and help to test the system under various settings, quickly and efficiently. They can be used to simulate different human-robot navigation scenarios (Kaur et al. 2022) with varying densities of humans to challenge the socially aware navigation system before its final deployment in the real world. Researchers have recently recognized the importance and usefulness of human simulations and proposed various methodologies and approaches (e.g. Pedsim, ORCA) to include human agents in robotic simulators. Although there are many simulators for simulating robots, only a few simulators support HRI (Kaur et al. 2022). Recently, some new simulation tools were proposed by Tsoi et al. (Tsoi et al. 2021, 2020, 2022) and Mizuchi and Inamura (2017) that allow easy data collection and evaluation with simulated human agents or avatars. The works in (Tsoi et al. 2021, 2020, 2022) focus on simulating semi-crowded or crowded navigational scenarios while that in (Mizuchi and Inamura 2017) focuses on multi-modal interactions. Besides, there are some interesting simulators (Favier et al. 2022; Hauterville et al. 2022; Pérez-Higueras et al. 2022) that allow the simulation of intelligent human agents with multiple behaviors in small numbers.

Regarding **datasets**, frequently human-human navigation datasets (e.g. ETH, UCY, etc.) have been used to test how close the robot's navigation behavior is to one of the humans in the datasets. Nevertheless, humans do not essentially perceive the robot the same way they perceive another human. Hence, some recent datasets like THÖR (Rudenko et al. 2020) and SCAND (Karnan et al. 2022) record the data of the robot navigating in the presence of humans. THÖR's data is obtained from a controlled indoor environment whereas SCAND contains data from both indoors and outdoors. As these datasets contain the natural reactions of the people towards a robot navigating in their environment, it could help researchers to understand human-robot navigation better and design mechanisms that incorporate this information. The datasets SocNav1 (Manso et al. 2020) and SocNav2 (Bachiller et al. 2022) propose a new approach using graph neural networks (Manso et al. 2019) to learn socially aware navigation conventions by using human feedback in simulated environments. Some recent pedestrian datasets like (Wang et al. 2022) provide enriched navigation information, including the first-person view, which is more natural compared to the classical top-down view. Further, all these datasets could also be employed to benchmark socially aware navigation systems (Jiang et al. 2022).

Benchmarks and metrics are required to enable every socially aware robot planning system to have some minimum standards before they could be deployed among humans. The growing interest in the field has led to the development of some benchmarking tools like SocialGym (Holtz and Biswas 2022), Socnavbench (Biswas et al. 2022) and SEAN (Tsoi et al. 2020, 2022). These benchmarks provide some performance metrics that could be used to compare different navigation frameworks numerically. The new version of SEAN (Tsoi et al. 2022) integrates Socnavbench and provides some rich environments to learn or test socially aware robot navigation strategies and collect data. A very recent work by Wang et al. (2022) proposes protocols for benchmarking crowd navigation algorithms with a set of metrics.

7 Proposals

The presented analysis provides a wide panoramic view of the current state of socially aware robot navigation. Although other recent surveys cover most of the relevant aspects involved in this field, they miss some key elements, such as the different types of robots and how their specific characteristics may affect navigation strategies. The effects of social context and the semantics of the environment are also frequently missing. The proposed taxonomy intends to fill those gaps, including all the items that could be present in any existing and future approach to socially aware robot navigation. Additionally, this survey has been designed to learn about *what has been done in the field* and to *identify areas that need more exploration and research*. Regarding this last point and taking our analysis into consideration, in this section, we put forward several proposals to enhance the current state of socially aware robot navigation.

Proposal 1: *Enhance human models to improve robot behaviors in socially aware navigation, including human intention prediction.*
For a robot to select the actions to reach a goal, they require information about its state and its environment. The robot's state is generally composed of its pose (*i.e.*, position and orientation) and its current velocity with the occasional inclusion of acceleration data (Gul et al. 2019). The environmental information is generally limited to the area that can be traversed by the robot; either using range or vision sensors, an obstacle map, or both. This information is typically enough for robots to navigate in human-free environments. socially aware robot navigation, however, requires information about humans, which are treated as special agents in the environment that robots should not collide with. Although most of the works reviewed in this article model humans using their instantaneous position only, some papers consider their speed, some consider human intentions to interact (Park et al. 2016; Ratsamee et al. 2013) and some others include immediate motion intent predictions (Peddi et al. 2020; Hsu et al. 2020) to improve the social behavior of the robot. Even though extending the variables considered to optimize robot behavior is positive, this information is still insufficient to build good human models. For instance, modeling the reactions of humans or the possible mental states involves a lot of uncertainty and variables like positions, velocities or motion intention cannot capture them efficiently. They require more information on action-reaction cycles (through studies) and human psychological models. This limitation on the human models directly affects the modeling of the robot's planning and contributes to unexpected robot behavior from time to time.

Proposal 2: *Design user-adaptive robot behaviors. It requires significant improvement in the robot's perception of humans.*
Further refinement in the robot's social behavior can be realized if the humans can be identified. The perception modules of robots can provide information about certain human characteristics (age, gender, height, etc.) that can be used to filter or shift the robot's behavior according to the type of human it is interacting with (Bera et al. 2019; Jiang et al. 2016; Patompak et al. 2016). With the ever-expanding applications of Artificial Intelligence in the computer vision community, we believe that the online realization of adaptive robot behaviors is not very far.

Proposal 3: *Define context-based benchmarks and set up universal standards in the field. A set of standard contexts and human actions needs to be identified for benchmarking.*
The dependency on context cannot be neglected anymore in socially aware robot navigation. Each context requires different types of behaviors and interactions. Even within the same environment, depending on the action a human is performing (for example walking leisurely, rushing to a place, running, approaching a place, etc.) the interactions change and robots should adapt to this. Human action recognition is another active field in computer vision that could soon provide robotic systems with enough information to handle the interactions better. The lack of universal standards and benchmarks makes it very hard to compare different socially aware navigation algorithms.

Proposal 4: *Focus on robot-specific parameters (e.g., shape, size) that can result in better interactions and develop strategies that can adapt to different robot characteristics.*
Studies have shown that the characteristics of robots affect interaction preferences (Golchoubian et al. 2021; Rasouli and Tsotsos 2019; Samarakoon et al. 2022). Surprisingly, these parameters are disregarded by most socially aware navigation algorithms.

Proposal 5: *Establish good communication protocols to convey the robot's intention.*
It has been shown that conveying the robot's intention has a positive impact on human-robot interaction (Senft et al. 2020). Implicit communication signals inspired by vehicles and/or humans and acknowledgment of human implicit communication have already been studied in some of the reviewed works (Che et al. 2020; Hsu et al. 2020; Szafir et al. 2014; Singamaneni et al. 2021). Some works like (Bevins and Duncan 2021; Hart et al. 2020; Hetherington et al. 2021; Toghi et al. 2021) employ explicit communication strategies to improve navigation and interaction. However, these are limited and there is very little research on timing and the means to communicate. This highlights the need for more user studies on interaction and communication strategies.

Proposal 6: *Explore alternatives to proxemics-based metrics. Well-designed human-robot interaction studies can provide clues about additional factors that affect human comfort around robots.*
The evaluation of socially aware navigation has always been challenging. Most discomfort metrics are based on proxemics theory and are not valid in many situations. Because of the lack of a clear rationale behind the relevance of such metrics, researchers tend to propose their own variations of metrics that are more suited to evaluate their systems. Further, the thresholds of the metrics are dependent on the situation, which makes it hard to define unified standards for socially aware navigation. All these issues make it difficult to compare the *social-awareness* of different socially aware robot navigation algorithms, and until recently, there were no datasets or tools to

benchmark socially aware navigation. The use of human-human interaction data to compare human-robot interactions is not always advisable and may result in false conclusions. Even though current benchmarks provide rich environments to test different frameworks under similar conditions, they use metrics that are not applicable to all human-robot navigation settings.

Proposal 7: *Prioritize considerations of comfort and trust in addition to safety during the design of socially aware robot navigation approaches.*
While significant research efforts have been devoted to ensuring safety in socially aware navigation across the different types of robots, there has been a notable gap in addressing comfort and trust. However, the critical aspects of comfort and trust, such as the prediction of the robot's motion, transparent decision-making, and reliable behavior, have received comparatively limited attention (Ferrer et al. 2017; Truong et al. 2017; Che et al. 2020). Further research efforts are needed to comprehensively address comfort and trust in socially aware navigation, considering the specific requirements across different types of robots.

Proposal 8: *Include the dynamic models of the other agents into the planning scheme.*
In relation to the *dynamics of the physical motion*, most of the works done up to date consider that human and robot move slowly. As socially aware navigation progresses this assumption may become more problematic, especially when considering entities, such as bicycles, motorcycles, or cars. Higher speeds make crucial for robots to account for these dynamics. The presence of fast-moving entities in an urban area introduces additional complexities and potential risks that the robot must consider when generating its plans and actions.

8 Future Challenges

All the proposals presented in the previous section can be considered achievable given the current state of the field. However, a number of challenges that will require further long-term research to be addressed and resolved remain. This section discusses some of these **future challenges**, including aspects that range from technological matters to regulations and considerations about the design of urban spaces.

The **relationship between humans and robots** poses unresolved issues despite established social conventions. Understanding various aspects of this relationship is essential for robots to effectively assist humans. They need to comprehend typical human behaviors, predict actions, and actively engage in cooperative tasks. First, *cultural differences can influence social norms*. In the pursuit of enhancing socially aware navigation, conducting research on social norms across diverse cultures is indispensable. Therefore, it is crucial to study how these norms affect navigational behaviors. Second, *individual preferences* influence human behavior and perception. To ensure successful and comfortable interactions with humans, it is essential to design socially aware robots with this key aspect in mind. The inclusion of this feature will play a vital role in fostering human acceptance of personal robots in the future. Third, a socially aware navigation system has to guarantee human *acceptability, safety, trust, and privacy*. Fourth, to effectively collaborate with people in tasks like navigating alongside them, robots need to estimate the *intentions of humans* being accompanied. Understanding and interpreting human intentions play a crucial role in ensuring seamless coordination and cooperation between robots and humans. While some research, including the Perception-Intention-Action model (Domínguez-Vidal et al. 2023), has been conducted on Human-Robot Cooperation tasks, the perception and understanding of human intentions remain, and that necessitates further investigation. Fifth, the occurrence of *abnormal human behaviors towards robots*, such as vandalism or attempts to obstruct robot navigation should also be considered. In such cases, robots will need to adapt their navigation strategies based on the observed human behaviors. This adaptive approach is essential to ensure the safety and functionality of the robot in dynamic and unpredictable environments.

Urban design constitutes another group of important challenges. Cities and urban areas are not prepared for the deployment of robots in open areas and buildings. Urban typology, like wide streets in new cities or narrow streets in historic districts, may necessitate adjustments in the type of robots allowed to circulate and the corresponding regulations. The segregation of areas where robots can freely navigate is an important issue, particularly in the context of personal robots or robots involved in goods delivery. Establishing clear boundaries or designated zones for robot movement becomes increasingly relevant to ensure the efficient and safe operation of these robots. Adequate segregation helps prevent unwanted interactions or conflicts between robots and humans, ultimately contributing to the seamless integration of robots into various domains. Finally, personal mobility devices, bicycles, motorcycles, or cars share the urban space besides humans. These different kinds of *agents* have particularities that will provoke new situations the robot has to take into account.

Currently, most **urban regulations** prohibit the circulation of autonomous robots in urban areas. To enable the integration of goods delivery robots, specific regulations similar to those for autonomous cars need to be established. This regulatory framework is vital in addressing the challenges unique to these robots and ensuring their safe and efficient operation in urban environments. By developing appropriate regulations, we can facilitate the widespread deployment of personal and goods delivery robots, prioritizing public safety and societal acceptance.

The research challenges in terms of **AI and decision-making** are very diverse. Significant advancements in *learning* have been achieved, however, socially aware navigation is limited by the lack of sufficient work in the helper domains. For instance, effectively acquiring knowledge about human preferences, intentions, and social norms remains a prominent challenge that requires resolution. Two crucial challenges arise in the context of robot navigation tasks. First challenge is to comprehend the *current situation* encountered by a robot, which is of utmost importance to complete the task safely. The detection and understanding of *conflict states* is the second major challenge. Short-term predictions and identification of potential conflict states provide the necessary information to anticipate the evolution of the current situation within a few seconds. This anticipation allows the robot to generate new plans and actions, adopting a proactive approach.

In tasks involving cooperation or negotiation with both a robot and a human, prediction skills play an important role in facilitating coordination and foreseeing possible future outcomes. By anticipating the task's dynamics, predictions can facilitate behavior adaptation, thereby enhancing effective coordination. This also applies to trajectory planning, which necessitates reasoning about multiple aspects in the present and the future, including the environment, the potential consequences of each agent's actions, and the expected behavior of human individuals. By taking into account these variables, robots can make well-informed decisions.

Last but not least, **evaluating the efficacy and efficiency** of socially aware robot navigation systems is one of the most difficult tasks. Traditional metrics for measuring robot navigation, such as path length or collision avoidance, may not represent the social side of interactions properly. Subjective aspects such as user experience, social acceptance, and perceived trustworthiness must be considered when evaluating socially aware robot navigation. It is important to develop strong assessment procedures that include these social characteristics to guarantee that social robots navigate in a way that is consistent with human expectations and promotes successful encounters.

9 Conclusions

The growing use of service and assistive robots as well as autonomous cars in human environments has made socially aware robot navigation an important research subject. The growing number of papers on socially aware robot navigation over the past six years is evidence of its relevance. Robots must be sociable or artificially sociable in order to be accepted by people. To evaluate the field from different angles, we analyzed 193 articles, classifying them into different taxa spanning across four different faceted taxonomies. This taxonomic analysis allowed us to identify the areas that require more attention and further research. Although the survey includes socially aware navigation for autonomous cars and drones, the main domain of interest in the papers found remains mobile robots.

Most of the previous surveys and other prior studies in the field are referenced in our study. Each of these studies has added to our understanding of the navigation of social robots that are aware of humans from several angles, including proxemics, planning, perception, mapping, and evaluation techniques. By offering taxonomy-based classifications of the publications in our survey, we believe we have contributed to this body of knowledge.

Future research has fresh chances and challenges as the area expands. The requirement to create more reliable algorithms and techniques that can precisely forecast and adapt to human behavior in dynamic contexts is one such difficulty. In order to properly communicate the robot's goals and behaviors to humans, techniques making use of multiple communication modalities must be developed. There is also a need to address the ethical and legal issues surrounding interactions between humans and robots as the usage of robots in healthcare, education, and other social domains expands.

Declaration of conflicting interests

The authors declare that there is no conflict of interest.

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