

EmPath: Follower-Aware Local Path Planning for Robot-Assisted Navigation of Blind and Visually Impaired Users

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Abstract. Safe navigation in crowded public environments remains a key challenge for deploying robotic mobility aids for people who are Blind or Visually Impaired (BVI), particularly when the robot must plan on behalf of a human partner under asymmetric perception and dense crowd conditions. We present EmPath, a local path planning framework for robot-assisted navigation that jointly considers follower-aware costs and crowd-aware motion prediction. EmPath integrates a novel accessibility-aware Social Force Model (SFM) to incorporate human-relevant interaction constraints into the planning objective, and improves robustness in dense crowds through multi-agent forecasting and SFM error correction. A spring-based coupling mechanism enables flexible robot-human coordination without rigid motion constraints. The framework is implemented in ROS 2 and evaluated on a new large-scale urban crowd dataset spanning multiple navigation difficulty levels, which also serves as a benchmark for follower-aware navigation in crowded environments. Results show that EmPath consistently reduces follower collision rates while improving trajectory smoothness and maintaining competitive navigation performance across a range of crowd densities.

Keywords: Assistive Robotics · Crowd Navigation · Follower-Aware Planning

1 Introduction

Navigating crowded public spaces is a fundamental challenge for people who are Blind or Visually Impaired (BVI), limiting their independence in daily urban life. Dense pedestrian environments introduce complex social dynamics that can compromise safety and navigation efficiency. Robotic mobility aids, such as robot guide dogs, hold promise for supporting independent mobility in these contexts. Evaluating assistive navigation systems directly with Blind and Visually Impaired (BVI) users in dense crowds presents ethical and practical challenges, including safety risks and limited experimental repeatability. We therefore use simulation grounded in real-world pedestrian trajectories to systematically evaluate follower-aware navigation under realistic crowd conditions.

Existing joint human-robot navigation systems often treat the robot and its human follower as a single coupled entity or assume that all members of a crowd, including

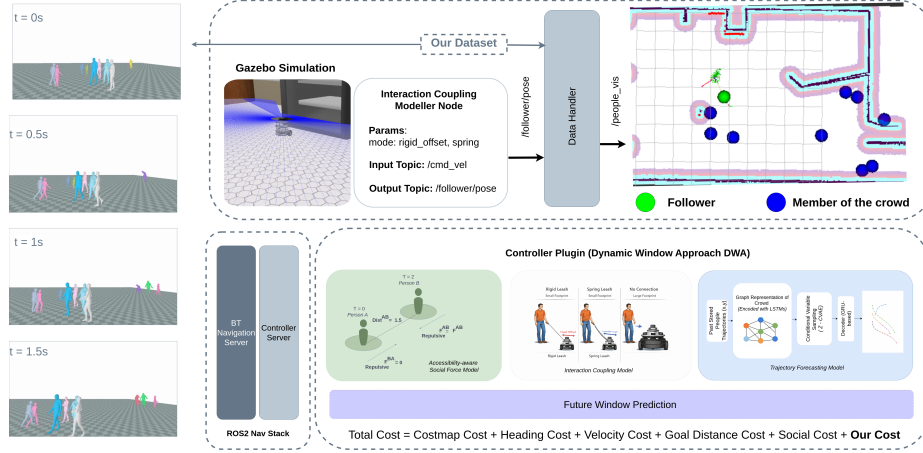


Fig. 1: Framework overview: EmPath is evaluated in simulation using real-world crowded urban data. Pedestrian states are loaded via a data handler node and passed to a ROS 2 [20] DWA-based controller [8, 31], where an accessibility-focused Social Force Model estimates crowd motion. A multi-modal trajectory forecasting service refines these predictions, while the follower’s trajectory is updated through an inter-coupled robot-follower model. A follower-aware cost, capturing collision risk to the follower alongside robot-crowd interaction costs, is used to update the robot’s velocity, producing socially aware navigation that prioritises follower safety. Robot is visualised in Gazebo [18]. Results are visualised in RVIZ [26].

the follower, have symmetric perception. These simplifications fail to capture the inherently asymmetric perception and interactions of a blind or visually impaired (BVI) follower, who must navigate collaboratively with the robot while simultaneously interacting with dense, dynamic crowds. Ignoring this asymmetry can lead to unsafe or socially disruptive behavior. Existing social path planners primarily focus on the robot’s ability to navigate safely within crowds. To the best of our knowledge, no prior work has developed a planner that explicitly considers navigation in dense urban environments while intentionally planning on behalf of a BVI follower. Some prior work has addressed mitigating the social impact of a robot navigating through crowds, but these approaches do not account for the collaborative dynamics with a human partner [31].

To address these challenges, we present **EmPath**, a follower-centred and socially aware path-planning framework implemented in ROS 2 [20]. EmPath explicitly models both the robot guide and the BVI follower, generating the robot’s local motion plan on behalf of the follower to support safe navigation in dynamic scenes. The system introduces an Accessibility-aware Social Force Model (SFM) to incorporate follower-specific perception, employs a multi-agent, multi-modal trajectory forecasting architecture to refine social force-based predictions [28], and leverages a new large-scale urban crowd dataset spanning multiple cities with graded levels of navigation complexity. By explicitly anticipating both the follower’s behaviour and crowd dynamics, we introduce a follower-centred cost function used within an extended Social Force Window Planner (SFWP) [31] based on a Dynamic Window Approach [8] that guides the robot in gen-

erating trajectories that are both safer and socially considerate. This approach places the follower’s safety at the forefront, reducing collisions, respecting personal space, and improving navigation accuracy in multiple dense crowd scenarios. To contextualise performance in the absence of prior follower-aware methods, we also evaluate against traditional non-collaborative-specific planners. EmPath outperforms traditional planners like Optimal Reciprocal Collision Avoidance (ORCA) [2] and a Social Force Window Planner (SFWP) [31], achieving a stronger balance between follower safety, social compliance, and task success, demonstrating that incorporating a follower-first approach into planning enables truly collaborative, socially aware human–robot navigation. Rather than introducing a single new planning component, EmPath contributes a follower-aware planning framework that integrates accessibility-aware perception, compliant human–robot coupling, predictive crowd forecasting, and follower-centred optimisation into a unified navigation system for assistive robotics.

This work presents a novel assistive navigation framework for robot-guided mobility in dense crowds with four primary contributions:

1. **Accessibility-aware social force model** that incorporates heterogeneous perception thresholds, enabling explicit modelling of asymmetric awareness between the guide, follower, and surrounding pedestrians.
2. **Follower-aware local planning** formulation with spring-based human–robot coupling, enabling flexible coordination while preserving personal space and safety during trajectory optimisation.
3. **Residual-corrected crowd forecasting** mechanism that combines physics-based interaction modelling with learned trajectory refinement to improve robustness in dynamic crowds.
4. **Multi-city benchmark dataset** with graded difficulty levels, enabling systematic evaluation of follower-aware navigation methods.

2 Related Works

2.1 Assistive Robot Navigation

Robot guides, often referred to as robot guide dogs, offer significant potential to support the independent mobility of blind and visually impaired (BVI) users [11]. One of the primary challenges these users face is navigating complex, dynamic environments independently. Prior work in robot guides has focused on areas such as robot locomotion [6, 36], human–robot motion modeling [15, 33], and designing interactive devices to improve comfort when navigating obstacle-rich spaces [4, 35].

Existing approaches do not adequately address dense urban crowds, a key requirement for everyday assistive navigation. To address this gap, we propose a follower-centric navigation framework that plans local paths on behalf of a physically connected BVI follower, enabling safe movement through crowded spaces.

2.2 Social Force Models in Robotics

The Social Force Model (SFM) is a computationally efficient, physics-inspired framework that describes pedestrian motion as the result of attractive and repulsive forces

between agents and their environment [12, 23, 24]. SFM has been widely applied in crowd simulation [19, 25, 27], emergency evacuation analysis [14], and human–robot navigation [16, 38], due to its ability to generate socially plausible trajectories with low computational overhead.

Despite its popularity, the classical SFM has known limitations in realistically reproducing pedestrian motion [5]. Numerous extensions have been proposed to improve realism by incorporating human field of view [37], group behavior, anticipatory motion [24], and other context-dependent adaptations [7, 13].

Existing formulations assume homogeneous agents with symmetric perception, presuming that all pedestrians have full visual awareness of their surroundings. This assumption limits SFM’s applicability in accessibility-focused scenarios. In the context of a robot guide assisting a visually impaired (BVI) user, pedestrian behavior is shaped by heterogeneous sensory capabilities. BVI users rely on non-visual cues, such as tactile feedback, auditory signals, or physical guidance, to perceive and navigate their environment, leading to fundamentally different interaction patterns compared to fully sighted pedestrians. To address this gap, we extend SFM to incorporate follower-specific dynamics, enabling simulations that reflect accessibility-aware interactions.

2.3 Socially-Aware Planning and Evaluation Metrics

Socially-aware path planning aims to generate robot trajectories that are not only safe and efficient, but also compliant with human social norms [1, 2, 17, 31, 32]. Such formulations shift the objective from purely self-centred navigation to interaction-aware planning.

In assistive navigation, these requirements are amplified by the presence of a human partner whose safety is paramount. For a robot guide, socially-aware planning must account not only for surrounding pedestrians but also for the guided user, whose movement, perception, and interaction capabilities differ from those of other agents in the environment. To address this, we introduce a navigation framework whose formulation encourages behaviours that prioritise the guided user’s experiential safety and perceptual constraints.

Models such as SFM provide a principled mechanism for encoding interaction dynamics, enabling the planner to reason about crowd behaviour while incorporating accessibility-related constraints. Evaluating socially-aware assistive navigation extends beyond traditional metrics such as collision rate or path efficiency. Common evaluation measures in socially-aware navigation [3, 9, 10, 30], including interpersonal distance, trajectory smoothness, and disturbance to nearby pedestrians, must be complemented by accessibility-focused metrics that reflect the guided user’s experience.

While SFM-based costs are well suited for socially-aware planning in simulation, deployment in real-world crowds introduces additional challenges. Human behaviour frequently deviates from idealised interaction models due to individual intent, environmental context, and unmodelled social cues, limiting the fidelity of purely model-driven approaches. To evaluate the applicability of our accessibility-aware SFM beyond simulation, we therefore leverage real-world pedestrian trajectory data. Our analysis indicates that SFM-derived costs provide a meaningful prior for local path planning;

however, discrepancies between predicted and observed motion motivate the need for adaptive mechanisms in real crowds.

To address this limitation, we introduce an error-corrected SFM forecaster that augments model-based predictions with data-driven adjustments. This hybrid approach improves robustness to behavioural variance while retaining the interpretability and computational efficiency of SFM. The forecaster is integrated into a ROS 2-based navigation framework [20], enabling socially-aware planning and evaluation in densely crowded environments. By grounding socially-aware objectives and metrics in real-world pedestrian data, the proposed system supports systematic validation of robot guide behaviour under realistic crowd conditions.

2.4 Crowd Datasets

Datasets capturing pedestrian crowds are essential for studying social interactions in navigation. Standard trajectory forecasting datasets, such as UCY and ETH [22], provide bird’s-eye views of crowded intersections with 2D pedestrian positions over time. While useful benchmarks, they represent stationary viewpoints and do not reflect the experience of a moving agent navigating through crowds. The JRDB dataset [21] includes both stationary and moving egocentric views from a robot on a university campus, capturing 3D positions of people over time. However, it is limited to one hour of data and lacks diversity in crowd density, social interactions, and environmental contexts, which restricts its ability to represent urban crowd navigation challenges. To address this gap, we collected data from YouTube, which provides non-stationary egocentric views of densely populated urban environments across multiple cities. Although captured from humans rather than robots, these videos offer a wide range of crowd densities and social interactions, approximating the challenges a robot would encounter in real-world urban navigation. We annotate 3D pedestrian trajectories to create a dataset with significantly more observations of socially complex crowds, supporting evaluation of our framework in varied urban environments.

3 Method

Our approach (Figure 1) integrates perception, prediction, and control within a unified socially aware navigation framework designed to operate on behalf of a Blind or Visually Impaired (BVI) follower in dense urban environments. At its core, EmPath models both the robot and follower as interdependent agents embedded within a dynamic crowd. Crowd motion is first represented through an accessibility-aware extension of the Social Force Model, in order to obtain an initial agent prediction in the future window of a Dynamic Window Approach (DWA) [8]. The physical and behavioural relationship between the robot and follower is captured through a spring-based human–robot coupling model, allowing flexible yet stable guidance and predictive motion of the follower. To anticipate complex pedestrian interactions, we incorporate a multi-agent, multi-modal trajectory forecasting module [28] that refines social force predictions through learned error correction. These components are unified within a

follower-centric, socially aware path planner that optimises the robot’s velocity by explicitly considering predicted crowd behaviour [31] and its impact on the follower as a follower-aware cost. The following subsections detail each component of the framework.

3.1 Accessibility-aware Social Force Model

We extend standard Social Force Models (SFM) to account for asymmetric human perception, enabling agents to exhibit different levels of environmental awareness ranging from full perception to none. In scenarios where the guided human has limited perceptual capability, the robot estimates and mediates social interaction forces on the human’s behalf. This formulation allows the robot to anticipate crowd interactions and provide guidance through the robot–human coupling mechanism while preserving the structure and computational efficiency of classical SFM.

Social Force Model We adopt the velocity-based Social Force Model (SFM) of Helbing and Molnar [12], in which pedestrian motion is governed by attractive and repulsive forces derived from relative position, velocity alignment, and angular interaction terms. Let F_{ij} denote the standard SFM interaction force between agents i and j . We retain the original SFM formulation and modify the perception and coupling mechanisms described below.

Perception Modelling Extension To model accessibility-aware perception, we introduce a distance threshold τ_i for each agent i , representing the minimum range at which the agent perceives repulsive forces from obstacles or other agents. This simplified formulation provides a tractable means of representing asymmetric environmental awareness while preserving the computational efficiency required for local planning. For a follower with no perception (e.g., blind or visually impaired), this threshold is small if not zero ($\tau_{\text{follower}} = 0.0$ m), whereas for sighted individuals, the threshold is larger to reflect visual awareness.

Formally, for an obstacle or agent j at relative position $\mathbf{d}_{ij}$, the repulsive force acting on agent i is modified as

$$\mathbf{F}_{ij}^{\text{rep}} = \begin{cases} \mathbf{F}_{ij}, & \|\mathbf{d}_{ij}\| \leq \tau_i \\ 0, & \|\mathbf{d}_{ij}\| > \tau_i \end{cases},$$

where $\mathbf{F}_{ij}$ is the standard SFM repulsive force. This formulation allows us to model heterogeneous perception: varying τ_i captures different levels of visual impairment or the use of assistive devices such as a cane.

3.2 Spring-Based Human–Robot Coupling Model

The human follower is connected to the robot guide through a non-rigid, spring-based coupling mechanism, inspired by the physical interaction between a guide dog and its handler. This coupling allows relative freedom of motion while enabling the robot to

exert gentle corrective influence when necessary. The resulting interaction preserves the user’s autonomy while providing continuous guidance along the planned trajectory.

We model a virtual interaction-based coupling force between two agents: a guide (the robot) and a follower (the human). The coupling force is composed of a spring-like term based on relative position and a damping term based on relative velocity, allowing the system to regulate separation while suppressing oscillatory behaviour.

Let the positions and velocities of the guide and follower be denoted by $\mathbf{p}_{\text{guide}}$, $\mathbf{v}_{\text{guide}}$ and $\mathbf{p}_{\text{follower}}$, $\mathbf{v}_{\text{follower}}$, respectively. The relative position and velocity are defined as

$$\Delta \mathbf{p} = \mathbf{p}_{\text{follower}} - \mathbf{p}_{\text{guide}}, \quad \Delta \mathbf{v} = \mathbf{v}_{\text{follower}} - \mathbf{v}_{\text{guide}}.$$

Coupling Force on the Follower The force acting on the follower consists of a spring term proportional to the relative displacement and a damping term proportional to the relative velocity $\mathbf{F}_{\text{follower}} = -k \Delta \mathbf{p} - \eta \Delta \mathbf{v}$, where k and η denote the spring and damping coefficients, respectively. In our implementation, we set $k = 30.0$ and $\eta = 6.0$.

Coupling Force on the Robot For our experiments the robot is assumed to have sufficiently high mechanical impedance relative to the coupling stiffness, such that interaction forces do not perturb its motion.

3.3 Follower-Aware Local Path Planner

The path planner generates plausible local trajectories that optimize a joint cost integrating both the robot’s [31] and the mediated human’s social forces. It is designed to produce motion that is safe and efficient, while leveraging robot perception to anticipate the need of deviations in the human follower’s path and intervene via the spring-based coupling mechanism.

Follower-Aware Cost To maintain social comfort, the planner computes repulsive forces acting on the follower due to nearby crowd members as perceived by the robot. Let $\mathbf{p}_{\text{follower}}$ denote the follower’s position and $\mathbf{p}_i$ the position of crowd member i , $i = 1, \dots, N$. The relative position vector from the follower to each crowd member is

$$\Delta \mathbf{p}_i = \mathbf{p}_{\text{follower}} - \mathbf{p}_i,$$

with corresponding unit vector

$$\hat{\mathbf{d}}_i = \frac{\Delta \mathbf{p}_i}{\|\Delta \mathbf{p}_i\|}.$$

The Euclidean distance to each crowd member is

$$d_i = \|\Delta \mathbf{p}_i\|.$$

For clarity, we present a simplified isotropic model for the social repulsive force:

$$\mathbf{F}_{\text{social},i} = A \exp\left(-\frac{d_i}{B}\right) \hat{\mathbf{d}}_i,$$

where A is the interaction strength and B is the characteristic distance for social influence. The total social force from all crowd members is

$$\mathbf{F}_{\text{social}} = \sum_{i=1}^N \mathbf{F}_{\text{social},i}.$$

The follower-aware cost used for trajectory planning is proportional to the magnitude of this force:

$$C_{\text{followerAware}} = \frac{w_e}{2} \|\mathbf{F}_{\text{social}}\|^2,$$

where $w_e = 5.0$ is a weighting factor that determines the importance of the follower’s safety and comfort in the planner. No direct force is applied to the follower; instead, this cost influences the trajectory optimization to plan on behalf of the follower.

Intuition and Integration This repulsive force ensures that the guide’s motion proactively protects the follower from nearby dynamic obstacles. By acting on the guide rather than directly on the follower, the planner respects the follower’s autonomy while leveraging the spring-based coupling to mediate safe guidance. These safety forces are combined with socially-aware SFM interactions and coupling forces to generate the final local trajectory used by the robot.

3.4 Error-Corrected SFM-Based Motion Forecasting

While accessibility-aware SFM provides a principled prior for human motion, real-world pedestrian behaviour often deviates from the model due to unobserved intent, environment context, or stochasticity in crowd interactions. To account for these discrepancies, we employ a learning-based forecaster that predicts corrections to SFM trajectories.

Specifically, we leverage the Trajectron++ framework [28], a graph-structured model for multi-agent trajectory prediction, and adapt it to our task of SFM error correction. Instead of predicting absolute future positions, the network is used to estimate the difference between the SFM-predicted trajectories and real human motion. During inference, the model uses only the observed motion history of surrounding pedestrians, and the robot’s planned future trajectory is not provided as an input. These predicted corrections are then added to the SFM output within the future window planner, producing a refined, accessibility-aware forecast that better captures real pedestrian behaviour prior to calculating the plausible trajectories cost.

This approach preserves the interpretability and efficiency of SFM while improving robustness to behaviours that violate model assumptions. It integrates seamlessly into the ROS 2 planning pipeline [20], allowing the robot to anticipate and mediate deviations in real-time.

3.5 Data Generation and Collection

We construct a large-scale urban crowd dataset from walking tours videos. Pedestrian trajectories are reconstructed in metric 3D space using dynamic-scene SLAM and automated tracking [34]. To ensure trajectory quality, we apply Gaussian smoothing to

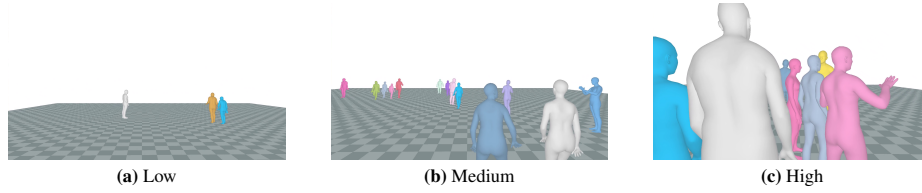


Fig. 2: Crowd difficulty levels examples

Table 1: Crowd difficulty statistics across train, validation, and test splits. Each split maintains balanced representation of low, medium, and high difficulty sequences.

Split	Difficulty	No. Seq.	Density (tracks/m)	Hull Area (m ²)	NN Dist. (m)	Interaction
Train	Low	519	3.60	15.81	1.63	0.69
	Medium	516	2.68	12.57	0.83	1.38
	High	519	1.63	7.82	0.52	2.35
Val	Low	52	3.57	15.38	1.71	0.58
	Medium	52	2.89	13.36	0.84	1.40
	High	65	1.61	7.57	0.53	2.30
Test	Low	41	3.45	15.10	1.62	0.67
	Medium	43	2.84	13.73	0.84	1.40
	High	46	1.87	9.08	0.52	2.40

global 3D pose sequences and remove failure cases such as overlapping tracks and physically implausible velocity spikes, which typically occur during extreme proximity to the ego pedestrian. Since our focus is mid- to long-horizon trajectory forecasting for local path planning, the videos are segmented into 6-second sequences prior to processing. The dataset contains 378,486 frames, 24,121 pedestrian tracks and 1,853 sequences. Crowd difficulty is quantified using density, mean nearest-neighbor distance, and interaction count, combined into a composite difficulty score. Intuitively, denser crowds, tighter interpersonal spacing, and increased local interactions yield more constrained and socially complex navigation scenarios, see examples in Figure 2. Sequences are stratified into low/medium/high difficulty splits for controlled evaluation. To enable principled evaluation, we construct train, validation and test splits with balanced representation of crowd navigation difficulty. These splits are used solely for organising simulation replay and evaluation in this work. See Table 1 for dataset statistics.

4 Evaluation

In order to evaluate the local path-planning pertaining to social interaction we use an environment with minimal objects. We then utilise our data with different levels of crowd difficulties to drive the entities in the simulation.

4.1 Evaluation Metrics

To assess the performance of the path planner, we evaluate metrics for both the robot and the human follower.

- **Time to goal:** Total time taken to reach the goal, $T_{\text{goal}} = t_{\text{goal}} - t_{\text{start}}$.
- **Time not moving:** Cumulative duration for which the robot’s velocity is zero during the interval $[t_{\text{start}}, t_{\text{goal}}]$.
- **Path length:** Total distance travelled along the trajectory, $L = \sum_{t=1}^{T-1} \|\mathbf{x}_{t+1}^{\text{robot}} - \mathbf{x}_t^{\text{robot}}\|_2$.
- **Heading changes:** Cumulative change in robot orientation, $\Delta\theta = \sum_{t=1}^{T-1} |\theta_{t+1}^{\text{robot}} - \theta_t^{\text{robot}}|$.
- **Number of collisions:** Total number of contacts with pedestrians, $N_{\text{collisions}}$.
- **Minimum safety distance:** Smallest distance between the robot and any pedestrian during the trajectory, $d_{\min} = \min_{t,i} \|\mathbf{x}_t^{\text{robot}} - \mathbf{x}_i^i\|_2$.
- **Average safety distance:** Mean distance to the closest pedestrian over the trajectory, $d_{\text{avg}} = \frac{1}{T} \sum_{t=1}^T \min_i \|\mathbf{x}_t^{\text{robot}} - \mathbf{x}_i^i\|_2$.
- **Personal space intrusions:** Percentage of trajectory samples where the follower intrudes into another pedestrian’s personal space, $P_{\text{pers}} = 100 \frac{1}{T} \sum_{t=1}^T \mathbb{1}(0.45 \leq d_t^{\min} < 1.2)$, where $d_t^{\min} = \min_i (\|\mathbf{x}_t^{\text{follower}} - \mathbf{x}_i^i\|_2 - r_{\text{follower}} - r_i)$.

Follower metrics For the follower, we evaluate the same spatial metrics, along with human-robot physical interaction measures.

- **Mean linear acceleration:** $\bar{a}_{\text{lin}} = \frac{1}{T} \sum_{t=1}^T \|\mathbf{a}_t\|_2$, where $\mathbf{a}_t$ is the follower’s linear acceleration.
- **Mean angular rate:** $\bar{\omega} = \frac{1}{T} \sum_{t=1}^T |\dot{\theta}_t|$, where $\dot{\theta}_t$ is the follower’s angular velocity.
- **Root-mean-square (RMS) jerk:** $J_{\text{lin}} = \sqrt{\frac{1}{T-2} \sum_{t=2}^{T-1} \|\mathbf{a}_{t+1} - \mathbf{a}_t\|_2^2}$, representing the linear smoothness of the follower’s motion.

While robot-centric metrics capture navigation efficiency, we prioritize follower safety and comfort using proxy measures including collision rate, safety distance, personal space intrusions, and motion smoothness. To enable fair comparison, exposure-sensitive metrics are normalized by time-to-goal.

4.2 Ablation Studies

Interaction Coupling In our experiments, the follower’s motion was coupled to the leader robot using two modes: a **rigid offset** and a **spring-damper**. In the rigid offset mode, the follower maintained a constant spatial offset of $(-1.0, -0.5)$ meters relative to the robot, effectively imitating a fixed physical tether. In the spring-damper mode, the follower was coupled to the robot via a *virtual* spring and damper with the same desired offset $(-1.0, -0.5)$. The spring applies a position-based force proportional to deviations from this offset ($k = 30$), while the damper applied a velocity-dependent force ($\eta = 6$) to smooth motion. The follower’s position was updated in real time from the net virtual force, with orientation aligned to its direction of motion (see Table 2).

Table 2: Duration-normalized motion metrics for rigid and spring connections, averaged across low-difficulty trials. Best values (improved smoothness and compliance) are highlighted in **bold**.

Connection	Accel (m/s^2)	RMS Jerk (m/s^3)	Heading Rate (rad/s)
Rigid	1.12	126.0	16.87
Spring	0.396	38.95	21.31

SFM-based Error Correction While the physics-based Social Force Model (SFM) provides an efficient estimate of pedestrian movement, it often fails to capture nuanced, real-world behaviors. To address this limitation, we implemented an SFM-based error correction method. Specifically, we reset the predicted positions of pedestrians in the SFM using a trajectory forecasting model [28]. The robot plans motions that minimize social forces on nearby pedestrians using the accessibility-aware SFM. We evaluate navigation with and without trajectory forecasting, demonstrating the benefits of predictive correction (see Table 3).

Table 3: Robot-only performance metrics for low-difficulty trials, comparing with and without the use of trajectory forecasting. Best values are highlighted in **bold**.

Metric	OFF	ON	Improvement
Path length [m]	25.62	16.04	↓ 37.4%
Cumulative heading changes [rad/m]	5.18	1.83	↓ 64.7%
Time to reach goal [s]	23.03	22.83	↓ 0.9%
Time not moving [s]	1.71	2.23	↑ 30.3%

4.3 Follower-Aware Path Planning vs. Other Planners

We investigate the role of follower-aware path planning (EmPath) in socially-aware robot guidance by modeling the robot and its human follower as dynamically coupled but behaviorally distinct entities. Experiments are conducted across low, medium, and high-difficulty crowd scenarios to evaluate how mediated coupling affects navigation efficiency, collision reduction, and interpersonal safety margins.

This analysis aims to determine whether EmPath provides benefits to both the robot and the follower across different crowd navigation difficulties in comparison to established non-collaborative social navigation path planners like ORCA [2] and other social force based approaches [31] in the absence of prior follower-aware methods.

5 Discussion

5.1 Spring vs Rigid Interaction Connections

Across a subset of low-difficulty trials, the spring connection consistently outperformed the rigid connection in metrics relevant to human-robot interaction (Table 2). After

Table 4: Robot performance across crowd difficulty levels (mean $\pm$ std). Bold = best; underline = second best.

Difficulty	Scenario	Time to Reach Goal(s)	Collision Rate (collisions/s)	Average Safety Distance (m)
Low	SFWP [31]	24.98 $\pm$ 9.65	0.87 $\pm$ 1.59	<u>2.45 $\pm$ 1.63</u>
	ORCA [2]	100.50 $\pm$ 31.84	0.11 $\pm$ 0.40	2.62 $\pm$ 1.32
	Ours	<u>42.28 $\pm$ 80.34</u>	0.24 $\pm$ 0.63	2.40 $\pm$ 1.60
Medium	SFWP [31]	29.05 $\pm$ 17.96	1.72 $\pm$ 3.44	1.51 $\pm$ 1.04
	ORCA [2]	108.11 $\pm$ 26.73	<u>0.97 $\pm$ 2.06</u>	1.72 $\pm$ 1.18
	Ours	51.82 $\pm$ 48.65	0.67 $\pm$ 1.22	<u>1.53 $\pm$ 0.96</u>
High	SFWP [31]	45.93 $\pm$ 37.63	2.30 $\pm$ 3.15	1.44 $\pm$ 1.40
	ORCA [2]	<u>109.18 $\pm$ 27.08</u>	<u>1.51 $\pm$ 2.71</u>	1.78 $\pm$ 1.34
	Ours	176.28 $\pm$ 236.52	0.19 $\pm$ 0.41	<u>1.55 $\pm$ 1.33</u>

Table 5: Follower performance across crowd difficulty levels (mean $\pm$ std). Bold = best; underline = second best.

Difficulty	Scenario	Path Length (m)	Heading Changes (rad/m)	Min. Safety Distance (m)	Space Intrusions (%)	Collision Rate (collisions/s)
Low	SFWP [31]	17.50 $\pm$ 10.81	3.62 $\pm$ 3.36	1.41 $\pm$ 1.43	21.74 $\pm$ 25.99	0.77 $\pm$ 1.96
	ORCA [2]	7.52 $\pm$ 3.42	351.09 $\pm$ 179.36	1.23 $\pm$ 1.10	10.41 $\pm$ 15.06	<u>0.73 $\pm$ 2.03</u>
	Ours	<u>15.14 $\pm$ 9.07</u>	4.21 $\pm$ 3.36	<u>1.24 $\pm$ 1.25</u>	<u>21.02 $\pm$ 24.07</u>	0.13 $\pm$ 0.38
Medium	SFWP [31]	4.51 $\pm$ 1.53	7.86 $\pm$ 7.90	0.58 $\pm$ 0.80	24.03 $\pm$ 22.30	<u>1.54 $\pm$ 2.51</u>
	ORCA [2]	8.81 $\pm$ 3.85	310.56 $\pm$ 168.03	0.46 $\pm$ 0.59	<u>24.31 $\pm$ 20.58</u>	2.11 $\pm$ 3.62
	Ours	<u>5.23 $\pm$ 1.59</u>	<u>8.13 $\pm$ 10.98</u>	<u>0.52 $\pm$ 0.81</u>	29.17 $\pm$ 21.38	0.36 $\pm$ 0.89
High	SFWP [31]	4.97 $\pm$ 1.58	8.84 $\pm$ 5.62	0.86 $\pm$ 1.43	<u>23.99 $\pm$ 21.25</u>	2.60 $\pm$ 3.67
	ORCA [2]	8.53 $\pm$ 4.65	365.10 $\pm$ 201.92	0.65 $\pm$ 1.13	21.51 $\pm$ 20.56	3.49 $\pm$ 6.46
	Ours	<u>5.50 $\pm$ 3.36</u>	7.50 $\pm$ 4.20	0.89 $\pm$ 1.43	26.13 $\pm$ 24.37	0.24 $\pm$ 0.37

normalizing for trial duration, the spring system exhibited substantially lower motion impulsiveness, with root-mean-square jerk reduced by approximately 69% (38.95 vs 126.0) and mean acceleration² reduced by roughly 65% (0.396 vs 1.12) compared to the rigid system. These reductions indicate smoother, less forceful motion, which directly translates to a more comfortable and pleasant experience for human participants. Maximum speeds remained comparable ($\sim$ 0.61 m/s spring vs $\sim$ 0.59 m/s rigid), well within the safe operational range of the small robot, ensuring the follower can track effectively without sudden, uncomfortable motions. The spring connection also showed slightly higher heading rate² (21.31 vs 16.87), reflecting increased rotational compliance that is physically achievable given the robot’s low inertia. Taken together, these results quantitatively support the conclusion that a compliant spring connection provides smoother, and more comfortable guidance for human-robot interaction. Importantly, the metrics were normalized by path duration due to the significantly longer completion times observed with the rigid connection.

5.2 SFM-based Error Correction

The results in Table 3 show that incorporating trajectory forecasting as an SFM-based error correction mechanism improves navigation efficiency and motion smoothness. Time to reach the goal shows a slight but consistent improvement (22.83 s vs. 23.03 s), suggesting that forecasting produces more realistic costs for plausible trajectories. Path length is substantially reduced (16.04 m vs. 25.62 m), indicating more globally consistent and efficient navigation decisions. Without forecasting, incorrect pedestrian states

lead to incorrect social costs for plausible trajectories causing oscillatory adjustments and longer trajectories, whereas forecasting enables more direct motion. Overall, forecasting mitigates limitations of purely physics-based SFM predictions. Rather than replacing the SFM, it acts as an error-correction layer that enhances pedestrian state estimation while preserving the social force framework. Even in low-difficulty scenarios, this approach yields measurable gains in efficiency and motion consistency, suggesting potential for greater benefits in more complex environments.

5.3 Follower-Aware Path Planning

We explore different path planners focused on crowd navigation, evaluating the success of robot and follower navigation separately across varying difficulty levels. Both ORCA [2] and the Social Force Window Planner [31] treat all agents in the scene symmetrically, whereas EmPath explicitly prioritises the follower’s navigation experience. Tables 4 and 5 consider the success of the path for the follower and robot separately.

Our results demonstrate that the proposed path planner achieves a strong balance between efficiency and safety compared to SFWP [31] and ORCA [2] across all crowd densities. For robot performance (Table 4), SFWP [31] reaches goals fastest in low- and medium-density scenarios but exhibits high collision rates, particularly in medium (1.72 ± 3.44 collisions/s) and high (2.30 ± 3.15 collisions/s) densities. ORCA [2] minimizes collisions effectively (e.g., 0.11 ± 0.40 collisions/s in low difficulty) but suffers from substantially longer travel times (e.g., 108.11 ± 26.73 s in medium difficulty). Our planner maintains low collision rates across all scenarios (0.24 ± 0.63 in low, 0.67 ± 1.22 in medium, 0.19 ± 0.41 in high) while keeping travel times significantly lower than ORCA [2] in low and medium difficulties, demonstrating both safe and efficient navigation. In high-density scenarios, the follower-aware objective often favours conservative manoeuvres that substantially reduce collisions at the expense of task completion time, reflecting the planner’s prioritisation of follower safety over efficiency. Follower-level results (Table 5) further highlight our planner’s advantage. It consistently achieves the lowest collision rates (0.13 ± 0.38 in low, 0.36 ± 0.89 in medium, 0.24 ± 0.37 in high) while maintaining reasonable path lengths and smooth trajectories. Compared to ORCA [2], our planner avoids erratic behavior and extreme heading changes, ensuring safe and predictable motion for followers.

Overall, our planner provides a robust trade-off between safety, and trajectory smoothness, outperforming SFWP’s [31] aggressive strategy and ORCA’s [2] overly conservative approach. These results validate the planner’s suitability for dynamic, human-populated environments, supporting its potential applicability to future real-world deployment. While these metrics do not directly measure user experience, they represent established proxies for safety and comfort in assistive navigation and provide an important intermediate validation step prior to human-subject evaluation.

6 Conclusion

In this work, we introduced EmPath, a follower-aware local navigation framework for robot-assisted mobility in dense crowds. By modeling the robot guide and human follower as perceptually asymmetric yet dynamically coupled agents, our approach moves

beyond conventional robot-centric planning toward follower-aware navigation. Through accessibility-aware social force modeling, compliant human–robot coupling, and predictive error correction, EmPath prioritises follower safety through improved collision avoidance and smoother guidance while demonstrating the benefits of explicitly modelling follower-aware navigation.

Simulation results demonstrate the importance of incorporating asymmetric perception and follower-aware constraints into local motion planning for assistive navigation. The current accessibility model adopts a simplified representation of visual impairment to enable systematic evaluation in simulation and does not capture the full spectrum of individual perception capabilities. As direct evaluation with BVI users in dense crowds raises significant ethical and safety considerations, simulation provides a critical intermediate step for validating safety and social compliance prior to deployment. Future work will focus on human-in-the-loop evaluation and real-world studies with BVI users in naturalistic environments, as well as investigating richer models of varying perception capabilities, and extending the framework toward multimodal interaction, incorporating verbal cues to support more robust and natural robot-assisted navigation in complex crowd settings.

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