Legible Uncertainty-Aware Robot Motion for Human-Shared Spaces

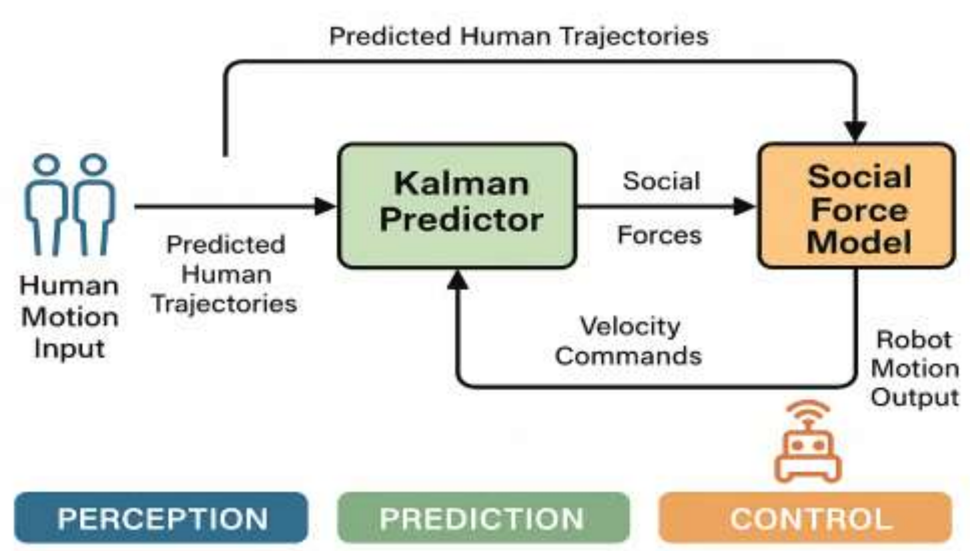
Yassine Kraiem*, Benard Adewole*, and Perci Wolday*.
Department of Computer Science and Mathematics, Alma College, Alma, MI 48801.
Department of Robotics, The University of Michigan, Ann Arbor, MI 48109.

Background

Humans move unpredictably, communicate intent implicitly, and expect technology to respect invisible social boundaries. Yet, many existing planners treat humans as moving obstacles rather than as partners in shared motion. This research addresses this gap by exploring how robots can anticipate and adapt to human behavior in real time. By combining predictive modeling with social-force-aware control, we aim to design motion policies that are not only safe and efficient, but legible so that humans can intuitively understand what the robot will do next. This legibility is key to building trust, comfort, and safety in human-robot environments.

Human-Aware Control Architecture

Our architecture integrates perception, prediction, and control in a unified feedback loop for human-aware navigation. Each agent in the environment is modeled as a dynamic system whose state (position, velocity) is estimated through a Kalman filter, capturing uncertainty in human motion. Predicted trajectories feed into a Social-Force Model, where interpersonal distances produce repulsive potentials representing social comfort zones.
A Model Predictive Controller (MPC) computes optimal velocity commands that minimize a composite cost: path deviation, time, and proxemic discomfort. The MPC re-plans at 10 Hz, enabling reactive, human-aware motion adaptation.



Human-Trajectory Prediction

Human motion in shared spaces is uncertain and non-linear, yet predictable within short horizons.
To model this, we used a discrete-time Kalman filter that estimates each pedestrian's position and velocity from noisy observations. The predictor updates at 10 Hz and propagates trajectories one second ahead, providing probabilistic state estimates to the control layer.

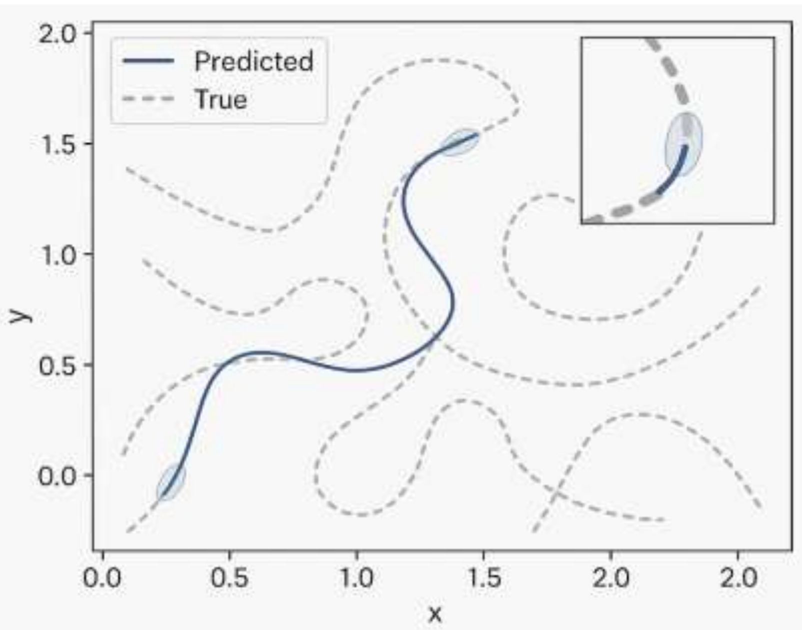


Figure 3. Kalman-filter-based trajectory prediction
Predicted paths closely follow observed human motion while capturing uncertainty in direction and velocity.

Each human is represented as a dynamic state

$$x_t = [p_x, p_y, v_x v_y]^T,$$

updated through motion and measurement models with Gaussian noise.

By quantifying uncertainty (σ_x, σ_y) around predicted paths, the robot can anticipate human intent and avoid intrusive maneuvers before they occur. This predictive layer forms the foundation for socially responsive navigation.

Social-Aware Motion Control

Building on the prediction layer, our control system uses Model Predictive Control (MPC) to generate smooth, collision-free, and socially acceptable robot trajectories in dynamic crowds. At each control cycle, the MPC minimizes a composite cost function that balances path efficiency, social comfort, and dynamic feasibility:

$$J = w_1 \parallel p_t - p^* \parallel^2 + w_2 C_{social} + w_3 \parallel \Delta v_t \parallel^2$$

where C_{social} represents the social-force penalty derived from the proximity to predicted human positions.
The controller enforces constraints to maintain a minimum interpersonal distance of 0.8 m, generating velocity commands that align with both physical safety and psychological comfort.

This formulation allows the robot to act *politely* slowing, yielding, or curving its trajectory in anticipation of human motion while remaining within 7 % of the shortest-path efficiency.

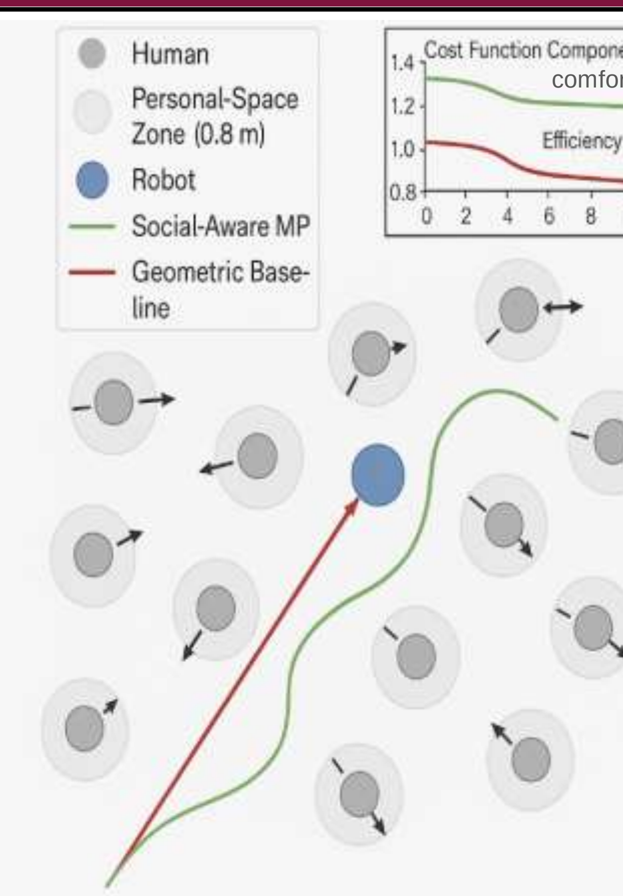


Figure 4. Social-aware Model Predictive Control generates human-friendly trajectories that maintain comfort zones while preserving path efficiency.

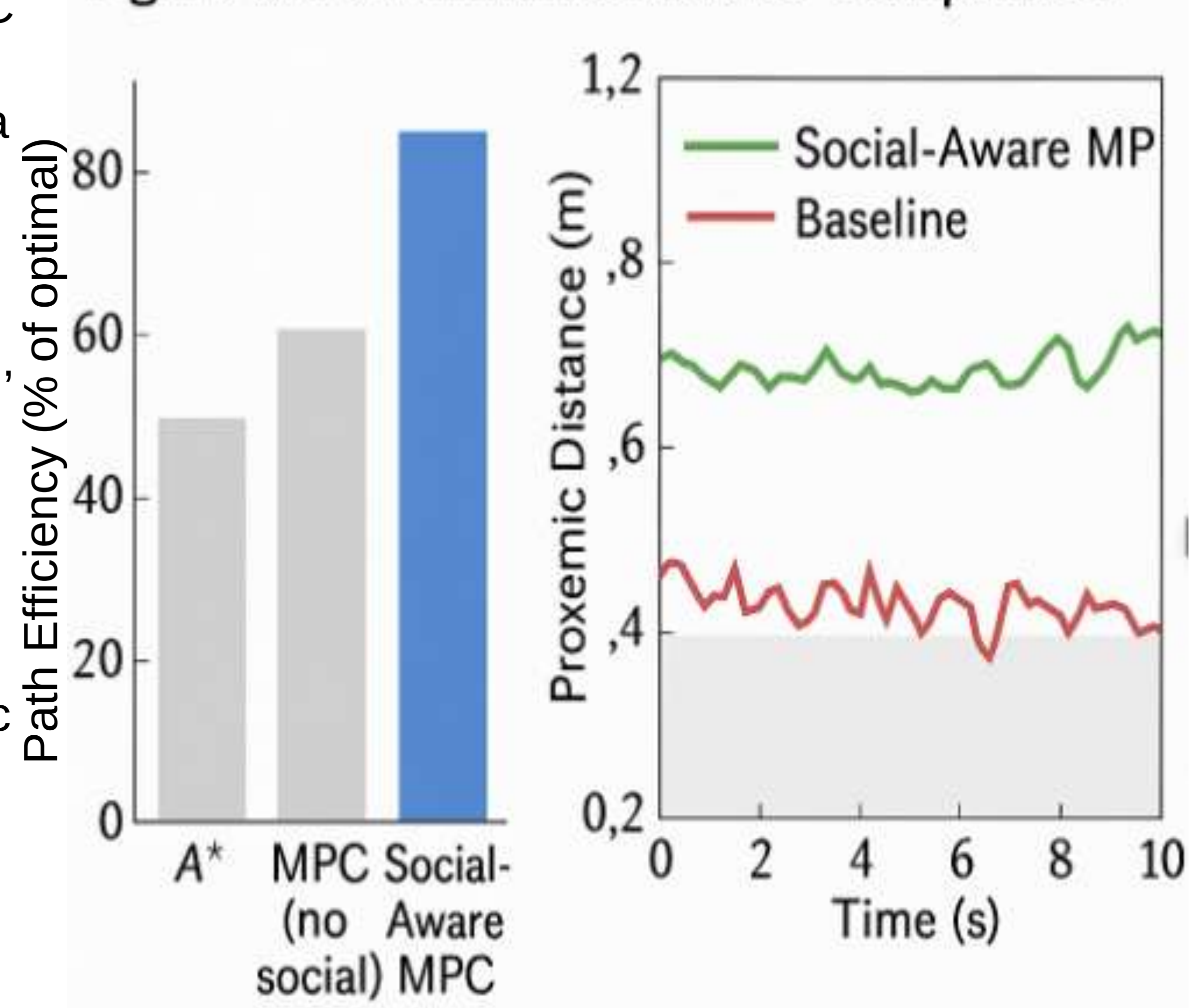
Reward Shaping and Behavioral Results

To balance human comfort and motion efficiency, we introduced a reward-shaping term into the MPC objective that explicitly penalizes *proxemic violations* instances where the robot intrudes into a person's personal space (< 0.8 m).
The shaped reward combines three objectives:

$$R = -(\alpha\, d_{prox}^{-1} + \beta\, \Delta t + \gamma\, \sigma_{pred})$$

where $d_{prox}$is the minimum human–robot distance, $\Delta t$the traversal time, and $\sigma_{pred}$the predicted uncertainty from the Kalman filter.
In simulation with 10 dynamic agents, the social-aware controller maintained an average proxemic distance of 0.87 m for 95 % of the trial time while keeping path efficiency within 7 % of the geometric optimum.
Motion smoothness improved significantly acceleration variance decreased by 28%, and the robot exhibited fewer abrupt turns, resulting in motion that felt intuitively human-aware.

Figure 5. Performance Metrics Comparison



Findings and Insights

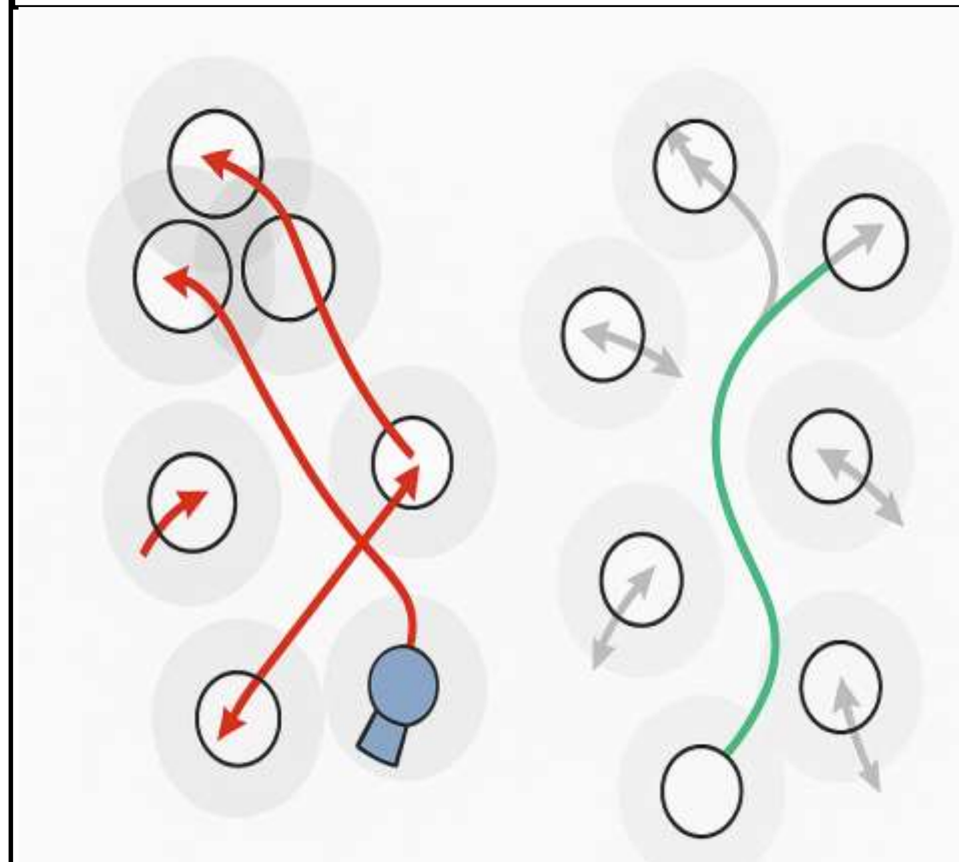


Figure 6. Legible motion emerges when control objectives incorporate human comfort and predictability.

Integrating predictive human models with social-force-aware control produced motion that felt *legible* and *trustworthy*.

The system preserved interpersonal comfort without compromising efficiency, generating trajectories that mirrored natural human patterns such as yielding and lane formation.
Most importantly, legibility proved not to be a byproduct of control but a design objective.

By embedding human proxemics and uncertainty directly into the cost function, the robot's behavior became both mathematically safe and socially intuitive demonstrating that future autonomous systems must treat human response as a control variable, not an afterthought.

Conclusions and Future Work

Our work demonstrates that combining predictive human modeling with social-force-aware control enables robots to navigate shared spaces both safely and intuitively. By encoding comfort and legibility directly into the control architecture, we bridge the gap between algorithmic efficiency and human social norms.
Moving forward, we plan to integrate Bayesian intent inference for real-time recognition of human goals and extend the framework to uncertainty-robust control on physical platforms.
These developments aim toward robots that move not just efficiently but *understandably* earning human trust through behavior that communicates intent as clearly as it achieves safety.

Acknowledgements and References

This research was carried out through a collaboration between Alma College and the University of Michigan Department of Robotics, under the technical supervision of Dr. Andrew Thall.

Computational support and resources were provided by the University of Michigan, whose facilities enabled large-scale multi-agent experiments and performance validation.

[1] Generating Legible Motions for Service Robots Using Cost-Based Local Planners (2024) — Introduces real-time legible motion planning for mobile robots in dynamic human environments.
[2] Insights Into Legible Motion From Interpersonal Interaction (2024) — Offers new understanding of legibility in human-robot collaboration.
[3] Effects of Robot Competency and Motion Legibility on Human Correction Feedback (2025) — Human study linking robot motion legibility to human feedback and trust.
[4] Socially Aware Robot Crowd Navigation via Online Uncertainty-Driven Risk Adaptation (2025) — Combines uncertainty modelling + MPC for crowd navigation.
[5] A Lightweight Crowd Model for Robot Social Navigation (2025) — Presents a new efficient crowd-prediction model for robots in dense environments.