Overlapping Social Navigation Principles: A Framework for Social Robot Navigation

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***Abstract*— As autonomous robots become integrated into society, they must socially navigate around humans. We propose that effective social robot navigation relies on three key principles: social norms, perceived safety, and legibility. Our framework, Overlapping Social Navigation Principles, suggests that the strength of each principle is influenced by the presence of other principles. To test our framework, we implemented SRN behaviors on an autonomous robot in a passing scenario and conducted an online study where participants ranked videos of different SRN behavior combinations. Our findings show that incorporating all three principles enhances SRN, with social norms having the greatest impact.**

I. Introduction

Effective Social Robot Navigation (SRN) is essential for robots to coexist with people. Yet, what makes a robot proficient at social navigation? Initially, the focus was on designing robots to avoid people as obstacles [1], [2], but it soon became clear that effective SRN requires treating humans as interactive agents, where a robot's behavior influences human experiences. In other words, "a socially navigating robot acts and interacts with humans or other robots, achieving its navigation goals while modifying its behavior so the experience of agents around the robot is not degraded or is even enhanced" [3]. Several principles — safety, comfort, legibility, politeness, social competency, understanding other agents, proactivity, and context-appropriate responses — have been proposed to guide SRN development [3]. However, the interaction of these principles and their collective impact on SRN remains unclear. For example, if a robot says "excuse me" while moving between people, this could be interpreted as legibility, politeness, social competency, and perhaps comfort. Moreover, a robot moving at unsafe speeds might violate social norms, raising questions about which factor most strongly affects SRN quality. The complexity of these interactions complicates system development, and researchers have called for more studies on SRN principles [4]. In response, we propose the Overlapping Social Navigation Principles framework, hypothesizing that three components—social norms, perceived safety, and legibility—are of primary importance, with varying influence on each other.

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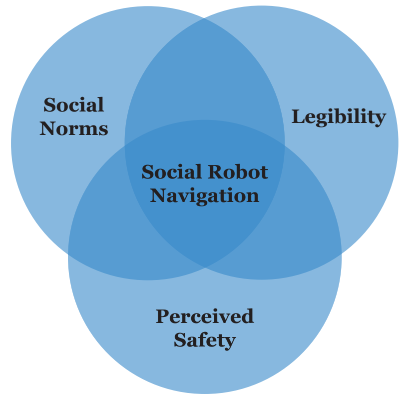
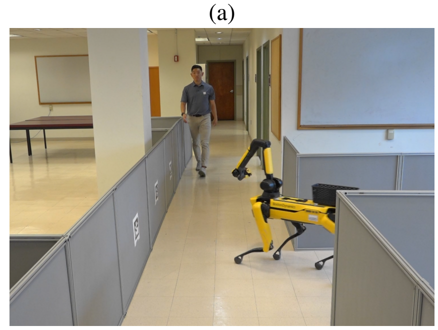


(a)



(b)

Fig. 1: We theorize that social norms, perceived safety, and legibility are key factors in social robot navigation. Our framework (a) shows these principles overlap, affecting each other. To test this, participants watched four videos of a robot navigating a hallway. The Ideal Pass video (b) shows the robot following social norms, maintaining safe speed, and using gestures for legibility.

Social Norms: When people pass each other in a hallway, they typically follow culturally accepted passing etiquette. Considering the human tendency to attribute human-like qualities to robots, it is reasonable to expect that robots follow similar social conventions [5]. In SRN, this has been achieved by programming robots to follow social norms, encompassing the established values, beliefs, attitudes, and behaviors set by groups of people [6]. Previous research has explored this concept in mobile robots by incorporating proxemics [7], [8], [9], [10], [11] (i.e., the spatial distances that people maintain in social situations [12]), social gaze [8], human-preferred path plans [9], [13], [14], human-like passing behavior [15], and acceptable robot speeds [16], [10]. For instance, Senft et al., 2020 [15] conducted a study that revealed humans prefer a robot exhibiting human-like crossing behavior in a hallway over a robot that did not. Fiore et al., 2013 [17] found that robots aligning with social norms are perceived as possessing a greater social presence, leading to positive interactions between people and robots [18]. Furthermore, individuals tend to rate robots that adhere to social norms as warmer [15], more predictable [19], and safer [14], all of which collectively contribute to a positive SRN experience for others. Considering the impact and broad overlap of social norms on other principles of social robot navigation, we propose it is one of the most important guiding principles for SRN systems.

Perceived Safety: Another component of SRN is perceived safety. When robots operate in close proximity to humans, the robot must be physically safe. This requirement has resulted in safety standards that provide guidance for the development and operation of robots in human environments [20], [21]. However, physical safety alone does not guarantee that a robot will be perceived as safe. A study conducted by Lasota and Shah, 2015 [22] demonstrated that a standard robot that treated participants as obstacles was perceived as less safe compared to a robot that maneuvered with an awareness of people and their goals. This insight has led to further research, indicating that perceived safety also varies depending on the robot's speed [23], [10], proximity [24], physical features [25], [26], [27], legibility [13], body movements [13], and direction of approach [28]. For instance, it has been found that optimizing perceived safety involves both ensuring physical safety in close proximity to participants and adapting the robot's speed according to participants preferences [24]. Perceived safety has also been found to overlap with comfort (safe robots engender more comfort) [7], [11], [8], [9], legibility (robots telegraphing their future actions are perceived as safer) [29], [30], understanding other agents (performing unsafe actions away from people is best) [24], and social norms as already discussed. Hence, SRN systems should enhance peoples' sense of safety by exhibiting behaviors that align with individuals' preferences and by not appearing unsafe.

Legibility: A third component of our framework is the concept of legibility, which refers to robot motion that allows an observer to confidently infer a robot's goal [31]. This behavior helps a robot communicate its intentions to others more effectively. In pursuit of understanding legible robot behaviors, researchers have incorporated lights [32], [33], [34], [35], [36], projectors [37], [38], [36], gaze [39], [33], [30], [17], and gestures [30]. Certain behaviors such as gestures or deliberate body movements [40], [14], [17] typically build upon the robot's naturally existing capabilities. In contrast, projectors or light fixtures are added features that give the robot distinct communication abilities. The effectiveness of each type of behavior can also vary. For example, Hart et al., 2020 [29] found that gaze results in fewer navigational conflicts than turn signal lights, while Angelopoulos et al., 2022 [30] found that diectic gestures resulted in fewer navigational conflicts than using gaze. Nevertheless, when properly integrated, there is potential for better human-robot collaboration [32], [34], higher levels of comfort [33], [40], [38], and reduction in navigation conflicts [29], [30]. In addition to the overlap between perceived safety, and social norms, as previously discussed, legibility also interacts with comfort [33], politeness [41], social competency [42], and context [16], [43]. By effectively conveying intent, robots can better facilitate interaction with humans, thereby advancing SRN.

A core component of our framework is the proposition that our three principles are interconnected (see Figure 1a). A robot can enhance its legibility by following social norms [44], and perceived safety can be enhanced by legible behavior [13]. Therefore, understanding how these principles interact is crucial for improving SRN. Prior studies have explored this question by integrating various combinations of SRN principles onto a mobile robot, utilizing social norms, safety, proxemics, legibility, or comfort [9], [45], [46], [10], [47], [48], [49], [41], but lacked empirical evidence for the effectiveness of these combinations. Pacchierotti et al., 2006 [50] designed a SRN system that encoded lateral distance, speed, and signaling, showing their impact on perceptions of SRN, though each specific contribution remain unclear [51], [52]. Hence, our work aims to clarify how each principle affects the others to better understand effective SRN.

Contributions: We introduce a novel framework called Overlapping Social Navigation Principles, which hypothesizes that social norms, perceived safety, and legibility are key components of social navigation. It predicts that robots integrating all three principles will be perceived as performing best and that overlaps in perceptions of these principles will occur. To test this, we conducted an online study comparing various combinations of these principles on an autonomous robot. Our contributions are: (1) A foundational framework for SRN systems, (2) The first study showing that combining social norms, perceived safety, and legibility is essential for effective SRN and their relative importance, (3) An open-source SRN stack with validated behaviors for each principle available at OSF for reproducing results or for integrating with other navigation algorithms [53], [54], [55], and (4) Three surveys measuring participant perceptions of social norms, safety, and legibility, laying the groundwork for future scale development.

II. Robot Design

Our goal was to design algorithms that enable an autonomous robot to exhibit social norms, perceived safety, and legibility both individually and together. Initially, we observed a robot's standard behavior, which included navigating down the middle path to optimize obstacle clearance and minimize the distance to its goal [56], and maintaining speeds between $0.381 m/s$ and $0.6 m/s$ [10], [52], [57], but lacking clear legibility signals. [1] Using this as a baseline, we implemented SRN behaviors to embody our three principles directly on the robot. We utilized a Spot robot, a quadruped

[1] Note that previous researchers have used a robot walking towards the right side as a legibility signal [51]; we decided to provide a more explicit display of legibility, much like gaze or gesture as described earlier.

with a 6 degree-of-freedom manipulator. Our framework consists of two main Python components: the Boston Dynamics Python interface and the social navigation module with A* for path planning [58] and Pure Pursuit for path following [59]. Rather than introducing new algorithms, we aimed to empirically evaluate the relationships and impact of the three principles. Thus, we present our algorithms to demonstrate how this was achieved. An open-source code implementation can be found at the following link OSF.

A. Social Norms

While numerous social norms are relevant in a social navigation context, we chose to implement a widely recognized and extensively explored social norm [60], [61], [43]: walking on the culturally appropriate side of a corridor. In our case, this meant walking on the right side of the hallway.

Algorithm 1 Social Norms

1: **function** GET SOCIAL COST(p_r, p_n, θ_h)
2: $\quad C_{3\times3} \leftarrow$ Social Norm Cost Matrix
3: $\quad [d_x, d_y] \leftarrow$ CalculateDifference(p_r, p_n)
4: $\quad [r_{d_x}, r_{d_y}] \leftarrow$ ApplyRotation(d_x, d_y, θ_h)
5: $\quad [i_x, i_y] \leftarrow$ TranslateToMatrixindices(r_{d_x}, r_{d_y})
6: $\quad SN_{cost} \leftarrow C_{3\times3}[i_x][i_y]$
7: $\quad$ **return** SN_{cost}
8: **end function**

We incorporated social norms into path planning by adding a heuristic that favors the right side of the hallway, as shown in Algorithm 1. The function uses the current A* node position p_r, neighbor node p_n, and hallway orientation θ_h (line 1). We define a social cost matrix $C_{3\times3}$ to guide the planner right (line 2). We take the difference between the current node and the neighbor node $[d_x, d_y]$ (lines 3), and transform it to align with the direction of the hallway $[r_{d_x}, r_{d_y}]$ (line 4). Then, we map the rotated values to correspond to indices within the cost matrix (line 5), denoted as $[i_x, i_y]$, which is used to determine the cost associated with moving to the neighbor node SN_{cost} (line 6–7).

B. Perceived Safety

As with other principles, there are many possible methods to manipulate perceived safety. Here we used a common approach from the literature — manipulating the robot's speed [24], [10], [16], [47], [62], [63].

Algorithm 2 Safety

1: **function** PFC($odom$, $path$, θ_h, S_w, is_safe, $is\_legible$)
2: $\quad [x_{la}, y_{la}] \leftarrow$ CalculateLookaheadPoint$(path)$
3: $\quad \kappa_{pfc} \leftarrow$ CalculateNearCurvature$(odom, x_{la}, y_{la})$
4: $\quad S_w \leftarrow$ UpdateWalkingState$(odom, path, \theta_h, \kappa_{pfc}, S_w)$
5: $\quad \lambda \leftarrow$ ScaleAngularVelocity$(S_w, is_safe, is_legible)$
6: $\quad v_t \leftarrow$ if is_safe then v_{safe} else v_{unsafe}
7: $\quad$ **return** $[v_t, v_t \cdot \kappa_{pfc} \cdot \lambda]$
8: **end function**

To ensure the robot's physical safety, we used the Spot robot's built-in controller, which features five stereo cameras with a four-meter obstacle detection range, allowing the robot to automatically avoid obstacles. For perceived safety, we implemented two speeds in the Path Following Controller (PFC), as shown in Algorithm 2. The controller adjusts speed from $0.5m/s$ (safe) to $1.3m/s$ (unsafe) based on the safety flag is_safe and legibility flag $is\_legible$ (line 1). The algorithm also utilizes the robot's odometry $odom$, computed path plan $path$, hallway frame rotation θ_h, and current walking state S_w. In line 2, the lookahead point position $[x_{la}, y_{la}]$ is computed, which is passed to the next function in line 3, for calculating the path curvature κ_{pfc}. In line 4, the robot's walking state is updated, taking into account the variables $odom$, $path$, θ_h, and S_w. The angular velocity scaling factor λ is tuned for smooth trajectories, accounting for the robot's arm extension, movement speed, and turn angle. Depending on the safety flag (line 6), the robot's target velocity v_t is set to either v_{safe} or v_{unsafe}. Finally, the controller commands the robot with the calculated linear and angular velocities (line 7).

C. Legibility

We explored various approaches to convey legibility during navigation. However, because the robot's morphology resembled a dog lacking facial features, using gaze was not a viable option. Moreover, prior work has demonstrated that both gaze and light signals can be challenging to interpret [29]. Thus, we chose a more effective and natural method for legible behavior: gestures [30], [64], [65], [66].

Algorithm 3 Legibility

1: **function** UPDATEARM($odom$, $path$, θ_h, κ_{pfc}, S_w)
2: $\quad \theta_d \leftarrow$ Diff$(\theta_{odom}, \theta_h)$
3: $\quad$ **if** $S_w \in \{$TIGHT TURN, MODERATE TURN$\}$ and $\theta_d \geq \alpha_s$ **then**
4: $\quad\quad \theta_h \leftarrow$ UpdateFrame(θ_h)
5: $\quad\quad S_w \leftarrow$ STRAIGHTEN
6: $\quad\quad$ Straighten arm towards forward direction
7: $\quad$ **else**
8: $\quad\quad \kappa_m \leftarrow$ FarCurvature$(d, steps, path)$
9: $\quad\quad$ **if** $|\kappa_m| \geq \alpha_m$ **then**
10: $\quad\quad\quad S_w \leftarrow$ TIGHT TURN
11: $\quad\quad\quad$ Gesture towards right of next hallway
12: $\quad\quad$ **end if**
13: $\quad\quad$ **if** S_w is WALK FORW. and $|\kappa_{pfc}| \geq \alpha_t$ **then**
14: $\quad\quad\quad S_w \leftarrow$ MODERATE TURN
15: $\quad\quad\quad$ Gesture towards middle of next hallway
16: $\quad\quad$ **end if**
17: $\quad\quad$ **if** S_w is STRAIGHTEN and $|\kappa_{pfc}| \leq \alpha_t$ **then**
18: $\quad\quad\quad S_w \leftarrow$ WALK FORW.
19: $\quad\quad\quad$ Gesture towards forward walking direction
20: $\quad\quad$ **end if**
21: $\quad$ **end if**
22: $\quad$ **return** S_w
23: **end function**

The robot showed legible behavior by using its arm to gesture towards its intended walking path, the process by which is detailed in Algorithm 3. In line 1, the robot's odometry $odom$, path plan $path$, hallway frame rotation θ_h, immediate path curvature κ_{pfc}, and the current walking state of the robot S_w is passed as input to the function. Next, if the robot is turning and the difference between the current heading θ_{odom} and the hallway frame rotation θ_h (line 2) is greater than a threshold value α_s (line 3), then the robot is determined to have turned into the next hallway. Therefore, the hallway frame is updated to signify the new hallway direction (line 4). This also transitions the robot into the STRAIGHTEN walking state (line 5), triggering the robot to straighten its arm (line 6). Next (line 8), we compute the future path curvature κ_m between a starting point positioned at distance d ahead of the robot and two consecutive points separated by a number of $steps$ along the $path$ segment. When the curvature κ_m surpasses a predefined threshold α_m (line 9), indicating an upcoming turn, the robot's walking state S_w is updated to TIGHT TURN (line 10). This instructs the robot to gesture towards the right side of the upcoming hallway (line 11). In line 13, if the robot's current walking state is WALK FORWARD and the immediate path curvature κ_{pfc} is greater than a predefined threshold α_t, then the robot transitions the current walking state to MODERATE TURN (line 14). This state triggers the robot to gesture towards the middle of the upcoming hallway. If the robot's current walking state is set to STRAIGHTEN and the immediate path curvature κ_{pfc} falls below a set threshold α_t (line 17), then the robot has completed the straightening process. As a result, the robot transitions the walking state to WALK FORWARD (line 18), instructing the robot to gesture towards the forward walking direction (line 19), and finally, returns the current walking state S_w (line 22). To calibrate the thresholds and arm movement speeds, we iteratively updated the values until the robot could navigate smoothly through each stage.

III. Scale Design

While there are many methods to measure social norms [67], [68], [69], [70], perceived safety [71], [72], [73], [74], [75], [76], [77], and legibility [78], [40], [79], no established scales specifically address these perceptions in the context of SRN. Existing scales for social norms, such as acceptability [80], [81], [82], [47], [83], perceived social intelligence [84], or social compliance [85], [86], [87], do not capture perceptions during SRN. For perceived safety, the Godspeed subscale [88], has poor reliability and includes items that negatively load on the factor [89]. Alternative scales like the Negative Attitudes towards Robots Scale (NARS) [47], Robot Anxiety Scale (RAS) [82], or Robotic Social Attributes Scale (RoSAS) [89] focus on anxiety and discomfort, which are related but distinct constructs from perceived safety. Legibility has been measured through the time for participants to identify a robot's goal based on its arm motion [31] or other ad-hoc metrics [78], [40], [79], none of which fully capture SRN-specific perceptions. To address this gap, we developed our own measurement scales (see Table I), inspired by prior work and adapted for SRN. Each Likert-item was rated from 1 (Strongly Disagree) to 6 (Strongly Agree). For perceived safety, our goal was to assess how much people perceived the robot lacked in safety. Therefore, higher levels of perceived safety indicate the robot was perceived as less safe. We envision these scales may serve as the first step towards fully validated measurement tools for evaluating the perception of social norms, safety, and legibility within the context of SRN. To quantify reliability, we used α and ω_{total} [90]. Our scales were measured at a reliability of $>= .85$ (α and ω), indicating strong results [91]. Thus, we consider our initially designed scales to be suitable for reporting as a foundational starting point for future researchers.

Social Norms: When the robot was navigating I thought the robot was ...
following a similar path to others
taking social expectations into account while navigating the area
taking the route through the area in a usual way
following social conventions while walking
following typical paths while it was moving through the area
Perceived Safety: If I were a person in the video, I would feel ...
anxious
likely to be harmed
in danger
afraid
unsafe
Legibility: When the robot was navigating I thought the robot's intended path was ...
communicated
understandable
clear
predictable

TABLE I: Questionnaires for measuring people's perceptions of the robot's social norms, safety, and legibility. Ratings were from 1 (Strongly Disagree) to 6 (Strongly Agree).

IV. Experiment

A. Method

1) Participants: A power analysis using the WebPower package [92] in R for a repeated measures study with four conditions was conducted. Our goal was to obtain .8 power to detect a medium sized effect (f=.25) at 0.05 α error probability, resulting in 176 participants required for this study. 200 online participants from CloudResearch were recruited. 34 participants missed the attention check, resulting in a total of 166 participants. All participants were above the age of 18; the average age was 43.7 (SD=13). There were 96 females, 69 males, and 1 person who preferred not to answer.

2) Materials: To evaluate our framework, we simulated a real-world scenario where a robot navigates a T-shaped hallway intersection, often found in hospitals [93] or grocery stores [94]. We designed a $1.5m$ wide hallway (see Figure 2), as per Americans With Disabilities Act (ADA) guidelines, with a human starting $6.25m$ away and the robot $1.2m$ from

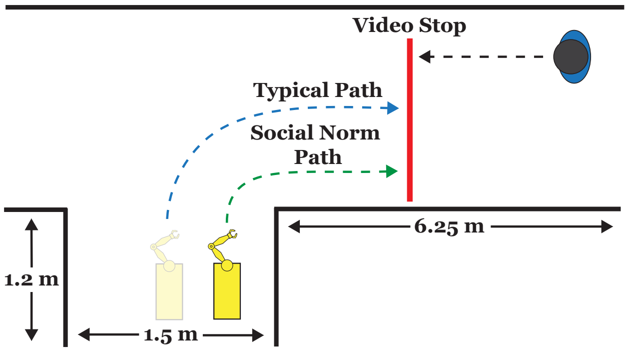


Fig. 2: The layout of our navigation scenarios portrayed in each video stimuli. All videos halt at the same location, and the passerby follows the same walking path.

a blind corner. The robot rounds the corner while the human approaches, leading to a head-on pass.

Videos: To illustrate our SRN scenario, we produced four videos displaying different combinations of the principles within our SRN framework The Ideal Pass video portrayed a robot that adhered to all of our proposed principles: followed social norms, behaved safely, and was legible (see Figure 1b). In the other three videos, one SRN principle was intentionally disabled. Each video was created using the autonomous code described in the §II. Examples of each video are available at the following link: OSF.

3) Procedure Design: We conducted a four way within-participant experiment. Participants first provided demographic information, then watched two videos: one showing people walking naturally on the right side of a hallway, and the other showing the robot navigating a room while gesturing toward where it was planning on going next. These videos introduced participants to the hallway space and the robot's capabilities as if they had observed the robot before. Next, participants saw each of the four SRN videos in a random order. They were able to rewatch the videos if they desired. After each video, participants were tasked with providing a brief description of the video and filling out the three scales (social norms, perceived safety, and legibility) described in §III. For each participant, scales were randomly presented but in a consistent order. Afterwards, participants were asked to describe each video and rank the four videos from the best navigation to the worst. Participants could rewatch any of the videos or reference their brief video descriptions. Finally, participants were asked to describe the task and give an explanation of the study's purpose.

B. Predictions

We had two primary predictions based on our Overlapping Social Navigation Principles framework. First, we expected that a robot adhering to all three of our SRN principles will receive a higher SRN rank compared to a robot that disables any one of our principles. Second, we expect that each principle will have an impact on other factors: participants may perceive a robot with poor legibility as also exhibiting lower levels of social norms when compared to an ideal socially navigating robot.

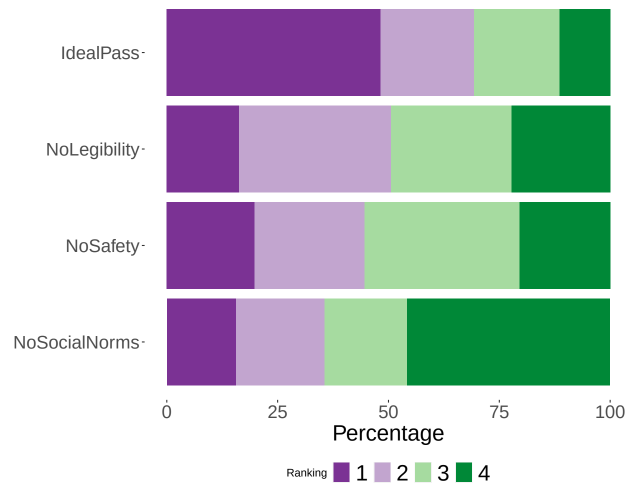


Fig. 3: Robots incorporating all three SRN principles consistently achieve higher SRN rankings. The No Social Norms condition was ranked worst, while No Legibility and No Safety conditions showed no significant ranking difference.

C. Results

The reliability of each scale — social norms, perceived safety, and legibility — were calculated using using α and ω_{total} from the psych package [90]. Each scale value was calculated by averaging all items for the scale. Our scales were measured at a reliability of $>=$ .85 (α and ω), thus indicating they are a strong initial starting point for future development [91]. Results can be observed in Figure 3.

1) Ranking Data: Our goal was to assess if the Ideal Pass condition was perceived as superior and to identify any significant differences among the other conditions. We examined this relationship using an ordinal mixed model regression. Ordinal regression allows us to use an ordinal dependent variable (ordinal data is assumed to violate normality assumptions because the distance between numbers is not metric). A mixed model allows us to take into account correlations between participants' scores. We used an ordinal mixed model to analyze the effects of the video (condition) on the ranked order of navigation considering random variation across participants. The analysis was performed using the R package ordinal [95]. We included the ranked order of navigation (ordinal 1 – 4) as the dependent variable and the categorical variable condition as the independent variable. We included participant as a random-effect factor. We used the R package emmeans [96] for pairwise comparisons.

Consistent with our hypothesis, participants rated the Ideal Pass condition better than all the other conditions (all $|\beta| > 1$; all $|z| > 5$; all $p < 0.001$). The No Social Norms condition was ranked worse than all other conditions (all $|\beta| > .7$; all $|z| > 3.5$; all $p < 0.005$), and the No Legibility and No Safety conditions were not ranked differently ($|\beta| = .016$, $|z| = .08$, $p > .98$) (see Figure 3).

2) Social Norms: Reliability analysis for the Social Norms scale output an α of .95 and an ω_{total} of .86. The overall ANOVA results indicated a statistically significant difference in mean Social Norms between at least two groups ($F(3, 495) = 143.2, MSE = 127.07, p < 0.001$). Tukey HSD Test revealed statistically significant differences for all pairwise comparisons as seen in Table II.

Comparison	t-Statistic	p-value
No Social Norms vs. Ideal Pass	t(495) = 19.371	p < 0.001
No Safety vs. Ideal Pass	t(495) = 8.312	p < 0.001
No Legibility vs. Ideal Pass	t(495) = 3.350	p < 0.005
No Social Norms vs. No Safety	t(495) = 11.060	p < 0.001
No Safety vs. No Legibility	t(495) = 4.962	p < 0.001
No Social Norms vs. No Legibility	t(495) = 16.022	p < 0.001

TABLE II: Pairwise comparisons for Social Norms.

3) Perceived Safety: Reliability analysis for the Perceived Safety scale output an α of .97 and an ω_{total} of .85. The overall ANOVA results indicated a statistically significant difference in mean Perceived Safety between at least two groups ($F(3, 495) = 91.86, MSE = 70.23, p < 0.001$). Tukey HSD Test revealed statistically significant differences for all pairwise comparisons as seen in Table III.

Comparison	t-Statistic	p-value
No Safety vs. Ideal Pass	t(495) = -10.783	p < 0.001
No Social Norms vs. Ideal Pass	t(495) = -14.474	p < 0.001
No Legibility vs. Ideal Pass	t(495) = -2.686	p = 0.0373
No Social Norms vs. No Safety	t(495) = -3.691	p = 0.0014
No Safety vs. No Legibility	t(495) = -8.097	p < 0.001
No Social Norms vs. No Legibility	t(495) = -11.788	p < 0.001

TABLE III: Pairwise comparisons for Perceived Safety.

4) Legibility: Reliability analysis for the Perceived Safety scale output an α of .94 and an ω_{total} of .92. The overall ANOVA results indicated a statistically significant difference in mean Legibility between at least two groups ($F(3, 495) = 64.27, MSE = 84.62, p < 0.001$). Tukey HSD Test revealed statistically significant differences for all pairwise comparisons as seen in Table IV.

Comparison	t-value	p-value
No Legibility vs. Ideal Pass	t(495) = 13.536	p = 0.0048
No Social Norms vs. Ideal Pass	t(495) = 9.171	p < 0.001
No Safety vs. Ideal Pass	t(495) = 6.445	p < 0.001
No Legibility vs. No Safety	t(495) = -7.091	p < 0.001
No Legibility vs. No Social Norms	t(495) = -4.364	p = 0.001
No Social Norms vs. No Safety	t(495) = 2.726	p = 0.0335

TABLE IV: Pairwise comparisons for Legibility.

V. Discussion

Our results provide support for our core hypothesis, emphasizing the importance of social norms, perceived safety, and legibility for achieving effective SRN. As illustrated in Figure 3, we observe a statistically significant trend, where the Ideal Pass condition consistently outranks the conditions that do not incorporate all three of our core principles. Furthermore, the Ideal Pass condition received higher ratings across all three of our subjective metrics: social norms, perceived safety, and legibility. This suggests that robots adhering to all three of our core SRN principles also enhance the effectiveness of each individual SRN principle.

Our results also highlight the intricate interplay between each principle, providing evidence for the formulation of our SRN framework, Overlapping Social Navigation Principles. If there were no overlap, the absent principle condition would be the only condition with lower measurements of that principle compared to the Ideal Pass. However, this was not the case. For example, for social norms, the No Social Norms, No Safety, and No Legibility conditions all resulted in statistically significant lower levels of social norms compared to the Ideal Pass condition. Similar trends were observed for perceived safety and legibility. This suggests that omitting any one of our principles causes other principles to perform worse, signaling an interdependence between principles. For example, the absence of legibility had the smallest, yet still significant, negative impact on other principles. Most impactful was the absence of social norms, which was perceived as less safe than the absence of safe behaviors itself. This underscores the effect social norms have beyond its own principle. As an implication of our results, robotics engineers must adopt a holistic approach when designing SRN systems, emphasizing all three proposed principles – social norms, perceived safety, and legibility – while placing particular importance on following social norms [97], [98].

VI. Limitations and Future Work

One limitation of our approach is that participants ranked videos based on preferences, which did not provide a quantitative measure of SRN quality. While our Likert-scales demonstrated high reliability, $>=$ .85, further testing is needed to confirm their validity and robustness. Therefore, future research should build on these metrics to develop comprehensive SRN measurement tools. Another limitation is that our study focused on evaluating each SRN principle individually, rather than employing a full factorial design with eight conditions. In the absence of established SRN metrics, we adopted a more focused ranking method to provide an initial exploration into this space. As a result, future work is necessary to further validate the interplay between principles, expand our framework to other potential principles (e.g., politeness or comfort), test our system in more dynamic or crowded settings, and integrate richer measurements (e.g., comfort distances or eye tracking).

VII. Conclusion

We introduced the Overlapping Social Navigation Principles framework, which identifies social norms, perceived safety, and legibility as key SRN principles, with each influencing the others. Our findings show that effective SRN requires all three principles, with social norms having the greatest impact, particularly on perceived safety.Hence, SRN designers roboticists should prioritize social norms.

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