Evaluation of Proxemic Scaling Functions for Social Robotics

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***Abstract*—This paper introduces and empirically evaluates two scaling functions to alter a robot's physical movements based on proximity to a human. Previous research has focused on individual aspects of proxemics, like the appropriate distance to maintain from a human, but has not explored autonomous methods to adapt robot behavior as proximity changes. This paper proposes that robots in a social role should modify their behavior using a continuous function mapped to proximity. The method developed calculates a gain value from proximity readings, which is used to shape the execution of active behaviors on the robot. In order to identify the effects of different mappings from proximity to gain value, two different scaling functions were implemented on an affective search and rescue robot. The findings from a 72 participant study, in a high-fidelity mock disaster site, are examined with attention given to a new measure to determine proxemic awareness. The results indicated that for attributes of intelligence, likability, proxemic awareness, and submissiveness, a logarithmic-based scaling function is preferred over a linear-based scaling function, and over no scaling function. In areas of participant comfort and participant stress, the results indicated both logarithmic and linear scaling functions were preferred to no scaling.**

***Index Terms*—Human–robot interaction (HRI), human–robot proxemics, proxemics, social robots.**

I. Introduction

THE distance between two agents during an interaction, known as proxemics, is a fundamental principle of social interaction. Proxemics was first described by anthropologist Edward Hall, who characterized the changes in social behavior between humans as a function of physical distance [1]. Hall postulated that there is an interaction space surrounding a human and that this space could be divided into distinct proximity zones. Argyle in [2] formalized four proximity zones, shown in Fig. 1, and provided qualitative characterizations of how people modulated their behavior in each zone. For example, a human who is talking with another person from across the room (Public Zone) may gesture and talk loudly in order to communicate, but

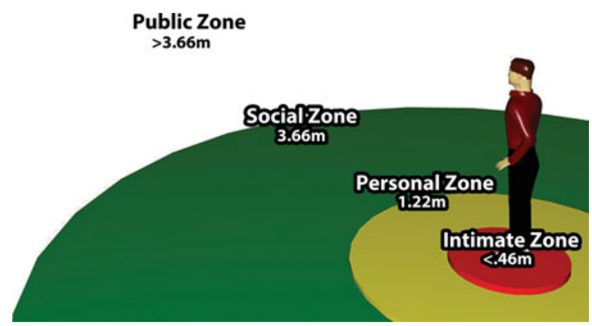

Fig. 1. Argyle's proximity zones.

as she enters the Personal Zone, her gestures and volume would significantly decrease in intensity. As another example, large or quick gestures which are acceptable in the Social Zone may be perceived as threatening or alarming in the Intimate Zone.

Proxemics has been shown to apply to human-agent and human-robot interactions (HRIs), consistent with Nass *et al.*'s Computers are Social Actors model where humans treat computers as if they were human [3]. The importance of proxemics for interactions between robots and humans has been documented and discussed in at least 25 papers dating from 1997 to the present [4]–[28]. Proxemics has proven to be expected and important across levels of human-likeness, indicating that both anthropomorphic and nonanthropomorphic robots benefit from observing proxemic standards. In 2010, Bethel and Murphy showed that two different nonanthropomorphic robots were perceived by study participants as more calming, friendly, and attentive when the robots' behaviors followed proxemic-based design guidelines to adapt body movement, posture, orientation, illumination, and sound rather than when operated in a faster, task-oriented manner without consideration of proxemics [8].

While previous research [8] established the need for proxemic scaling of a robot's behaviors, there remains a need to develop a mechanism for proxemic scaling that is generalizable to all robots and behaviors. Previous studies have focused on particular aspects of proxemics, such as appropriate distances to maintain from humans, appropriate approach angles, and learning a user's preferences concerning personal space [4], [7], [9], [10], [12]–[19], [24]–[28]. To develop a generalizable method of proxemic scaling of robot behaviors, a function needs to be implemented to scale the behaviors within a determined set of boundaries, based on distance readings between the agents, and the behaviors modified according to the proximity zone(s) involved. The research indicates that there is a strong need for a more complete understanding of proxemics as it relates to HRI. The design of a practical framework for the

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consistent implementation and modification of robot behaviors based on proximity would be beneficial to both the HRI and social robotics communities.

This paper proposes such a framework by addressing the following questions: *What is the most suitable continuous scaling function?* and *What is an operational architecture to map that function onto specific behaviors on a specific robot?* The paper posits that proxemic behaviors can be modeled as a single *continuous scaling function* which captures the change across three of the proximity zones, similar to the inverse square law from physics, which captures gravitational pull. This paper shows that visible factors which contribute to the robot's physical behavior in an environment must be considered when developing an operational architecture for proxemic scaling. These attributes include velocity of approach, velocity of joints involved in the behaviors, and the magnitude of affective expression for each joint. The article offers an *operational architecture*, or high-level descriptive architecture, following Levis *et al.* to generalize the process of transforming proximity into appropriate joint movements [29]. Two possible proximity-based scaling functions were identified as part of this research effort: 1) linear and 2) logarithmic. The developed high-level descriptive architecture, was implemented on a mobile robot with a robot head attached, and evaluated with 72 participants in a search and rescue scenario following a protocol established in [8].

The remainder of the article is organized as follows. Section II summarizes the related work in HRI to establish the state of the practice. Section III justifies the selection of two possible scaling functions—*linear* and *logarithmic*—and details the operational architecture. The implementation of proxemic scaling on the Survivor Buddy robot is captured in Section IV. Section V describes the details of an experiment conducted with 72 participants designed to evaluate each proxemic scaling function. The results in Section VI illustrate support for proxemic scaling functions with *logarithmic* scaling being rated as better or equal to *linear* scaling in all areas which were affected by proxemic scaling. The results and their implications are discussed in Section VII. Section VIII concludes that the while both *logarithmic* scaling and *linear* scaling have significant impacts on some ratings, in other factors, *logarithmic* scaling is preferred to *linear* and *no* scaling.

II. Related Work

A review of the prior HRI literature indicates that proxemics has been widely examined within HRI, with at least 22 studies investigating some aspect of proxemics. However, the modification of a robot's behaviors by using a continuous function of distance has not yet been examined.

The most studied attribute of proxemic behavior is determining the appropriate distance, angle, and speed for a robot to approach a person. However, existing work has established these parameters as constants, that do not change dynamically as the robot becomes closer to the human [4], [7], [9], [10], [12]–[19], [24]–[28]. Prior research has also examined learning these parameters for particular users over time, but again has not considered dynamically altering the parameters as a factor of distance [7], [14], [18], [24].

Three studies [4], [6], [8] have explored the effects of altering a robot's behavior based on proximity but have not produced a formal continuous proxemic scaling function or an operational architecture for proxemic scaling. Mizoguchi *et al.* [4] appears to be the first to alter the navigational velocity of a small mobile robot approaching a seated or standing person based on proximity. However, the study did not formalize a mathematical relationship between velocity and proximity. Several interactive, but statistically insignificant, trials showed that humans infer familiarity and intelligence from varying speed and proximity. Later, Tasaki *et al.* [6] changed a robot's sensory-motor modalities as a factor of the discrete proximity zone occupied by the human. In this set of experiments, if the person was located in the Public Zone, the robot would speak, act, and move toward the person. If the person was determined to be in the Social or Personal Zones, the robot would only speak and act or display behaviors toward the person, and when the person was located in the Intimate Zone with respect to the robot, it would only speak. Finally, Bethel *et al.* [8] showed that two different mobile robots that used prescriptive design guidelines for affective expression based on proximity zones were perceived as significantly more calming, friendly, and attentive in comparison with robots which did not follow guidelines based on proximity. In this study, a search and rescue robot approached a stationary participant (laying down) and followed either a stepwise prescriptive design to adapt its behavior, or performed at a constant rate. This is most similar to the study conducted in this paper, however this paper extends the prescriptive design guidelines into an operational architecture for autonomously scaling behavior based on proximity.

III. Approach

Combining prior psychological and HRI research, this paper posits that maintaining a *perceived consistent stimulus level* as the robot traverses proximity zones will produce the least amount of arousal, and produce a more positive interaction with the robot [30]. The general approach taken by this paper was to decrease the magnitude of the robot's actuation as the distance between the human and robot decreased, causing the stimulus level to be perceived as the same at all distances. The mapping of distance to control magnitude can be achieved using different methods; however for this research, three methods of mapping were examined: *logarithmic*, *linear*, and *no direct mapping*. These scaling functions were implemented in an operational architecture.

A. Choice of Representative Scaling Functions

Logarithmic and *linear* scaling functions were developed for the experimental evaluation of this project. Both captured the design recommendations developed by Bethel *et al.* [8], where the magnitude or intensity of body movement, posture, orientation, illumination, and sound decrease as the distance between the human and robot decreases. The *logarithmic* function was inspired by the *Weber–Fechner Law* of perception in

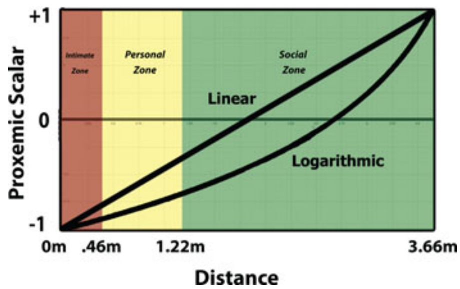

Fig. 2. Linear and logarithmic scaling functions over the standard relative distances for Western cultures [2].

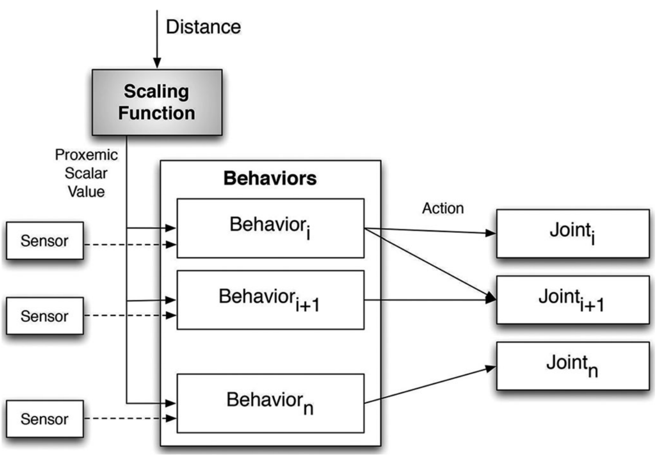

Fig. 3. Operational architecture for proxemic scaling.

Psychology, which states that *the perception of stimuli is logarithmically related to the magnitude of the stimuli* [30]. This was expected to be a good fit because of its basis in perceptual psychology. A *linear* function was also selected because of its wide appearance in linear interpolation and regression. The two scaling curves are illustrated in Fig. 2, note that scaling does not occur in the Public Zone and thus is not shown.

The logarithmic scaling function was represented by the base function $y = ln(x + a) + b$, where y was the proxemic scalar value and x was the distance between the robot and human. The variables a and b were selected depending upon the exact desired fit of the curve. For this experiment, the proxemic scalar value was bound between -1 and $+1$ and the distances between 0 and 3.66 m (the start of the Public Zone following [2]). Using these boundaries as endpoints, the scaling equation became $y = -ln(-x + 4.22) + .44$.

The linear function was represented by the base function $y = mx + b$, where y was the proxemic scalar value and x was the distance between the robot and human. Using the boundaries of $(3.66, 1)$ and $(0, -1)$ as endpoints, it was calculated that the scaling equation was $y = .55x - 1$.

B. Operational Architecture for Proxemics

The operational architecture for proxemics addresses the issue of scaling an arbitrary robot platform with multiple behaviors and degrees of freedom. Fig. 3 illustrates how the operational architecture scales behaviors, following general behavior-based robotics principles [31]. The *scaling function* module accepts the sensed *distance* from the human and computes the *proxemic scalar value*. The proxemic scalar value is passed to each behavior. Each behavior uses the scalar to modify its output *action*, which is executed on one or more joints or actuators. For example, a navigational behavior may use the proxemic scalar value to control the velocity of the wheels or tracks. However, the dimensions of actuation, which are informed by the proxemic scalar value, are not limited to simple velocities or ranges, but can also include factors such as the number of iterations. In the situation in which head nodding to indicate a "yes" response is required for an interaction, the behaviors in the Social Zone would require vigorous head nodding behaviors with a larger amplitude of head movement and possibly more repetitions or iterations compared with a "yes" response in the Intimate Zone.

This approach is generic in nature, as it allows the specifics of each robot and each robot behavior to be accounted for during the implementation phase. The architecture uses the scaling function to moderate the system-wide proxemic scalar value. This proxemic scalar value is then passed to each behavior, which may use its own means for interpreting it. The simplest form of interpreting the proxemic scalar value would be to use a direct or linear mapping. For example, if the bounded proxemic scalar value space were -1 to $+1$, a behavior should execute in its most restrictive form at -1 and in its most exaggerated form at $+1$.

IV. Implementation

The operational architecture for proxemic scaling was implemented on an expressive mobile robot to enable the experimentation described in Section V. The mobile robot platform consisted of a mobile inspection robot as a base and had a four degree of freedom robot "head" attached. The system could detect the relative distance between the robotic platform and the person and compute the proxemic scalar value to be used to modify the platform's behaviors with respect to the magnitude of its outputs. The combined robotic platform was capable of autonomous movement to a goal, could convert text to speech with the simultaneous generation of an appropriate engagement behavior (e.g., nodding up and down of the head while saying the word "yes").

A. Robot Platform

The robotic platform shown in Fig. 4 consisted of an Inuktun Extreme robot with a Survivor Buddy affective robot head and a Hokuyo laser-based proximity sensing package attached. The Inuktun VGTV Extreme platform is a tracked inspection robot with a maximum speed of 0.45 m/s. The Survivor Buddy 2.0 head uses a 7-inch MIMO 740 touchscreen monitor, webcam, microphone, and a speaker system mounted on a neck. It has four degrees of freedom that permits the head to pan, tilt, and roll while the neck is used to raise and lower the head. Mounting a Survivor Buddy head on the Extreme robot created a mobile head robotic platform. A Hokuyo URG-04LX laser range finder was also mounted on the Extreme to measure relative distance from the robot to the human. Control modules and the

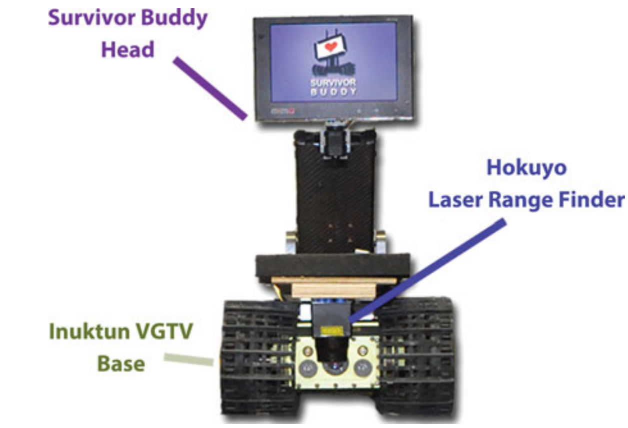

Fig. 4. Inuktun extreme and survivor buddy hardware platform.

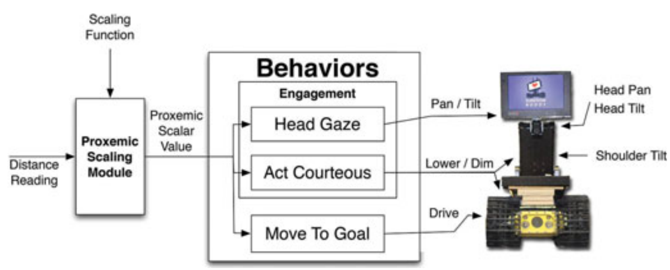

Fig. 5. Implemented behaviors and mapping onto joints and actuators.

operational architecture were implemented in $C\#$ using a Windows 7 environment.

B. Robot Behaviors and Proxemic Scaling

Three behaviors were implemented for evaluation purposes as shown in Fig. 5: *head gaze*, *act courteous*, and *move to goal*.

The *head gaze* and *act courteous* behaviors formed the more abstract social engagement behavior, while *move to goal* progressed the robot along its path. The *head gaze* behaviors are parallel to those used by humans during conversation (fixations and aversion based on dialogue) and are detailed by Cassell *et al.* [32]. A fixation is displayed by the robot's head looking directly at the user's face. An aversion is a slight glance (pan and tilt of the head) away from the fixation point. During face to face conversations, humans routinely use fixations and aversions. The *head gaze* behaviors implemented in this system were previously evaluated by Srinivasan and Murphy on the same robotic platform without proxemic scaling [33]. The robot was also capable of expressing explicit "yes" and "no" head gestures. The *act courteous* behavior refers to the robot using its neck to lower its head, and dimming its headlights. Fig. 6 shows snapshots of the robot's explicit head gestures and head lowering behavior across time.

The *head gaze* behavior actuated two of the Survivor Buddy joints, the head pan and head tilt. The *head gaze* behavior was scaled on the dimensions of speed and range. The behaviors were created by specifying a minimum and maximum speed (8 to 45 deg/sec) and range (8 to 30 deg) (as determined appropriate by a review of empirical human head gaze behavior studies

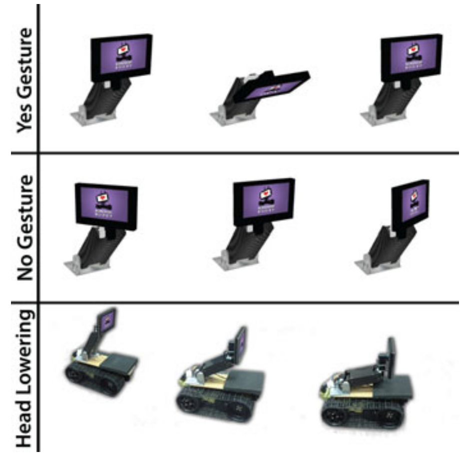

Fig. 6. Illustration of the robot's head movements.

conducted by Srinivasan and Murphy [33]). These values were set to correspond to the -1 and $+1$ proxemic scalar values, respectively, using a linear interpolation for values between these boundaries. It is important to note that although individual behaviors provide their own interpolation method for applying the proxemic scalar value, the proxemic scalar value itself is generated using a separate scaling function, which is the subject of this paper's investigation. The overall mapping for the *head gaze* behavior was ($[-1,+1] \rightarrow [8\text{ deg/sec}, 45\text{ deg/sec}]$) for speed and ($[-1,+1] \rightarrow [8\text{ deg}, 30\text{ deg}]$) for range of motion.

The *act courteous* behavior produced head lowering and head-light dimming actions. Acting courteous limited elevation of the robot's social status by having it reduce its physical height as it approached, a behavior that is often recognized as submissiveness [34]. The behavior was displayed by lowering the Survivor Buddy head and simultaneously adjusting the head tilt as the robot approached the human. The behavior was created by mapping -1 to a neck position of 5° and $+1$ to a position of 60° ($[-1,+1] \rightarrow [5\text{ deg}, 60\text{ deg}]$). These values were selected as they represent the hardware limitations of the robot, where 60° is fully raised position of the head, and 5° is the fully lowered position of the head. The velocity was set to a maximum of 25 deg/sec, as this is the maximum safe speed of the joint. These values were set to correspond to the -1 and $+1$ proxemic scalar values, respectively, using a linear interpolation for values in between these endpoints. The head-light dimming feature mapped a lighting intensity value of 5% to -1 and 100% to $+1$ ($[-1,+1] \rightarrow [5\%, 100\%]$). These values represent the lowest setting that allows illumination and the highest setting of the headlights respectively. The values between -1 and $+1$ were calculated using a linear interpolation.

A *move to goal* behavior was designed for the base Extreme robot, to allow the robot to move toward the human participant. This behavior constrained the velocity of the Extreme base robot. The behavior mapped the -1 proxemic scale value to $.1$ m/s and $+1$ proxemic scale value to $.45$ m/s ($[-1,+1] \rightarrow [.1, .45]$). These values correspond to the lowest speed possible and the highest speed possible. In order to

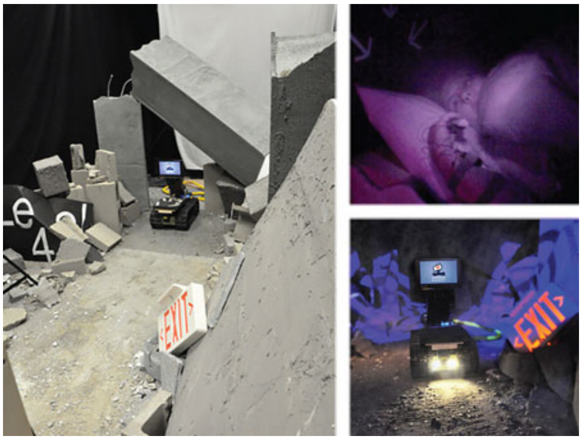

Fig. 7. Simulated disaster site.

determine the speeds for values between -1 and $+1$ a linear interpolation was used.

V. Experiments

An experiment was designed to evaluate the *linear* and *logarithmic* scaling functions against the *no-scaling* condition using 72 participants. Three hypotheses concerning the impact of proxemic scaling were formed, and 13 measures were used to evaluate the impact of proxemics on the participant's overall impression of the robot.

A. Hypotheses

Based upon the review of the literature presented in Section II, three hypotheses were formed:

1) *H1: Participants will rate a robot that uses proxemic scaling as having better performance than one that does not.*
2) *H2: Participants will rate their experience as more favorable for a robot that uses proxemic scaling, in comparison with one that does not.*
3) *H3: Participants will rate the performance of a robot that follows*logarithmic*scaling higher in comparison with a robot that follows a*linear*scaling or*no-scaling*method.*

B. Experimental Design

A 1×3 between-participants study was designed to compare three conditions: *no-scaling* (control condition, proxemic scalar value $= 0$), *linear* scaling, and *logarithmic* scaling. The *no-scaling* condition was selected to represent the way robots have traditionally been operated. The possibility of other scaling functions is discussed further in Section VII-C. The experimental scenario was a search and rescue situation, high-fidelity physical simulation of a disaster and is an extension of [8], which illustrated that an extreme setting may invoke responses from participants. The "trapped" participant to be rescued was placed in a moderately confined area inside a small darkened lab outfitted as a parking garage collapse site with realistic collapsed concrete columns and parking garage floors, as well as prop concrete, rebar, and glass debris (see Fig. 7). The environment was equipped with a full theatrical stage lighting system in order to provide optimal visibility without sacrificing a lifelike effect. Hidden barriers ensured that collision with the participant was not possible. The robot approached the participant to relay information about the disaster and to elicit the participant's health status following 911 and medical triage protocols. The robot used a synthetic voice, changed navigational movements, engagement behaviors, and illumination based on its proximity to the participant.

C. Experimental Measures

The study used preinteraction and postinteraction questionnaires to evaluate the robot. The preinteraction questionnaires consisted of a State Trait Anxiety Inventory [35], Big 5 Personality Traits [36], and 14 demographic questions. The postinteraction questionnaires consisted of a State Trait Anxiety Inventory and a set of questions targeting nine attributes of perceived robot performance and four attributes of the participant's experience. With the exception of the proxemic awareness measure and submissiveness item (expected effect from head-lowering behavior), which were developed as part of this research effort, all items were obtained from previous HRI studies and were grouped together through subjective interpretation [8], [37], [38]. These areas were selected as they had proven important in prior HRI studies and were applicable to human–robot proxemics. The STAI was performed to ensure participants exited the study with a similar level of anxiety as they entered the study, and was not evaluated as part of the findings. The Big 5 Personality Traits questionnaire was obtained from a previous HRI study and included 30 words that participants rated on a one to seven scale as describing or not describing themselves [37]. Most of the questions were based on a one to seven point scale with the exception of the Self-Assessment Manikin [39], which was on a one to nine point scale. Some questions used a Semantic Differential format; however, most questions used a Likert scale format with one indicating strong disagreement or strongly negative and seven indicating strong agreement or strongly positive. Attributes that were measured with multiple items were checked for internal consistency using a robust *Cronbach's Alpha* statistic (where $\alpha < .70$ is inconsistent) [40]. Several questions were coded in reverse order to prevent participants from uniformly selecting a single rating. The following measures were included:

1) Comfort: Comfort was measured as the index of three items.

a) The robot made me nervous. (Reverse Coded).
b) The robot made me feel relaxed.
c) Agitated/Comforted Self-Assessment Manikin (Adjusted to 7 point scale).

The index's interreliability was measured using a robust *Cronbach's Alpha* ($\alpha = 0.70$).

2) Empathy: Empathy was measured as the index of six items:

a) How inattentive/attentive was the robot?
b) The robot was focused on me.
c) The robot saw the situation from my perspective.
d) The robot was concerned about me.
e) The robot was oblivious to my emotional state. (Reverse Coded)

f) The robot was empathetic.

Cronbach's Alpha ($\alpha = 0.75$).

3) Experienced enjoyment: Experienced enjoyment was measured as the index of four items:

a) How much did you like the experience?
b) How willing would you be to do this again?
c) How dissatisfied/satisfied were you?
d) How bored/interested were you?

Cronbach's Alpha ($\alpha = 0.80$).

4) Groupness: Groupness was measured by a single item, which graphically illustrated the overlap between participant and robot, obtained from [38].

5) Human-like appearance: Human-like appearance was measured by a single item, which asked:

a) How human-like did the robot look?

6) Intelligence: Intelligence was measured as the index of three items:

a) How ignorant/knowledgeable was the robot?
b) How intelligent/unintelligent was the robot?
c) The robot was aware of its surroundings.

Cronbach's Alpha ($\alpha = 0.93$).

7) Likability: Likability was measured using a single item, which asked:

a) How much did you like the robot?

8) Personableness: Personableness was measured as the index of five items:

a) How depressed/cheerful was the robot?
b) How unfriendly/friendly was the robot?
c) How pessimistic/optimistic was the robot?
d) How unhappy/happy was the robot?
e) The robot had a personality.

Cronbach's Alpha ($\alpha = 0.68$).

9) Positive outlook: Positive outlook was measured as the index of two items:

a) Positive/Negative Self-Assessment Manikin;
b) Hopeful/Despairing Self-Assessment Manikin.

Cronbach's Alpha ($\alpha = 0.80$).

10) Proxemic awareness: The Proxemic awareness measure was developed for this study, and was measured as the index of nine items:

a) How considerate of personal space was the robot?
b) How aware was the robot of its proximity to you?
c) How comfortable were you with the speed at which the robot moved toward you?
d) How comfortable were you with the speed at which the robot moved its head?
e) How much did the robot obey social standards while interacting with you?
f) How much control of its movement did the robot have?
g) The robot moved too quickly. (Reverse Coded)
h) The robot was sluggish. (Reverse Coded)
i) The robot moved naturally.

Cronbach's Alpha ($\alpha = 0.83$).

11) Stress: Stress was measured as a single item, which asked:

a) To what extent did you feel stressed?

12) Submissiveness: Submissiveness was measured as a single item, which asked:

a) How submissive was the robot?

13) Trust: Trust was measured as the index of four items:

a) How trustworthy was the robot?
b) How foolish/sensible was the robot?
c) I would be bothered if the robot touched me.
d) The robot would not hurt me.

Cronbach's Alpha ($\alpha = 0.63$). Note this is below the threshold of .70 for consistency within the group.

D. Experimental Method

The experiment consisted of four stages: 1) participant check in and pre-interaction questionnaires, 2) preinteraction arousal (viewing of parking garage collapse video), 3) interaction with the robot, and 4) postinteraction questionnaires. Of these, stages 2 and 3 merit further description.

In the *preinteraction arousal* stage, the participants were asked to stand in an area where a curtain obscured the simulated disaster site. The lights in the area were turned off and the participant was asked to move the curtain aside and lay down on their right side in an area which measured 3 ft $\times$ 3 ft $\times$ 8 ft and was enclosed on all but one side. This aligned the participants head with the soon to be approaching robot. A small hidden barrier, coupled with a slight elevation prevented the robot from being able to physically collide with the participant, but maintained the illusion that collision was possible from the participant's point of view. The participant was covered with a sleeping bag, then shown a brief dramatic video, which depicted a first person view of a parking garage collapse. Flashes of light followed by lighting sufficient to see the robot, were activated during the collapse sequence of the video, which allowed the simulated disaster site and the robot to become visible to the participant.

The preinteraction arousal and interaction with the robot lasted approximately 10 to 13 min, depending on the speed of responses from the participant. A robot operator oversaw the experiment and triggered the next step in the script, but the robot generated the synthetic speech, engagement and navigational behaviors, and proxemic scaling autonomously. The robot used its laser range finder to measure the distance from the participant's chest (the participant laying on their right side) to the robot. The robot approached the participant in stages and conducted a dialog with engagement behaviors in each of the three proximity zones (as shown in Fig. 8) and had physical contact with the participant in the Intimate Zone. The robot started at the boundary of the Public and Social Zones, 3.66 m away from the participant. It stopped at 2.44 m (the middle of the Social Zone), 1.22 m (the boundary of the Social and Personal Zones), 0.84 m (the middle of the Personal Zone), and between 0.3 to 0.1 m (depending on physical ability) from the participant (Intimate Zone). Prior to the first movement toward the participant, the robot verbally warned the participant that it would be moving toward them. The robot spent approximately two minutes at each distance and performed head gaze acts as well as fixations on objects in the scene, providing coverage of the known social contexts, as described in [33]. At the last position, the robot asked the participant to place their hand on

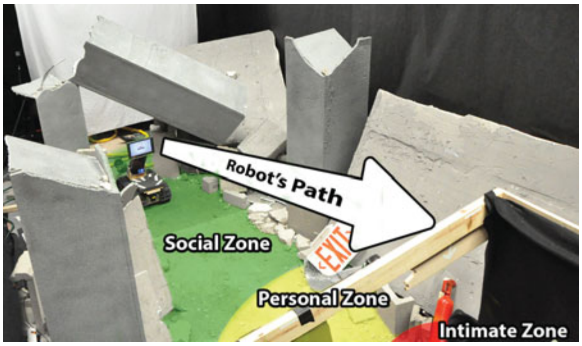

Fig. 8. Robot's path.

the base of the robot, with the premise of checking vital signs. The interaction concluded with the participant being told the rescuers had arrived, and the Survivor Buddy head closing on the base to signify no further engagement.

E. Participants

A total of 72 participants (41 male, 31 female) took part in the study. Participants were drawn from a campus-wide email invitation to students, staff, and faculty at Texas A&M University's College Station campus. Participants ranged in age from 18 to 65 years ($M = 27.92$, $SD = 11.14$). Participants had a wide range of occupations including students, technicians, professors, administrative staff, medical professionals, engineers, librarians, and firefighters. The ethnic backgrounds of participants consisted of 58% Caucasian, 23% Asian, 8% Hispanic, 5% African American, 4% Middle Eastern, and 4% American Indian. Using a one to seven scale, participants answered several demographic questions. On average, participants rated their experience with computers as 5.5 ($SD = 1.05$). Video game experience among participants was moderate, with a mean of 4.33 ($SD = 1.79$). Robot experience was low with a mean of 2.44 ($SD = 1.43$). Of the 72 participants, 43 reported interacting with pets on a regular basis. Enthusiasm for robots among participants was moderate ($M = 5, SD = 1.27$). Additionally, most participants indicated beliefs that robots would play a large role in the future ($M = 6.03, SD = 0.86$).

VI. Experimental Results

As a result of the study, 72 evaluations of the robot, 24 for each condition, were analyzed. The analysis indicated partial support for H1, H2, and H3. Six of the thirteen measures (Intelligence, Likability, Proxemic Awareness, Submissiveness, Comfort, and Stress) were found to be significantly impacted by proxemic scaling, with *logarithmic* scaling impacting all six areas, while *linear* scaling impacted four of the areas.

A. Data Analysis

The data was first analyzed for normality among each condition for each measure using the Shapiro–Wilk test [40]. Each of these tests indicated a significant deviation from normality, requiring the use of robust statistical tests for further analysis. A

TABLE I
Means and Standard Deviations for Each Attribute and Condition

	Attribute	No Scaling	Linear	Logarithmic
Perceived Robot Performance	Empathy	$M = 5.33$ $SD = .81$	$M = 5.42$ $SD = .96$	$M = 5.43$ $SD = .97$
	Groupness	$M = 2.88$ $SD = .80$	$M = 3.08$ $SD = .72$	$M = 3.67$ $SD = 1.09$
	Human-like Appearance	$M = 2.42$ $SD = 1.28$	$M = 2.38$ $SD = 1.41$	$M = 2.46$ $SD = 1.50$
	Intelligence	$M = 5.19$ $SD = 1.24$	$M = 5.81$ $SD = 1.22$	$M = 6.35$ $SD = .63$
	Likability	$M = 5.5$ $SD = 1.32$	$M = 5.88$ $SD = 1.3$	$M = 6.5$ $SD = .88$
	Personableness	$M = 5.59$ $SD = .74$	$M = 5.48$ $SD = .72$	$M = 5.82$ $SD = .62$
	Proxemic Awareness	$M = 4.98$ $SD = .64$	$M = 5.61$ $SD = .83$	$M = 6.23$ $SD = .53$
	Submissiveness	$M = 4.21$ $SD = .98$	$M = 4.92$ $SD = 1.35$	$M = 6.17$ $SD = 1.27$
	Trust	$M = 5.62$ $SD = .95$	$M = 5.66$ $SD = 1.05$	$M = 6.17$ $SD = .87$
Participant's Experience	Comfort	$M = 4.78$ $SD = .80$	$M = 5.44$ $SD = .57$	$M = 5.70$ $SD = .74$
	Enjoyment	$M = 6.16$ $SD = .78$	$M = 6.26$ $SD = .89$	$M = 6.39$ $SD = .75$
	Positive Outlook	$M = 7.4$ $SD = 0.81$	$M = 7.75$ $SD = 0.91$	$M = 7.77$ $SD = 0.85$
	Stress	$M = 3.29$ $SD = 1.04$	$M = 2.38$ $SD = 1.24$	$M = 1.71$ $SD = 1.30$

robust ANOVA (bootstrap of 2000) was performed to observe the effect of scaling condition on the dependent variables. A posthoc analysis was conducted for the results of the ANOVA using Tukey's HSD. In order to further account for other sources of variance, a robust ANCOVA was performed to observe the effects of scaling condition, while accounting for potential covariates (like personality, gender, age, etc.).

Table I reports the means and standard deviations for each group and measure, while Table II indicates the results from the F-tests, the significance values, and the effect sizes from the ANOVA. Additionally, comparison results with significance values and effect sizes using Cohen's d are presented for those comparisons that had significant results. Section VI-D details the covariates and their significance and effect size values (as Cohen's $\hat{f}$). Cohen's $\hat{f}$ and Cohen's d effect sizes are interpreted by the following scales:

Effect Size	Cohen's $\hat{f}$	Cohen's d
Small	0.10 - 0.24	0.20 - 0.49
Medium	0.25 - 0.39	0.50 - 0.79
Large	0.40+	0.80+

TABLE II
SIGNIFICANCE VALUES AND EFFECT SIZES BASED ON THE ANOVA AND FOLLOW-UP TUKEY TESTS FOR PAIRWISE COMPARISONS

	Attribute	No v Lin	No v Log	Lin v Log
Perceived Robot Performance	Empathy $F(2,57) = 0.36$ $p = .70$	$t(57) = .52$ $p = .86$	$t(57) = -.42$ $p = .91$	$t(57) = -.84$ $p = .68$
	Groupness $F(2,57) = 2.11$ $p = .13$	$t(57) = 1.54$ $p = .27$	$t(57) = 1.85$ $p = .15$	$t(57) = .59$ $p = .82$
	Human-like Appearance $F(2,57) = 1.11$ $p = .34$	$t(57) = -.65$ $p = .79$	$t(57) = .91$ $p = .64$	$t(57) = 1.49$ $p = .30$
	Intelligence $F(2,57) = 6.03$ $p = .004, \hat{f} = .37$	$t(57) = 1.98$ $p = .12$	$t(57) = 3.44$ $p = .002$ $d = .91$	$t(57) = 1.1$ $p = .51$
	Likability $F(2,57) = 9.02$ $p < .001, \hat{f} = .47$	$t(57) = 2.1$ $p = .08$	$t(57) = 3.76$ $p < .001$ $d = 1.0$	$t(57) = .78$ $p = .71$
	Personableness $F(2,57) = 0.43$ $p = .65$	$t(57) = -.42$ $p = .91$	$t(57) = .11$ $p = .99$	$t(57) = .89$ $p = .64$
	Proxemic Awareness $F(2,57) = 30.5$ $p < .001, \hat{f} = .91$	$t(57) = 3.8$ $p < .001$ $d = 1.01$	$t(57) = 7.81$ $p < .001$ $d = 2.07$	$t(57) = 2.86$ $p = .01$ $d = .76$
	Submissiveness $F(2,57) = 30.43$ $p < .001, \hat{f} = .90$	$t(57) = 2.77$ $p = .02$ $d = .73$	$t(57) = 7.73$ $p < .001$ $d = 2.05$	$t(57) = 3.9$ $p < .001$ $d = 1.03$
	Trust $F(2,57) = 0.09$ $p = .92$	$t(57) = .23$ $p = .97$	$t(57) = .42$ $p = .91$	$t(57) = .06$ $p = .99$
Participant's Experience	Comfort $F(2,57) = 11.73$ $p < .001, \hat{f} = .55$	$t(57) = 3.55$ $p < .001$ $d = .94$	$t(57) = 4.04$ $p = .001$ $d = 1.07$	$t(57) = .13$ $p = .99$
	Enjoyment $F(2,57) = 0.52$ $p = .95$	$t(57) = -.27$ $p = .96$	$t(57) = .17$ $p = .98$	$t(57) = .3$ $p = .95$
	Positive Outlook $F(2,57) = 2.42$ $p = .10$	$t(57) = 1.92$ $p = .13$	$t(57) = .001$ $p = .99$	$t(57) = -2.04$ $p = .10$
	Stress $F(2,57) = 29.79$ $p < .001, \hat{f} = .90$	$t(57) = -2.68$ $p = .02$ $d = -.71$	$t(57) = -7.7$ $p < .001$ $d = -2.04$	$t(57) = -1.99$ $p = .11$

Grey highlights indicate statistical significance.

TABLE III
CORRELATIONS BETWEEN PARTICIPANT TRAITS AND DEPENDENT VARIABLES

Participant Trait	Corr. Direction	Correlated Variable
Robot's Role In Future $F(1,57) = 4.8, p = .03$	Positive $\hat{f} = .08$	Enjoyment
Robot's Role In Future $F(1,57) = 18.43,\ p < .001$	Negative $\hat{f} = .32$	Stress
Agreeableness $F(1,57) = 7.43,\ p = .009$	Positive $\hat{f} = .13$	Robot Intelligence
Agreeableness $F(1,57) = 7.77,\ p = .007$	Positive $\hat{f} = .14$	Enjoyment
Conscientiousness $F(1,57) = 18.37,\ p < .001$	Positive $\hat{f} = .32$	Comfort
Conscientiousness $F(1,57) = 5.43,\ p = .02$	Positive $\hat{f} = .10$	Positive Outlook
Conscientiousness $F(1,57) = 6.8,\ p = .01$	Negative $\hat{f} = .12$	Stress
Female $F(1,57) = 12.81,\ p < .001$	Positive $\hat{f} = .23$	Robot Intelligence
Male $F(1,57) = 4.8,\ p = .03$	Positive $\hat{f} = .08$	Stress

B. Scaling Preferred To No-Scaling

The data provides partial support for H1, which states: *Participants will rate a robot which uses proxemic scaling as having better performance than one which does not*. In the attributes of Submissiveness and Proxemic awareness, the data indicated a significant preference for the *logarithmic* condition in comparison with the *no-scaling* and *linear* conditions. For the attributes of Intelligence and Likability, only *logarithmic* scaling showed significant improvements in ratings. In the attributes of Empathy, Groupness, Human-like appearance, Personableness, and Trust, proxemic scaling did not have a significant effect. Further research needs to be performed related to Trust and Personableness due to a lack of reliability in Cronbach's Alpha related to these attributes.

The data also lends partial support to H2, which states: *Participants will rate their experience as more favorable for a robot which uses proxemic scaling, in comparison with one that does not*. Ratings of Comfort and Stress indicated significant differences in the *linear* scaling and *logarithmic* scaling conditions in comparison with the *no-scaling* condition. The areas of Enjoyment and Positive outlook were not significantly affected by proxemic scaling.

C. Logarithmic Scaling

The results indicated partial support for H3 (*Participants will rate the performance of a robot which follows logarithmic scaling higher in comparison with a robot which follows a linear scaling or no-scaling method*). The data showed that when proxemic scaling was significantly preferred to no-scaling, the *logarithmic* condition was either comparable to the *linear* case, or significantly better than the *linear* case. In the areas of Intelligence and Likability, *logarithmic* scaling was significantly better than *no*-scaling and no difference was indicated between the use of *linear* scaling versus *no*-scaling. For the attributes of

Proxemic awareness and Submissiveness of the robot, *logarithmic* scaling was preferred over the linear scaling and no-scaling conditions.

D. Covariate Influence on Measured Attributes

A total of 12 traits (Gender, Age, Education Level, Time with Pets, Conscientiousness, Agreeableness, Introversion, Computer Experience, Robot Experience, Video Game Experience, Enthusiasm for Robots, and Robot's Role in the Future) were considered as potential covariates to the primary factor of scaling condition. Table III details the correlations identified between participant traits and dependent variables.

VII. Discussion

The results indicate that while the choice of proxemic scaling function may not impact the participant's interpersonal relationship with the robot, it does impact the degree of competence attributed to the robot. Additionally, evaluations of the robot were found to be correlated with the participant's beliefs about the role of robots in the future, personality traits, and gender. While alternative scaling functions are possible, prior work in perceptual Psychology highlights the importance of the *logarithmic* function [30]. Although this study was performed in the US&R domain, it is expected to generalize to other social interaction domains where the robot is given ample social attention.

A. Scope and Importance of Proxemic Scaling

This study focused on obtaining a continuous function to map proxemic behavior, while previous studies have focused on discrete zone-specific behaviors [8]. This study did not compare using discrete heuristic-based zone behavior to scaled continuous behavior, instead it compared continuous scaling functions. However, as noted in Section III, the behavior of the robot in both *logarithmic* and *linear* conditions meets the heuristics of zone-specific behavior derived from Argyle by Bethel. Therefore, this work is an extension of zone-specific heuristic-based approaches. The effects observed are a combination of using Argyle's zones and a scaling function across those zones.

The results suggest that the choice of proxemic scaling function impacts the degree to which the robot is perceived as a competent agent, but may not heavily influence the participant's interpersonal relationship with the robot. Attributes of empathy, groupness, personableness, and trust were not affected by the proxemic scaling condition. Proxemic scaling was determined to be beneficial for the perception of robot intelligence, likability, and submissiveness and aids in proxemic awareness. The proxemic scaling conditions did affect the participants' comfort and stress levels, indicating that proxemic scaling does extend beyond the direct evaluation of the robot.

Proxemic scaling functions may not facilitate all aspects of a HRI, but if not used at all, or poorly designed, it could have a negative impact on social interactions. It is not surprising that the *logarithmic* scaling function was more effective for some aspects of perceived robot performance, as it corresponds to the profile of phenomena following the *Weber–Fechner Law* observed in the natural world [30]. The findings presented also indicate that for comfort and stress, any type of scaling was more favorable than no scaling. This illustrates the importance of including some form of proxemic scaling when designing social robots.

B. Effects of Participant Traits on Evaluations

Participants who rated robots as *having a large role in the future* reported higher Enjoyment levels and lower Stress levels when interacting with the robot. It is possible that participants who felt robots had a larger role in the future also felt confident about the abilities of robots, which was then projected onto the robot, and led to an increased sense of well-being during the interaction. It is recommended that this question be included in future studies to examine other possible covariate effects.

Overall, *agreeableness* was found to be correlated with Perceived Intelligence and Enjoyment. A potential explanation is found in the idea that more agreeable personalities will be more likely to provide higher ratings of an interaction scenario. *Conscientiousness* was correlated with increases in Comfort, increases in Positive outlook, and decreases in Stress potentially indicating that participants with higher self-evaluations of conscientiousness were more likely to be hopeful, regardless of proxemic scaling condition.

The gender covariate results indicated a correlation between the male gender and increased stress. However, female participants showed a correlation with attributing more Intelligence to the robot than males. It is possible that the attribution of higher Intelligence to the robot aided in decreased Stress levels. Surprisingly, no significant covariate effects were found based on the amount of time participants spent with pets.

C. Potential for Other Scaling Functions

Although the *logarithmic* curve (ProxemicScalar $= -ln$ $(-\text{distance} + 4.22) + .44$) was evaluated positively for measures which were affected by proxemic scaling, there is the potential that different parameters, a different function, or having a unique function for each affective expression could elicit even better responses from participants. For example, a related function of the *Weber–Fechner Law*, discussed in Section III-A, is *Steven's Power Law*, which might allow for more fine grained control of proxemic scaling. Steven's Power Law is defined as magnitude $= kI^a$ (k being a proportionality constant), which allows for a wide range of exponents, a, depending on the sensation type, which could lead to a different type of curve which is not purely logarithmic. A list of a values is currently known for many sensation types. For example, the a value for brightness is .33, while the value for electric shock is 3.5. Additionally, although not explored in this paper, other functions like a sigmoid or logistic function may prove to be favorable in comparison with a simple linear function.

In addition to choice of scaling function, a choice between continuous and discrete or step-wise functions can also be made. Bethel *et al.* [8] illustrated using proxemic heuristics (i.e., a step function) to adjust a robot's actuation was favorable to a constant-level function. It is also possible that different continuous functions apply to different portions of proxemic space.

D. Generalizability to Environments, Tasks, Robots, and Populations

Additional research is needed to confirm that the results found in this study are generalizable to other environments, tasks, robots, and populations. The search and rescue scenario used in this study has the benefit of focusing ample attention on the robot, making social engagement with the robot pivotal to success in the scenario. For this reason, this paper is likely most generalizable to scenarios in which the robot is given ample social attention and is a critical social player in the scenario.

This study investigated a ground robot approaching a human. Other scenarios could include a human approaching a ground robot, or another type of robot [e.g., unmanned aerial vehicle (UAV)] approaching or being approached by a human. While it is expected that the framework of Argyle's proxemic zones will generalize to most ground robot scenarios, the transitions between zones and use scaling functions are the subject of further validation. Proxemic scaling may also be useful for nonground robots, like UAVs, however it is likely that human perception of these types of robots is sufficiently distinct enough to require different scaling functions. In addition, constraints and variations on the type of motion displayed by other robots (e.g., angular velocity) will likely influence the choice of proxemic scaling function.

VIII. CONCLUSION

This paper investigated the choice of a single, continuous scaling function to duplicate human–human proxemic effects for human–robot interaction and found that employing a *logarithmic* scaling function based on the proximity of a robot from a human during interactions was shown to be favorable to *linear* or *no* scaling for measures of Intelligence, Likability, Proxemic awareness, and Submissiveness. Furthermore, the use of either *logarithmic* or *linear* scaling functions based on proxemics leads to significantly higher ratings in areas of Proxemic awareness, Submissiveness, Comfort, and decreased Stress. Furthermore, These ratings were obtained from a demographically diverse set of 72 participants in a realistic search and rescue scenario.

As likability often shapes a persons overall evaluation of another agent, robot designers are likely to find employing the *logarithmic* scaling function advantageous [41]. Furthermore, since participants prefer a machine to match their level of submissiveness [42], these results offer insight into the level of submissiveness obtained by each of the scaling functions, with *logarithmic* being evaluated as the most submissive. In the area of intelligence, which is commonly an evaluation of the agents competence [43], the *logarithmic* scaling function elicited higher ratings of robot intelligence, indicating the importance and power of using proximity-based scaling of nonverbal behaviors.The favorable ratings for the logarithmic scaling function, based on the *Weber–Fechner* law highlights the relationship of the human–robot interaction to the psychology of perception and the benefits for the human–robot interaction.

The identification of a single, continuous proxemic scaling function enables the autonomous generation of replicable proximity-based behaviors for Wizard of Oz studies, teleoperation, animatronics, and puppetry. The *operational architecture for proxemic scaling*, developed as part of this research effort to generate appropriate proximity-based behaviors, allows critical aspects of social interaction to be managed autonomously. The operational architecture illustrates how a single scaling function can be used within a standard behavioral robotics framework to modify multiple behaviors on robots with one or more joints or actuators.

Findings based on specific traits of the participants contribute to the broader implications of proxemics in human–robot social interaction. Participants who saw robots as having a large role in the future enjoyed their experience with the robot more, and experienced decreased stress. The study also contributes to improving HRI research methods by showing the need to incorporate proxemics into social interaction experiments, determining which attributes are useful for what effects, and identifying useful demographic questions. This research demonstrates that the use of proxemics influences the perception of the robot's social competence; therefore, an HRI experiment in which the robot does not behave in a manner consistent with proxemic guidelines may negatively confound research findings. This paper demonstrates that proxemic scaling can be incorporated into an autonomous robot in a consistent, replicable manner using the operational architecture for proxemic scaling.

The study raises new research questions. While the single *logarithmic* scaling function for all affective expressions (movement, pose, illumination, sound, etc.) appears sufficient to support favorable evaluations of the robot, using a family of functions tailored for each expression may produce even better results.

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