Human social motor solutions for human–machine interaction in dynamical task contexts

Patrick Nalepka, Maurice Lamb, Rachel W. Kallen, Kevin Shockley, Anthony Chemero, Elliot Saltzman, and Michael J. Richardson

*Centre for Elite Performance, Expertise and Training, Macquarie University, Sydney, NSW 2109, Australia; †Department of Psychology, Macquarie University, Sydney, NSW 2109, Australia; ‡Center for Cognition, Action & Perception, Department of Psychology, University of Cincinnati, Cincinnati, OH 45220; §Department of Physical Therapy & Athletic Training, Sargent College of Health & Rehabilitation Sciences, Boston University, Boston, MA 02215; and ¶Haskins Laboratories, New Haven, CT 06511

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Multiagent activity is commonplace in everyday life and can improve the behavioral efficiency of task performance and learning. Thus, augmenting social contexts with the use of interactive virtual and robotic agents is of great interest across health, sport, and industry domains. However, the effectiveness of human-machine interaction (HMI) to effectively train humans for future social encounters depends on the ability of artificial agents to respond to human coactors in a natural, human-like manner. One way to achieve effective HMI is by developing dynamical models utilizing dynamical motor primitives (DMPs) of human multiagent coordination that not only capture the behavioral dynamics of successful human performance but also, provide a tractable control architecture for computerized agents. Previous research has demonstrated how DMPs can successfully capture human-like dynamics of simple nonsocial, single-actor movements. However, it is unclear whether DMPs can be used to model more complex multiagent task scenarios. This study tested this human-centered approach to HMI using a complex dyadic shepherding task, in which pairs of coacting agents had to work together to corral and contain small herds of virtual sheep. Human–human and human–artificial agent dyads were tested across two different task contexts. The results revealed (i) that the performance of human–human dyads was equivalent to those composed of a human and the artificial agent and (ii) that, using a “Turing-like” methodology, most participants in the HMI condition were unaware that they were working alongside an artificial agent, further validating the isomorphism of human and artificial agent behavior.

Significance

Human–machine interaction (HMI) is becoming ubiquitous within today’s society due to rapid advances in interactive virtual and robotic technologies. Ensuring the real-time coordination necessary for effective HMI, however, requires both identifying the dynamics of natural human multiagent performance and formally modeling those dynamics in ways that can be incorporated into the control structure of artificial agents. Here, we used a dyadic shepherding task to demonstrate that the dynamics of complex human multiagent activity cannot only be effectively modeled by means of simple, environment-coupled dynamical motor primitives but that such models can be easily incorporated into the control structure of artificial agents to achieve robust, human-level HMI performance.

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Data deposition: The code for the shepherding task, sheep dynamics, and artificial agent model has been deposited in GitHub, https://github.com/MultiagentDynamics/Human-Machine-Shepherding. The data reported in this paper have been deposited in the Open Science Framework, https://osf.io/ke6mv.

1To whom correspondence may be addressed. Email: patrick.nalepka@mq.edu.au or michael.j.richardson@mq.edu.au.

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DMPs for Complex Multiagent Tasks: A Shepherding Example

Previous research modeling and designing artificial systems utilizing DMPs has focused on either nonsocial or minimally goal-directed task contexts (although refs. 42 and 49 discuss modeling more complex task contexts). The aim of this work was to expand the feasibility of DMPs for HMI by demonstrating the effectiveness of such an approach within the context of a complex, goal-directed multiagent task. An excellent paradigmatic example of multiagent activity found in several species is group coralling and containment, which is oftentimes seen in animal shepherding and hunting behavior (50–52). Such shepherding and containment behavior require the coordination of multiple coactors to control a dynamically changing environment (e.g., the containment of herds of animals or fleeing prey). To solve the task, coactors must divide the task space appropriately and switch between multiple behavioral modes depending on changing environmental states (e.g., transitioning between prey pursuit and herd containment). Such behavior is not only necessary for the survival of certain predators but has applications in robotic crowd control, security, and environment hazard containment systems (52–55). Furthermore, parallels can be made to other human group behaviors, such as military and team sports performance that requires problem solving and decision making among multiple actors.

Human dyadic shepherding has been recently investigated as a paradigmatic example of complex goal-directed dyadic coordination in our previous work (19). Inspired by previous work utilizing a single-player object control task (56), the shepherding task required human dyads, standing on opposite sides of a game field projected on a tabletop display, to cooperatively herd, corral, and contain simulated “sheep” agents (rolling brown spheres) within a predefined target region (the red circles in Fig. 1 A and B). The participants controlled virtual “sheepdogs” (blue and orange cubes...
in Fig. 1A and B) using a handheld motion sensor. Sheep movement entailed both stochastic and deterministic qualities. When left undisturbed, each sheep would exhibit Brownian motion, randomly rolling around the game field. However, when a participant’s hand/sheepdog came within a specific distance of the sheep, the sheep would react by moving in the opposite direction, away from the participant’s hand/sheepdog location. The level of task difficulty was manipulated by changing herd size (i.e., three, five, or seven sheep), with participants given the task goal of keeping the sheep within the target region for as long as possible during 1-min trials. A successful trial was defined to have occurred if participants were able to contain the sheep for 70% of the last 45 s of each trial (i.e., 31.5 s within the last 45 s). Finally, task failure was also defined to occur (and trials ended early) if any one of the sheep were outside the target containment region, COC behavior results.

**This Study**

Across two experiments, this study tested whether low-dimensional models consisting of fixed point and limit cycle DMPs can, when embodied in the control architecture of a virtual avatar working alongside human novices, achieve robust HMI in more complex, goal-directed multiagent task contexts—in this case, within the context of a dyadic shepherding task (19). These experiments compared novice human participants completing the dyadic shepherding task with either another human coactor or a virtual artificial agent whose end-effector movements were controlled by task-specific relations of the shepherding model detailed in Fig. 1C (again, *Materials and Methods* has details about the task-specific modifications). Pursuant to the primary aim, the study sought to determine whether novice participants, when working with the artificial agent, can learn to adopt and maintain COC behavior in a way comparable with human–human COC discovery as an efficient means to complete the shepherding task. Furthermore, the study sought to determine whether interacting with the artificial agent is perceived as natural by assessing participant believability that their partner was a human coactor. For experiment 1, the same tabletop shepherding task used by Nalepka et al. (19) was used. However, in contrast to Nalepka et al. (19), participants completed the task within a fully immersive VR environment. Participants viewed the shepherding task environment from a first-person perspective via an Oculus Rift head-mounted display and completed the task by controlling the end effector movements of a humanoid crash test dummy avatar using a handheld motion sensor. A participant’s coactor was also represented as a humanoid crash test dummy avatar (Fig. 2A). To validate this VR setup, we first instructed dyads of novice participants to complete the VR shepherding task together (experiment 1a), with the expectation that these novice dyads would exhibit the same (i.e., replicate) behavioral dynamics observed by Nalepka et al. (19). After this, experiment 1b compared the behavioral dynamics and performance of novices who completed the shepherding task together with the artificial agent (i.e., the model-controlled crash test dummy) with those who worked together with an expert confederate participant. For both conditions, the confederate posed as a naïve participant who sat beside participants in the waiting area. Participants were told to one room, while the confederate (who participants were told would be their partner) was taken to an adjacent laboratory. Participants were not allowed to verbally communicate with each other (in any condition), and for both the artificial agent and confederate conditions (experiment 1b), participants were told that their partner would complete the task remotely from an adjacent laboratory. Accordingly, during a postexperiment funnel debriefing session (61), we also assessed whether the novice participants remained in belief that they were working with a human during the experiment or if there was a kind of “eureka” or sudden insight moment for participants, with those dyads that discovered COC behavior achieving nearly 100% containment success after its discovery. Both S&R and COC behaviors reflect task-specific realizations of environmentally coupled point attractor and limit cycle dynamics. This is illustrated in Fig. 1C, where the system equations (Eqs. F1–F3 in Fig. 1C) for the time-evolving end effector movements of each agent’s hand/sheepdog (where \( i = 1–2 \)) are defined in polar coordinates with respect to the center of the target containment region, \( (r_0, \theta_0) = (0, 0) \). As a generalizable model of two-agent S&R and COC shepherding behavior (*Materials and Methods* has experiment-task-specific adaptations and expanded description), a discrete or point attractor damped mass spring equation (Eq. F1 in Fig. 1C) is used to define an agent’s radial distance from the center of the game field, and a nonlinear hybrid system, capable of both discrete (point attractor) and rhythmic (limit cycle) behavior (Eq. F2 in Fig. 1C) (ref. 36 has details), is used to define an agent’s polar angle dynamics. Note that, during agent i’s S&R behavior, the sheep farthest from the center of the game field at time \( t \) [denoted by the subscript \( sf \)] on that agent’s side of the field defines the target location (i.e., attractor location) of the sheep in both Eq. F1 in Fig. 1C (radial target coordinate, where distance \( r_{min} \) is the agent’s preferred minimum distance away from the sheep, ensuring repulsion of the sheep toward the target region) and Eq. F2 in Fig. 1C (polar angle coordinate). That is, each agent is coupled to the movements of the farthest sheep on their side of the field. The agents are also coupled to each other via a dissipative coupling function in Eq. F2 in Fig. 1C. This interagent coupling (44, 45) ensures stable in-phase synchronization during COC behavior and reflects the natural behavioral synchrony phenomena commonly observed between interacting agents more generally (ref. 47 has a review).
Fig. 2. Experiment 1 setup, behaviors, and results. (A) Depiction of the shepherding task used in experiment 1 modeled after the experimental room in which testing took place (19) (Upper). First-person perspective of the shepherding task with initial sheep (modeled as spheres) arrangement (Lower). The sheepdogs (orange and blue cubes) were controlled via the movements of a handheld motion sensor on a tabletop of similar dimension. The goal was to contain the sheep within the red target region. (B, Upper) Average power spectra across participants in each dyad type (novice-novice in experiment 1a; novice–confederate and novice–artificial agent in experiment 1b) calculated from the last 45 s of all successful trials. (B, Lower) Average power spectra of each participant type in the novice-confederate and novice-artificial agent conditions. (C) Shepherding performance metrics for successful trials across behavioral mode and condition: S&R novice-novice dyads—dyads that only exhibited successful S&R behavior; COC novice-novice dyads—performance during COC-classified trials from dyads that discovered COC behavior; and novice-confederate and novice-artificial agent dyads—performance during successful COC-classified trials from dyads in both conditions. Performance metrics were containment time—the amount of time (seconds) that all sheep were contained within the red target region; sheep distance—the mean sheep distance from the center of the target region; herd spread—the average herd spread (centimeters squared) measured by computing the convex hull formed by all of the sheep (the convex hull is defined by the smallest convex polygon that can encompass an entire set of objects, like a rubber band placed over a set of pegs); and herd travel—defined as the cumulative distance (centimeters) that the herd’s COM moved during the trial. The herd’s COM was computed by taking the mean sheep’s position. Error bars represent SE.

Results
Experiment 1a. Fifteen novice–novice dyads were recruited to complete the shepherding task in the VR environment with the centrally located target region specified (Fig. 2A). Overall, the behavioral dynamics exhibited by these novice–novice dyads replicated the findings of Nalepka et al. (19). All dyads initially adopted the S&R mode of behavior, but not all were able to successfully complete the task, with only nine (60%) of dyads reaching eight successful containment attempts within the 45-min testing period (M = 29.06 min needed, SD = 6.89). Importantly, a small subset of successful dyads (n = 3) discovered and transitioned to COC behavior over the course of experimental testing (M = 7 COC trials of 8, SD = 1.73). In such trials, a dyad’s behavior was classified as COC when both participants exhibited a small subset of successful dyads that only exhibited successful S&R behavior (Fig. 2C). That is, the novice–novice dyads that adopted COC behavior were able to contain the sheep for a greater period (containment time P = 0.004, d = 2.56), which was the explicit task goal, as well as keep the sheep closer to the center of the containment region (sheep distance P = 0.005, d = 2.63) and minimize the overall movement of the herd (herd travel P = 0.03, d = 2.25).

Experiment 1b. Eleven participants completed the virtual shepherding task together with the coacting virtual avatar whose end effector movements were artificially (model) controlled. Another 10 participants completed the virtual shepherding task together with the coacting virtual avatar who was controlled by the expert human–confederate. As expected, the results demonstrated that novices were able to successfully complete the shepherding task together with the artificial agent, including learning to use COC.
behavior, and reached performance levels equivalent to those exhibited by novice–confederate dyads. More specifically, 20 of 21 dyads (95.23%) achieved task success—completing eight successful herding trials within the 45-min testing period—with all novice participants utilizing COC behavior for at least one-half of all successful trials (M = 6.90 trials, SD = 1.25). Furthermore, although the lone dyad that did not achieve eight successful trials was in the novice–artificial agent condition, the dyad obtained two successful trials during the 45-min period—one of which the novice performed COC-classified behavior.

With respect to task performance, dyads in both the artificial agent and confederate conditions reached success in a similar amount of time (confederate: M = 8.62 min, SD = 1.63; artificial agent: M = 9.32 min, SD = 1.16; P = 0.29, d = 0.49). Moreover, novice dyads that completed the task with the artificial agent also achieved levels of herding performance (i.e., herd containment time, sheep distance from the center, herd spread, and herd travel) equivalent to those novices who completed the task with the confederate (all P ≥ 0.15). The equivalence of novice–confederate and novice–artificial agent performance compared with novice–novice performance can be discerned from an inspection of Fig. 2C.

Finally, during the postexperiment debriefing session, seven (63.64%) of novices who completed the task with the artificial agent thought that they were interacting with a human and did not note anything odd in their partner’s behavior. The remaining four (36.36%) novices indicated that they suspected that their partner may not have been human (i.e., computer driven). Common statements from these latter participants were “my partner moved very quickly” and “I didn’t understand why they worked harder than they had to.” Interestingly, one novice who completed the task with the confederate thought at times that the behavior was “computer like.”

The statements regarding the artificial agent moving “too quickly” (Fig. 2D) were due to the artificial agent having a greater speed than the confederate (M = 1.18 Hz, SD = 0.01) than the confederate (M = 0.90 Hz, SD = 0.08; P < 0.001, d = 4.82). Likewise, novices completing the task with the artificial agent attempted to frequency match with their partner, as they also exhibited faster oscillatory behavior (M = 0.98 Hz, SD = 0.14) than their peers working with the confederate (M = 0.86 Hz, SD = 0.09; P = 0.04, d = 1.02). Despite attempts to frequency match with the artificial agent, the frequency difference in novice–artificial agent dyads was greater (M = 0.22 Hz difference, SD = 0.11) than those in the novice–confederate condition (M = 0.05 Hz difference, SD = 0.06; P = 0.001, d = 1.87). This resulted in less stable coordinative relative-phase relationships within novice–artificial agent dyads compared with novice–confederate dyads (P = 0.001, d = 2.01)—consistent with past research indicating that incidental/unintentional rhythmic coordination is less likely to occur and is less stable when it does occur as the frequency difference between movements increases (62). It was because of this oscillatory frequency difference that novice–artificial agent dyads had more successful trials that deviated from in-phase/antiphase coordination (M = 4.94 normalized trials, SD = 2.46) than for novice–confederate dyads (M = 0.72 normalized trials, SD = 0.80; Mann–Whitney U = 63; P = 0.001).

It should be noted that, although coupled human–human dyads are typically attracted toward in-phase or antiphase patterns of COC behavior, such stable relative-phase relationships are not essential for task success. Rather, they are simply a natural consequence of the visual informational coupling that constrains the rhythmic movements of interacting individuals to in-phase and antiphase patterns of behavioral coordination (i.e., synchronization) more generally (47). Indeed, task success for COC dyads due to this behavioral mode creating a spatiotemporal perimeter around the herd, with any interagent relative-phase relationship ensuring task success.

Experiment 2a. As noted above, the task goal in experiment 2 was for novice–novice and novice–artificial agent dyads to corral all of the sheep together anywhere within the game field. That is, no target region was specified a priori, and dyads were free to self-choose where to contain the sheep. The sheep were considered contained or successfully herded together when they were all within 19.2 cm of each other, consistent with the containment demands in experiment 1. When this happened, the color of the sheep changed from brown to red, providing visual feedback to participants that the sheep had been successfully herded together. At the start of each trial, the sheep were randomly scattered throughout the task environment (Fig. 3A shows an example initial arrangement); again, a trial was considered successful if the herd remained within 19.2 cm of each other for a minimum of 70% of the last 45 s of each 2-min trial.

Overall, the participants in experiment 2 exhibited the same behavioral dynamics observed in Nalepka et al. (19) and experiment 1; 13 of 19 (61.90%) novice–novice dyads successfully completed the unconstrained shepherding task (i.e., performed eight successful trials within the 45-min testing period), with a mean completion time of 27.69 min (SD = 7.25). All 13 of the novice participants completing the task with the artificial agent achieved task success and did so in significantly less time than novice–novice dyads (P = 0.002, d = 1.35), with novice–artificial agent dyads having a mean completion time of 19.69 min (SD = 4.23).

With regard to COC discovery, 6 of 13 (46.15%) novice–novice dyads exhibited behavior classifiable as COC. This was fewer than the five (41.67%) novice–novice dyads that only adopted S&R behavior while also keeping the sheep closer together and minimizing herd movement (all P < 0.001, d ≥ 2.53).

In experiment 1, novice–artificial agent dyads were unable to frequency match (M = 0.27 Hz difference, SD = 0.18) to the extent that novice–novice dyads did (M = 0.05 Hz difference, SD = 0.08; P = 0.002, d = 1.63). Similar to experiment 1, this was due to the artificial agent producing a significantly greater peak oscillatory frequency (M = 1.19 Hz, SD = 0.02) compared with novices in the dyad (M = 0.91 Hz, SD = 0.18) (Fig. 3B), who did not differ in the average frequency of novice–novice dyads that discovered COC (M = 0.90 Hz, SD = 0.16; P = 0.88, d = 0.08). Furthermore, novice–novice dyads that discovered COC behavior had less deviation from predominantly in-phase/antiphase coordination (M = 1.06 normalized trials, SD = 1.27) than novice–artificial agent dyads (M = 5.47 normalized trials, SD = 2.29; Mann–Whitney U = 4.50, P = 0.003). Similar to experiment 1, this discrepancy was due to a greater magnitude of relative-phase variability for novice–artificial agent dyads compared with novice–novice dyads (P = 0.02, d = 1.67).

Finally, the herding performance of novice–novice and novice–artificial agent dyads that discovered and adopted COC was comparatively similar (Fig. 3C). Although novice–artificial agent dyads kept the sheep to a smaller area (herd area P = 0.02, d = 1.18) and stabilized their mean movement to a greater degree (herd travel P < 0.001, d = 2.57), dyads in both groups reached near ceiling on the explicit task goal measure of containment time (P = 0.06, d = 0.94). Novice–novice and novice–artificial agent dyads also exhibited equivalent performance regarding the mean sheep distance away from the herd’s center of mass (COM; P = 0.17, d = 0.17).

Experiment 2b. Following the inability of the artificial agent to frequency match with participants in experiments 1 and 2a, a new sample of 20 naïve participants completed COC. Experiments 1 and 2a had the same design as in experiment 2b but with a modified artificial agent capable of adapting its movement frequency during COC behavior. One participant could not complete the task within the 45 min allotted, and one participant was excluded from analysis for adopting an individualistic strategy, which involved circling
around the entire herd. For the latter participant, although this behavior had been witnessed by two dyads in ref. 19, this behavior was outside what was typically observed in ref. 19 as well as experiments 1 and 2a, and therefore, the behavior of this participant was excluded from analysis.

Of the remaining 18 participants, 14 (77.78%) utilized COC behavior at least once (one participant had one successful COC trial, and one had two, while the remaining 12 had at least five successful COC trials; $M = 7.25$). Importantly, for successful COC trials, the average frequency difference between the novice and artificial agent during COC behavior was 0.04 Hz (SD = 0.05). This was not significantly different from the frequency difference observed between novice–novice dyads in experiment 2a ($P = 0.86$, $d = 0.08$), confirming that the frequency adaptations to the original shepherding model were successful (Fig. 3B). The resulting effect was an overwhelming predominance of stable in-phase and antiphase behavior, such that only 1 (0.01%) trial of a total of 90 successful COC trials deviated from in-phase/antiphase behavior. The resulting effect on participant interaction with the artificial agent was that, although participants in experiment 2b were told that their partner was a computer-controlled artificial agent, 7 (38.89%) of 18 participants indicated afterward that, at times, they thought that they were completing the task alongside an actual human coactor. These findings are, therefore, consistent with findings of refs. 43 and 48, which also indicated that participants attribute human agency to interactive artificial agents that exhibit human-like behavioral dynamics.

**Discussion**

This study tested the efficacy of DMPs as a suitable control architecture for interactive artificial agents completing complex and dynamic multiagent tasks with human coactors. For this study, a dyadic shepherding task was used, which captures the key features of goal-directed multiagent activity, including task division, decision making, and behavioral mode switching (19). Two experiments were conducted in which novice human participants were required to complete the shepherding task with either another human actor or a virtual artificial agent whose end effector movements were defined by a low-dimensional dynamical model composed of environmentally coupled point attractor and limit cycle dynamics.

As expected, the results revealed that HMI performance was equivalent to human–human performance, with human–human and human–artificial agent systems exhibiting the same robust patterns of S&R and COC behavior that characterized the performance of human dyadic shepherding (19). Moreover, S&R and COC behaviors were observed in both defined (experiment 1) and undefined (experiment 2) containment contexts, which not only further highlights the robust generalizability of these two behavioral modes but also, indicates that the emergence of COC behavior is not simply a function of specifying a circular target region [as was the case in experiment 1 and in the original study by Nalepka et al. (19)]. In both task contexts, optimal performance involved immobilizing the sheep together as a collective herd by applying lateral forces evenly distributed around a predefined or self-selected area of containment. Of particular significance is that a qualitatively similar behavioral strategy is observed across a range of other animal herding and hunting systems—such as the formation of a circle around lone prey in wolf pack hunting (50) or the creation of a “bubble net” to encircle herring in group humpback whale hunting (51)—despite differences in morphological and environmental constraints acting on these disparate animal systems. In sheeptdog herding contexts specifically, similar patterns of (S&R-like) pursuit and (COC-like) oscillatory behavior are also observed (52, 63, 64). Such patterns are also common in many team sports contexts (65, 66), implying that the patterns of S&R and COC behavior observed here reflect context-specific realizations of the lawful dynamics that define functional shepherding behavior more generally (20, 31).

With respect to the latter claim, we freely acknowledge that the current tabletop, laboratory-based task methodology used in this study prevents any definitive conclusions regarding the degree to which the S&R and COC behavioral modes of shepherding behavior observed here might transfer to more real-world or complex multiagent shepherding task environments. Future research could address this limitation by investigating shepherding problems in larger shepherding environments and from a first-person perspective (i.e., where individuals must move by walking or running around a large area or field). The shepherding task could also be expanded to require individuals to transition from collection and containment to sheep transportation (i.e., moving a herd from one location to another). Furthermore, online perturbations, like the introduction of new sheep or altering team composition and member capabilities, could be introduced, which may lead to role differentiation and role switching for task success. Together, these more complex shepherding scenarios would help to further detail not only the lawful processes that promote the emergence of stable and...
robust multiagent shepherding behavior but also, other forms of
everyday multiagent or social motor coordination.

Although most participants discovered and maintained COC
behavior when working alongside the artificial agent, it is
important to appreciate that one participant (7.69%) in experiment
2a and four (21.19%) participants in experiment 2b completed
the task without adopting COC behavior, indicating that the emergence
and maintenance of COC behavior may depend on specific in-
teractions or contextual experiences with the task environment.

By scaffolding interactive environments as a comember of a team
(or as a “teacher” or “coach” embedded in the task context), arti-
factual agents can potentially serve a promising role in implicit skill
acquisition contexts, an alternative to utilizing artificial systems for
explicit “trajectory shaping” of ideal behaviors (67, 68). Alterna-
tively, artificial agents embodying human-like dynamics can take
the role of humans in situations where recruitment is difficult,
such as large-scale training exercises, or provide more varied team
composition or role assignment for more robust team coordination
in light of perturbations (69). As demonstrated by human “dynamic
clamp” methodologies, the use of artificial agents as members of dyadic
or group contexts can also allow researchers to deduce
unidirectional effects of the (artificial) member on the rest of the
group to better understand the processes underlying social in-
teractions and diagnosis of social disorders (23, 43, 48, 70).
Outside of using assistive artificial systems for skill acquisition or
training to prepare for future social encounters, embodying ro-
botic systems with human-like dynamics may facilitate action
prediction and safety in domains, such as advanced manufacturing
(e.g., handing objects from robot to human), where the move-
ment capabilities of such systems are not readily apparent (71, 72).

Although most participants were unaware that they were
working alongside an artificial agent in experiment 1b, the few
participants who detected the artificial agent noted that its be-
haviors during COC were “too quick.” This deficit in the human-
nature of the proposed model was addressed in experiment
2b by including an adaptive frequency function (i.e., frequency
parameter dynamics) that operated to match a human actor’s
natural movement frequency (73). The resulting effect led a
subset of participants to attribute human agency to the artificial
agent, although they were informed that it was a computer-
controlled player. It remains unclear whether this attribution
was due to the artificial agent’s ability to modulate its movement
frequency or the increased occurrence of stable in-phase and
antiphase COC behavior that such frequency modulation afford-
ded. Regardless, consistent with refs. 43 and 48, a combination of
adaptive frequency dynamics and modulations in interagent
coupling strength does seem to facilitate the naturalness of HMI
(14, 43, 48). Recent work by ref. 74 has provided additional
support for the tangible benefits for such adaptations in HMI,
demonstrating how the use of dynamical primitives can be ex-
tended to include “interaction primitives” that promote move-
ment adaptation to particular user styles to facilitate physical
human–robot interaction during a high five or object handover
task. This is to be expected, however, given that interacting in-
dividuals tend to spontaneously and reciprocally adapt their
behaviors during social interaction (45, 47, 75). Indeed, when
producing rhythmic movements with another person, individuals
naturally adapt their movement frequencies to be in alignment
(i.e., exhibit frequency entrainment) (45, 76), with such fre-
quency modulation lingering in “social motor memory” even
after the interaction has ended (75, 77). In other social motor
tasks, participants who resemble similar “motor signatures” are
known to coordinate their behaviors more than those who are distant
(4, 45, 75, 78). Such movement adaptation has nu-
merous social and emotional consequences (79) and is associated
with increased rapport and the success of future interactive task
performance (80). Thus, one could hypothesize that it is this
movement modulation and reciprocal entrainment that led to
attributions of human agency observed in this study. This hypothesis
could be tested in future research as well as whether reciprocal
adaptation might also operate to increase the degree to which
human actors accept or trust interactive artificial agents (12).

In conclusion, this study demonstrated the usefulness of a
human-inspired model of multiagent coordination for HMI and
provides clear evidence that the task/behavioral dynamics of
complex human multiagent coordination can be generatively
modeled from a relatively simple set of DMPs. Consistent with
previous research demonstrating how individual (single-agent)
perceptual motor behavior can be effectively modeled using
similar dynamical primitives (39, 41) or low-dimensional task-
dynamic models (20, 21, 31), the implication is that the organiza-
tion and context-specific regularity or control of embedded single-
agent or multiagent perceptual motor behavior are often a natural
and emergent consequence of the physical, informational, and task
goal constraints that define a given task context (21, 22, 31). In
conjunction with contemporary system optimization methods and
reinforcement and machine-based learning approaches, it there-
fore seems clear that models composed of interactive or coupled
dynamical primitives not only hold great promise for the devel-
opment of robust, human-centered HMI systems but also, have
the potential to provide a generalized modeling framework for
understanding how and why the dynamic patterns of goal-directed,
human multiagent environment activity emerge within a given task
context. Indeed, while it might be difficult to deduce the “equations
of mind” (81, 82) from DMP models alone, exploring the generative
potential of such models with regard to capturing the dynamic
stabilities of human and social activity will likely provide insights
about how intentional and cognitive states emerge and operate to
shape and enhance the lawful dynamics that define (multi-jagent
environment task performance.

Materials and Methods
Shepherd Model. Eqs. F1–F3 in Fig. 1C were modified to account for human-
specific adaptations observed in ref. 19. The equations governing the radial
and angular components of the agent’s movement were modified as follows:

\[ r_i + b r_i + \gamma (r_i - (r_{ai}/j + r_{ai}i) - (1) - (r_i + \Delta r_i) = 0 \]  

\[ \dot{\theta}_i + \beta \dot{\theta}_i + \alpha \dot{\theta}_i + \gamma \dot{\theta}_i = \dot{\theta}_i (\theta_i - (\theta_i + \Delta \theta_i)) = \dot{\theta}_i \dot{\theta}_i \quad (2) \]

For Eq. 1, variables \( r_i \), \( r_s \), and \( r_f \) represent the radial component of agent \( i \)’s \( j \) (\( j = 1, 2 \)) current position, velocity, and acceleration at time \( t \), respectively. Parameters \( b_i \) and \( r_i \) are the linear damping and stiffness terms, respectively, for the damped
mass spring function. Eq. 1 reduces the difference between agent \( i \)’s current
radial distance \( r_i \) and the distance of the targeted sheep on agent \( i \)’s side of the
field game \( r_{ai}(t) \). To ensure that the targeted sheep is repelled toward the
correct direction, agent \( i \) maintained a distance \( r_{ms} \) away from \( r_{ai}(t) \).

For Eq. 2, variables \( \dot{\theta}_i \), \( \dot{\theta}_i \), and \( \dot{\theta}_i \) represent the angular component of agent \( i \)’s current position, velocity, and acceleration at time \( t \), respectively. Parameters \( b_i \) and \( \dot{\theta}_i \) are the linear damping and stiffness terms, re-
respectively. The Rayleigh \( (\dot{\theta}_i^2) \) and van der Pol \( (\gamma \dot{\theta}_i \dot{\theta}_i) \) escape term allow
for oscillatory behavior to emerge (36). The coupling function to the right of
Eq. 2 couples the angular component of agent \( i \)’s position and velocity
to those of their partner \( j \) (35). The format of the coupling function allows for
the model’s angular movements of both agents to achieve the stable
in-phase and antiphase modes of behavior observed in ref. 19 and during in-
terpersonal rhythmic coordination more generally (35, 47) when the reso-
nant frequency between agents is sufficiently small. Parameters \( A \) and \( B \)
index coupling strength, such that \( |AB| > |A| \) allows for both stable in-phase and
antiphase solutions to emerge.

Parameter \( b_i \) was modulated to allow for behavioral mode switching
from S&R and COC behavior. The rate of change of \( b_i \) was modeled with
Eq. 3, where \( \sigma \) and \( \sigma \) are fixed parameters that determine the rate of change
of \( b_i \) while \( r_i + \Delta r_i = 0 \) is the radial distance that demarcated S&R and COC
behavior:

\[ b_i + \sigma \Delta b_i = \sigma (r_i + \Delta r_i) = (r_i + \Delta r_i) = 0 \]  

Critically, the model exhibited S&R behavior when \( r_{ai} \leq 2 r_f \) and COC
behavior when \( r_{ai} \geq 2 r_f \). Furthermore, when performing COC behavior, the
model’s radial and angular components were no longer coupled to the
targeted sheep \( (\theta_i, \dot{\theta}_i) \) but instead, performed oscillatory movements around
Participants were recruited from the University of Cincinnati. Participants were defined as the sheep on agent i’s side of the game field that was farthest from the sheep’s COM. Eqs. 1–4 were the finalized model used in experiments 1b and 2. The parameter values utilized were as follows: $\Delta t = 0.161641$, $\gamma = 2.22228$, $\beta = 61.6225$, $\omega = -0.2$, $B = -0.2$, $\delta = 23.08993$, and $\alpha = 0.592988$. The values were the result of a parameter search using a genetic evolutionary algorithm, where the environment from experiment 1 was used to assess parameter fitness. Parameters $r_a$ and $r_{\text{ref}}$ were then adjusted manually to match observations from ref. 19, while $A$ and $B$ were fixed constants set to $-0.2$. Following the results from experiments 1 and 2a, Eq. 5 was included to adapt the artificial agent to individual differences in the frequency of movement during COC (43, 73):

$$\omega - \alpha C_i - (1 - \xi) e_i \frac{\Delta \hat{v}_i}{\sqrt{\theta_1^2 + \theta_2^2}} = 0. $$

In Eq. 5, $\omega = \omega_{\text{ref}}$ and thus, Eq. 5 affected the time-varying nature of $\omega_i$ in Eq. 2. Parameter $\omega_{\text{ref}}$ was set to be the preferred frequency of the model, which was set to 5.652 rad/s. This value was determined from the relationship $\omega/2\pi = \text{frequency (36)}$, which was, on average, 0.90 Hz for novice–novice dyads in experiment 2a. During S&R behavior, $\omega$ approached $\omega_{\text{ref}}$, where $\nu$ is the parameter relaxation time. During COC behavior, $\omega$ was also influenced by the current angular position, $\theta_i$, of the human participant, where $\epsilon$ is the coupling strength of the participant’s influence. For experiment 2b, $\nu = 1$, and $\epsilon = 2$. In simulation, these parameter values reached $\omega$ convergence between two coupled artificial agents, where the artificial agent with $\omega_{\text{ref}} = 5.652$ adapted its oscillatory frequency to another agent with natural frequency that was within 0.2-Hz difference, consistent with what is found in the human literature of incidental visual coordination (62).

Participants. Participants were recruited from the University of Cincinnati (experiments 1 and 2a) and Macquarie University (experiment 2b) in exchange for partial course credit as part of a psychology course requirement. Informed consent was obtained at the beginning of the experiment session. The task, procedure, and methodology were reviewed and approved by the institutional review boards of the University of Cincinnati and Macquarie University. All participants were right handed and were naïve to the task and purpose of the experiment.

Experiment 1. Thirty undergraduate students (15 female, 15 male), recruited into 15 dyads, participated in experiment 1a. Twenty-one undergraduate students (8 female, 12 male, 1 undisclosed) participated in experiment 1b. Each participant was randomly assigned to complete the experiment with a confederate (10 participants) or with the artificial agent (11 participants). The participants ranged in age from 18 to 23 y old.

Experiment 2a. Fifty-two undergraduate students (35 female, 17 male) participated in experiment 2. Thirty-eight participants were recruited into 19 dyads, while the remaining 14 participants completed the experiment together with the artificial agent. The participants ranged in age from 17 to 23 y old. One participant in the novice–artificial agent condition was later excluded due to a computer malfunction.

Experiment 2b. Following the findings of experiments 1 and 2a, an additional 20 undergraduate students (12 female, 8 male) were recruited to complete the shepherding task from experiment 2 alongside a modified version of the artificial agent capable of adapting its movement frequency during COC. The participants ranged in age from 18 to 25 y old.

Apparatus and Task. For both experiments, the task was designed using the Unity 3D game engine (version 5; Unity Technologies) and presented to participants via the Oculus Rift DK2 (VR) headset (Oculus VR). The virtual environment was modeled such that there was a 1:1 mapping between the virtual and real experimental testing rooms. While wearing the VR headsets, the task was presented on the virtual tabletop colocated with a physical table in the real environment—the real table provided a physical surface for participants to move their handheld sensors on while controlling the end effector movements of their virtual avatar in the virtual environment. Participants used wireless LATUS motion-tracking sensors operating at 96 Hz (Polhemus Ltd.). Participants moved the sensors along the tabletop, and their hand movements translated 1:1 to the controlled end effector (modeled as a cube). In the virtual world, participants were embodied as "crash test dummies" whose motion was controlled using an inverse kinematic calculator given the inputs from the participant’s hand and head position (3D model and calculator supported by RootMotion). Separate computers were used to power the VR headsets, and a local area network was used to transfer data using Unity 3D’s UNET peer-to-peer-authoritative protocol. Agent- and task-state variable communication was updated at 50 Hz. Only hand position data were transferred across the network to control for the lack of head motion dynamics in the artificial agent condition. The task involved participants corralling and containing seven autonomous and reactive sheep (modeled as spheres, 2.4-cm diameter). The sheep exhibited Brownian dynamics, where a randomly directed force would be applied at a rate of 50 Hz if left alone. To contain the sheep, agents had to move their sheepdog/cube near the sheep. If either sheepdog was within 12 cm of the sheep, the sheep was replaced with another sheep that was directly away from the agent’s sheepdog at a rate inversely proportional to the distance between the sheep and the agent-controlled cube. The code used for the shepherding task and sheep dynamics can be found at https://github.com/MultiagentDynamics/Human-Machine-Shepherding/ (83).

Experiment 1. Participants were instructed to contain the sheep within the centrally located red containment circle (19.2-cm diameter) (Fig. 2A). The game field was a fenced area measuring $1.17 \times 0.62$ m. Trials were 60 s in duration, and participants were instructed to keep the sheep contained within the red circle for at least 70% of the last 45 s of the trial. The sheep were considered contained if all of the sheep had at least some part of their sphere within the 19.2-cm containment circle. At the end of each trial, participants received visual feedback on their containment percentage. Participants were informed that, to receive credit toward the shepherding task, they should successfully contain the sheep for eight or more successful trials within the 45-min testing period. As an incentive to cooperate with their partner, participants were informed that the experiment would automatically end after eight successful trials had been completed and that they would receive full research credit even if it occurred well before the 45-min testing period (otherwise, the program closed automatically after 45 min).

At the start of a trial, the sheep would appear within the containment region (Fig. 2A has the initial arrangement). Trials lasted a maximum of 60 s but would end early if one of two things occurred during a trial: if a sheep managed to collide with the surrounding fence or if all sheep managed to escape the centrally located area measuring 28.8 cm in diameter (displayed as the white annulus surrounding the red containment region). If a trial ended prematurely, no score was given for that trial. When a trial ended, the sheep and the participant’s partner disappeared. To initiate the next trial, both participants moved their cubes to a designated start location 24 cm from the center of the game field on their respective side of the game field.

Experiment 2. The task was modified from experiment 1. The task space was expanded to cover a fenced area of $1.5 \times 0.8$ m. No containment circle was displayed to participants. Instead, the containment circle (19.2-cm diameter) was invisible and centered on the sheep’s COM, calculated as the mean position of the sheep at time $t$. The artificial agent’s polar task space was expanded to the area centrally centered on the sheep’s COM as opposed to the center of the game field as in experiment 1. For each trial, the sheep were randomly scattered across a 0.5 $\times$ 0.8 cm-boxed region centered on either the left, center, or right one-third of the task space (Fig. 3A has an example initial
arrangement). Unlike experiment 1, no premature trial failure conditions were applied. If a sheep contacted the bordering fence, a repulsive force was applied, the sheep orthogonal to the fence, causing the sheep to move toward the field. Finally, the trial length was increased to 2 min to allow for additional time to collect the sheep.

Participants were informed that the task goal was to bring the randomly scattered sheep together. If all of the sheep were sufficiently contained, participants received visual feedback that the herd were adequately contained by changing the sheep's color from brown to red. To discourage participants from taking advantage of the limited size of the task space, participants only received visual feedback if the herd's COM was at least 10.8 cm from the bordering fence. Participants received a point if the herd were within the invisible 19.2-cm circle centered on the herd's COM for at least 70% of the last 45 s of the trial. Like in experiment 1, the sheep were considered contained if all of them had some portion of their sphere within the (invisible) containment area. As with experiment 1, participants had 45 min to obtain eight successful trials.

Procedure. 

Experiment 1. Before consent, participants sat in the waiting area together (experiment 1a) or alongside a confederate coinvestigator, who posed as a participant, (experiment 1b). Both individuals were brought into the suite and were either taken to the same room (experiment 1a) or directed to one of two experimental rooms (experiment 1b). After consent, participants were given a hard hat and had to wear the motion tracker on their right hand and head. The rules and goal of the task were explained to participants, and participants proceeded to move through the experiment at their own pace with their partner virtually present on the opposite side of the table. Note that participants in the novice-novice condition were told that they could not talk to each other, and the experimenter enforced this no talking rule.

For experiment 1b, participants were always sent to the same experimental room, and while they were reviewing the consent form, the coinvestigator was walked to an adjacent room by the experimenter. The experimenter returned to the room with the participant and told the participant that the partner was to be supervised by another experimenter, while the lead experimenter remained in the room with the participant to answer any questions that the participant had. The participant's partner was either controlled by the confederate or the artificial agent. The confederate had knowledge of the S&R and COC behavioral modes. Also, the confederate was told to implement COC behavior when the herd were within the containment region and to not encroach on the novice participant's side of the task space. After the conclusion of the task, participants were funnel debriefed as to the purpose of the experiment and asked whether they had any doubts that they were completing the task with a human partner at any time during the experiment.

Experiment 2. Participants were either recruited as dyads (in the novice-novice condition) or as individuals (in the novice-artificial agent condition and for experiment 2b). Participants in the novice-novice condition completed the task together in separate rooms and were told that they were working together to complete the herding task. Participants in the novice-artificial agent condition and experiment 2b were told that they would be working alongside an artificial agent. For participants working with the artificial agent, the capabilities of the artificial agent were never disclosed; participants were only informed that the agent was there to assist them in completing the herding task. After consent, participants were given their respective VR headsets and handheld motion controllers. The rules and goal of the task were explained to participants, and participants proceeded to move through the experiment at their own pace. After completion, participants were debriefed as to the purpose of the experiment.

For experiment 2b, participants were always sent to the same experimental room, and participants received visual feedback that the sheep were adequately contained by changing the sheep's color from brown to red. To discourage participants from taking advantage of the limited size of the task space, participants only received visual feedback if the herd's COM was at least 10.8 cm from the bordering fence. Participants received a point if the herd were within the invisible 19.2-cm circle centered on the herd's COM for at least 70% of the last 45 s of the trial. Like in experiment 1, the sheep were considered contained if all of them had some portion of their sphere within the (invisible) containment area. As with experiment 1, participants had 45 min to obtain eight successful trials.

COC Classification. COC behavior was defined by the presence of a strong oscillatory component operationalized as a peak frequency component between 0.5 and 2 Hz. S&R behavior was classified as having a peak oscillatory frequency below 0.5 Hz. Welch's power spectral density estimates (MATLAB's pwelch function) were conducted to determine the oscillatory frequency with the most power between 0.2 and 0.8 Hz. The angular component of agent movements were low-pass filtered at 10 Hz using a fourth-order Butterworth filter and linearly detrended. The analysis was windowed at 512 samples, with 50% overlap. For COC classification in experiment 1, the polar coordinate axis was aligned with the center of the containment region. For COC classification in experiment 2, the polar coordinate axis was centered on the herd's herdm's COM.

In addition to a strong oscillatory component, a second feature of COC behavior is the emergence of a stable in-phase or antiphase relative-phase relationship between the partner's or the artificial agent. The confederate was told to implement COC behavioral modes. Also, the confederate was told to implement COC behavior when the sheep were within the containment region and to not encroach on the novice participant's side of the task space. After the conclusion of the task, participants were funnel debriefed as to the purpose of the experiment and asked whether they had any doubts that they were completing the task with a human partner at any time during the experiment.

For experiment 2b, participants were always sent to the same experimental room, and participants received visual feedback that the sheep were adequately contained by changing the sheep's color from brown to red. To discourage participants from taking advantage of the limited size of the task space, participants only received visual feedback if the herd's COM was at least 10.8 cm from the bordering fence. Participants received a point if the herd were within the invisible 19.2-cm circle centered on the herd's COM for at least 70% of the last 45 s of the trial. Like in experiment 1, the sheep were considered contained if all of them had some portion of their sphere within the (invisible) containment area. As with experiment 1, participants had 45 min to obtain eight successful trials.

Data Reduction, Preprocessing, and Measures. Consistent with analyses performed by Nalepka et al. (19), positional ($x,y$) values of the handheld sensor were converted to polar (r,$\theta$) coordinates. For each respective agent, the angular component was centered on the intersection of the agent's sagittal and transverse planes, with values of $(3\pi/2,\pi/2)$ in the game field. This allowed for accurate representation of an agent's movement, including sagittal plane crossings on the partner's side of the game field. All analyses were conducted on the last 45 s of the trial.

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