I Know Your Next Move: Action Decisions in Dyadic Pick and Place Tasks

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Abstract

Joint pick and place tasks occur in many interpersonal scenarios, such as when two people pick up and pass dishes. Previous studies have demonstrated that low-dimensional models can accurately capture the dynamics of pick and place motor behaviors in a controlled 2D environment. The current study models the dynamics of pick-up and pass decisions within a less restrictive virtual reality mediated 3D joint pick and place task. Findings indicate that reach-normalized distance measures, between participants and objects/targets, could accurately predict pick-up and pass decisions. Findings also reveal that participants took longer to pick-up objects where division of labor boundaries were less obvious and tended to pass in locations maximizing the dyad's efficiency. This study supports the notion that individuals are more likely to engage in interpersonal behavior when a task goal is perceived as difficult or unattainable (i.e., not afforded). Implications of findings for human-artificial agent interactions are discussed.

Keywords: affordances; joint action; pick and place tasks; decision making; virtual reality;

Introduction

An essential issue in understanding interpersonal human behavior is determining how individuals spontaneously coordinate their actions to achieve a common task goal. Many everyday tasks involve coordinated actions between individuals, without requiring explicit communication or a priori planning, to effectively meet shared goals (Allsop et al., 2016; Nalepka et al., 2019). A commonality between such tasks, such as setting the dinner table or industrial operations (including assembly line production and product delivery), is that they often involve pick and place behaviors, which entail selecting an object from a group of objects and moving it to a particular location (Lamb et al., 2017).

An ecological dynamics perspective of interpersonal behavior posits that motor behavior spontaneously emerges from intertwining social, biological, and cognitive systems in which the individuals are embedded (Newell, 1986; Richardson, Dale, & Marsh, 2014). Specifically, the primary assumption of the ecological dynamics framework is that the interaction between individual, task, and environmental constraints leads to the emergence of different action possibilities available to individuals (termed "affordances"), which drive individuals' action decisions (Lopresti-Goodman et al., 2009; Newell, 1986). These affordances (e.g., "climability" of stairs) can be captured by body-scaled ratios, typically measured as a ratio between action relevant properties of the task environment and the individual's capabilities (Michaels, 2003; Warren, 1984).

Pick and Place Tasks

Pick and place behaviors have been extensively studied within fields of cognitive and human movement sciences, to examine individual (e.g., Flash & Hogan, 1985; Rosenbaum, et al., 1990) and interpersonal performance (e.g., Meyer, van der Wel, & Hunnius, 2016; Richardson et al., 2007). Much of this research has focused on analyzing the movement trajectories and velocities produced during these tasks, with experimental studies demonstrating differences in the behavioral dynamics when performed individually versus in pairs (e.g., Becchio et al., 2008; Georgiou et al., 2007). Recently, studies by Lamb et al. (2017, 2019) developed a highly controlled 2D virtual reality (VR) mediated joint pick and place task, involving participants moving and passing disk-shaped objects by sliding them across a tabletop. Using this task, Lamb et al. (2017, 2019) effectively demonstrated not only that pick and place movements can be modelled by dynamical primitives of human movement behaviors but also that action decisions can be modelled using low-dimensional models of fundamental task-relevant constraints (see Lamb et al., 2019 for action selection equations).

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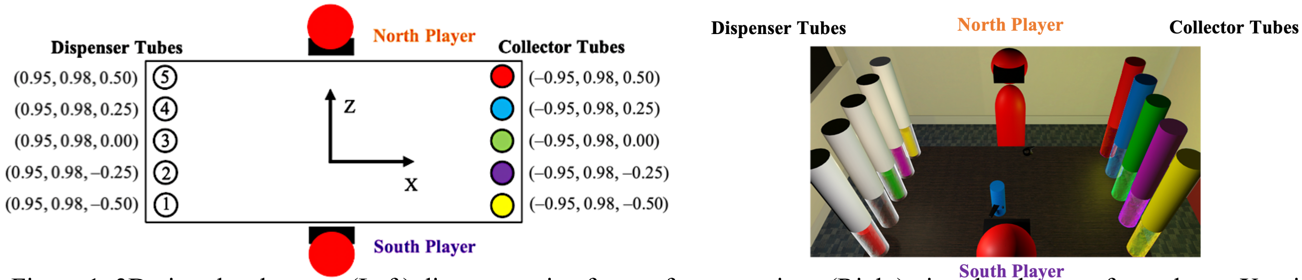

Figure 1: 3D virtual task setup. (Left) diagrammatic of setup from top view; (Right) virtual task space from above. X-axis, Y-axis (measured from ground), and Z-axis coordinates are given (in meters) for the center of collector and dispenser tubes.

By experimentally manipulating the appearance and target location of the objects, Lamb et al. (2017, 2019) also determined that object pick-up and pass decisions in a 2D VR environment could be effectively explained by 2D body-scaled ratios of affordances. Specifically, pick-up decisions were accurately predicted by how close an object was from the participant's and their co-actor's hand and passing decisions were predicted by how far the object's target location was from the participant's hand (normalized by reach). Lamb et al. (2017, 2019) also revealed that the location that the participants passed the objects tended to cluster in two regions, with one cluster per pass direction.

A limitation of the task environment used by Lamb et al. (2017, 2019) was that participants' movements were restricted through limited pick-up range of objects, limiting hand movements to a 2D horizontal plane, and requiring participants to keep their hand stationary (near their body) between trials. Consequently, while these studies successfully modelled the interpersonal decision dynamics with regard to the 2D distances of objects and target locations from participants' hands, in reality, these affordance measures are more likely to be a function of individuals' overall body and limb measurements and positions.

The Current Study

The current study aimed to extend the previous research of Lamb et al. (2017, 2019) by identifying and modelling the behavioral dynamics of action decisions (pick-up and pass decisions) within a less restrictive 3D joint pick and place task. The study also examined the effect of increasing the complexity of the pick and place task (via increasing number of decisions) on the behavioral dynamics. To achieve these aims, this study used a modified version of Lamb et al. (2017)'s joint pick and place task, adapted to a 3D VR environment, and manipulated the number of objects (single/multiple) available to be picked up at any given time.

Methods

Participants

32 participants (21 female and one non-binary; 28 right-handed) ranging from 17 to 35 years of age (M = 20.72 years, SD = 5.29 years) were recruited from an Australian university. There was ample variability in participants' height (range = 159.00 – 202.00 cm, M = 170.00 cm, SD = 8.63 cm) and arm length (range = 67.00 – 84.00 cm, M = 71.63 cm, SD = 3.78 cm). All participants gave written informed consent, and the ethical aspects of this study were approved by the Macquarie University Human Research Ethics Committee.

Materials

The Pick and Place Task The experimental task used in the current study required participants to pick up virtual cylindrical objects (height = 15 cm, radius = 5 cm) appearing through dispenser tubes and drop them off in collector tubes on the opposite end of the table (see Figure 1). Objects were colored (yellow, purple, green, blue, or red) and needed to be dropped off in the correspondingly colored collector tube. After an object appeared, any participant could pick it up and either drop it off or pass it to their co-actor. All participants worked in pairs and performed simple, single object (SO) and complex, multiple object (MO) versions of the task. In SO trials a new object appeared when the previous was dropped off, however in MO trials, a new object could appear at any time (with ≤ five objects available at once). In MO trials, participants could swap their objects if they were both holding one, resulting in both objects passed simultaneously.

Experimental Setup The experiment took place in a 2.8 m x 4.1 m laboratory room at an Australian university, where participants stood on opposite sides of a 2.2 m x 1.2 m table with a height of 0.81 m. The laboratory table and room were simulated within the virtual environment in their true location and size. The VR environment was designed using Unity (Unity Technologies, 2021) and SteamVR (Valve Corporation, 2021) and was presented to the participants through HTC Vive Tobii VR Integration headsets and hand controllers (HTC Vive & Tobii Pro, 2017). Participants wore one headset and held one controller each, which appeared within the virtual environment in their true location and size. Participants' bodies were represented as simple red avatars in the virtual environment (see Figure 1) and the avatars' height was calibrated to match the height of participants by matching the locations of their headsets. Objects were picked up when they contacted the controllers and could not be released unless dropped off or passed. Objects were dropped off by placing them under the correct collector tube.

Before the experimental trials began, participants were allowed to familiarize themselves with the VR environment in a short practice block, where they were informed on how to complete the task. Participants were instructed to refrain from talking and complete trials as quickly as possible and were free to move around as needed. Participants completed four groups of trials: 2 x 40 SO and 2 x 80 MO trials, apart from the first pair who completed a longer version of the task: 300 trials in total (trials were subsequently shortened to minimize any possible fatigue). SO and MO blocks were of different length to balance the total time taken per block. The order of SO/MO trials were counterbalanced across pairs to counteract any order effects, such as practice effects.

Measures and Design This study used a nested repeated measures experimental design. Primary measures were: (1) pick-up (which participant in the pair: north/south, picked up the object); (2) object pick-up time (how many seconds after being dispensed was the object picked up, normalized by distance of object at appearance); (3) pass (did the participant pass the object to their co-actor after pick-up: yes/no); and (4) pass location. Independent variables were: (1) task version (SO/MO); (2) object appearance location (which dispenser the object appeared in); (3) object target location (which collector tube the object was to be dropped-off in); (4) standing location to object (standing-object) distance; and (5) standing location to target (standing-target) distance. (4) and (5) were measured as planar distances (top view) from the participants' headsets to the location of the object and target, respectively. Distances were normalized by participants' reach, quantified by their arm length, similar to the measures used by Lamb et al. (2017, 2019).

Results

Analyses were conducted using Stata/MP 17.0 and MATLAB (MathWorks, 2020). Multiple models predicting decision dynamics were tested, however, only the most robust findings are presented for sake of brevity. Specifically, while adding other affordance measures to Lamb et al. (2017, 2019)'s proposed pick-up and pass models sometimes yielded marginally significant increases in *Pseudo-*R^2, adding such predictors tended not to markedly increase the models' predictive power, often exhibiting severe multicollinearity.

Pick-Up Decisions

Pick-ups were evenly distributed across north and south players, in SO and MO trials. Participants picked up objects dispensed on their side of the table in 99.73% of SO trials and 98.42% of MO trials. Participants also more frequently picked up objects with target locations on their side of the table. This disparity in pick-up rate was slightly less apparent in the MO trials versus SO trials. To examine if the original model from Lamb et al. (2019) could predict pick-up decisions, a multilevel logistic regression model was fitted with pair identifier as a random factor for both players and the results are presented in the following subsections.

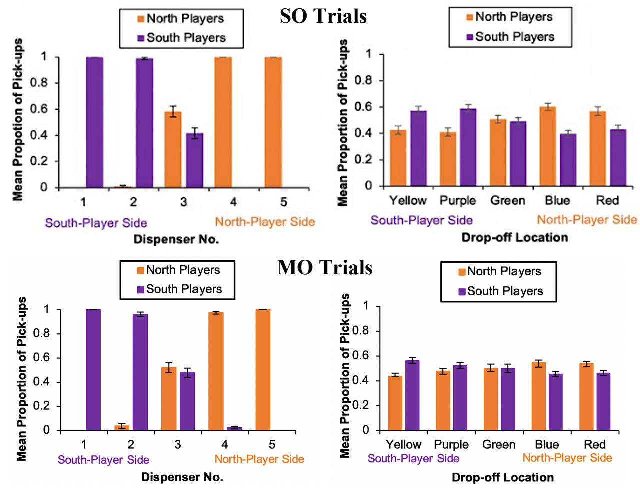

Figure 2: Pick-up proportions for north and south players.

SO Trials The original model classified 91.91% of pick-up decisions, exhibiting almost perfect discrimination of pick-ups by north and south players and strong concordance between observed pick-ups and those predicted by the model (see Table 1). Due to large symmetry of task set-up between players, two separate multilevel logistic regression models were run for north and south players, which indicated that standing-object distance was a strong significant predictor of pick-up decisions. Specifically, every 1-unit decrease in standing-object distance significantly predicted 4.07e+11% and 9.34e+5% increased odds of pick-up for north ($z = 16.28$, $p < .001$) and south players ($z = –17.33$, $p < .001$).

Post hoc analyses revealed that for the objects dispensed in the central tube (i.e., dispenser no. 3), standing-target distance significantly predicted pick-up over and above standing-object distance. Specifically, 1-unit decrease in standing-target distance led to 4.07e+11% and 9.44e+5% increased odds of pick-up for north ($z = –7.56$, $p < .001$) and south players ($z = –3.13$, $p = < .001$). Similarly, for green objects (requiring drop-off in the central collector tube), standing-object distance significantly predicted pick-up over and above standing-target distance, where 1-unit decrease in standing-target distance led to 1.16e+5% and 1.57e+3% increased odds of pick-up for north ($z = –3.97$, $p < .001$) and south players ($z = –6.36$, $p < .001$), respectively.

MO Trials Multilevel analyses on MO Trials yielded similar results. The original model classified 92.80% of total pick-up decisions, with almost perfect discrimination of pick-ups by north and south players and strong concordance (see Table 1). Standing-object distance was a strong significant predictor of pick-up decisions, where a 1-unit decrease resulted in 3.37e+3% and 4.20e+4% greater odds of pick-up

Table 1: Logistic regression coefficients for the model adapted from Lamb et al. (2019) predicting pick-up in (1) SO and (2) MO trials. *Pseudo-*R^2 = McFadden's R^2.

Model	LR χ^2			*Pseudo-*R^2	AUC		κ		
	Value	*df*	*p*		Value	95% CI	Value	*z*	*p*
SO model	239.82	2	< .001	.30	0.980	[0.969, 0.983]	.84	30.20	< .001
MO model	551.67	2	< .001	.38	0.984	[0.981, 0.987]	.86	43.62	< .001

by north ($z = -14.36$, $p < .001$), and south players ($z = -15.62$, $p < .001$). Post hoc multilevel logistic regression analyses again revealed that for the objects dispensed in the central tube, standing-target distance significantly predicted pick-up over and above standing-object distance. Specifically, 1-unit decrease in standing-target distance led to 592.94% and 570.92% increased odds of pick-up for north ($z = -2.64$, $p = .008$) and south players ($z = -2.50$, $p = .013$). Similarly, for green objects, standing-object distance significantly predicted pick-up over and above standing-target distance, where 1-unit decrease in standing-target distance led to 1.30e+6% and 1.80e+5% increased odds of pick-up for north ($z = -4.91$, $p < .001$) and south players ($z = -3.96$, $p < .001$).

Object Pick-up Time

Object pick-up time was significantly shorter in the second block of SO ($M = 0.95$ seconds, $SD = 0.24$) and MO trials ($M = 2.86$ seconds, $SD = 0.79$) than the first block of SO ($M = 1.15$ seconds, $SD = 0.30$) and MO ($M = 3.62$ seconds, $SD = 0.93$) trials ($z = 2.33$, $p = .018$; $z = 3.15$, $p = .002$, respectively), suggesting pairs improved their performance efficiency with practice. Moreover, object pick-up time was greater in MO trials ($M = 4.78$ seconds, $SD = 2.38$) versus SO trials ($M = 1.05$ seconds, $SD = 0.22$), $z = 3.46$, $p < .001$.

Table 2: Regression and contrast coefficients for pick-up time by object appearance location, in SO trials. *$p < .05$. **$p < .001$.

Dispenser no.	*B*	*SE*	95% CI	*z*	*Beta*
1 vs 3	–0.62	0.05	[–0.72, –0.52]	–12.08**	–.42
2 vs 3	–0.36	0.05	[–0.47, –0.25]	–6.67**	–.25
4 vs 3	–0.61	0.05	[–0.71, –0.52]	–12.34**	–.42
5 vs 3	–0.80	0.05	[–0.90, –0.70]	–15.55**	–.51
Contrasts	Contrast Coefficient		*SE*	95% CI	
3 vs 1, 2, 4, 5	0.30**		0.02	[0.25, 0.34]	
2, 4 vs 1, 5	0.11**		0.01	[0.08, 0.14]	

Table 3: Regression and contrast coefficients for pick-up time by (1) object appearance location and (2) target location, in MO trials. *$p < .05$. **$p < .001$.

Dispenser no.	*B*	*SE*	95% CI	*z*	*Beta*
1 vs 3	–1.18	0.21	[–1.59, –0.77]	–5.65**	–.15
2 vs 3	–0.92	0.21	[–1.33, –0.52]	–4.46**	–.11
4 vs 3	–1.40	0.20	[–1.79, –1.02]	–7.13**	–.17
5 vs 3	–1.75	0.20	[–2.15, –1.35]	–8.59**	–.22
Contrasts	Contrast Coefficient		*SE*	95% CI	
3 vs 1, 2, 4, 5	0.66**		0.08	[0.49, 0.82]	
2, 4 vs 1, 5	0.15**		0.07	[0.02, 0.28]	
Collector tubes	*B*	*SE*	95% CI	*z*	*Beta*
Yellow vs Green	–0.43	0.19	[–0.81, –0.05]	–2.24*	–.05
Purple vs Green	–0.13	0.20	[–0.53, 0.27]	–0.62	–.02
Blue vs Green	–0.40	0.21	[–0.80, < 0.01]	–1.94	–.05
Red vs Green	–0.72	0.19	[–1.09, –0.35]	–3.80**	–.09
Contrasts	Contrast Coefficient		*SE*	95% CI	
Green vs Yellow, Purple, Blue, Red	0.21*		0.08	[0.05, 0.36]	
Purple, Blue vs Yellow, Red	0.16*		0.07	[0.02, 0.29]	

SO Trials Multilevel linear regression models, with pair identifier as a random factor, indicated that object appearance location significantly predicted object pick-up time, Wald $\chi^2(4) = 295.67$, $p < .001$ (see Table 2). Here, the further away the object was dispensed from the table's center (dispenser no. 3), the quicker the object was picked up.

MO Trials Similar to SO trials, there was a significant effect of object appearance location on object pick-up time, with objects dispensed further from the middle picked up quicker, Wald $\chi^2(4) = 84.91$, $p < .001$ (see Table 3). Unlike SO trials, target location was also a significant predictor, where object pick-up time increased as target locations moved from the center of the table to the ends, Wald $\chi^2(4) = 17.54$, $p = .002$. There was also a significant interaction between object appearance and target location on object pick-up time, $\chi^2(16) = 36.75$, $p = .002$, where objects were picked up slower when

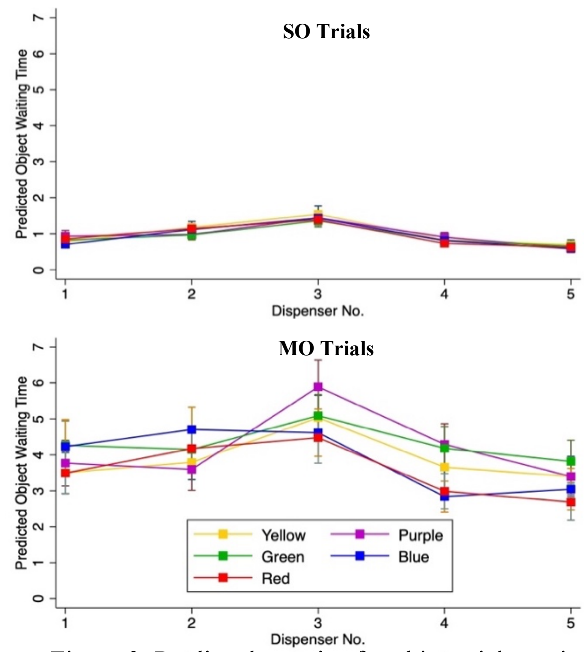

Figure 3: Predicted margins for object pick-up time.

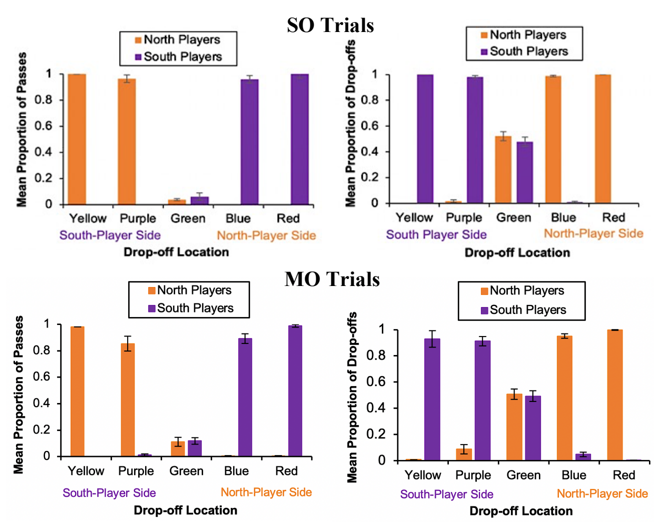

Figure 4: Pass proportions for north and south players.

division of labor boundaries (i.e., who should pick-up/drop-off the object) appeared less obvious (see Figure 3). For example, slower pick-up times were more typical for blue objects in dispensers 1 and 2 (versus 4 and 5), and purple objects in dispensers 4 and 5 (versus 1 and 2).

Pass Decisions

On average, a pass occurred in 33.82% of SO and 36.12% of MO trials, where 74.95% of MO passes were part of a swap. Pass rate was equally distributed within pairs, and differences in pass rate between SO and MO trials were non-significant, $t(15) = 1.22$, $p = .241$. Participants passed 96.20% and 87.31% of objects requiring drop-off on their co-actor side of the table, and < 10% and < 11.80% of the green objects in SO and MO trials, respectively. Similarly, participants tended to drop-off objects with target locations closer to them. To examine if the Lamb et al. (2017) model could predict passing, multilevel logistic regression models were fitted with pair identifier as a random factor for each player.

SO Trials The original model correctly classified 94.62% and 93.97% of total pass decisions in north and south players, respectively, demonstrating useful discrimination of pass decisions and strong concordance (see Table 4). Standing-target distance was a strong significant predictor of pass decisions, where a 1-unit increase resulted in 4.09e+7% and 3.85e+6% greater odds of passing by north ($z = 9.79$, $p < .001$) and south players ($z = 10.11$, $p < .001$), respectively.

MO Trials The original model correctly classified 81.56% and 84.40% of total pass decisions in north and south players, respectively, demonstrating useful discrimination of pass decisions, but substantially lower concordance than SO trials (see Table 4). Hierarchical analysis revealed that the addition of standing-object distance for the co-actor, significantly and substantially improved model fit, demonstrating almost perfect discrimination, and correctly classifying 87.04% and 88.39% of total pass decisions in north and south players, respectively. Standing-target distances were both significant predictors, where increasing distance for the participant and decreasing distance for the co-actor predicted greater odds of passing in north players (OR = 7.60e+2, $z = 14.21$, $p < .001$; OR = 4.29e–3, $z = –12.08$, $p < .001$), and south players (OR = 7.64e+3, $z = 14.88$, $p < .001$; OR = 4.92e–3, $z = –11.16$, $p < .001$), respectively.

Pass Locations

A k-means cluster analysis using Monte Carlo sampling of randomized reference distributions was performed to identify patterns in the location at which participants passed objects.

Table 4: Logistic regression coefficients for models predicting pass decisions in (1) SO and (2) MO trials. *Pseudo-R^2* = McFadden's R^2. *$p < .05$. **$p < .001$.

Model	LR χ^2			*Pseudo-R^2*	AUC		κ			Δ*Pseudo-R^2*	Δκ
	Value	*df*	*p*		Value	95% CI	Value	*z*	*p*		
Original model											
SO model											
North players	446.00	1	< .001	60	0.984	[0.975, 0.992]	.88	22.42	< .001	—	—
South players	409.00	1	< .001	.57	0.983	[0.976, 0.991]	.86	22.79	< .001	—	—
MO model											
North players	73.29	1	< .001	.07	0.888	[0.870, 0.907]	.58	21.07	< .001	—	—
South players	171.61	1	< .001	.16	0.924	[0.909, 0.938]	.66	23.93	< .001	—	—
Model 2 (added standing-object for the co-actor)											
MO model											
North players	132.65	2	< .001	.14	0.940	[0.927, 0.952]	.71	25.71	< .001	.07**	0.13**
South players	207.40	2	< .001	.22	0.955	[0.945, 0.965]	.75	27.07	< .001	.06**	0.09**

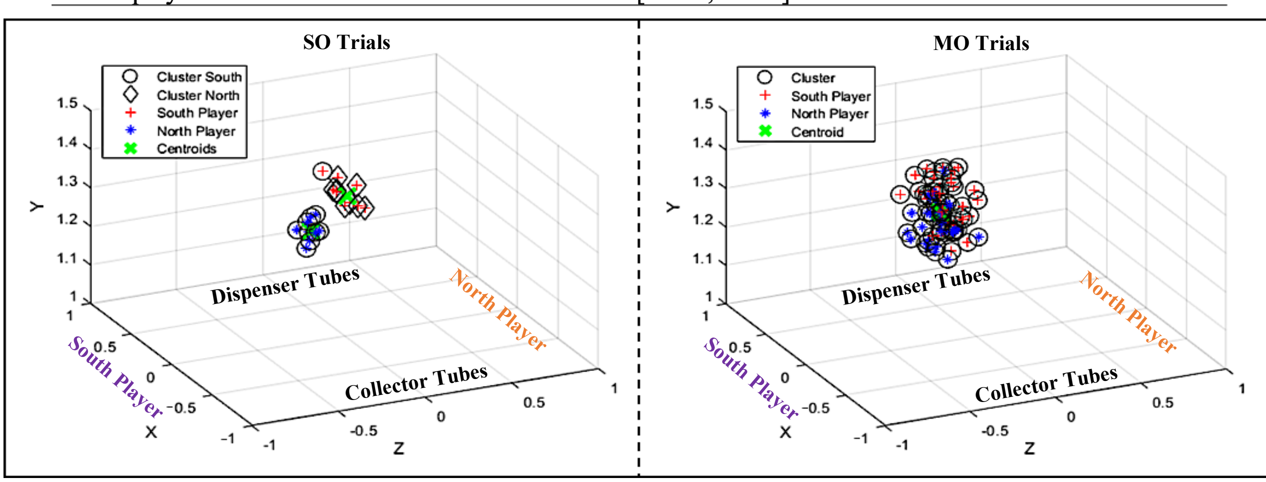

Figure 5: Prototypical examples of clustering of pass locations for a pair in the (*left*) SO and (*right*) MO task.

SO Trials The analysis revealed that the optimal number of clusters across pairs, was two clusters: a north and a south cluster, such that participants passed the objects at a location closer to their co-actor's side of the table. Clusters significantly differed in their Z-axis coordinates, $t(15) = 9.10$, $p < .001$, $d = 2.52$, and were approximately located in midway between the dispensers and the collectors (see Figure 5).

MO Trials Unlike SO trials, cluster analysis on MO trials revealed only one central passing cluster. This could be a consequence of a large proportion of swaps, indicating that participants tended to coordinate object passes and pass locations to increase the efficiency of the task (see Figure 5).

Discussion

The purpose of this study was to investigate the behavioral dynamics underpinning action decisions in 3D joint pick and place tasks to eventually result in a parsimonious affordance-based model predicting interpersonal pick-up and pass decisions. In that regard, the study was able to demonstrate the efficacy of low-dimensional models based on affordances in capturing multidimensional pick and place action decisions with varying complexity. This was achieved through utilizing body-scaled measures and manipulating task constraints through an experimental design.

Modelling Action Decisions

Participants' pick-up decisions were driven almost completely by object distance, and in cases where the object appeared equidistant from both agents, by target location. Specifically, participants were more likely to pick up an object when it was closer to them (i.e., more "graspable") and further from their partner (controlling for reach). Conversely, pass decisions were driven primarily by the distance of the target location, where participants were more likely to pass the object when the drop-off location was further away from them (i.e., less "placeable") and closer to their co-actor in the complex task. Consistent with affordance literature (Lamb et al., 2017, 2019; Richardson et al., 2007), this implies that individuals are more likely to employ their co-actor's help when task achievement becomes difficult to attain by oneself. In the complex task, participants' pass decisions were also driven by the co-actor's location. Moreover, participants more frequently dropped off objects on their co-actor's side of the table, thus extending the drop-off affordance boundary. We posit that with greater task demands, individuals' may be more likely to take on more uncomfortable tasks, prioritizing overall speed of task completion.

Pick-up and pass action decision findings were consistent with the ecological dynamics framework and validated the accuracy of 2D pick and place action selection models (Lamb et al., 2017, 2019) within a 3D task environment. However, for valid integration of pick and place models in practical contexts, future research must verify this study's findings in more life-like environments, as the virtual task design (whilst strengthened the study's internal validity) could not simulate the full complexities of real-life pick and place environments.

Object Pick-up Time

Findings revealed that objects appearing in the middle of both participants were picked up slower than objects closer to a single participant. This discrepancy could be reflective of decision time or hesitancy associated with ambiguity in division of labor boundaries and emergence of heuristic rules. We hypothesize that when objects are equidistant from and thus graspable by two people, agents will check if their co-actor is approaching the object before deciding to perform a pick-up. Thus, pick-up decisions where affordances are equivalent for more than one agent may involve conscious feedback systems or hierarchy between teammates instead of more automatic processes. In the complex task, object pick-up time was also determined by object target location (where objects with more central target locations were picked up slower), and by an interaction between appearance and target location. This demonstrates that pick-up decisions are not only influenced by affordances but also the actions' cost.

Modelling Pass Locations

Consistent with affordance research (e.g., Meyer et al., 2016; Ray & Welsh, 2011) and the shared-effort model of motor behavior (Santamaria & Rosenbaum, 2011), participants' passing behavior prioritized efficiency of task completion via minimizing travelling distance and therefore movement costs (Török et al., 2019) of the dyad. In the simple task, each participant tended to pass in a location near their co-actor, thus maximizing their co-actor's comfort, however, in the complex task, participants tended to perform swaps in one central location on the table, reducing their combined effort.

Conclusion

This study examined the effects of changing task constraints on object pick-up and passing decisions in a 3D joint pick and place task. In doing so, this study demonstrated efficacy for affordance-based models in predicting 3D joint pick and place action decisions, thus providing a unique insight into the behavioral dynamics of regularly occurring interpersonal coordination. Furthermore, this study demonstrated that when complexity of a task is increased, a greater number of parameters may modulate the behavioral dynamics of a task and therefore become involved in determining action decisions. Emerging research suggests interpersonal behavioral dynamics' models may be integrated in artificial agents (AAs) for expertise training (Kümmel, Kramer, & Gruber, 2014), motor rehabilitation, and social skill development (Matarić et al., 2007; Turner et al., 2013). As such, the ability of these models to accurately capture human behavior provides unique avenues for future research in developing human-like AAs for robust and seamless human-AA interactions. These models can be further used to validate and/or train AAs using a hybrid deep reinforcement learning-dynamical motor primitives approach (Patil et al. 2021), where agents can discover strategies by interacting with the environment whilst still scaffolded by essential human movement behaviors.

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