

Four fundamental dimensions underlying the perception of human actions

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Abstract

We evaluate the actions of other individuals based upon a variety of movements that can reveal critical information to guide decision making and behavioural responses. These signals can convey a range of information about the actor, including their goals, intentions and internal mental states. Although progress has been made to identify cortical regions involved in action processing, the organising principles underlying our representation of actions still remains unclear. In this paper we aimed to investigate the conceptual space that underlies action perception by assessing which characteristics are fundamental to the perception of actions executed by other human individuals. We recorded 240 different actions using motion-capture and used this data to animate a volumetric avatar that performed the different actions. Two-hundred and thirty participants then viewed these actions and rated the extent to which each action demonstrated 23 different action characteristics (e.g., avoiding-approaching, pulling-pushing, weak-powerful, etc.). We analysed this data using Exploratory Factor Analysis to examine the latent factors underlying visual action perception. The best fitting model was a four-dimensional model with oblique rotation. We named the factors: unfriendly-friendly, feeble-formidable, unplanned-planned, and adduction-abduction. The first two factors of friendliness and formidableness explained approximately 22% of the variance each compared to planned and abduction that explained approximately 7-8% of the variance each, as such we interpret this representation of action space as having 2+2 dimensions. A closer examination of the first two factors suggests a potential overlap with the way we evaluate facial traits and emotions, whilst the last two factors of planning and abduction appear unique to actions.

Introduction

The organising principal underlying our mental representations is that features of our external world are represented in different internal workspaces or ‘conceptual spaces’ (Allen, 1984; Gärdenfors, 2004b). These spaces capture the similarities and differences between items of a domain and enable further classification, naming and responses to the information. Uncovering the organisation of psychological, and underlying neural, representations of our external world has been fundamental to progress in psychology and neuroscience over recent decades (Gärdenfors, 2004b; Shepard, 1987).

Evidence suggests that items from different domains and across several different modalities are represented within their own conceptual spaces, such as colour (Bonnardel et al., 2016), face identity (Catz, Kampf, Nachson, & Babkoff, 2009; Nishimura, Maurer, & Gao, 2009), face traits (Oosterhof & Todorov, 2008; Sutherland et al., 2013), sound effects (Scavone, Lakatos, Cook, & Harbke, 2001), odours (Bao et al., 2019), tactile textures (Hollins, Bensmaia, Karlof, & Young, 2000) and the taste of wine, (Ballester, Dacremont, Le Fur, & Etievant, 2005; Ballester, Patris, Symoneaux, & Valentin, 2008). The structure of each conceptual space is specific to the domain, with items in the domain that are perceived to be more similar being positioned closer to each other within the conceptual space, whilst dissimilar items are located further apart. For example, within colour space colours that are more similar, such as blue and turquoise, are positioned closer within colour space than less similar colours, such as blue and orange (Bonnardel et al., 2016). Although, items in a domain can be evaluated on a wide range of different characteristics, not all characteristics are fundamental to the representation of the domain. Instead patterns of similarity among items or clusters of similar items determine the dimensions that structure the conceptual space (Gärdenfors, 2004a). These dimensions are the fundamental factors that define the structure of the conceptual space, and the meaningful information on which we make decisions about the items. For example, we can evaluate faces on a range of different characteristics including trustworthiness, dominance, youthful attractiveness, sexual dimorphism, intelligence and confidence

(Oosterhof & Todorov, 2008; Sutherland et al., 2013). However, it appears we evaluate face traits principally on the underlying fundamental factors of trustworthiness and dominance (Oosterhof & Todorov, 2008). Similar results identifying these two factors have been observed by Sutherland et al. (2013), however, their use of a more varied range of naturalistic faces suggested an additional third factor of youthful attractiveness was also important. Uncovering these fundamental dimensions of face trait space has led to further theoretical advances including understanding preconscious face perception (Stewart et al., 2012), and dissociating the role of different neural structures underlying face processing (Getov, Kanai, Bahrami, & Rees, 2015).

Gärdenfors and Warglien (2012) proposed that human actions might also be represented within a conceptual space, as an 'action space'. They suggested that action space would represent principally the movement, as such the kinematics of the body, the forces exerted at each body and limb joint and the spatio-temporal properties. However, we evaluate actions on a range of different characteristics, for example, the action of hugging another individual can be understood in terms of the action kinematics (lifting both arms in front of the body followed by articulation at the elbows), in terms of the action goals (to grasp another individual close to the body) or in terms of the actor's intentions (to console another individual). The ability to perceive and understand the actions of other individuals in these different ways is crucial to our memory of our social environment and guides how to respond optimally to other people (Becchio, Sartori, & Castiello, 2010; Blake & Shiffrar, 2007; Knoblich & Sebanz, 2006; Macrae, Duffy, Miles, & Lawrence, 2008). These higher, more abstract levels of evaluation including action goals and actor intentions would not be accounted for within Gärdenfors and Warglien's (2012) action space proposal which centred principally around body movements.

Instead, action space may additionally represent these higher levels of abstraction, as suggested by different theoretical models suggesting that actions are represented at multiple levels (e.g. Ciaramidaro et al., 2007; Hamilton & Grafton, 2006; Ondobaka & Bekkering, 2012; Van Overwalle & Baetens, 2009;

Wurm & Lingnau, 2015). Most proposals suggest that we evaluate actions on their movement (kinematic or spatio-temporal properties), actions goals and actor intentions. However, they can disagree as to the number of levels at which actions can be understood, how many sub-levels underlie understanding of action goals and actor intentions, and which neural substrates underpin these different processes. For example, Hamilton and Grafton (2006) separate action goals into ‘immediate goals’ and ‘task goals’, Ciaramidaro et al. (2007) distinguish private and social goals and intentions, whilst Wurm and Lingnau (2015) refer to concrete, intermediate and abstract levels of action understanding. Furthermore, there is likely to be an interaction between how we understand these actions at these different levels given the interplay between the processing of the different types of action information (e.g. Gunns, Johnston, & Hudson, 2002; Loucks & Pechey, 2016; Montepare, Goldstein, & Clausen, 1987; Paterson, Pollick, & Sanford, 2001). Therefore, any comprehensive action space is likely to not just represent body movements, but also more abstract information about the purpose of actions and their motivation.

Various prior attempts have been made to assess action space, however, these have either not attempted to assess which fundamental dimensions underly action space, nor always taken into account the unique qualities of the action domain. Giese, Thornton, and Edelman (2008) have shown that actions can be represented within a low-dimensional perceptual space, and the structure of this action representation is closely related to the physical similarity of the movement of the joints of the actor. Although, the limited number and type of actions tested (types of locomotion) couldn’t allow an assessment of the dimensionality of a more general action space. Some have taken a different approach, by assessing actions defined in the very widest sense (‘discrete, meaningful events caused by one or more human, living, or non-living entity’; (Thornton & Tamir, 2022). Their approach was to assess how we organise our understanding of verbs (as proxies for actions) and identified 6 separate dimensions underlying their representation: Abstraction, Creation, Tradition, Food, Animacy, and Spiritualism. However, some of these verbs were either particularly abstract, or could not be motorically executed by human beings, whilst other verbs described complex sequences of activities. It is not, therefore,

immediately clear how this framework that was built on the evaluation of such a diverse set of verbs might relate to a conceptual space that represents solely the domain of discrete visible human actions (Wurm & Caramazza, 2019). Whilst others have examined the organisation of the neural representation of images of actions by combining fMRI and behavioural methods (Tucciarelli, Wurm, Baccolo, & Lingnau, 2019). Here, they asked participants to arrange images of 28 actions within a 2-dimensional space in 5 different ways according to: the semantic similarity of the actions, the body parts involved in the actions, the likely context in which the actions occur, the type of movement involved in the action, and the type of object involved in the actions. The pattern of activity within the action observation network (Decety & Grèzes, 1999) was best represented by the organisation of actions according to semantic similarity. Principal components analysis suggested that when participants organised the actions by semantic meaning, 3 main components could explain the majority of observed variance. Although this analysis could not identify appropriate labels for the 3 dimensions, it did suggest actions may be distinguished according to: type of change induced by the action, the type of need fulfilled by the action, and the degree to which the action is directed towards another person. Whilst such a 3-dimensional model of action organisation may best explain Tucciarelli et al. (2019) data, the lack of movement present in their stimuli, the relatively small set of actions, and the constraints of the task where participants only organised actions based upon semantic similarity, may have limited this study's ability to fully reveal other potential dimensions and the organising principles of an action space (Tucciarelli et al., 2019).

In this paper we aimed to investigate the conceptual space that underlies action perception by assessing which characteristics are fundamental to the perception of actions executed by other human individuals. Our approach was to use a data-driven method similar to Sutherland et al. (2013) who determined face trait space from assessments of a diverse range of naturalistic faces. We wanted to assess how people perceive actions in a broad a range as possible from multiple levels of abstraction that can be used to evaluate actions, from the movement to the goals and intentions. Similar to (Sutherland et al., 2013), we asked participants to evaluate 240 diverse dynamic whole-body actions on 23 different

characteristics and then used an exploratory factor analysis to determine the latent factors underlying action perception. (Howard, 2016; Schmitt, 2011).

Methods

Stimuli

Two hundred and forty different actions were chosen to represent a broad a range of action types as possible based upon the examination of 12 different databases of actions (see supplementary materials for full list), as well as additional deliberate and accidental actions opportunistically recorded during the recording process. Actions were recorded (at 60 fps) from 4 actors (2 female) using a 32-channel motion capture suit (Noitom, Noitom International, Inc., FL. USA). Each of the 240 actions were performed by both a male and a female actor (480 actions in total, 120 actions per actor). In addition, actors were asked to perform three versions of each of their 120 actions in a fashion that the actor felt was most natural. In total we recorded 1,440 action exemplars (240 actions x 2 genders x 3 versions). Each of these actions were subjected to quality checks, pre-processing and cropping so that the recording only featured the most typical presentation of the intended action (see supplementary materials for details). In order to select the final 240 action stimuli, each of the 1,440 actions were presented on screen by an androgynous volumetric avatar (see supplementary materials) using Unity 3D (Unity, San Francisco, CA. USA). Three of the authors (LV, NB, GM) evaluated all of the actions on whether they were representative of the intended action (on a 1-9 Likert scale), and whether the motion capture recording was of good quality (yes/no). This data was first used to eliminate those action exemplars that were of poor quality. Two of these actions (crossing arms and touching abdomen (stomach-ache)) were rated as poor quality by all reviewers and were therefore replaced by additional actions (failing to catch a ball and petting a dog). Second, the maximal average rating of each action type executed by a male and female actor was used to select the best 480 actions that represented the intended action (240 male, 240 female actions). Finally,

for actions where the male and female examples were rated the same the examples were pseudo-randomly selected so that the final stimuli set of 240 action recordings contained equal numbers of actions performed by male and female actors, were closely balanced for actions from the different actors, and closely balanced for social actions and whether the actions were transitive (see Table 1). The final 240 action stimuli selected were all seen as good quality recordings and showed high average representativeness (mean = 8.075; min = 6.333, max = 9). In order to ensure that our final actions used in the experiment were brief and showed only a single action, we cropped (in time) the actions to eliminate early standing and preparatory actor movements (e.g. approaching objects/people, picking up a knife before executing a cutting action) and later retreating movements of the actors. This resulted in the final 240 actions ranging in duration between 1.67 s and 3 s, 100-180 frames at 60 fps (mean duration = 2.5 s, SD = 0.46 s). Finally, to generate files to use in the online experiment, actions were then rendered on screen using Unity 3D (Unity, San Francisco, CA. USA) with the avatar for each action positioned in the centre of the screen, with adjustments made to travelling actions to ensure they remained fully visible for the duration of the action. Actions were captured (Bailey & OBS Studio Contributors, 2020), and then edited using DaVinci Resolve16 (Blackmagic Design, Melbourne, Victoria, Australia) to generate 240 separate .mp4 files (each 1280 x 1080 pixels, 60 fps, H.264 codec with Network Optimisation to allow for faster streaming). Figure 1 shows an example action, whilst all actions used during the rating experiment can be found freely available online at the Open Science Framework (<https://osf.io/4vew8/>).



Figure 1. Illustration of frames (1, 13, 25, 37, 49, 61, 73, 85, 97) from the catching action.

Table 1

Distribution of actions included in the final set of 240, across actors, sociality, and transitivity

Sex	Actor		Sociality		Transitivity	
	1 st	2 nd	Social	Non-Social	Transitive	Non-Transitive
Female	50	70	40	80	46	74
Male	53	67	35	85	47	73

Stimuli validation

To establish whether the 240 actions were seen by naïve observers as representing the intended actions we conducted a separate online experiment, designed and run via the Gorilla Experiment Builder (Anwyl-Irvine, Dalmaijer, Hodges, & Evershed, 2021; Anwyl-Irvine, Massonnié, Flitton, Kirkham, & Evershed, 2019). Each of the 240 actions were named based upon a description of the intended action required of the actor during motion capture process, described as a verb, (e.g., “walking”, “celebrating (together)”, “wiping (surface)”, etc). Participants rated each of the 240 action videos on a 1-9 Likert scale for the extent to which it represented their interpretation of the respective description (1 = the description does not represent the action at all; 5 = the description to some extent does represent the action; 9 = the description exactly and fully represents the action). During each trial participants were presented with a description of the action at the top of the screen, after 1500ms a fixation cross (duration 200ms) was displayed in the centre of the screen followed by the action video. After the video finished playing, the description and video disappeared, and a 1-9 Likert scale with response buttons appeared on screen. Participants were required to respond as quickly as possible to encourage first impressions of the actions; if participants took over 2 seconds to respond they were prompted to “please respond faster!”. Twenty-four catch trials were also included, in which the descriptions and action videos purposefully did not

match up, to check that the participants were completing the experiment in good faith. The experiment included 264 trials in total and was divided into four blocks of 66 trials with up to a minute break in between each block. The experiment took on average 40 minutes to complete.

Participants ($n = 30$; mean age = 20.27; SD age = 7.16; females = 28) were recruited through the internal University of York SONA system and compensated with course credit ($n=28$) or recruited opportunistically ($n=2$). The ratings of how representative each description was of the respective action video was averaged across participants, giving an average representativeness rating for each description and action video pairing; with a higher rating indicating that the description is more representative of the action video. These ratings per action video were analysed, and results indicated that generally the descriptions were representative of the action video, with an average rating across all action videos of 6.79 (SD = 0.43). The highest representativeness rating for a single action video was 8.63, the lowest was 2.63 with only 30 out of 240 description and action video pairings being rated below 5. An analysis of the distribution of representativeness ratings showed a negative skew of -1.08, indicating that a higher number of description and action video pairings had representativeness ratings above the mean (see Figure 2).

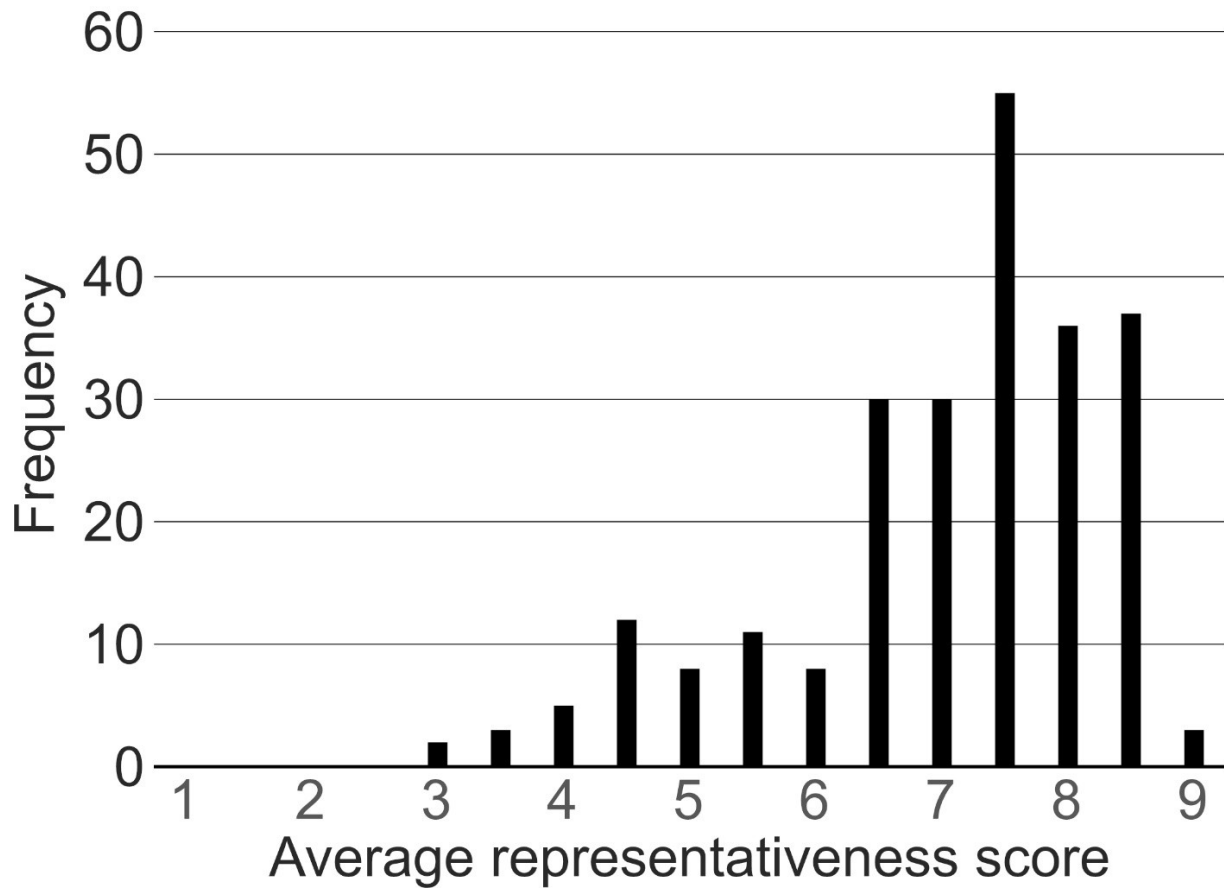


Figure 2. Frequency histogram illustrating the distribution representativeness scores for the 240 actions.

In general, we consider these ratings to indicate that the descriptions are representative of the actions displayed in the videos. Although there are a few cases of description and action pairings being a little less representative, participants were still able to identify that the action displayed in the videos matched the given description of the intended action.

Selection of action characteristics

Our aim was to determine as comprehensive a range of characteristics as possible that people use to evaluate actions. We first selected a broad range (in terms of actions, actors, contexts, viewpoints) of

500 different photorealistic videos of naturalistic actions available in a number of openly available online action databases (see supplementary materials for list). These video dimensions varied in size and duration (widths 160-720 pixels x heights 120-576 pixels, durations 0.85-24 s). All videos were converted (using ffmpeg, <https://ffmpeg.org/>) to .mp4 format, audio information removed, and saved at a framerate of 25 frames per second (fps).

Action characteristics were determined in an unconstrained characteristic identification experiment as *per* Oosterhof and Todorov (2008). One hundred and six participants (41 recruited via social media, 65 for course credit) completed the experiment remotely via an online experimental survey tool (Qualtrics, Provo, UT). The experiment was approved by the ethics committee of the Department of Psychology, University of York and performed in accordance with the ethical standards laid down in the 1990 Declaration of Helsinki; all participants provided informed consent.

The 500 naturalistic action videos were arbitrarily separated into 10 blocks of 50 different actions, and participants were allocated to one of the ten blocks of 50 actions. In total, each block of 50 actions was seen by between 10 and 13 participants. Initially, participants viewed a consent form before viewing the actions. Subsequently, on each trial a pseudo-randomly selected action video was presented on a white screen, above which was the text “Describe what comes to mind when you see this action”, and below the action was a text box in which participants were to indicate their responses. The question asked was deliberately broad as actions can be understood on multiple levels of abstraction (Hamilton & Grafton, 2006; Van Overwalle & Baetens, 2009), and we didn’t want to constrain participants’ responses to just one interpretation of the stimulus. Participants had as long as they liked to indicate as many words as they liked associated with the action. Once they were happy with their response, they clicked a button on the screen to proceed to the next trial.

In total 13,539 words were reported by the 106 participants, of which 2,303 were unique. Initially, two individuals (author NB and a research assistant) independently classified these words into

broad characteristics, and as *per* Oosterhof and Todorov (2008), and then subsequently met to agree upon a final list of 31 characteristics (see Table S1). Of those 31 characteristics, 23 related to the actions themselves (accounting for 70.20% of participant's descriptions), whilst 8 other characteristics related to non-action specific aspects of the stimuli (e.g. person descriptors, locations, personality traits, abstract concepts, and objects).

Action characteristics ranged from two ends of a spectrum, for example 'weak-powerful', 'disapproving-approving', and 'lowering-raising'. The characteristics included descriptions of simple kinematic properties of the action (e.g., low speed-high speed, fluent-hesitant and uncontrolled-controlled), to more abstract goals and intentions of the action, (e.g., making-breaking, rejecting-desiring, and threatening-protecting). In order to determine which of the two extremes should lie at which end of a Likert scale, a further 14 participants were asked to indicate which was the most intuitive position on the Likert scale for the two extremes of each action quality. The results indicated that for all 23 action characteristics between 64.3% and 100% of participants agreed upon position, and this order was used in the subsequent rating experiment.

Rating experiment participants

Two hundred and thirty participants (93 females, 136 males, 1 prefer not to say; mean age = 25.95, SD = 9.63) conducted the rating experiment. This ensured that a minimum of 10 participants rated each action on one of 23 different action characteristics. This decision was made following the methods used in Sutherland et al. (2013) in which a minimum of 6 participants rated each of the stimuli for each characteristic. Participants were either recruited via Prolific (n=206) and compensated £3, via the internal University of York SONA system (n=9) and compensated with course credit or recruited opportunistically through social media (n=15). All participants had normal or corrected-to-normal vision. This research project was approved by the ethics committee of the Department of Psychology, University

of York, and was performed in accordance with the ethical standards laid down in the 1990 Declaration of Helsinki.

Experimental Procedure

For an exploratory factor analysis, a 10:1 ratio of items to characteristics is considered appropriate (Howard, 2016; Kyriazos, 2018), thus the experimental design consisted of the 240 actions each rated on the 23 different action characteristics. Two hundred and thirty participants each viewed all 240 actions rating them on 1 of the different characteristics, where 10 participants were allocated to each characteristic. The experiment was implemented via the Gorilla Experiment Builder (Anwyl-Irvine et al., 2021; Anwyl-Irvine et al., 2019). Once participants entered the experiment site through an internet browser on either a laptop or desktop computer, participants completed a consent form and entered simple demographic information (age and gender). Instructions on the experimental task were then displayed, including which of the 23 action characteristics the participant was going to evaluate the actions on. Before the experiment itself, participants took part in a set of 8 practice trials identical to those used during the experiment. On each trial, participants viewed first a 750 ms fixation cross, then the video of the action for its duration, and finally a response screen showing a 1-9 Likert scale where the participant had to indicate their immediate evaluation of the action by clicking an onscreen button with the mouse. Once a response was registered, the next trial commenced. If participants failed to respond within 2 seconds of the end of the action, a prompt “Please respond quickly” appeared at the top of the response screen to encourage quick first impressions of the actions (see Figure 3). Following completion of the practice trials, participants began the experiment itself. The experiment consisted of 244 trials in total, 240 trials where each of the 240 different actions were shown, and an additional 4 catch trials. During catch trials the response screen explicitly asked the participant to press a specific button, these were included to assess participant attention during the experiment. The experiment was divided into blocks of

61 trials, where participants were allowed a break in between blocks of up to 1 minute, to help maintain concentration throughout the duration of the task. A progress bar was presented on screen along with the response buttons to provide participants with an indication of how far through the experiment they were; on average the experiment took approximately 30 minutes to complete.

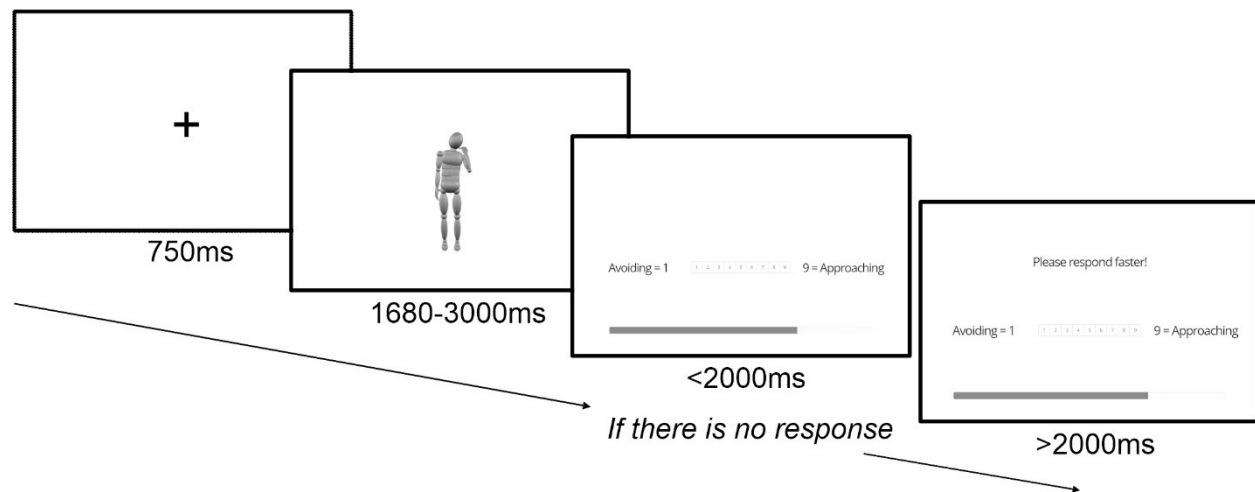


Figure 3. Standard trial structure for the rating of all 23 characteristics. Illustrated is a trial for the “Avoiding-Approaching” characteristic. Following presentation of the action response buttons are presented on screen, along with an experimental progress bar.

Data Analysis

Data was analysed using the ‘irr’ (Gamer, Lemon, Fellows, & Singh, 2019), ‘psych’ (Revelle, 2022), ‘performance’ (Lüdecke, Ben-Shachar, Patil, Waggoner, & Makowski, 2021), ‘datawizard’ (Makowski, Lüdecke, Patil, Ben-Shachar, & Wiernik, 2021), ‘parameters’ (Lüdecke, Ben-Shachar, Patil, & Makowski, 2020), and ‘lavaan’ (Rosseel, 2012) packages in R Studio (R Core Team, 2020). Ratings of each of the 240 actions on each characteristic were averaged across each group of 10 participants. An exploratory factor analysis (EFA) was first selected to analyse the data because the research aim was

exploratory and there were no strong prior hypotheses as to which factors underlie the perception of actions (Schmitt, 2011). The final interpretation of the model considered the context that the analysis was exploratory, and these factors were likely to be correlated (Fabrigar, Wegener, MacCallum, & Strahan, 1999; Schmitt, 2011). Once suitable exploratory factor analysis models were generated we ran confirmatory factor analysis conversions. This was done by randomly partitioning the data into 50% model and test proportions and running an EFA analysis on the 50% model proportion, then converting this model to a CFA using the 50% test proportion. The relative goodness of fit of competing CFA models were assessed to establish the best fitting CFA model, and by extension the best fitting EFA model for the data.

Results

Five participants were tested and subsequently removed from the data analysis and replaced due to poor data quality. This was determined as participants who met two of the following three criteria: > 1 minute to respond to one of the trials, and > 3 seconds to respond in over 10% of trials. For the exploratory factor analysis, for each of the 23 characteristics a mean average of the 10 participants ratings of the 240 different actions was used. One participant had an incomplete trial, as such one action's average rating for one of the characteristics was based on 9 participants ratings instead of 10.

Reliability

The intra-class correlation coefficient (Koo & Li, 2016) was calculated for each of the 23 characteristics to assess the consistency of ratings between the 10 participants. A two-way model with “average” unit of ratings was used for each of these analyses, the results of which are presented in Table 2. Two characteristics were found to have poor inter-rater reliability ($\kappa < .5$), 10 were moderate ($.5 < \kappa < .75$), 10 were good ($.75 < \kappa < .9$) and 1 was excellent ($\kappa > .9$; see Table 2). The two characteristics with poor inter-rater reliability (Breaking-Making and Removing-Adding) were removed from all subsequent analyses (Koo & Li, 2016).

Table 2

Inter-rater reliability for each group of 10 participants rating actions on one of the 23 characteristics

Characteristic	kappa	95% Confidence Interval	F-Statistic	Interpretation
Accidental - Intentional	.869	$.843 < \kappa < .893$	$F(239,2151) = 7.65, p < .001$	Good
Angry - Happy	.915	$.898 < \kappa < .93$	$F(239,2151) = 11.8, p < .001$	Excellent
Anti-Social - Pro-Social	.74	$.689 < \kappa < .787$	$F(239,2151) = 3.85, p < .001$	Moderate

Anxious - Confident	.802	.762 < κ < .838	F(239,2151) = 5.37 , p<.001	Good
Approaching - Avoiding	.727	.671 < κ < .777	F(239,2151) = 3.94 , p<.001	Moderate
Breaking - Making	.485	.385 < κ < .575	F(239,2151) = 2 , p<.001	Poor
Disapproving - Approving	.752	.681 < κ < .807	F(239,2151) = 5.1 , p<.001	Good
Hesitant - Fluent	.728	.673 < κ < .777	F(239,2151) = 3.84 , p<.001	Moderate
Hiding - Uncovering	.717	.669 < κ < .773	F(239,2151) = 3.62 , p<.001	Moderate
Ignoring - Communicating	.835	.798 < κ < .867	F(239,2151) = 6.81 , p<.001	Good
Ingesting - Expelling	.521	.428 < κ < .605	F(239,2151) = 2.16 , p<.001	Moderate
Lowering - Raising	.796	.744 < κ < .839	F(239,2151) = 5.87 , p<.001	Good
Low-Speed - High-Speed	.773	.705 < κ < .825	F(239,2151) = 5.64 , p<.001	Good
Pulling - Pushing	.787	.744 < κ < .825	F(239,2151) = 4.9 , p<.001	Good
Rejecting - Desiring	.783	.739 < κ < .823	F(239,2151) = 4.92 , p<.001	Good
Releasing - Getting	.566	.480 < κ < .643	F(239,2151) = 2.35 , p<.001	Moderate
Removing - Adding	.424	.310 < κ < .527	F(239,2151) = 1.74 , p<.001	Poor
Straightening - Bending	.601	.513 < κ < .677	F(239,2151) = 2.88 , p<.001	Moderate
Subordinate - Dominant	.738	.686 < κ < .785	F(239,2151) = 3.94 , p<.001	Moderate
Threatening - Protecting	.821	.783 < κ < .855	F(239,2151) = 6.08 , p<.001	Good
Uncontrolled - Controlled	.642	.566 < κ < .709	F(239,2151) = 3.13 , p<.001	Moderate
Untrustworthy – Trustworthy	.617	.532 < κ < .690	F(239,2151) = 2.99 , p<.001	Moderate
Weak - Powerful	.846	.812 < κ < .876	F(239,2151) = 7.25 , p<.001	Good

The averaged ratings of the actions for each of the remaining 21 characteristics were normally distributed when plotted on a histogram. The Kaiser-Meyer-Olkin criterion (Dziuban & Shirkey, 1974; Kaiser, 1974) for each of 21 characteristics indicated that one of the characteristics 'Straightening-Bending' had a measure of sampling adequacy (MSA) value below .6 (.503) and so did not psychometrically relate to the rest of the data. The other 20 characteristics had MSA values ranging from .641 ('mediocre') to .94 ('marvellous'; see Table 3). Thus, the characteristic of 'Straightening-

Bending' was removed from all subsequent analyses. For the remaining 20 characteristics the overall KMO MSA value was .88 ('meritorious'). Furthermore, Bartlett's test of sphericity was significant ($\chi^2(190) = 3637.72, p < .001$). These measures both indicated that the characteristics were sufficiently psychometrically related for an exploratory factor analysis to be conducted.

Table 3

Measures of sampling adequacy for action

characteristics

Characteristic	MSA
Accidental - Intentional	.838
Angry - Happy	.884
Anti-Social - Pro-Social	.914
Anxious - Confident	.876
Approaching - Avoiding	.94
Disapproving - Approving	.893
Hesitant - Fluent	.865
Hiding - Uncovering	.924
Ignoring - Communicating	.836
Ingesting - Expelling	.878
Lowering - Raising	.908
Low-Speed - High-Speed	.853
Pulling - Pushing	.854
Rejecting - Desiring	.909
Releasing - Getting	.641
Straightening - Bending	.503
Subordinate - Dominant	.888
Threatening - Protecting	.853
Uncontrolled - Controlled	.725
Untrustworthy – Trustworthy	.922
Weak - Powerful	.893

Determining the model

Two methods were used to determine the number of factors to extract (Fabrigar et al., 1999; Howard, 2016): first a visual scree plot analysis (Zoski & Jurs, 1990) and second a Parallel Analysis (Patil, Singh, Mishra, & Donovan, 2008, 2017). These methods were selected because parallel analysis is generally considered to be one of the more robust methods and although visual scree plot analyses can be variable it is an intuitive and generally accurate method (Zwick & Velicer, 1986). Visual analysis of the scree plot indicated that although two latent factors are distinctively above the break or 'elbow', two further factors were also above the straight line, and so were

considered additional 'non-trivial factors' (Zoski & Jurs, 1990). In agreement, the Parallel Analysis (Patil et al., 2008, 2017) indicated that four factors should be extracted.

Initially a four-factor principal axis factoring (PAF) solution (Howard, 2016) was run and an oblique rotation of 'direct oblimin' was applied to allow for correlations between the factors (Costello & Osborne, 2005; Fabrigar et al., 1999; Schmitt, 2011). A PAF was used as it gives accurate results with a lower number of assumptions than maximum likelihood (Howard, 2016) and gives more accurate results than principal component analysis (PCA) if communalities are low (Kahn, 2006). Furthermore, PAF is preferable when determining the latent factors underlying a potentially non-normally distributed dataset, as was the case here. We rotated the model to improve fit, (Schmitt, 2011), selecting an oblique rotation to allow for correlations. This was because it was anticipated that the dimensions would be correlated as generally this is the case with psychological factors (Fabrigar et al., 1999; Schmitt, 2011). In addition, an oblique rotation method can produce both correlated and uncorrelated factors, and so if the factors are uncorrelated an oblique rotation method would still produce reliable results. Whereas, an orthogonal rotation method forces uncorrelated factors which, if the factors are to any degree correlated, would produce a less accurate model with potentially inflated item loadings for would-be correlated factors. (Costello & Osborne, 2005; Schmitt, 2011).

The subsequent structure matrix of the four-factor model (Table 4) was interpreted following a more conservative .50-.30 interpretation of Howard (2016) .40-.30-.20 rule. This was based upon the suggestion by Tabachnick and Fidell (2007) that the primary loading should be above .45, instead of .4 (Howard, 2016). Hence, in this experiment, characteristics were considered as substantial loadings if they had a primary loading above .5 and cross loadings below .3. Our four-factor model accounted for 59.9% of the variance in the data. For clarity we named the factors without using any of the words used to define the action characteristics (Reio Jr & Shuck, 2015).

Table 4

Correlations between characteristics and latent factors. Communality values represent the amount of variance in each characteristic that is accounted for by the model

Characteristic	Factor 1	Factor 2	Factor 3	Factor 4	Communality
Accidental - Intentional	.212	.056	.775	.143	.831
Angry - Happy	-.051	.926	-.005	-.008	.848
Anti-Social - Pro-Social	.342	.736	.017	.087	.745
Anxious - Confident	.703	.251	.186	-.009	.745
Avoiding - Approaching	.27	.672	-.008	.073	.570
Disapproving - Approving	-.174	.837	.167	-.034	.810
Hesitant - Fluent	.722	-.043	.289	-.121	.641
Hiding - Uncovering	.544	.381	-.012	.094	.530
Ignoring - Communicating	.656	.117	-.112	.101	.489
Ingesting - Expelling	.144	-.019	.007	.725	.646
Lowering - Raising	.626	.284	-.133	.084	.509
Low-Speed - High-Speed	.714	-.008	-.07	.011	.491
Pulling - Pushing	-.04	-.092	.132	.756	.611
Rejecting - Desiring	.247	.781	.038	-.105	.784
Releasing - Getting	.234	-.094	.079	-.651	.323
Subordinate - Dominant	.722	-.17	.181	.117	.702
Threatening - Protecting	-.434	.629	.059	-.205	.701
Uncontrolled - Controlled	-.116	.116	.757	-.055	.608
Untrustworthy -	-.143	.687	.104	-.121	.583
Trustworthy					
Weak - Powerful	.789	-.108	.067	.19	.818

Note: substantial loadings are highlighted in bold and defined using an adjusted, more conservative, interpretation of Howard's (2016) .40–.30–.20 rule, with primary loadings above .5 and cross loadings below .3.

The first factor, 'Feeble-Formidable', accounted for 22.1% of variance. 'Feeble' represented, in descending order of influence, the substantial loadings of weak, subordinate, hesitant, low-speed, anxious, ignoring, and lowering. Whilst 'Formidable' represented, in descending order of influence, the substantial loadings of powerful, dominant, fluent, high-speed, confident, communicating, and raising. The second factor, 'Unfriendly-Friendly', accounted for 22% of the variance. 'Unfriendly' predominantly represented the substantial loadings of angry, disapproving and rejecting, but also untrustworthy and avoiding. Whilst 'Friendly' predominantly represented the substantial loadings of happy, approving and desiring, but also trustworthy and approaching. The third factor, 'Unplanned-Planned', accounted for 7.2% of the variance, a smaller proportion than the first two. 'Unplanned' represented the substantial loadings of accidental and uncontrolled. Whilst 'Planned' represented the substantial loadings of intentional and controlled. The fourth factor, 'Adduction-Abduction', accounted for a similarly small proportion of the variance of 8.6%. 'Adduction' represented the substantial loadings of pulling, ingesting, and getting, which were considered to reflect movement towards the trunk of the body or away from the observer. 'Abduction', in contrast, represented the substantial loadings of pushing, expelling, and releasing, which reflect movement away from the trunk of the body or towards the observer. Within factor correlations are illustrated in Table 5.

Table 5

Between-factor correlation matrix of r values for the four-factor model

	Feeble- Formidable	Unfriendly- Friendly	Unplanned- Planned	Adduction- Abduction
Feeble-Formidable				
Unfriendly- Friendly	.15			
Unplanned- Planned	.29	.32		
Adduction-Abduction	.44	-.26	.06	

Due to the first two factors accounting for a much larger proportion of the variance, higher Eigen values, and are more overdetermined with a larger number of substantially loading characteristics than the third and fourth factors, we regard the model as having 2+2 factors. With ‘Feeble-Formidable’ (Eigenvalue = 6.531) and ‘Unfriendly-Friendly’ (Eigenvalue = 4.598) being the more influential factors, whilst ‘Unplanned-Planned’ (Eigenvalue = 1.015) and ‘Adduction-Abduction’ (Eigenvalue = 0.84) being the less influential factors.

Testing model fit

As the first two factors explained a much larger proportion of the variance in the data than the second two factors, we ran model comparisons of the competing 2- and 4-factor models to confirm whether a 4-factor model was a more appropriate fit for the data than a 2-factor model. This is particularly important as the third extracted factor (Planned-Unplanned) may be considered a less robust or unstable factor because it has fewer than three substantially loading characteristics and so it is less overdetermined (Costello & Osborne, 2005; Hogarty, Hines, Kromrey, Ferron, & Mumford, 2005). As such a 2-dimensional model, that does not include this potentially unstable factor, may be a more reliable representation of the data. In addition, because between factor correlations were weak, comparisons of models with an oblique rotation and an orthogonal rotation were also run. The purpose of this was to verify our anticipation that an oblique model, rather than an orthogonal model, would be more appropriate for the representation of action perception, in line with the general pattern seen in psychological phenomena (Fabrigar et al., 1999; Schmitt, 2011). Model comparisons were run by converting the EFA models of interest into confirmatory factor analyses (CFA) to assess and compare the relative goodness-of-fit of the competing models of interest. This was necessary as to allow the EFA models to be truly exploratory (Schmitt, 2011) the PAF factor extraction method was selected, however PAF solutions do not allow for goodness-of fit indices (Howard, 2016).

In this analysis, four-factor and two-factor EFA models were extracted using PAF with both oblique and orthogonal rotations. These four EFA models (2 factor orthogonal, 2 factor oblique, 4 factor orthogonal and 4 factor oblique) were converted to CFA models by randomly partitioning the data into 50% model and test proportions, with 120 actions randomly allocated to the model proportion and 120 actions allocated to the test proportion. An EFA analysis was run on the 50% model proportion, then this was converted to a CFA using the 50% test proportion. This process was simulated 200 times as the goodness-of-fit statistics for each model were dependent upon the random partitioning of the data into the 50% model and 50% test proportions during each simulation, and 200 samples were required for AIC values to be reliable (Hooper, Coughlan, & Mullen, 2008). Following similar methods to those used by Sutherland et al. (2013) the mean average and 95% confidence intervals of a number of goodness-of-fit statistics were compared (see Table 6), including: the model χ^2 (Hooper et al., 2008), Confirmatory Fit Index (CFI; Hu & Bentler, 1999), root mean square error of approximation (RMSEA; Hooper et al., 2008) and Akaike information criterion (AIC; Akaike, 1974; Hooper et al., 2008).

Whether the average goodness-of-fit statistics for each of the converted CFA models met the traditional thresholds of acceptability was not considered, for a number of reasons. First the CFA model goodness-of-fit statistics for each simulation was dependent upon the random partitioning of the data, and which 120 actions were allocated to the model and test proportions. Thus, the average CFA goodness-of-fit statistics are not direct measures of the original goodness-of-fit of the EFA models. Secondly, there is some debate about the implementation and interpretation of traditional goodness-of-fit statistics as the statistics, such as chi-square, RMSEA, and CFI, can be sensitive to sample size and potentially non-normally distributed data, as is the case with the current data set, (Dogan, Ozaydin, & Yilmaz, 2015; Kyriazos, 2018) and the thresholds for statistics may be arbitrary (Lai & Green, 2016). Thirdly, the interpretation of the AIC values is limited to which model has the relatively lowest value, as this indicates the best fitting model, because the absolute AIC value is not indicative of how well the model fits the data (Akaike, 1974). Due to these reasons, and that the aim of this EFA to CFA conversion analysis was to

distinguish which of the respective EFA models was comparatively the better fit to the data, whether the CFA models average goodness-of-fit statistics met the traditional thresholds was not considered. Instead, the analysis focused on which CFA model had the better average goodness-of-fit statistics, as this indicated which of the respective original EFA models was the better fit for the data. The average goodness-of-fit statistics from the 200 simulations of the 4 different models are presented in table 6.

Table 6

Means and 95% confidence intervals of the goodness-of-fit statistics from the 200 simulations of the CFA models with 2 or 4 factors, and oblique and orthogonal rotations.

Model	χ^2 (df), p-value	RMSEA, p-value	CFI	AIC
	[95% CI of χ^2]	[95% CI of RMSEA]	[95% CI]	[95% CI]
2 Factors Orthogonal	$\chi^2(169) = 823.367, p < .001$ [813.121, 833.614]	.179, $p < .001$ [.178, .181]	.638 [.634, .643]	6244 [6231, 6258]
2 Factors Oblique	$\chi^2(169) = 807.686, p < .001$ [801.347, 814.024]	.177, $p < .001$ [.176, .178]	.647 [.644, .649]	6229 [6218, 6240]
4 Factors Orthogonal	$\chi^2(164) = 675.152, p < .001$ [668.256, 682.049]	.161, $p < .001$ [.160, .162]	.717 [.714, .720]	6106 [6095, 6118]
4 Factors Oblique	$\chi^2(164) = 691.251, p < .001$ [682.637, 699.865]	.163, $p < .001$ [.162, .165]	.709 [.705, .713]	6122 [6110, 6134]

As shown in table 6, the four-factor model was a better fit than the two-factor model, as indicated by the lower mean AIC, RMSEA and model χ^2 , and higher CFI. This comparison also shows that the four-factor model with orthogonal rotation may be a better fit than that with oblique rotation, however this difference is less distinct as the 95% CIs are overlapping for the AIC and CFI, and the upper 95% CI of the RMSEA and χ^2 for the 4-factor oblique model are very similar to the lower 95% CI for the orthogonal model. Given that previous suggestions that an oblique rotation that allows for correlated

factors is more appropriate (Fabrigar et al., 1999; Schmitt, 2011), it was decided that this small distinction between the goodness-of-fit between the models was not sufficient, and the 4-factor model with oblique rotation was optimal.

To verify the reliability of the factors in the selected 4-factor model with oblique rotation, two-way intra-class correlation coefficients with “average” unit of ratings were run to assess the consistency within the average ratings of the characteristics that substantially loaded onto each factor were run (Koo & Li, 2016)(see Table 7). For the purposes of this analysis the average ratings for the negative substantial loading “Releasing-Getting” characteristic for the Adduction–Abduction factor were reversed, so that the characteristic represented “Getting-Releasing” and all substantial loadings for this factor were in the same direction. All substantially loading characteristics for the other factors were positive loadings and so did not require this adjustment.

Table 7

Inter-rater reliability for the four factors within the substantially loading characteristics.

Characteristic	kappa	95% Confidence Interval	F-Statistic	Interpretation
Feeble - Formidable	.896	[.875, .915]	F(239,1434) = 9.65 , p<.001	Good
Unfriendly - Friendly	.907	[.888, .925]	F(239,956) = 10.8 , p<.001	Excellent
Unplanned - Planned	.755	[.684, .81]	F(239,239) = 4.08 , p<.001	Good
Adduction - Abduction	.703	[.631, .762]	F(239,478) = 3.36 , p<.001	Moderate

The results of the intraclass correlation coefficient show that all four factors demonstrate an acceptable degree of inter-characteristic reliability (Koo & Li, 2016). In line with the 2+2 structure of the 4-dimension model with oblique rotation, the two more influential factors, Feeble-Formidable and

Unfriendly-Friendly, had notably higher intraclass correlation coefficients than the two less influential factors, Unplanned-Planned and Adduction-Abduction.

Response Times

Although this experiment did not explicitly aim to analyse response times, an interesting effect was observed whilst calculating the average response time for each characteristic (see Table 8). Across all actions for all characteristics the average response time to trials was 1125ms (SD = 586ms). However, there was a broad grouping of the average speed of response times for each characteristic by the factors the characteristics load onto. All characteristics that substantially loaded onto the Unfriendly-Friendly factor had the fastest average response times (range 946-1059 ms). In contrast, the characteristics that substantially load onto the Feeble-Formidable factor had longer reaction times, between 1108 ms and 1157 ms. Even longer reaction times were seen for the two factors that substantially loaded onto Unplanned-Planned, between 1196 ms and 1206 ms. Whilst the characteristics that load onto Adduction-Abduction, did not appear to show any particular pattern in response times.

Table 8

Average response times for each characteristic in order of fastest to slowest and the factor the characteristic substantially loads onto

Characteristic	Factor	Mean	SD
Angry - Happy	Unfriendly - Friendly	946.22	399.33
Rejecting - Desiring	Unfriendly - Friendly	1001.73	607.53
Disapproving - Approving	Unfriendly - Friendly	1032.05	410.97
Untrustworthy - Trustworthy	Unfriendly - Friendly	1032.05	517.66
Approaching - Avoiding	Unfriendly - Friendly	1058.70	517.57
Threatening - Protecting		1059.03	415.62
Ingesting - Expelling	Adduction - Abduction	1067.99	1000.91

Anxious - Confident	Feeble - Formidable	1108.37	409.41
Lowering - Raising	Feeble - Formidable	1110.36	438.04
Hesitant - Fluent	Feeble - Formidable	1125.69	540.94
Weak - Powerful	Feeble - Formidable	1133.51	551.7941
Low-Speed - High-Speed	Feeble - Formidable	1141.61	553.98
Subordinate - Dominant	Feeble - Formidable	1157.41	473.21
Pulling - Pushing	Adduction - Abduction	1188.24	640.76
Uncontrolled - Controlled	Unplanned - Planned	1196.48	484.42
Accidental - Intentional	Unplanned - Planned	1206.17	488.95
Releasing - Getting	Adduction - Abduction	1210.15	479.18
Anti-Social – Pro-Social		1223.61	560.34
Ignoring - Communicating	Feeble - Formidable	1238.30	603.38
Hiding - Uncovering		1313.91	637.52

The characteristic that loads most substantially onto each factor is highlighted in bold. Blank rows represent that the characteristic had no primary substantial loading onto a factor.

To explore this pattern further a one-way independent measures Analysis of Variance (ANOVA) was conducted in IBM SPSS 28. This analysis examined if participants' average response times to the 240 actions differed depending upon which of the four factors the rated characteristic loaded onto. Here, 70 participants' average ratings were allocated to the Feeble-Formidable group (10 participants for each of the substantially loading 7 characteristics; mean=1145ms, SD=25ms), 50 participants' average ratings were allocated to the Unfriendly-Friendly group (mean=1014ms, SD=25ms), 20 participants' average ratings to the Unplanned-Planned group (mean=1201ms, SD=51ms), and 30 participants' average ratings to the Adduction-Abduction group (mean=1155, SD=44ms). Shapiro-Wilk tests of normality showed that participants' average response times were normally distributed for all four factors (Feeble-Formidable = $W(70)=.966$, $p=.052$; Unfriendly-Friendly = $W(50)=.978$, $p=.484$, Unplanned-Planned = $W(20)=.913$, $p=.074$; Adduction-Abduction = $W(30)=.978$, $p=.757$). A Levene's test for homogeneity of variance was non-significant ($F(3,166)=1.08$, $p=.361$), indicating equal variances between the factors.

The main effect of factor was significant (see Figure 4), indicating that there were significant differences in participants' average response time depending upon which of the four factors the rated characteristic loaded onto ($F(3,166)=5.92, p<.001$). Hochberg's GT2 post hoc tests were selected for pairwise comparisons as there were large differences in sample size for each factor (Stoline & Ury, 1979). Average response times to characteristics that loaded onto Unfriendly-Friendly were significantly faster than average response times to characteristics that loaded onto the Feeble-Formidable ($p=.005$), Unplanned-Planned ($p=.005$) and Adduction-Abduction ($p=.022$) factors. All other pairwise comparisons were non-significant ($p>.05$).

Discussion

The results of the exploratory factor analysis indicated that a 4-dimensional model with oblique rotation was the most appropriate model of the perception of dynamic human actions. These four factors were Feeble-Formidable, Unfriendly-Friendly, Unplanned-Planned and Adduction-Abduction and they represent the fundamental dimensions that form the conceptual space underlying action perception. The first two factors of Feeble-Formidable and Unfriendly-Friendly explained a larger proportion of the variance (22.1% and 22% respectively) then the second two factors a smaller proportion (Unplanned-Planned 7.2% and Adduction-Abduction 8.6%). In addition, we observed broad groupings in the speed of the responses for each characteristic by the factors the characteristics substantially loaded onto. Ratings of the characteristics that loaded onto the Unfriendly-Friendly factor had significantly faster average response times than ratings of characteristics that loaded onto the other three factors, whilst there were no significant differences between comparisons of ratings loading onto the other factors. Although, non-significant in this analysis, a general observation of the average response time for the different characteristics was that characteristics that loaded onto Feeble-Formidable were next fastest, followed by characteristics that loaded onto Unplanned-Planned, and that there was no distinctive pattern of average response time for characteristics that loaded onto Adduction-Abduction.

The two first factors (Feeble-Formidable and Unfriendly-Friendly), refer to more abstract action properties (Ciaramidaro et al., 2007; Van Overwalle & Baetens, 2009). These 2 fundamental action space dimensions have some parallels to those observed for face trait space (Oosterhof & Todorov, 2008; Sutherland et al., 2013), where dominance and trustworthiness are fundamental to face trait evaluation, and to the fundamental dimensions observed in a 2-dimensional space of emotions (Bliss-Moreau, Williams, & Santistevan, 2019; Feldman Barrett, 2017), namely arousal and valence. Our action space dimension of Feeble-Formidable represents similar characteristics for actions as dominance does for face trait perception and arousal for emotion perception (indeed the action characteristic dominance loaded onto our Feeble-Formidable factor). Equally our action space dimension of Unfriendly-Friendly represents similar characteristics for actions as trustworthiness does for face trait perception and valence does for emotion perception. In our study, the action characteristics of trustworthiness, approaching, and happiness loaded onto our Unfriendly-Friendly factor, whilst face trustworthiness, approachability and smiling loaded onto Sutherland et al.'s (2013) valence/trustworthiness factor. Although conceptual spaces are typically domain dependent, these similarities in the fundamental dimensions defining the conceptual spaces for these different domains may reflect some aspect of a single broader cross-domain conceptual space for the social evaluation of other individuals. While not directly equivalent, cross-modal conceptual spaces have already been observed for the perception of objects in both visual and tactile modalities e.g. Gaissert, Wallraven, and Bulthoff (2010), suggesting that conceptual spaces might not be restricted to the particular physical characteristics of the sensory information.

Our first fundamental action space dimension of Formidableness appears to reflect the assessment of an actor's ability to implement their intentions. Determining this information from actions requires assessments of both simple movement characteristics - like action speed, fluency and power, but also more abstract characteristics including the dominance and confidence of the actor. These more abstract social evaluations include assessments of others within the context of a social hierarchy, judgments that have shaped the evolution of the human mind (Cummins, 2000), and brain (Zink et al., 2008). Our second

fundamental action space dimension of Friendliness also encompasses an evaluation of abstract qualities related to the intentions of the actor. Here the dimension is perhaps simpler to interpret with either ends of the continuum representing whether the actor represents someone an individual would want to interact with or not. Social cooperation has numerous evolutionary benefits (Dugatkin, 1997), is pervasive between humans (Stevens & Hauser, 2004) and develops early (Warneken & Tomasello, 2007). Together, these two primary action space dimensions we identify here represent relatively abstract qualities of human actions that are related to fundamental evaluations that we need make to operate successfully within our complex social environment.

The two more minor factors Unplanned-Planned and Adduction-Abduction explain a smaller proportion of the variance in our model of action perception and both share weak correlations with the first two factors. Nevertheless, both a Parallel Analysis and model comparisons using EFA to CFA conversions showed that these were distinct separate factors underlying action perception. Importantly, and in contrast to the 2 primary dimensions underlying action space, these factors appear to underlie judgments that would be specific within the action domain.

The Unplanned-Planned dimension may reflect evaluations during ongoing predictions we make about the intentions and outcomes of other people's actions. Actions are the principal way that individuals influence their environment (including observers of these actions), we are constantly making predictions about how others will act and updating these predictions when they are violated (Flanagan & Johansson, 2003; Friston, Mattout, & Kilner, 2011). Successful action prediction is important to successful social interactions (Sebanz & Knoblich, 2009) and develop during infancy (Monroy, Meyer, Schröer, Gerson, & Hunnius, 2019). Action prediction involves several brain regions including early visual processing areas (Maffei, Giusti, Macaluso, Lacquaniti, & Viviani, 2015) as well as the extended Mirror System (Kilner, Friston, & Frith, 2007). And activity within these cortical regions may underpin the evaluation of actions on the Unplanned-Planned dimension of action space we identify here.

As with the Unplanned-Planned dimension, the ‘Adduction-Abduction’ dimension appears to reflect evaluation of a quality that could largely be unique to the action domain. The characteristics assessed that load onto this dimension involve the movements of limbs or objects towards (ingesting, pulling, getting) and away (expelling, pushing, releasing) from the actor. These reflect movements that can only be executed by an animate agent. However, these types of body movements can covary with size changes in the image of the actor at the retina. Movement of limbs away from the body typically result in an increase in the area of the retina subtended by the actor, whilst limb movements towards the body will decrease this area. Similar size changes are also commensurate with movements towards and away from the observer respectively, a property of all physical objects and not just actors. It remains to be seen whether the Adduction-Abduction dimension we observe here is entirely unique to the kinematics of dynamic human actions with respect only to the actor themselves, or also has some relationship with movements of the actor with respect to the observer. In the latter case, this dimension may also have some importance in the representation of the social relevance of the action to the observer. For example, approaching actors may afford potential social opportunities or represent threats, retreating actors will be less relevant to the observer.

The dimensions we have identified here show some relationships with the principal components that best explained semantic categorisation of actions in Tucciarelli et al. (2019) behavioural study, although they cannot be directly mapped onto each other. The semantic categories that varied along their first principal component varied according to the type of change induced by the execution of their actions. With change of location at one extreme through change of internal state in the middle to change of external state at the other extreme. This component is not directly comparable to our Adduction-Abduction dimension; however, Adduction-Abduction does represent the way actors change the external state of their environment (through moving it towards or away from them). Tucciarelli’s third component appeared to represent how an action might be directed towards another individual or not. There are some parallels here with our Unfriendly-Friendly dimension, where ‘friendly’ actions involve positive

interactions with others, whilst actions executed alone are in the middle of this dimension. Unfriendly actions directed towards another individual lie at the other end of our dimension. Such unfriendly actions were not categorised in Tucciarelli's experiment, and so we don't know where they may lie within their model. However, they may lie the other side of the actions executed alone to the 'friendly' actions that they tested; thus, their third component might best explain categorisation of actions along a friendly-alone-unfriendly continuum akin to our Unfriendly-Friendly dimension.

The differences between our 4-dimensional model of action space and other attempts at evaluating action space, in particular Tucciarelli et al. (2019) 3-dimensional model of action categorisation can be explained by substantive differences in the methodologies used. Tucciarelli et al. (2019) required participants to arrange static images of actions according to similarity of 'meaning', this precluded action comparisons on other qualities, like the nature of the movements themselves, or perhaps more abstract qualities to do with actor intentions. In contrast, we asked participants to rate dynamic actions on 23 pre-determined characteristics that encompassed a greater range of ways that actions can be evaluated. Even greater are the differences between the way Thornton and Tamir's (2022) 6-dimensional model of actions was determined and the way we measured action space here. Their participants evaluated action verbs, many of which could not be executed by a human actor. It thus remains to be determined to what extent their ACT-FAST model represents the perceptual qualities of dynamic human actions.

The design of our study did not allow for particularly accurate measures of response times when evaluating different action characteristics, as it was not an explicit reaction-time task, tasks were conducted remotely on devices not configured for measuring reaction times, and participants were required to indicate their response only after the completion of each presented action. Nevertheless, we observed a clear grouping of response times for three of the factors, perhaps reflecting shared processing of the characteristics that loaded substantially onto each factor. Furthermore, average response times to characteristics that loaded onto the Unfriendly-Friendly factor were significantly faster than the average

response times to the characteristics that loaded onto the other three factors. There are two possible explanations for this observation. First, these grouped response times reflect some aspect of the stimuli themselves. Possibly information on Unfriendliness (and Friendliness) may be available earlier following the onset of the stimulus resulting in the shortest response times for characteristics that loaded onto this factor. For example, body form information like actor posture will be available from the first stimulus frame and may allow early detection of the relevant characteristics. Whilst information on the other factors may occur later as the actions unfold with time, and with the availability of motion information. Alternatively, reaction times to the different characteristics may reflect differences in their processing times. Their sequence may represent their relative importance to the observer: the degree of friendliness or unfriendliness of another individual is most critical, as this factor may cue the potential of a threat or not to the observer and as such is detected quickest. The degree of formidableness and abduction of the action may then help us interpret how to respond to the other individual. Whilst determining the degree of planning behind the action is potentially less important to the observer

Although the model of action space found in the current experiment explains a relatively large proportion of the variance (59.9%), this experiment was dependent upon ratings of the 23 characteristics that had been predetermined. We believe that these characteristics were comprehensive, given they were driven by a larger independent subset of actions and action words. Nonetheless, the requirement of predetermined characteristics means that the analysis and subsequent model were dependent upon the characteristics selected, which has the potential to produce a less representative model of action space. For example, the importance of Unplanned-Planned as a latent factor may be overstated due to the exploratory factor analysis method simply grouping the accidental-intentional and uncontrolled-controlled characteristics into a single latent factor, because they are generally much more like one another, compared to the similarities between the other eighteen included characteristics. This may explain why Unplanned-Planned was extracted as the third factor despite explaining the smallest proportion of variance and having only two substantially loading characteristics, when the traditional threshold suggests

that at least 3 substantial loadings are required for the factor to be considered robust (Costello & Osborne, 2005; Hogarty et al., 2005). Nonetheless, the intraclass correlation coefficient for this factor indicated that the inter-characteristic reliability was “good”, a Parallel Analysis (Patil et al., 2008, 2017) indicated that 4 factors should be extracted, and the EFA to CFA conversion analysis found that a 4-dimensional model was a better fit for the data than a two-dimensional model. Thus, although this factor has fewer substantially loading characteristics than traditional thresholds would permit, it appears to be an influential latent factor of action perception. Nonetheless, an alternative truly data driven method of determining action space, like multidimensional scaling (Ding, 2018), would help to confirm the factors we identify here.

Our measure of action space is based upon evaluations of actions conveyed by a grey, androgynous avatar without a face, real-world context, or objects or other people observable during transitive and social actions. This ensured participants focused solely on the nature of the action itself, without judging non-action qualities of the stimulus. Action evaluation in the real world will involve the incorporation of many different sources of additional social, contextual, and other multimodal information. Lastly, the current experiment asked participants to explicitly evaluate actions. This procedure is uncommon in real-world social environments, as such further experiments will be required to understand whether our implicit evaluations of other peoples’ actions are based upon an organisation of action space along the 4-dimensions we describe here.

In conclusion the current study found that action space could be best described by a 2+2 factor model of action perception. This consisted of two substantial factors of Formidableness and Friendliness, which parallel similar dimensions identified in both face trait space and emotion space, and perhaps contribute towards a more generalised social perception space. In addition, the two minor factors of Planned and Abduction, appear to be particularly action specific and could, respectively, represent the nature of predictions we make about other peoples’ actions and visual qualities of actions.

Supplementary materials

Stimuli

List of action databases inspiring action selection

Action selection was based upon an assessment of a diverse range of current action databases: Point-Light Action Corpus (Shipley & Brumberg, 2005); CAVIAR Test Case Scenario (Fisher, Santos-Victor, & Crowley, 2004); Inferring intentions from biological motion: A stimulus set of point-light communicative interactions (Manera, Schouten, Becchio, Bara, & Verfaillie, 2010); The 20BN-“something-something” Dataset V2 (Goyal et al., 2017); Depth-included Human Action video dataset (Lin, Hu, Cheng, Hsieh, & Chen, 2012); HMDB: a large human motion database for human motion recognition (Kuehne, Jhuang, Garrote, Poggio, & Serre, 2011); Learning Human Actions from Movies (Laptev, Marszalek, Schmid, & Rozenfeld, 2008); IAS-Lab Action Dataset (Munaro, Ballin, Michieletto, & Menegatti, 2013; Munaro, Michieletto, & Menegatti, 2013); The LIRIS human activities dataset (Wolf et al., 2014); NTU RGB+D 120 Action Recognition Dataset (Jun Liu et al., 2019; Shahroudy, Liu, Ng, & Wang, 2016); ShakeFive2 (Van Gemeren, Poppe, & Veltkamp, 2016); UCF101 - Action Recognition Data Set (Soomro, Zamir, & Shah, 2012). These action databases included a total of 619 actions; frequently occurring actions from across all databases (e.g. sitting down, throwing) were automatically included in our list of 240. Other actions were selected to try and ensure that a diverse range of human movements were included, involving both transitive and social actions, whilst also ensuring that any actions were feasible to capture using motion capture suits indoors (e.g. skiing and surfing were not included).

Motion capture procedure and stimuli processing

Actions were performed by four actors (2 females, aged 23 and 59; 2 males aged 25 and 58) from one family group (due to government restrictions in social interactions during the coronavirus pandemic). Following motion capture, all recordings were cleaned within the Perception Neuron proprietary software Axis Neuron (Perception Neuron, Noitom, Miami, Florida, USA) to ensure consistent model alignment, and to set joint stiffness, step stiffness, and step constraint to optimise sensor placement with respect to the floor and ensure a realistic looking action by eliminating out of place/impossible sensor recordings. This was important as to allow for the use of motion capture recordings presented on characters for gaming purposes (for example) the Axis Neuron software allows for motion capture recordings of actions to be more fluid, however for our purposes we required the actions to look as natural as possible. Anti-magnetism was also applied to the whole body to account for local magnetic fields. Finally, a smooth factoring, which countered issues with any minor shaking and shifting of sensors, was applied. The full action recordings were initially cropped from the first frame in which movement of the actor (distinct from the natural oscillation of the body) began until the final frame of the last meaningful action movement before the body returned to a neutral position. An additional 30 frames (500ms) were included after the end of the action as a buffer. Once adjusted the final 1440 actions were exported as BioVision (.bvh) files.

Avatar development

The avatar was designed in Unity 3D (Unity, San Francisco, CA. USA) based upon the standard format of a .bvh file with the hips as a root 3D shape and the other body parts as further connected 3D shapes. This allowed the action to be presented via the X, Y and Z rotation of each relative body part from the root of the hips (Meredith & Maddock, 2001). The avatar was initially designed similar to that used in Roether, Omlor, Christensen, and Giese (2009) so that the body appeared human-like, in 3 dimensions with a grey surface. However, no personal characteristics (e.g. age or gender) could be

derived from the avatar (e.g. from overall body shape, surface texture, clothing, facial characteristics etc., see Figure S1).

To assess how participants perceived the gender of the avatar, we initially conducted a short study where participants ($n=14$) were showed a static image of the waving avatar and they were asked to write a short biography for the avatar. Participants responses to the short biography showed that the avatar was not consistently presumed to have any distinctive characteristics. However, 7 participants assumed the avatar was male, the other 7 made no assumptions about avatar sex, suggesting a bias in perceived sex. Waist-hip ratios are well known cues to body sex e.g. (Molarius, Seidell, Sans, Tuomilehto, & Kuulasmaa, 1999). We, therefore, conducted a second study where participants ($n=14$) altered the width of the components that make up the avatar's torso (collar, chest, upper spine, middle spine, lower spine and hips) so that the avatar appeared to first appear stereotypically feminine, then masculine, then androgynous. The width of each torso component was averaged across participants to generate feminine, masculine and androgynous bodies (see Figure S1).

The feminine body had a waist-hip ratio of 0.795:1, the masculine 1.062:1, and the androgynous 0.941:1. To generate an avatar that was perceived as neither male nor female, the final avatar torso component widths were set to the average of the feminine and masculine bodies. Although the final avatar waist-hip ratio (0.918:1) was slightly more masculine than feminine compared to that obtained by (Molarius et al., 1999), it was slightly more feminine than the ratio obtained from the androgynous avatar. This was deemed to be a good balance between masculine and feminine body shapes, especially given that, perhaps more importantly. all our action stimuli would be in motion and dynamic cues to gender tend to dominate structural cues (Mather & Murdoch, 1994) when these cues are in conflict.

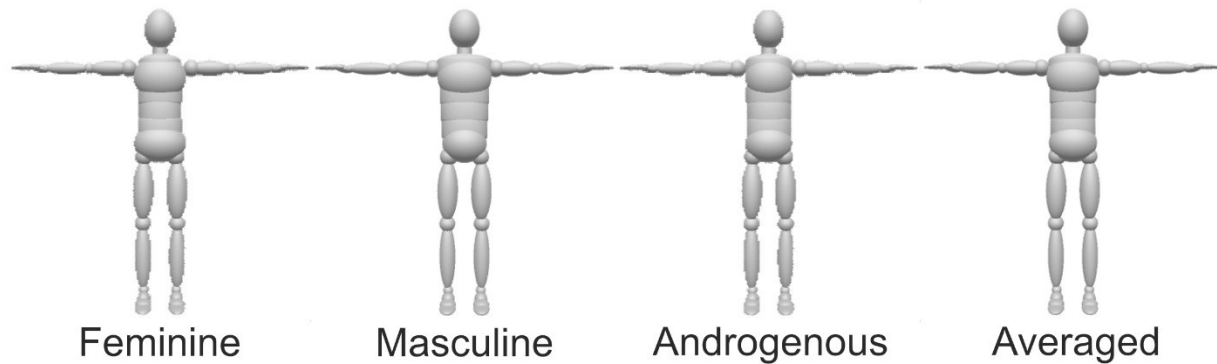


Figure S1: Images of the feminine, masculine, androgynous determined by participants, and final averaged avatar used during the rating experiment.

Selection of action characteristics

List of action databases for selecting action characteristics: Actions as space time shapes (Gorelick, Blank, Shechtman, Irani, & Basri, 2007), the UCF Sports Action Data Set (Rodriguez, Ahmed, & Shah, 2008; Soomro & Zamir, 2014), the UCF YouTube Action Data Set (Jingen Liu, Luo, & Shah, 2009), the UCF101 Action Recognition Data Set (Kuehne et al., 2011), the Hollywood 2 human actions and scenes data set (Marszalek, Laptev, & Schmid, 2009), the KTH Recognising human actions dataset (Schuldt, Laptev, & Caputo, 2004), the UT interaction dataset (Ryoo & Aggarwal, 2010), and IXMAS Actions (Weinland, Özuysal, & Fua, 2010).

Table S1

Proportions of action words related to each characteristic. Characteristics are presented in the order determined during testing and are grouped by characteristic category

Characteristic	Characteristic category	Word proportion (%)
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Avoiding/Approaching	Action goal	5.00
Releasing/Getting	Action goal	4.20
Hiding/Uncovering	Action goal	3.00
Ingesting/Expelling	Action goal	1.60
Breaking/Making	Action goal	2.00
Pulling/Pushing	Action goal	5.70
Lowering/Raising	Action goal	6.10
Removing/Adding	Action goal	2.20
Disapproving/Approving	Action intention	0.90
Ignoring/Communicating	Action intention	3.10
Rejecting/Desiring	Action intention	3.70
Accidental/Intentional	Action intention	2.00
Angry/Happy	Action intention	4.30
Anti-social/Pro-social	Action intention	2.50
Threatening/Protecting	Action intention	2.10
Straightening/Bending	Action movement	2.80
Uncontrolled/Controlled	Action movement	6.90
Hesitant/Fluent	Action movement	2.70
Low speed/High speed	Action movement	3.20
Weak/Powerful	Action movement	5.20
Anxious/Confident	Action trait	2.10
Subordinate/Dominant	Action trait	1.20
Untrustworthiness/Trustworthiness	Action trait	0.40
Object	Non-action category	7.40
Abstract concepts	Non-action category	6.30
Body part	Non-action category	1.70
Personality trait	Non-action category	1.60
Person descriptor (inc. nationality, occupation)	Non-action category	3.00
Location/Place	Non-action category	1.20
Sport	Non-action category	7.80
Unclassifiable	Non-action category	0.80

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