Appendix: Exploring Personality in Human-Object Interactions

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We aim to investigate if there are any latent features regarding personality expression in complex object interaction sequences. If so, can those latent features' expression be controlled using OCEAN factors, and how distinguishable would the results be from manual, Laban-based augmentations?

A. Dataset Statistics

The statistics of the selected subset of the GRAB [1] dataset are shown in Table 1. Note that a set of subjects interacts with more than one object category, and some action definitions are shared across objects while causing distinct behaviors.

Object	Action	Subject	Sequence	Frame
Bowl	1	4	4	305
Cup	1	8	8	690
Flashlight	1	7	14	1930
Frying pan	1	4	4	460
Hammer	1	10	22	2510
Knife	2	4	6	805
Mug	1	10	20	2030
Scissors	1	5	6	735
Teapot	1	6	10	1115
Wineglass	1	7	8	635
TOTAL	8	10	102	11215

Table 1 Statistics of the customized GRAB dataset.

B. Augmentation Details

To augment our annotated dataset, we modified the OCEAN2LE mapping in [2]. We transposed the normalization axis while keeping the significant portions. We multiplied the resulting matrix in Table 2 with Laban Movement Analysis (LMA) Effort parameters to obtain the OCEAN trait adjustments. A factor of 1 for *Space* would cause a 0.86 increase on *Openness*, -0.86 in Conscientiousness, and 0.896 in Neuroticism.

Effort	Space	Weight	Time	Flow
O	0.86	0.0	0.0	1.0
C	-0.86	0.0	0.91	-1.0
E	0.784	0.0	-0.997	1.0
A	0.0	0.685	1.0	0.0
N	0.89	0.0	0.0	0.776

Table 2 Matrix to calculate OCEAN delta trait values from LMA effort parameters.

We explain the details of each LMA Effort manipulation by the augmentation framework in the sequel.

B1. LMA Space

The target bones are paired with the second parent of their attached bone, namely the *"Limit"* bone. Limit bones are the upper arm and leg bones for hand and foot targets, respectively. The delta vector V_L between the limit and target bones is calculated for each frame and decomposed into the frontal (V_L^f) and longitudinal (V_L^l) components for rotation. The rotation amount R is proportional to f_s and has a maximum of 15 degrees. When f_s is negative, and the distance between symmetric target joints d_{sym} is below the max limit distance,

f_{sym} is applied as a correction term. f_{sym} is non-zero in case the target limbs are *not* crossing each other. f_{sym} is calculated as follows:

$$f_{\text{sym}} = \begin{cases} |1 - \frac{|d_{\text{sym}} - \|\mathbf{V}_L\||}{\|\mathbf{V}_L\|}|, & \text{not crossing} \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The final R value is multiplied by the f_{sym} and is used to find the frontal (shift_f) and longitudinal (shift_l) shifts as below. Figure 1 provides an example visualization of a "cup" object in "pour" action, showing the effect of the *space* parameter.

$$\begin{aligned} \mathit{shift}_f &= (V_L^f \cdot \cos(R) - V_L^l \cdot \sin(R)) - V_L^f \\ \mathit{shift}_l &= (V_L^f \cdot \sin(R) + V_L^l \cdot \cos(R)) - V_L^l \end{aligned} \quad (2)$$

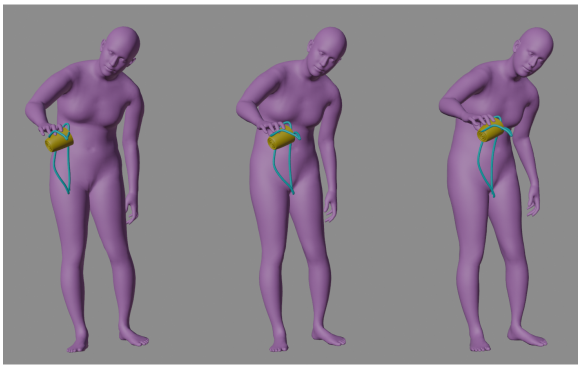

Fig. 1 Example augmentations with *space* from −0.75 to 0.75; left to right. Notice the change is subtle, as seen in object height, due to the enclosed posture of the subject.

B2. LMA Weight

The weight factor primarily affects the "pelvis" bone of the subject; the effect is scaled according to the midpoint M between the two foot targets. This midpoint is used to calculate shifts on sagittal and frontal axes shift_{sf}. In contrast, the distance between the pelvis and the floor d_{lim} determines the longitudinal shift shift_{ln}. The distance between M and the pelvis is indicated as d_p (Equation 3). When the shift factor f_w is negative, the distance between the pelvis and either of the upper leg bones is calculated as d_n, and the distance between the lower foot bone and its upper leg bone is as d_l (Equation 4). The shifts are combined into a 3D vector and applied to the pelvis and the hand joints. For neck and spine bones, positive and negative f_w rotate around the frontal axis in 15 and 5 degrees, respectively. Example visualization in Figure 2 indicates that increased *weight* influences the subject as if the "cup" is heavy.

$$\mathit{shift}_{sf} = \begin{cases} d_p \cdot f_w, & \text{if } f_w > 0, \\ 0, & \text{if } f_w = 0 \end{cases} \quad (3)$$

$$\mathit{shift}_{ln} = \begin{cases} \frac{d_n}{20} \cdot f_w, & \text{if } f_w \geq 0, \\ \max(\frac{d_n - d_l}{10}, 0) \cdot f_w, & \text{otherwise} \end{cases} \quad (4)$$

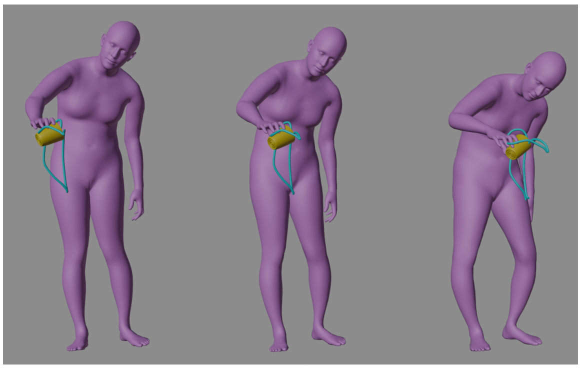

Fig. 2 Example augmentations for *weight* between −0.75 and 0.75; left to right. The subject bends forward like the "cup" is a heavy object.

B3. LMA Time

The shift amount s_k is calculated according to the time factor f_t (Equation 5). The new shift $S(i)$ for keyframe i is calculated in the incremental fashion where N is the total number of keyframes, except the first frame (Equation 6). The shift can be noticed in different subject postures in Figure 3.

$$s_k = \begin{cases} f_t + 1, & \text{if } f_t \geq 0, \\ \frac{1}{|f_t|+1}, & \text{otherwise} \end{cases} \quad (5)$$

$$S(i) = s_k + i \cdot |1 - s_k|/N \quad (6)$$

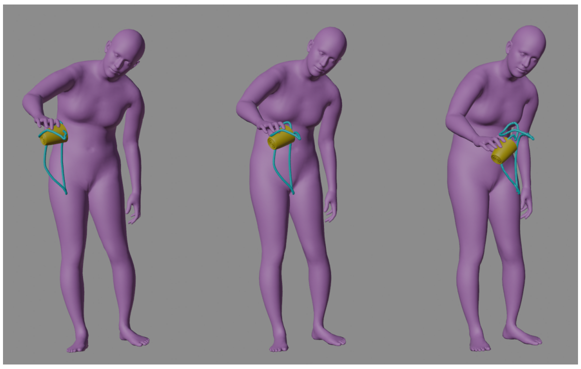

Fig. 3 Example augmentations for *time* between −0.75 and 0.75; left to right. Due to the resolution change, the subject can be seen in a different pose at the same timestep as others.

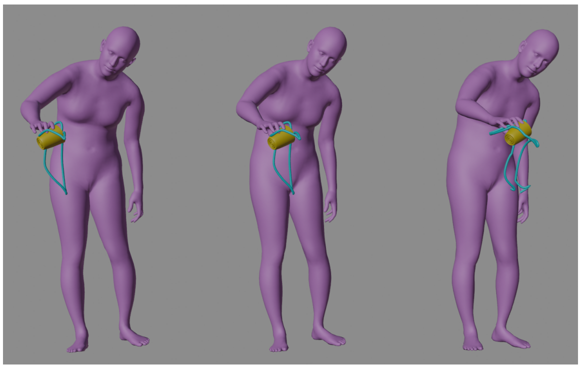

Fig. 4 Example augmentations for *flow* between −0.75 and 0.75; left to right. The increased flow alters the object's trajectory, as seen in differences in blue lines.

B4. LMA Flow

The decimation amount is determined as f_{dec}=0.9 · $|f_f|$. For positive values of f_f, random keyframes are selected to add noise to their rotations. The noise is sampled from two normal distributions with means $\mu_1 = -2f_f$ and $\mu_2 = 2f_f$ and common standard derivation of 0.75. If the sampled noise is above 2 in magnitude, it is resampled, as higher f_f values result in less variation. The range of frames is also calculated using random distribution, varying from 5 to 30, which is determined empirically (Equation 7). Altering the flow changes the trajectory of the object due to changes in the subject's pose, as seen in Figure 4.

$$\begin{aligned} range_{min} &= 5 + (1 - f_f) \cdot 15 \\ range_{max} &= 5 + (1 - f_f) \cdot 35 \end{aligned} \tag{7}$$

We investigate if there are any latent features regarding personality expression in complex object interaction sequences. If so, can those latent features' expression be controlled using OCEAN factors, and how distinguishable would the results be from manual, Laban-based augmentations?

C. Neural Personality Control

We depict the effect of using different OCEAN values for the network input on the generated animation in Figure 5. We observe that Openness impacts the general body posture; High Openness appears as a standing tall figure. Conscientiousness affects the object's motion trajectory; High Conscientiousness results in a steady trajectory that helps the figure appear more confident and determined. Extraversion affects the animation speed, which also impacts the object's trajectory; High Extraversion results in quick movements. Agreeableness impacts the posture in the vertical axis; High Agreeableness is portrayed as a bowing figure to signal friendliness and humbleness. Neuroticism affects the range of movement and, hence, the steadiness of the object's trajectory; High Neuroticism is portrayed with an unsteady object trajectory with anxious movements.

Although the OCEAN input can be a mix of different factors, we focus on single-trait changes to limit the number of animations in our user studies. For a single animation regarding "pour" action with "cup" object, the effect of altering multiple factors simultaneously can be seen in Figure 6. We altered multiple OCEAN factors across columns on all *red* agents, where each row represents a different timeframe. On the first column, we set *Openness*, *Extraversion*, and *Agreeableness* to 1, while setting other factors to 0 **(OEA=1 and CN=0)**. Notice how the body is positioned and the object is moved compared to the *green* agent in the rightmost column, which is the original motion. The agent leans forward while spreading both its legs and arms. We set all the aforementioned factors on the second column to -1, while setting other factors to 0 **(OEA=-1 and CN=0)**. The posture becomes more upright, and the object moves within a limited space. In the third column, we also changed the rest of the factors, *Conscientiousness* and *Neuroticism*, to 1

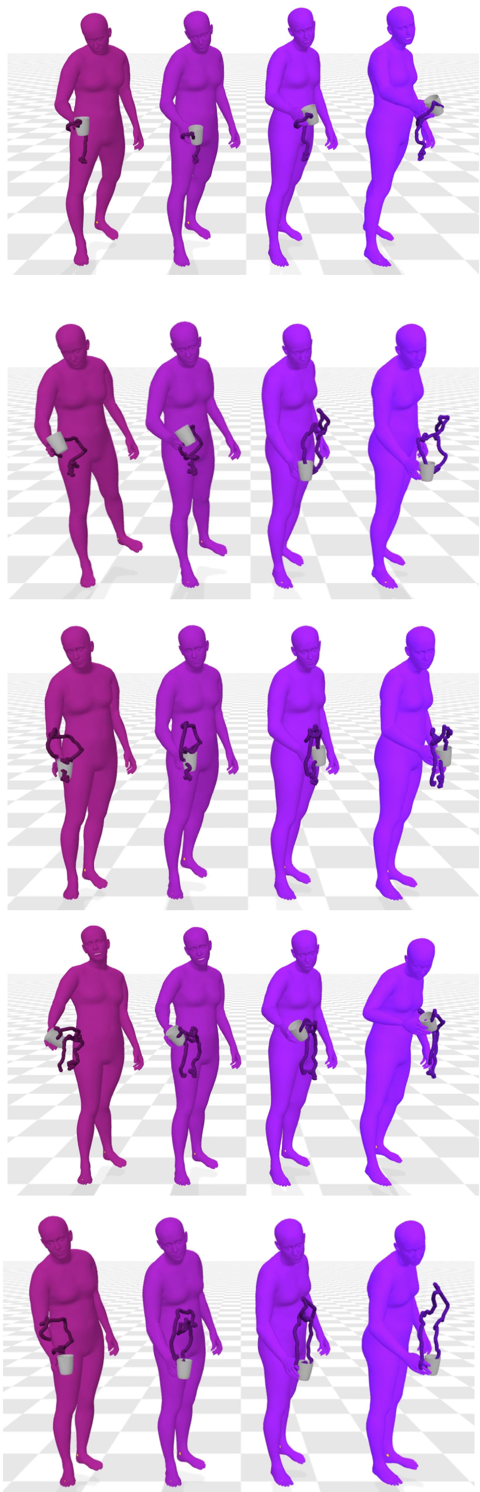

Fig. 5 The effect of OCEAN values on the network output: From left to right, the factor ranges from -1 to 1. Each row contains the range for a specific trait. From top to bottom: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

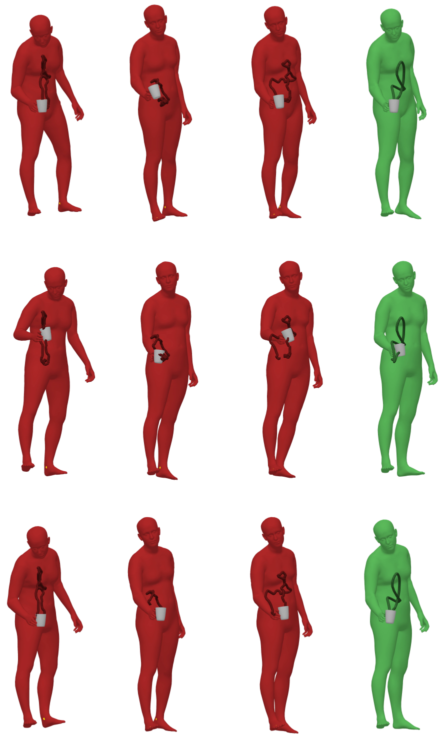

Fig. 6 Altering multiple OCEAN factors can affect the original motion differently. From left to right as altered OCEAN factors: **(OEA=1 and CN=0)**, **(OEA=-1 and CN=0)**, **(OEA=-1 and CN=1)**, and the original unaltered motion.

(OEA=-1 and CN=1). Due to changes in both factors, which have conflicting effects, the object trajectory becomes bizarre, yet more similar to the original trajectory. It is clear how the motion can be authored in noticeable ways when the provided factors are aligned towards similar effects.

D. User Study Details

We performed two user studies. The first is for dataset annotation and training, and the second is for assessing the quality of the generated animations. We recruited our participants from the Prolific platform and our local community. We provided participants a link to our online website for both user studies. We collected optional demographic data for participants in Prolific using the platform itself, while the local community is provided with an option to do so. A subset of participants in our local community completed both studies, while participants from Prolific only completed either. As the motions were selected and

displayed randomly, no participant who participated in both studies showed identical motions between studies. The participants' demographics are as follows:
For the first user study:

- Gender: 50% male, 36% female and 14% not provided.
- Age: Between 18 and 65.
- Nationality: 36% Türkiye, 20% South African, 16% United States, 14% Others, and 14% not provided.

For the second user study:

- Gender: 45% male, 44% female, 11% not provided.
- Age: Between 18 and 82.
- Nationality: 36% United States, 20% United Kingdom, 8% South African, 22% Others, and 14% not provided.

E. Human-Object Interaction

We asked questions regarding motion quality to obtain further insight into human-object interactions. The additional questions include:

- From scale 0 to 1, how realistic is the motion?
- Is the motion accurate according to its original action label?
- How hot/cold, heavy/light, and soft/hard is the object perceived?
- Which aspects of the motion inspired your decision the most: Body pose, gaze, object trajectory, or finger articulations?

Figure 7 depicts the user ratings regarding the perceived realism of the animation for each object category. Although the rated samples belong to the same dataset and are captured using the same setup, they received different realism scores for each object category. This behavior could be due to subjects having different performance qualities regarding objects. The capture setup includes actual objects, but since the focus is on the grabbed object, they do not include secondary objects. For example, the cup the subject interacts with is empty; thus, the recorded actors perform any drinking or pouring action. Similarly, there is no other object in the scene for the scissors to cut. Consequently, we observe decreased perceived realism of object categories needing care. We observe that the flashlight and scissors categories received relatively low realism scores, likely because these objects are relatively challenging to act with without a clear objective.

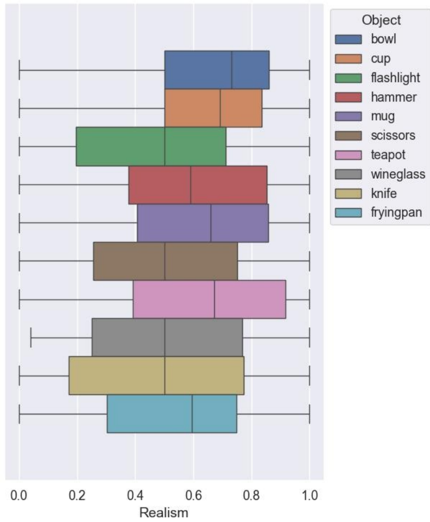

Fig. 7 Realism score distributions for each object category in the first user study. A high realism score means the participants perceive the sample as realistic and human-like.

Figure 8 shows the objects' perceived temperature, weight, and softness ratings per category. Although the animations use the same object, the participants' perception varies based on the performance. This measurement likely relates to the participant's previous experience with the object. For example, flashlights and scissors are often lighter than hammers, and we observe such results in the answers we receive. On the other hand, specific categories, like bowl and cup, received more varied answers. Future work can examine whether expressing specific personality traits influences objects' perceived temperature, weight, or softness. Our annotations include these measurements per rated sample and the personality annotations for such analysis.

Figure 9 shows which aspects of the rated samples were practical in participants' answers to the personality questions. Participants focused on different animation elements when describing the subject's personality, which also depends on the object category. For example, body pose is more pronounced when the object interaction includes

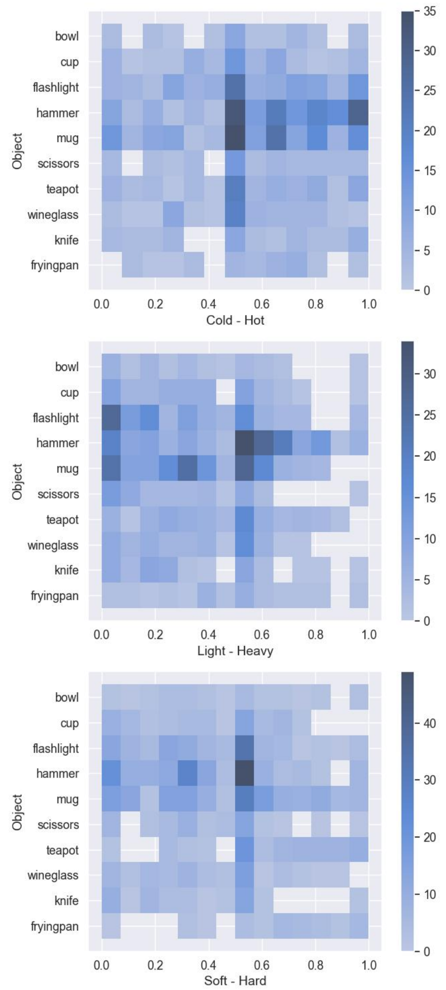

Fig. 8 Additional measurements for each object category. The top matrix depicts the perceived temperature (cold or hot), the middle matrix depicts the perceived weight (light or heavy), and the bottom matrix shows the perceived softness (soft or hard). The ratings do not vary much regarding softness but have distinct results for weight.

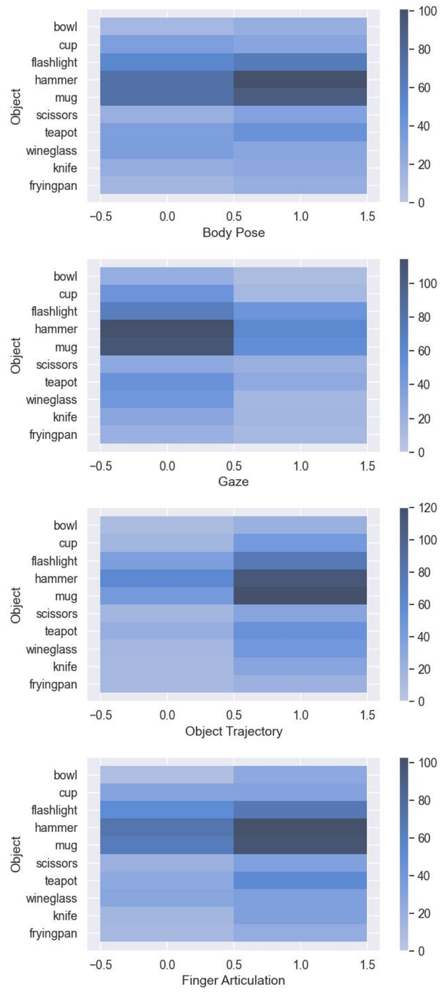

Fig. 9 The participants' answers to the questions that ask which aspects of the motion they consider influential on their ratings. For different object categories, the animation elements that participants find influential vary.

more dramatic pose changes, as in the hammer category. Gaze receives more attention when arm movements are limited. Participants found the object trajectory to be important regardless of the object type. We also observe that finger articulation is pretty important. Consequently, any personality manipulation in animations with object interaction should focus on redesigning the body pose and object trajectory. Our annotations include per-sample ratings for these answers so that future work can examine if the participants' personality ratings are influenced by the elements they focus on. For example, the participants who focus on different elements could perceive the same animation to express different traits.

F. Comparison User Study

We generated a subset of motions and altered their isolated traits using either method to assess the synthesis performance of our augmentation module and authoring network. We can identify differences more clearly compared to combined modifications via isolated alteration. We determine a single motion, mostly "natural" for each object, based on its OCEAN annotations. We calculated the overall magnitude of the OCEAN traits and selected motions closest to 0.

We altered each OCEAN trait separately for selected motions and combined them in separate tasks for isolated evaluation. We assigned each participant ten tasks, with each task containing five motions. We altered their OCEAN trait via LMA Effort parameters for two motions. To calculate the required parameters based on the altered trait, we used Table 3, which is based on [2]. We first determine the difference between the annotated trait value and both $-1, 1$. For example, an *Openness* with -0.2 will get -0.8 and 1.2 delta values. We negate all the signs in the original matrix and multiply it by our OCEAN delta to obtain the required LMA Effort parameters. For instance, an *Openness* increase with a magnitude of 1.5 results in 1.38 in *space* and 1.39 in *flow*.

We synthesized two other motions by our neural generator. We set the changed trait to -1 or 1 and keep the remaining traits intact. The object is snapped to the fixed grasp of the subject after the motion is synthesized using our neural generator.

We repurposed the framework of the first study and extended it for simultaneous comparison between five motions. For each motion, the participants are asked to annotate each OCEAN factor in normalized form of the Ten-Item Personality Inventory (TIPI) scale [-3, 3] and evaluate the realism and accuracy of the motion according to the displayed action label. Under each motion, a slider is provided for the relevant question with an appropriate scale. Similar to the first user study, participants can control the camera and time of the motions for better visibility. The participants are also provided with a visual help screen at the beginning and during the study. Figure 10 shows a screenshot from our comparison user study.

G. Unabridged Model Performance Comparisons

As object interaction generally lacks social context, we only expect consciousness and neuroticism OCEAN factors to be expressed. If so, controlling those factors alone would result in perceivable differences from the original motions. We show the unabridged results of the second user study in Table 4. Here, we include the trait and object combinations that did not result in significant differences between groups. For Agreeableness, for instance, neither the augmentation nor the neural network model could synthesize distinguishable differences while altering the personality of the original motion. However, all object and action types are subject to perceivable differences in at least one of the traits.

The results show that the consciousness alterations significantly impacted the perceived personality, where neuroticism resulted in a limited scale. Even though using augmented data improved the realism of the network outputs, their expressive capabilities are more subtle than purely augmented motions in terms of diversity.

Effort	O	C	E	A	N
Space	0.920	-0.9265	0.8929	0.0	1.0
Weight	0.0	0.0	0.0	1.0	0.0
Time	0.0	0.856	-0.99	-1.0	0.97
Flow	0.931	-0.938	1.0	0.0	0.762

Table 3 Matrix to calculate LMA effort parameters from OCEAN delta trait values.

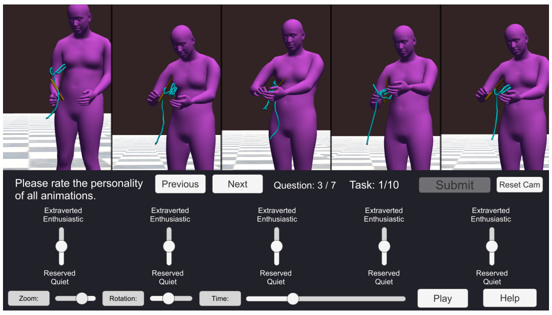

Fig. 10 Our comparison user study visualizes five motions simultaneously and includes camera and animation time controls. Each motion is annotated separately for OCEAN traits and realism. In case the user requires help, a separate help window is shown.

References

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[2] Durupinar, F., Kapadia, M., Deutsch, S., Neff, M., Badler, N.I.: PERFORM: Perceptual approach for adding OCEAN personality to human motion using Laban Movement Analysis. ACM Transactions on Graphics **36**(1) (2016). Article No 6, 16 pages

	Category	Base–ANeg		Base–NNeg		Base–APos		Base–NPos		ANeg–NNeg		ANeg–APos		NNeg–NPos		APos–NPos	
		ρ	Δ	ρ	Δ	ρ	Δ	ρ	Δ	ρ	Δ	ρ	Δ	ρ	Δ	ρ	Δ
O	*Bowl*	.832	-.933	.998	.267	.962	.600	.996	.333	.663	1.200	.428	1.533	.999	.067	.998	-.267
	Cup	.996	.250	.991	-.312	.968	-.438	.968	.438	.922	-.562	.851	-.688	.806	.750	.702	.875
	Flashlight	.999	-.077	.999	.077	.999	.077	.999	.000	.999	.154	.999	.154	.999	-.077	.999	-.077
	Fryingpan	.936	-.600	.694	1.000	.694	1.000	.909	-.667	.242	1.600	.242	1.600	.206	-1.667	.206	-1.667
	Hammer	.940	-.417	.999	-.083	.821	-.583	.998	-.167	.973	.333	.998	-.167	.999	-.083	.940	.417
	Knife	.999	.188	.856	.750	.999	.188	.856	.750	.944	.562	.999	.000	.999	.000	.944	.562
	Mug	.906	.786	.801	1.000	.326	1.714	.415	1.571	.999	.214	.840	.929	.969	.571	.999	-.143
	Scissors	.999	-.188	.745	-.875	.993	-.312	.999	.000	.876	-.688	.999	-.125	.745	.875	.993	.312
	Teapot	.510	1.286	.074	2.143	.019	2.571	.510	1.286	.827	-.857	.510	1.286	.827	-.857	.510	-1.286
	Wineglass	.998	.235	.991	.353	.521	1.235	.991	-.353	.999	.118	.710	1.000	.897	-.706	.267	-1.588
	Drinking	.832	-.933	.998	.267	.962	.600	.996	.333	.663	1.200	.428	1.533	.999	.067	.998	-.267
	Pouring	.996	.250	.991	-.312	.968	-.438	.968	.438	.922	-.562	.851	-.688	.806	.750	.702	.875
C	*Bowl*	.000	-3.062	.627	-.938	.686	-.875	.916	-.562	.018	2.125	.013	2.188	.980	.375	.990	.312
	Cup	.551	-1.067	.729	.867	.911	.600	.671	.933	.055	1.933	.133	1.667	.999	.067	.989	.333
	Flashlight	.179	-1.867	.968	-.533	.989	-.400	.873	-.800	.505	1.333	.407	1.467	.998	-.267	.989	-.400
	Fryingpan	.563	-1.200	.360	-1.467	.999	.067	.720	-1.000	.997	-.267	.510	1.267	.977	.467	.669	-1.067
	Hammer	.054	-2.214	.388	-1.429	.992	-.357	.819	-.857	.861	.786	.149	1.857	.952	.571	.970	-.500
	Knife	.010	-2.067	.548	-.933	.999	.133	.940	.467	.351	1.133	.005	2.200	.160	1.400	.982	.333
	Mug	.060	-2.214	.624	-1.143	.868	-.786	.999	-.143	.679	1.071	.404	1.429	.732	1.000	.932	.643
	Scissors	.010	-2.533	.395	-1.333	.984	-.400	.900	-.667	.502	1.200	.045	2.133	.900	.667	.997	-.267
	Teapot	.633	-1.200	.885	-.800	.885	-.800	.913	-.733	.990	.400	.990	.400	.999	.067	.999	.067
	Wineglass	.048	-2.214	.165	-1.786	.809	-.857	.137	-1.857	.982	.429	.422	1.357	.999	-.071	.707	-1.000
	Drinking	.000	-3.062	.627	-.938	.686	-.875	.916	-.562	.018	2.125	.013	2.188	.980	.375	.990	.312
	Pouring	.551	-1.067	.729	.867	.911	.600	.671	.933	.055	1.933	.133	1.667	.999	.067	.989	.333
E	*Bowl*	.999	-.067	.999	-.133	.088	1.933	.779	.867	.999	-.067	.072	2.000	.675	1.000	.620	-1.067
	Cup	.905	-.667	.905	.667	.094	1.933	.933	.600	.410	1.333	.009	2.600	.999	-.067	.410	-1.333
	Flashlight	.848	-.750	.999	.000	.305	1.438	.986	.375	.848	.750	.033	2.188	.986	.375	.607	-1.062
	Fryingpan	.998	.188	.998	-.188	.761	.750	.999	.062	.976	-.375	.901	.562	.995	.250	.814	-.688
	Hammer	.989	-.333	.938	-.533	.989	.333	.998	.200	.998	-.200	.869	.667	.825	.733	.999	-.133
	Knife	.989	-.333	.999	.000	.006	2.467	.962	.467	.989	.333	.001	2.800	.962	.467	.041	-2.000
	Mug	.996	.333	.864	.867	.894	.800	.984	.467	.974	.533	.984	.467	.991	-.400	.996	-.333
	Scissors	.971	-.500	.883	-.750	.912	.688	.631	-1.125	.998	-.250	.581	1.188	.990	-.375	.172	-1.812
	Teapot	.995	.333	.999	.000	.082	2.200	.982	.467	.995	-.333	.191	1.867	.982	.467	.256	-1.733
	Wineglass	.969	.467	.924	.600	.373	1.333	.999	.200	.999	.133	.762	.867	.982	-.400	.538	-1.133
	Drinking	.999	-.067	.999	-.133	.088	1.933	.779	.867	.999	-.067	.072	2.000	.675	1.000	.620	-1.067
	Pouring	.905	-.667	.905	.667	.094	1.933	.933	.600	.410	1.333	.009	2.600	.999	-.067	.410	-1.333
A	*Bowl*	.999	-.067	.995	-.267	.112	-1.667	.582	-1.000	.998	-.200	.139	-1.600	.815	-.733	.862	.667
	Cup	.770	-1.000	.912	.733	.971	.533	.812	.933	.267	1.733	.389	1.533	.999	.200	.990	.400
	Flashlight	.348	-1.250	.844	-.688	.746	-.812	.514	-1.062	.918	.562	.966	.438	.981	-.375	.996	-.250
	Fryingpan	.798	-.857	.999	.071	.691	-1.000	.844	-.786	.747	.929	.999	-.143	.798	-.857	.999	.214
	Hammer	.976	.400	.976	.400	.933	.533	.998	.200	.999	.000	.999	.133	.998	-.200	.988	-.333
	Knife	.564	-1.000	.993	-.286	.632	-.929	.967	-.429	.819	.714	.999	.071	.999	-.143	.943	.500
	Mug	.997	-.267	.632	-1.067	.577	-1.133	.906	-.667	.833	-.800	.788	-.867	.985	.400	.973	.467
	Scissors	.802	-.857	.581	-1.143	.357	-1.429	.409	-1.357	.996	-.286	.947	-.571	.999	-.214	.999	.071
	Teapot	.999	.214	.984	-.429	.954	-.571	.618	-1.143	.930	-.643	.865	-.786	.901	-.714	.954	-.571
	Wineglass	.979	-.375	.996	.250	.979	-.375	.999	-.125	.877	.625	.999	.000	.979	-.375	.996	.250
	Drinking	.999	-.067	.995	-.267	.112	-1.667	.582	-1.000	.998	-.200	.139	-1.600	.815	-.733	.862	.667
	Pouring	.770	-1.000	.912	.733	.971	.533	.812	.933	.267	1.733	.389	1.533	.999	.200	.990	.400
N	*Bowl*	.999	.000	.838	.733	.000	3.667	.791	.800	.838	.733	.000	3.667	.999	.067	.001	-2.867
	Cup	.999	-.200	.999	-.200	.868	.800	.900	-.733	.999	.000	.745	1.000	.967	-.533	.349	-1.533
	Flashlight	.872	-.800	.904	-.733	.705	1.067	.904	.733	.999	.067	.178	1.867	.406	1.467	.995	-.333
	Fryingpan	.998	.286	.828	.929	.926	.714	.988	.429	.948	.643	.988	.429	.979	-.500	.998	-.286
	Hammer	.975	-.467	.999	.200	.707	1.000	.997	.267	.914	.667	.343	1.467	.999	.067	.882	-.733
	Knife	.875	.733	.205	1.667	.985	.400	.836	.800	.744	.933	.993	-.333	.792	-.867	.985	.400
	Mug	.999	.125	.138	2.062	.519	1.375	.310	1.688	.185	1.938	.610	1.250	.993	-.375	.996	.312
	Scissors	.999	-.125	.976	.438	.040	2.125	.708	.938	.940	.562	.025	2.250	.960	.500	.494	-1.188
	Teapot	.993	.357	.262	1.714	.136	2.000	.114	2.071	.497	1.357	.303	1.643	.993	.357	.999	.071
	Wineglass	.999	.133	.983	.467	.956	.600	.999	.200	.995	.333	.983	.467	.998	-.267	.990	-.400
	Drinking	.999	.000	.838	.733	.000	3.667	.791	.800	.838	.733	.000	3.667	.999	.067	.001	-2.867
	Pouring	.999	-.200	.999	-.200	.868	.800	.900	-.733	.999	.000	.745	1.000	.967	-.533	.349	-1.533
Re.	*All*	.000	-.549	.000	-.768	.000	-1.217	.000	-.705	.387	-.219	.000	-.668	.986	.063	.000	.513
Ac.	*All*	.144	-.049	.016	-.066	.000	-.136	.271	-.042	.928	-.017	.000	-.087	.796	.024	.000	.094

Table 4 Tukey HSD adjusted p-values (ρ) and the mean differences (Δ) between the different models for each object category and OCEAN factor. We display all values, including the insignificant results. Each column compares different model pairs: **Base** for original animation, **ANeg** and **APos** represent negative and positive changes using the augmentation framework, respectively. **NNeg** and **NPos** represent the same changes applied using the motion authoring network, respectively. We examine the factor that the system aims to alter for each personality group; for example, when the system aims to change Openness, we evaluate the performance based on perceived Openness. Realism (Re.) and Accuracy (Ac.) scores are calculated across all objects. Significant results are colored with Green for $\rho < 0.05$, and Blue for $\rho < 0.1$. We did not get any significant results for Agreeableness.