Check for updates

# Perceptions of AI in Animation Production

Dalong Hu, Minsoo Choi, Nandhini Giri, Christos Mousas, and Nicoletta Adamo-Villani(✉)

Department of Computer Graphics Technology, Purdue University, West Lafayette, IN 47907, USA
nadamovi@purdue.edu

**Abstract.** We explored how people perceived animations created by artificial intelligence (AI)-driven motion capture, manual keyframe technique, and AI-driven motion capture with manual cleanup methods. We presented our participants with short, full-body animation clips created using the three methods. Participants rated the appeal and naturalness of the animations, and we asked them to discern the creation method. Results revealed differences in perceived appeal and naturalness between manually created animations and those generated through AI-based methods, with manual animations consistently rated higher in appeal and naturalness. However, participants could not discern creation methods regardless of animation experience level, demonstrating an accuracy equivalent to random guessing. The qualitative analysis highlighted diverse perspectives with negative and positive views on AI use, with the most mentioned theme being the importance of quality regardless of creation method. The overwhelming majority of participants asserted that the degree of automatization would influence participants' perceived value and effort put into an animation. Still, this group did not show divergent ratings, nor did it affect their overall agreeableness towards using AI in creative fields. This study contributes insights into the intersection of animation and AI, informing creators about the effect of different creation methods on audience perceptions.

**Keywords:** AI · Animation · Perception · Machine learning · Motion capture · Appeal · Naturalness

## 1 Introduction

Recent developments in machine learning have impacted many creative fields, including animation. In digital arts, there is controversy over artificial intelligence (AI)-generated art displacing and stealing from artists [9]. Still, the same concerns have not been as apparent in the animation sector. Perhaps because animation needs more control and purposeful specificity in a cut to facilitate overarching narratives. A common weakness in generative AI is precisely the lack of control over results, which limits it to the level of simulating technique


P. Machado et al. (Eds.): EvoMUSART 2025, LNCS 15611, pp. 82–93, 2025.
https://doi.org/10.1007/978-3-031-90167-6_6

[10]. Nevertheless, due to the resurgence in discussion over the role of AI in creative production, it is essential to understand people's perceptions towards machine learning in animation as well.

Traditionally, according to Chen et al. [2], marker-based motion capture (MoCap) "heavily relies on high-quality marker data, assuming precise localization, outlier elimination, and consistent marker tracking." Standard MoCap systems entail inertial sensors or are optical marker based. This usually requires a studio to optimize working conditions and costly cameras to guarantee visual data quality. MoCap data is also labor-intensive and time-consuming to edit [2,3]. With AI-driven MoCap, it is now possible to extract motion data with relative accuracy from simple videos, potentially making MoCap more affordable, portable, flexible, and robust. However, it is necessary to evaluate how accurate AI-driven Mocap is and investigate whether it requires human adjustment. Therefore, in this paper, we investigate how people perceive and are affected by fully manual, fully AI-driven MoCap, and human-adjusted AI-driven MoCap-made full body character animations. With our study, we aim to answer the following research questions:

- **RQ1**: Does perceived appeal and naturalness differ across the different animation methods?
- **RQ2**: Do differences exist based on participants' experience level and gender?
- **RQ3**: Can people correctly categorize the animation stimuli into their respective degrees of automation?
- **RQ4**: Does the degree of automatization influence the perceived value and effort put into an animated piece?

We organize our paper as follows. In Sect. 2, we discuss related work. In Sect. 3, we explain the study methodology. Section 4 shows the data analysis, and Sect. 5 presents the discussion. Finally, we have our conclusion in Sect. 6.

## 2 Literature Review

### 2.1 Perceptions of Naturalness and Appeal in Animated Characters

Advances in technology have resulted in the renewed investigation of people's perceptions. Wei et al. [11] compared facial animation methods to see which method created the most recognizable and perceptually natural animated facial emotions. Among the four creation methods of skeleton, blendshape, audio-driven, and visual-driven, their study found that the skeleton followed by the blendshape model had the highest naturalness ratings and recognition rate. Their findings suggest that "artist-created animated facial emotions can be recognized more accurately than the computer-generated ones." Lei et al. [7] compared LinEuler, Slerp, and Squad interpolation methods to see which is perceived as most natural in upper body character animations. They found that the Squad interpolation method was perceived as significantly more natural than LinEuler and Slerp, with experienced participants being able to distinguish differences between the latter two better. Hammer and Adamo [5] applied differing levels of the traditional animation principle of exaggeration to a realistic 3D cat model to see its effect on perceived believability and appeal. Their no-exaggeration clip was perceived as more appealing and believable, and the low-exaggeration clip performed worse in appeal and believability than the high-exaggeration clip. The authors attributed their findings to the clip falling into the uncanny valley. Thus, they conclude that if exaggeration is to be employed at all, it is better to implement higher levels of it.

### 2.2 AI in Creative Field

Since generative AI has advanced so far that it has the potential to replace the artist completely, Sun et al. [10] believe that developments in the area of AI art are in a different order compared to previous precedents. Shan et al. [9] note that generative AI models profit from an artist's years of training without compensating them, using as little as 20 pieces of artwork to train a model to mimic an artist's style. To combat mimicry attacks, they built a tool called Glaze that "cloaks" an image by applying small style transfer perturbations to disrupt the mapping of a model's latent space. Campbell et al. [1] examine AI-created synthetic advertising and how consumers respond. They state that "consumers generally prefer authentic products and experiences," so if there is a high awareness of ad falsity, the ad's persuasiveness decreases. Greater creativity could offset the negative effects of manipulation to a certain degree, but repeated use would render it commonplace and thus dull. Additionally, some researchers have focused on generative AI in music. Jin et al. [4] presented a user interface to allow users to generate music through generative AI and edit AI-generated music. Specifically, they employed AI to generate music based on a reference video and song and provided editing tools to mix generated music. Also, Lee et al. [8] proposed an AI-based methodology to generate lyrics based on given required words and MIDI files. They trained deep learning models to generate lyrics matching music and vocabulary constraints with syllable alignment.

### 2.3 Differentiating and Comparing AI and Manual Creation in Animation

Sun et al. [10] focused on whether participants could differentiate between human and AI-generated paintings that were generated through two style transfer applications. Seventy percent (70%) of their participants had painting experience, but they could not differentiate between human and AI-made paintings. One pattern they found is that participants were more likely to judge a painting as human-made if it evoked more emotion than any technical qualities. Edström [3] compared manual keyframe animation to animations generated by an Artificial Neural Network (ANN) that takes data from user input and MoCap. The majority of their participants preferred the ANN-generated locomotion animations and viewed them to be more realistic, natural, and smooth. One hundred percent (100%) of the experienced individuals correctly guessed which animation set was AI-generated. The AI-created one was perceived as having a higher quality, but the inexperienced participants were split in terms of whether that meant it was handmade or AI-generated. Their study was limited to only simple locomotion, which AI can perform well due to abundant data and a straightforward motion. Kappagantula et al. [6] presented a method to algorithmically generate deictic gestures for animated pedagogical agents, investigating whether the timing and number of their automatically generated gestures could match a manually made version. The timing and number of gestures were considered equivalent, and two-thirds of viewers had no preference. However, deictic gestures follow simple rules, leading to relatively easier automatization, which is their study's limitation. Another example of a comparative study between manual and automatic is Zhang et al. [12], which assessed the use of an AI MoCap system compared to manual technique when applied to the official competitive race walking scene. The coordinates that the AI MoCap system produced were statistically similar enough to those manually created. For further development, they noted results could be improved by increasing the number of cameras beyond the minimum of two they used.

## 3 Methodology

### 3.1 Study Design

The study used a within-group design and collected quantitative and qualitative data. The stimuli were 15 short animation clips of a character performing full-body motions (5 clips per creation method [$5 \times 3 = 15$]). The independent variable of this study was the method of stimuli creation, with three levels: manual creation, AI MoCap generated, and AI MoCap with human cleanup. The three experimental conditions were (see Fig. 1):

- **Manual**: An animator with six years of experience in animation was given two hours to author the motion using Maya with video reference.
- **AI MoCap**: Motion was extracted from video reference using DeepMotion and applied to the character rig directly without editing.
- **AI MoCap with human cleanup**: The animator was given one hour to clean up the AI MoCap-generated animation using Maya.

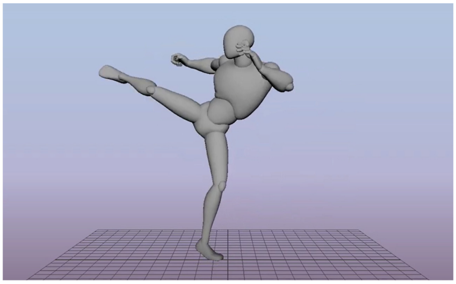
For a realistic pipeline with time constraints and to compare the instantly generated AI-driven MoCap method fairly, the human manual method was given a working time limitation of two hours, and the human cleanup allotted time was one hour. The amount of time to be allotted to the animators in the fully manual and manual cleanup conditions was set by a group of experienced professional animators.

There are many commercial AI MoCap providers accessible to the general public that provide a relatively similar level of quality. After the authors' experimentations, we used DeepMotion due to the lower perceived foot sliding. Motion references were taken from MOTION ACTOR Inc.[1] due to their range of

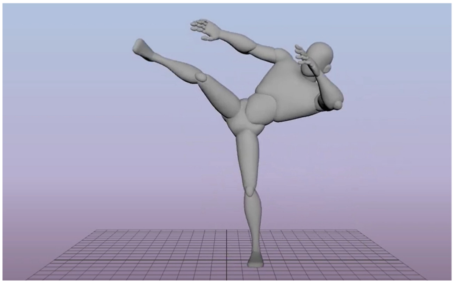
[1] https://www.youtube.com/@MotionActorInc.

dynamic full-body motion videos targeted for entertainment use, such as games and animation. We used Autodesk Maya for human authoring and cleaning up the AI MoCap results, which is considered representative industry-standard software. Since the study was focused on full-body actions, we used `anim_matt`'s Body Mechanics Rig.[2] The animation stimuli included five sets of three videos. Each set was based on one motion, with one video for each creation method. The five motions were backhand strike, roundhouse kick, back handspring, and strong punch.

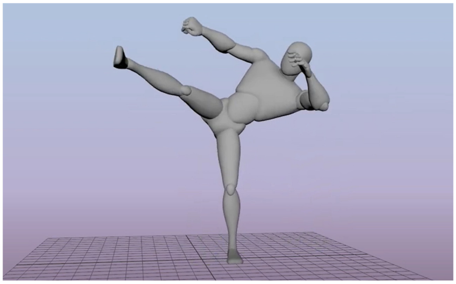
(a) Motion reference



(b) Manual



(c) AI MoCap



(d) AI Mocap with human cleanup

**Fig. 1.** Frames extracted from the motion reference and animation stimuli

### 3.2 Participants

Seventy-eight people participated in the study; 16 responses were discarded due to lack of completion, leaving 62 responses to be used for analysis. The participant pool comprised 42 males and 20 females (age range: 18–34 years old). Twenty-three of the participants stated they were experienced in animation, referenced from Edström [3] and defined as having studied animation at a university level or possessing equivalent experience.

[2] https://anim-matt.gumroad.com/l/hcAMR.

### 3.3 Evaluation Instrument and Study Procedure

Participants were sent an email with a link to an online Qualtrics survey comprising two sections. In the first section, the perceived quality of the stimuli was measured. The videos were presented to the participants in randomized order, and for each video, participants were asked to rate the naturalness and appeal of the animation on a 7-point Likert scale (1=low; 7=high). Naturalness is widely examined in related animation studies [3,5,7,11], and so is appeal [5], which is necessary because an animation can be appealing but not natural and vice versa. The participants were then asked to categorize each video into one of the three creation methods: human manual, AI MoCap, and AI MoCap with human cleanup.

The second section included demographics questions and questions about the participants' perceptions and biases about AI. This section focused on answering one of our research questions (**RQ4**) through the following questions: "Do you agree or disagree with the use of AI in creative fields, and animation specifically?" (quantitative question on a 7-point Likert scale); "Does the degree of automatization influence your perceived value of and effort put into an animation?" (yes or no question); and "If the creation method was not AI motion capture but completely computer-generated motions, how would that impact your perception of the piece?" (open-ended question).

## 4 Data Collection and Analysis

### 4.1 Analysis of Perceived Appeal and Naturalness

Participants rated the appeal and naturalness of each video on a 7-point Likert scale. A one-way repeated measures analysis of variance (ANOVA) was conducted to compare the effect of the creation method on appeal ratings in AI, manual, and AI with manual cleanup creation conditions. There was a significant effect of the creation method, Wilks' $\Lambda = .624$, $F[2, 60] = 18.097$, $p = .000$, $\eta_p^2 = .376$. The pairwise Bonferroni comparisons indicate a significant difference in the scores for the AI creation method ($M = 4.69$, $SD = 1.34$) and the manual creation method ($M = 5.33$, $SD = 1.05$) conditions; $p = .000$, and a significant difference between the AI with manual cleanup creation method ($M = 4.71$, $SD = 1.35$) and the manual creation method conditions; $p = .000$. However, there was no significant difference between the AI and AI with manual cleanup creation methods.

For naturalness, there was a significant effect of the creation method, Wilks' $\Lambda = .573$, $F[2, 60] = 22.393$, $p = .000$, $\eta_p^2 = .427$. Post-hoc Bonferroni comparisons showed a significant difference in scores for the AI creation method ($M = 4.46$, $SD = 1.41$) and the manual creation method ($M = 5.25$, $SD = 1.02$) conditions; $p = .000$, and also a significant difference between the AI with manual cleanup creation method ($M = 4.53$, $SD = 1.39$) and the manual creation method conditions; $p = .000$.

### 4.2 Analysis of Gender and Experience Level

Independent samples t-tests were conducted to compare differences in ratings between genders. While there were options besides male or female, none of the participants chose them, and there was no statistically significant difference in appeal and naturalness ratings for gender. There was no significant difference in AI creation method appeal ratings for male ($M = 4.61$, $SD = 1.24$) and female ($M = 4.86$, $SD = 1.56$) groups; $t(60) = -.672$, $p = .504$. There was no significant difference in manual creation method appeal ratings for male ($M = 5.37$, $SD = 1.03$) and female ($M = 5.47$, $SD = 1.12$) groups; $t(60) = -.707$, $p = .482$. There was no significant difference in AI with manual cleanup creation method appeal ratings for male ($M = 4.62$, $SD = 1.30$) and female ($M = 4.89$, $SD = 1.45$) groups; $t(60) = -.716$, $p = 0.477$. There was no significant difference in AI creation method naturalness ratings for male ($M = 4.35$, $SD = 1.26$) and female ($M = 4.70$, $SD = 1.70$) groups; $t(60) = -.918$, $p = -.362$. There was no significant difference in manual creation method naturalness ratings for male ($M = 5.14$, $SD = 0.91$) and female ($M = 5.47$, $SD = 1.21$) groups; $t(60) = -1.197$, $p = .236$. There was no significant difference in AI with manual cleanup creation method naturalness ratings for male ($M = 4.42$, $SD = 1.27$) and for female ($M = 4.77$, $SD = 1.62$) groups; $t(60) = -.919$, $p = .362$.

Independent samples t-tests were conducted to see if experience level influenced ratings. There was no significant difference in ratings for the three creation methods across appeal and naturalness. There was no significant difference in AI creation method appeal ratings for experienced ($M = 4.88$, $SD = 1.31$) and inexperienced ($M = 4.58$, $SD = 1.36$) groups; $t(60) = -.831$, $p = .409$. There was no significant difference in manual creation method appeal ratings for experienced ($M = 5.57$, $SD = .93$) and inexperienced ($M = 5.19$, $SD = 1.11$) groups; $t(60) = 1.345$, $p = .184$. There was no significant difference in AI with manual cleanup creation method appeal ratings for experienced ($M = 4.98$, $SD = 1.26$) and inexperienced ($M = 4.55$, $SD = 1.38$) groups; $t(60) = 1.221$, $p = .227$. There was no significant difference in AI creation method naturalness ratings for experienced ($M = 4.55$, $SD = 1.40$) and inexperienced ($M = 4.41$, $SD = 1.43$) groups; $t(60) = .368$, $p = .714$. There was no significant difference in manual creation method naturalness ratings for experienced ($M = 5.37$, $SD = 1.01$) and inexperienced ($M = 5.17$, $SD = 1.03$) groups; $t(60) = .727$, $p = .470$. There was no significant difference in AI with manual cleanup creation method naturalness ratings for experienced ($M = 4.74$, $SD = 1.36$) and inexperienced ($M = 4.41$, $SD = 1.41$) groups; $t(60) = .888, p = .378$.

### 4.3 Analysis of Bias and Perception

A Pearson product-moment correlation coefficient was computed to assess the relationship between answering their perception that they would be influenced and their agreeableness towards using AI in creative fields. There was no correlation between the two variables: $r = .184$, $n = 61$, $p = .157$.

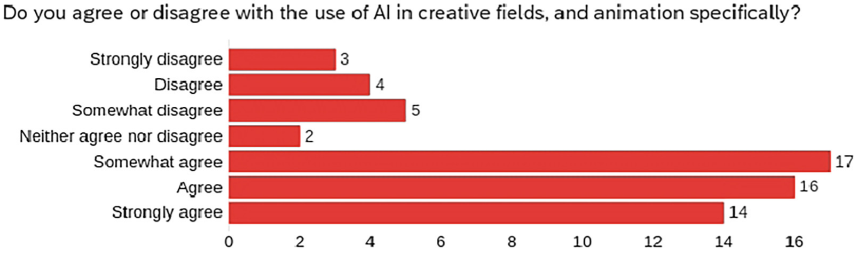



**Fig. 2.** Distribution of agreeableness on AI usage in creative fields

Additionally, independent-sample t-tests were conducted to compare whether those who answered their perceptions would be influenced have a significant difference in the appeal and naturalness ratings compared to those who stated they would not be influenced. Overall, there was no statistically significant difference in ratings, whether they answered they would be influenced, between all three creation methods for appeal and naturalness.

The specifics are as follows: There was no significant difference in AI creation method appeal ratings for would be influenced ($M = 4.64$, $SD = 1.39$) and would not be influenced ($M = 5.07$, $SD = 0.85$) conditions; $t(60) = -.861$, $p = .393$. There was no significant difference in manual creation method appeal ratings for would be influenced ($M = 5.31$, $SD = 1.08$) and would not be influenced ($M = 5.50$, $SD = 0.94$) conditions; $t(60) = -.479$, $p = .633$. There was no significant difference in AI with manual cleanup creation method appeal ratings for would be influenced ($M = 4.66$, $SD = 1.39$) and would not be influenced ($M = 5.07$, $SD = 1.00$) conditions; $t(60) = -.815$, $p = .418$. There was no significant difference in AI creation method naturalness ratings for would be influenced ($M = 4.46$, $SD = 1.39$) and would not be influenced ($M = 4.50$, $SD = 1.65$) conditions; $t(60) = -.082$, $p = .935$. There was no significant difference in manual creation method naturalness ratings for would be influenced ($M = 5.21$, $SD = 1.02$) and would not be influenced ($M = 5.53$, $SD = 1.02$) conditions; $t(60) = -.827$, $p = .412$. There was no significant difference in AI with manual cleanup creation method naturalness ratings for would be influenced ($M = 4.47$, $SD = 1.43$) and would not be influenced ($M = 4.98$, $SD = 1.09$) conditions; $t(60) = -.960$, $p = .341$. This means that despite the overwhelming majority of participants (87%) answering their perceptions on value and effort would be influenced, under the condition of not being certain what the creation method was, this did not translate into their ratings for naturalness and appeal, and neither did it influence their relative agreeableness to the usage of AI in creative fields (Fig. 2).

### 4.4 Qualitative Analysis

Participants were asked to respond qualitatively: *"If the creation method was not AI motion capture but completely computer-generated motions, how would* *that impact your perception of the animation?"* There were various perspectives, and the overall response could not be summed up as positive or negative. However, several common themes did arise from thematic analysis. The number of responses for each theme was counted, and responses could belong to multiple themes if appropriate, such as by asserting a distinguishable common opinion or having related keywords. Forty-eight responses were analyzed; not every survey respondent left a qualitative response. Many participants prioritized the importance of the quality and naturalness of animation, regardless of its creation method. Twenty-two responses can be grouped into this theme. For example, P48 stated, *"So long the animation looks natural, it will not affect my perception of the animation."* Other participants prioritized the artistic value of human creation, preferring animations that show human creativity and expression. Sixteen responses met this criterion. For instance, P38 asserted, *"It is lazy to use AI to create something that is emotional. Animation is a form of Art, and Art is emotional."*

Respondents frequently mentioned the role of emotional connection and personality in animation. Eighteen respondents preferred animations that exhibit human-like characteristics and personality traits, which they believed could be better achieved through human involvement. P37 noted, *"I feel like if it was completely created by the computer, I would not like it. I feel it needs personality that humans can create,"* highlighting the importance of emotional connection and the underlying belief that computers cannot achieve that human aspect.

There were also conflicting opinions surrounding worth and effort. Seven responses viewed computer-generated motions as having less effort and value, such as P26 saying, *"I would think it a bit lazy just to use AI even if it is easier. I associate it with a cheaper but less quality product"* and P24 stating, *"I would think that less effort has been put in and it is a bit lazier when fully generated by a computer."* Six others appreciated AI's potential efficiency and innovation, with P28 even saying, *"I would love it even more! I want AI to take all of our jobs genuinely."* Nine participants expressed interest in exploring the capabilities of AI, such as P31 by saying, *"I would be very confused and fascinated about AI, would definitely try to use AI to make my games' animation,"* suggesting readiness to experiment with novel approaches. Many participants said that, in the end, it would depend on the quality of the product. A nuanced perspective was brought up by P11 who said that human creation *"May look better but cost too many human resources, so I agree to use AI in this field,"* suggesting consideration of resource allocation and efficiency in production.

## 5 Discussion

Through statistical and qualitative analyses, several interesting conclusions emerged. Analyses of perceived appeal and naturalness revealed significant differences between manually created animations and those generated through AI (**RQ1**). Participants consistently rated manually created animations higher in appeal and naturalness than AI-generated ones. However, no significant difference existed between perceptions of stimuli created using AI alone and those with manual cleanup afterward. These findings support Wei et al. [11], who found that human-made facial emotions through skeleton and blendshape animation were more natural and recognizable than machine-driven creation methods. On the contrary, Zhang et al. [12] found that AI MoCap performed similarly enough to manual-entered 3D joint data, but this could be due to their use of a high-end system with two cameras. In contrast, our study used a single camera angle input to a commercially accessible AI MoCap provider. Neither gender nor experience level significantly influenced participants' ratings of animation appeal and naturalness across the different creation methods (**RQ2**).

Discernment capability analysis indicated that participants could not accurately distinguish between animation creation methods, with an overall discernment rate equivalent to chance guessing (**RQ3**). Sun et al. [10] findings supported participants' inability to distinguish, where in their study on having participants judge AI and human paintings, "participants mistook the AI paintings for human paintings." Experience level made no difference in discernment accuracy. Despite using the exact definition for experienced, this study contradicts [3], where 100% of their experienced participants correctly guessed the AI-generated animations. This could be because Edström's [3] AI animations were ANN-generated locomotion animations synthesized from MoCap data, while this study used AI MoCap to extract full body motions from videos. Thus, we argue that people cannot distinguish manual animations from AI MoCap-extracted motions at the blocking stage of animation. Despite being unable to distinguish creation methods, participants' perceptible preference for manually created animations in terms of appeal and naturalness suggests that although participants cannot state the difference, they can feel it.

Participants overwhelmingly expressed that the degree of automatization would influence animation's perceived value and effort (**RQ4**). However, this sentiment did not translate into differing ratings between the manual and AI-related creation methods, nor did it affect their overall agreeableness towards using AI in creative fields. Additionally, qualitative analysis of participants' responses highlighted diverse perspectives, with no conclusive overall positive or negative perception (**RQ4**). This contrasts with the survey results of [9], where artists held significantly negative views on the use of AI. This could be because this study focuses on animation and has more general participants than the artist community participants [9]. The negative views that did appear were similar to those in Shan et al.'s study [9]. Of the diverse perspectives, some prioritized a human touch, others expressed enthusiasm for the innovations in AI, and still others valued efficiency or overall quality.

One limitation of this study is that it can only represent the current development of the specific AI technology used; in this case, the AI MoCap of DeepMotion may not represent all AI MoCap alternatives. Future work will need to be done following new developments in AI. Similarly, this study only investigates AI-driven MoCap, which only represents some possible current and future uses of AI. Additional research will need to be done to cover other applications of AI. This study only used one rig for all the stimuli, which can influence perceptions of naturalness and appeal, especially when relating to MoCap. Future studies could use multiple rigs to offset this influence, but this study chose an appropriate rig that would produce acceptable results with the MoCap.

The implications of this study give creators more informed choices on the use of AI in animation. A common theme among qualitative responses was the prioritization of quality, and even at this animation blocking stage, manually created animations were rated higher in appeal and naturalness. Despite being unable to distinguish creation methods, participants could feel differences in the animation quality. These results are limited to current technology. However, knowledge of perceptions of appeal and naturalness across differing methods, viewer discernment accuracy, and multifaceted opinions on degrees of automatization can inform pedagogy and policy on artificial intelligence applications.

## 6 Conclusion

This study set out to examine participants' perceptions towards the use of AI in animation. The experiment included 15 stimuli videos, comprised of five sets of different motions, with each set having one of the three creation methods. The participants rated the videos for appeal and naturalness, attempted to distinguish the creation method and provided feedback on their perceptions of AI use in animation. We found that participants could not distinguish between the creation methods, regardless of experience level. Still, the manually created animations were rated higher in appeal and naturalness than those made with AI-based methods. Despite most participants saying the degree of automatization would influence their perceptions, their ratings did not differ significantly, nor were they less agreeable to using AI. Qualitative responses highlighted many conflicting themes, but the most prominent theme was the importance of quality regardless of the creation method.

**acknowledgment.** This project was supported by an NSF RETTL Award (award number: 2201019).

**Conflict of Interest.** The authors declare no conflict of interest.

## References

1. Campbell, C., Plangger, K., Sands, S., Kietzmann, J.: Preparing for an era of deepfakes and AI-generated ads: a framework for understanding responses to manipulated advertising. J. Advert. **51**(1), 22–38 (2022)
2. Chen, K., Wang, Y., Zhang, S.H., Xu, S.Z., Zhang, W., Hu, S.M.: Mocap-solver: a neural solver for optical motion capture data. ACM Trans. Graph. (TOG) **40**(4), 1–11 (2021)
3. Edström, O.: Evaluating the quality of 3D character animation produced by artificial neural networks: a user study (2020)
4. Frid, E., Gomes, C., Jin, Z.: Music creation by example. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, pp. 1–13 (2020)

5. Hammer, M., Adamo, N.: Audience perception of exaggerated motions on realistic animated animal characters. In: Brooks, A., Brooks, E.I. (eds.) ArtsIT/DLI -2019. LNICST, vol. 328, pp. 88–102. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-53294-9_7
6. Kappagantula, S., Adamo-Villani, N., Wu, M.L., Popescu, V.: Automatic deictic gestures for animated pedagogical agents. IEEE Trans. Learn. Technol. **13**(1), 1–13 (2019)
7. Lei, X., et al.: Perceived naturalness of interpolation methods for character upper body animation. In: Bebis, G., et al. (eds.) ISVC 2021. LNCS, vol. 13017, pp. 103–115. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-90439-5_9
8. Ma, X., Wang, Y., Kan, M.Y., Lee, W.S.: AI-lyricist: generating music and vocabulary constrained lyrics. In: Proceedings of the 29th ACM International Conference on Multimedia, pp. 1002–1011 (2021)
9. Shan, S., Cryan, J., Wenger, E., Zheng, H., Hanocka, R., Zhao, B.Y.: Glaze: protecting artists from style mimicry by {Text-to-Image} models. In: 32nd USENIX Security Symposium (USENIX Security 2023), pp. 2187–2204 (2023)
10. Sun, Y., Yang, C.H., Lyu, Y., Lin, R.: From pigments to pixels: a comparison of human and AI painting. Appl. Sci. **12**(8), 3724 (2022)
11. Wei, M., Adamo, N., Giri, N., Chen, Y.: A comparative study of four 3D facial animation methods: skeleton, blendshape, audio-driven, and vision-based capture. In: Brooks, A.L. (ed.) ArtsIT 2022. LNICST, vol. 479, pp. 36–50. Springer, Cham (2023). https://doi.org/10.1007/978-3-031-28993-4_3
12. Zhang, D., Ji, Z., Jiang, G., Jiao, W.: Using AI motion capture systems to capture race walking technology at a race scene: a comparative experiment. Appl. Sci. **13**(1), 113 (2022)