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3D Character Motion Representation Reflecting Five-Factor Personality Traits †

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Abstract

Two generation conditions for 3D walking motions were compared, reflecting the Big Five personality traits: initial-frame-dependent generation and latent-vector-only generation. Human walking motion data were encoded using a long short-term memory variational autoencoder and a centroid latent vector derived from three training motions was used to generate intermediate motions. Generated motions were evaluated by estimating openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN) traits with Gemini ten times per motion and calculating mean values and 95% confidence intervals. The results suggest that initial-frame-dependent generation strongly inherited the characteristics of the input frame, whereas latent-vector-only generation included the training-motion average within the 95% confidence interval for all OCEAN factors and more stably represented intermediate personality-expressive motion.

Keywords: 3D walking motion generation; Big Five personality traits; OCEAN model; LSTM-VAE; latent space interpolation; non-player characters

1. Introduction

As character representation in games has become more sophisticated, non-player characters (NPCs) exhibit human-like individuality and behavior. Therefore, it is necessary to generate natural motions that reflect personality in in-game characters, using the openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN) model based on the Big Five theory as personality parameters. In addition, by learning the correspondence between human motion data and OCEAN parameters, we investigate the possibility of generating walking motions corresponding to intermediate points in personality space.

In this study, we consider two generation conditions: one in which the first frame of each training motion is given as the initial input to the decoder, and another in which only the centroid of the latent vectors is used. In the former, the influence of the initial frame may remain in the generated result, whereas in the latter, the intermediate representation in latent space may be reflected more directly. In this study, we compare the estimated OCEAN values under both conditions using the same centroid latent vector and examine which condition can represent more intermediate and stable motions.

2. Related Work

To improve the human-likeness and sense of immersion of NPCs, studies have been conducted on the integrated treatment of personality, emotion, and social relationships.

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Ochs et al. proposed a dynamic model of personality, emotion, and social relationships [1], and Sales et al. showed that emotional states influence NPC behavioral performance through affective agents based on the Big Five, the pleasure, arousal, and dominance model, and Ortony, Clore, And Collins model [2]. Baffa et al. integrated OCEAN-based personality, emotion models, and state machines to represent different responses of NPCs and changes in their relationships with players [3]. Furthermore, Bicalho et al. introduced cultural background and modeled the influence of cultural dimensions on NPC behavior [4].

On the other hand, in studies focusing on interactive and social personality expression, Chowanda et al. proposed ERiSA, which performs behavior selection based on social relationships and personality [5], and Georgeson et al. developed extended AI, an adaptive personality engine based on the 30 facets of the Five Factor Model [6]. In addition, Alavi et al. proposed Minecraft persona-driven dialogue, a large language model-based persona-consistent dialogue dataset [7]. Hughes et al. summarized the relationship between the Big Five and emotion regulation [8], and Forgas showed that emotions influence the judgment and execution of interpersonal behavior [9]. Kim et al. proposed group-level honesty-humility, emotionality, extraversion, agreeableness, conscientiousness, and openness to experience, a personality scale for game characters, providing a foundation for applying personality theory to game characters [10]. These studies suggest that personality traits may appear as behavioral differences through emotion regulation and interpersonal responses.

Previous studies have mainly focused on emotion estimation, state transitions, social relationship updates, and dialogue consistency. However, there has been insufficient research on generating continuous 3D walking motions corresponding to intermediate points in personality space and comparing the effects of differences in initial conditions on the generated results. Therefore, in this study, we generate walking motions associated with OCEAN parameters using LSTM-VAE and compare initial-frame-dependent generation with latent-vector-only generation.

3. Materials and Methods

3.1. Motion Data Acquisition

Human walking motion data were acquired using Kinect in Unity. The acquired skeletal information was applied to a 3D model and organized as time-series data of joint positions and postures. In this study, a basic validation was conducted using three types of walking motions.

3.2. Motion Generation Models

For motion generation, we used an encoder–decoder LSTM-VAE that compresses motion sequences into latent representations and reconstructs them (Figure 1).

In the encoder, the entire motion sequence is input, and the mean μ and log variance $\log\sigma^2$ of the latent distribution $q(z \mid x)$ are estimated from the final hidden state of the LSTM. A latent variable z is then obtained using the reparameterization trick. In the decoder, the initial hidden state h_0 and initial cell state c_0 are generated from z, and the motion sequence is reconstructed autoregressively. In this study, we evaluated differences in the decoder's starting conditions and defined two conditions: one in which the first frame is given as the initial input, and another in which the initial input is generated from the latent variable. In the following comparison, we evaluated how these differences in starting conditions affect the generated results (Figures 2 and 3).

3.2.1. Initial-Frame-Dependent Generation

In the initial-frame-dependent generation, the average of the latent mean vectors μ obtained from the three training motions was used as the centroid latent vector z, which

served as a common condition. Then, the first frame of each training walking motion was provided as the initial input y_0 to the decoder, and the entire sequence was generated autoregressively (Figure 2). Specifically, the first frames of Walk1, Walk2, and Walk3 were used as initial inputs, respectively. This allowed us to compare the influence of the initial frame on the same latent representation.

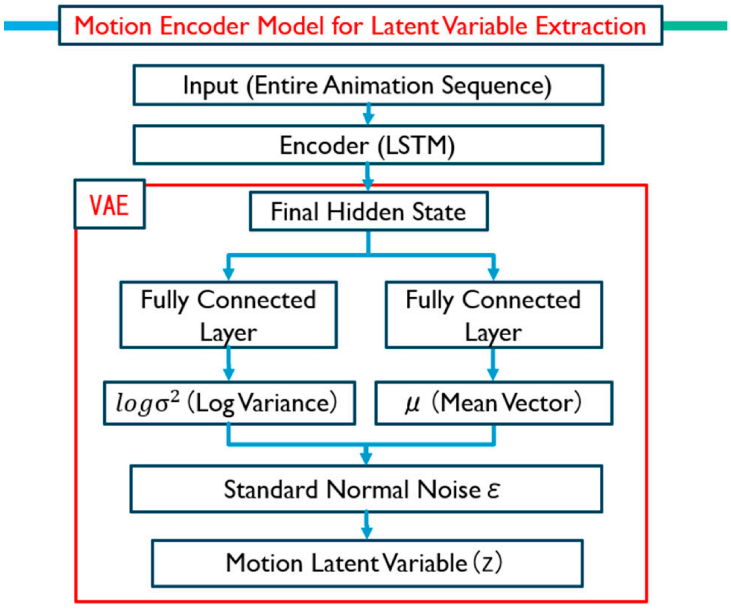


Figure 1. Overall architecture of the proposed walking motion generation model. The entire motion sequence is input, and latent variables are extracted using an LSTM encoder and VAE.

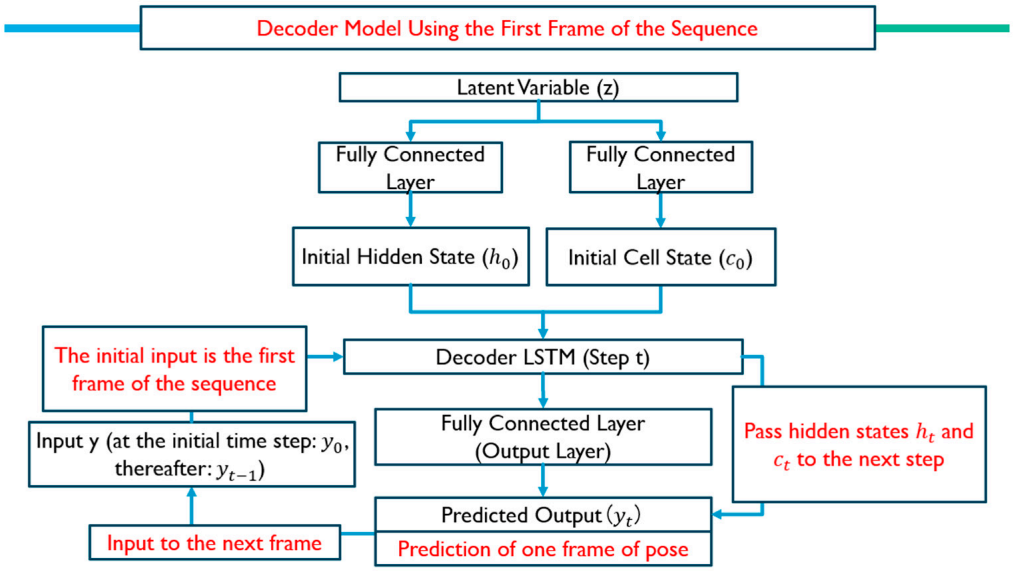


Figure 2. Initial-frame condition walking motion generation model. A decoder model that generates a motion sequence using the first frame of the sequence as the initial input.

3.2.2. Latent-Vector-Only Generation

In the latent-vector-only generation, no external initial frame was provided, and the motion sequence was generated using only the centroid latent vector z as the condition (Figure 3). Under this condition, the initial input y_0 is also generated from the latent variable z through a linear transformation, so the entire generated sequence is considered to reflect the latent representation more directly. In addition, for the length of the generated

sequence, we used the rounded average length of the three training motion sequences. This enabled generation with an intermediate sequence length that did not depend on the length of any specific training motion.

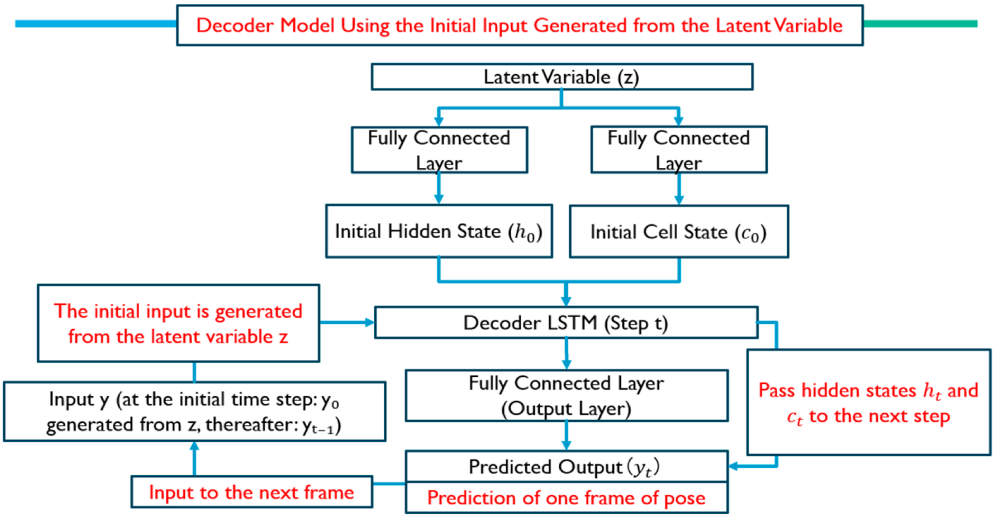


Figure 3. Latent-only condition walking motion generation model. A decoder model that generates the initial input from the latent variable and then generates the motion sequence.

3.3. Personality Parameter Estimation and Evaluation

For evaluation of the generated motions, OCEAN estimation using the Gemini model was employed. Each motion video was input together with the same prompt, and the five OCEAN factors were estimated 10 times for each motion. From the obtained estimates, the mean value and 95% confidence interval for each factor were calculated. For comparison, the average of the OCEAN estimated mean values of the three motions used for training (Walk1, Walk2, and Walk3) was defined as the training motion average (WalkAllAverage). Evaluation was conducted from three perspectives: the difference from the training motion average, the variability caused by initial conditions, and whether the training motion average was included within the 95% confidence interval of each generated motion. Through this evaluation, we examined which of the two methods, initial-frame-dependent generation or latent-vector-only generation, more stably reflected the intermediate characteristics of the training motion group.

4. Result

4.1. OCEAN Estimates of Training Motions

Table 1 shows the estimated mean OCEAN values of the three motions used for training. The average OCEAN values obtained from the three motions were openness = 0.530, conscientiousness = 0.747, extraversion = 0.687, agreeableness = 0.523, and neuroticism = 0.337.

Table 1. Estimated mean OCEAN values of the three motions used for training and their overall average.

Animation	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Walk1	0.380	0.710	0.340	0.540	0.550
Walk2	0.610	0.780	0.890	0.500	0.210
Walk3	0.600	0.750	0.830	0.530	0.250
WalkAllAverage	0.530	0.747	0.687	0.523	0.337

4.2. Comparison of Initial-Frame-Dependent and Latent-Vector-Only Generation

Table 2 summarizes the estimated mean OCEAN values under each generation condition. In the initial-frame-dependent generation, large differences were observed among WalkCenter1, WalkCenter2, and WalkCenter3. In particular, extraversion varied from 0.395 to 0.895, with a difference of 0.500. Differences among conditions were also observed in openness and neuroticism. In contrast, WalkCenter generated by latent-vector-only generation showed openness = 0.450, conscientiousness = 0.725, extraversion = 0.485, agreeableness = 0.5203, and neuroticism = 0.460, indicating an overall intermediate tendency relative to the average of the training motions.

Table 2. Estimated mean OCEAN values for each generation condition.

Animation	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
WalkCenter1 (frame-dependent)	0.410	0.625	0.395	0.525	0.500
WalkCenter2 (frame-dependent)	0.625	0.660	0.890	0.480	0.275
WalkCenter3 (frame-dependent)	0.665	0.505	0.895	0.440	0.295
WalkCenter (latent only)	0.450	0.725	0.485	0.520	0.460

Figure 4 shows the OCEAN estimation results for both generated and training motions. In the latent-vector-only generation, the result was less likely to show an extreme bias relative to the training motion average. In contrast, in the initial-frame-dependent generation, WalkCenter1 showed a tendency closer to Walk1 (Figure 4b), while WalkCenter2 and WalkCenter3 showed tendencies closer to Walk2 and Walk3, respectively, as shown in Figure 4c,d. These results suggest that even when using the same centroid vector, the generated motion strongly inherits the characteristics of the initial input frame.

4.3. Comparison by 95% Confidence Intervals

We compared whether the training motion average (WalkAllAverage) was included within the 95% confidence interval of the OCEAN estimated values for each generated motion. In the initial-frame-dependent generation, different factors included WalkAllAverage within the 95% confidence interval depending on the initial input frame. The results for each generation condition are described below.

For WalkCenter1, only A included WalkAllAverage within the 95% confidence interval, whereas O, C, E, and N were outside the confidence interval (Table 3). In particular, the estimated mean value of E was substantially lower than WalkAllAverage, suggesting that the influence of the initial input frame was strongly reflected in the generated motion.

Table 3. Estimated mean OCEAN values, 95% confidence intervals, and inclusion judgment of the training motion average for WalkCenter1 obtained by initial-frame-dependent generation. Red values and blue values for WalkAllAverage indicate values outside and inside the confidence interval, respectively.

WalkCenter1	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Average	0.410	0.625	0.395	0.525	0.500
95% Confidence Interval	0.108	0.116	0.201	0.051	0.162
Lower Bound	0.302	0.509	0.194	0.474	0.338
Upper Bound	0.518	0.741	0.596	0.576	0.662
WalkAllAverage	0.530	0.747	0.687	0.523	0.337

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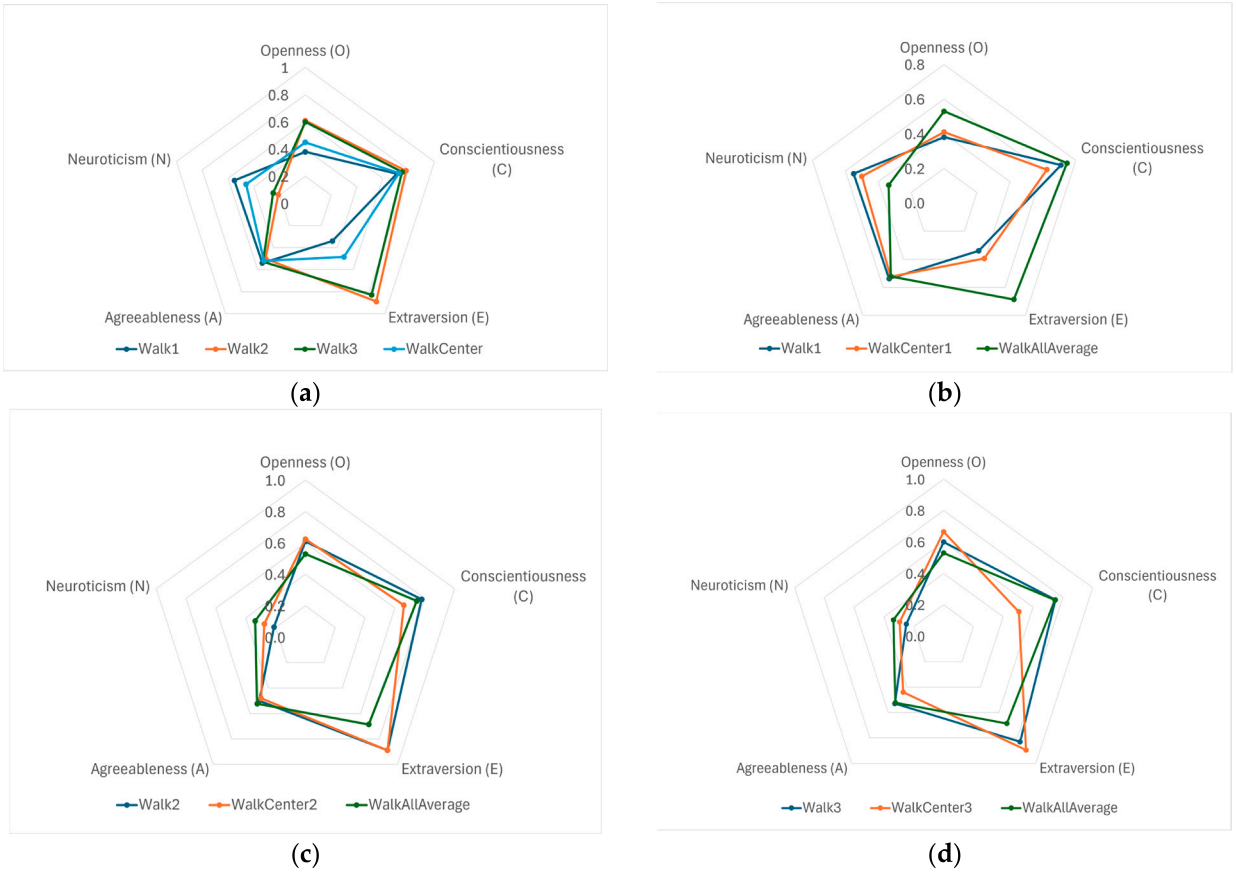


Figure 4. Radar charts showing the OCEAN estimated values of generated walking motions and training walking motions: (**a**) Comparison of WalkCenter (latent only) and Walk1–Walk3 (training data). (**b**) Comparison of Walk1, WalkCenter1, and WalkAllAverage. (**c**) Comparison of Walk2, WalkCenter2, and WalkAllAverage. (**d**) Comparison of Walk3, WalkCenter3, and WalkAllAverage.

For WalkCenter2, C and N included WalkAllAverage within the 95% confidence interval, whereas O, E, and A were outside the confidence interval (Table 4). In particular, the estimated mean value of E was higher than WalkAllAverage, showing a tendency different from that of WalkCenter1. These results indicate that even when the same centroid latent vector is used, the impression of the generated motion changes substantially depending on the difference in the initial frame.

Table 4. Estimated mean OCEAN values, 95% confidence intervals, and inclusion judgment of the training motion average for WalkCenter2 obtained by initial-frame-dependent generation. Red values and blue values for WalkAllAverage indicate values outside and inside the confidence interval respectively.

WalkCenter2	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Average	0.625	0.660	0.890	0.480	0.275
95% Confidence Interval	0.051	0.123	0.023	0.030	0.088
Lower Bound	0.574	0.537	0.867	0.450	0.187
Upper Bound	0.676	0.783	0.913	0.510	0.363
WalkAllAverage	0.530	0.747	0.687	0.523	0.337

For WalkCenter3, only N included WalkAllAverage within the 95% confidence interval, whereas O, C, E, and A were outside the confidence interval (Table 5). In particular, O and E were higher than WalkAllAverage, while C and A were lower. These results indicate that

the influence of the initial frame remained strong in WalkCenter3 as well, and it did not consistently show an intermediate tendency close to the training motion average.

Table 5. Estimated mean OCEAN values, 95% confidence intervals, and inclusion judgment of the training motion average for WalkCenter3 obtained by initial-frame-dependent generation. Red values and blue values for WalkAllAverage indicate values outside and inside the confidence interval respectively.

WalkCenter3	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Average	0.665	0.505	0.895	0.440	0.295
95% Confidence Interval	0.048	0.117	0.036	0.077	0.093
Lower Bound	0.617	0.388	0.859	0.363	0.202
Upper Bound	0.713	0.622	0.931	0.517	0.388
WalkAllAverage	0.530	0.747	0.687	0.523	0.337

In WalkCenter generated only from the centroid of latent vectors, WalkAllAverage was included within the 95% confidence interval for all indicators O, C, E, A, and N (Table 6). This result suggests that latent-vector-only generation may more stably reflect the average characteristics of the training motion group.

Table 6. Estimated mean OCEAN values, 95% confidence intervals, and inclusion judgment of the training motion average for WalkCenter generated only from the centroid of latent vectors. Red values and blue values for WalkAllAverage indicate values outside and inside the confidence interval respectively.

WalkCenter	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Average	0.450	0.725	0.485	0.520	0.460
95% Confidence Interval	0.140	0.097	0.240	0.056	0.179
Lower Bound	0.310	0.628	0.245	0.464	0.281
Upper Bound	0.590	0.822	0.725	0.576	0.639
WalkAllAverage	0.530	0.747	0.687	0.523	0.337

5. Discussion

The results of this study showed that, in walking motion generation using a centroid vector, the way in which the initial frame is given greatly affects the generated result. In the initial-frame-dependent generation, even with the same centroid latent vector, the factors that included WalkAllAverage within the 95% confidence interval differed among WalkCenter1, WalkCenter2, and WalkCenter3. In particular, E was lower than WalkAllAverage in WalkCenter1, whereas it was higher in WalkCenter2 and WalkCenter3, suggesting that Extraversion is a factor particularly susceptible to the influence of initial conditions.

In contrast, in WalkCenter generated only from the centroid of latent vectors, WalkAllAverage was included within the 95% confidence interval for all factors. This suggests that, under our evaluation setting, latent-vector-only generation more stably reflects the average characteristics of the training motion group. However, in terms of the mean values, E tended to be lower and N somewhat higher, indicating that the ideal intermediate motion was not reproduced perfectly.

This study also has limitations. First, the evaluation depends on OCEAN estimation by Gemini, and the bias of the estimator must be taken into account. Second, the comparison targets were limited to only three walking motions, resulting in limited motion diversity. Third, although latent-vector-only generation can suppress initial-frame dependency, challenges may remain in terms of motion continuity and posture stability.

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6. Conclusions

We compared initial-frame-dependent generation and latent-vector-only generation in 3D walking motion generation based on Big Five personality traits. The results showed that latent-vector-only generation included the training motion average within the 95% confidence interval for all OCEAN factors and reflected intermediate characteristics more stably, although the generated results in the initial-frame-dependent generation strongly depended on the initial input frame. These results suggest that generation conditions that eliminate initial-frame dependency may be effective for evaluating intermediate personality-expressive motions. In further studies, it is necessary to verify the effectiveness of this method by expanding the target motions for evaluation and improving the evaluation methodology. These findings provide practical insights into designing stable personality-driven motion generation for NPCs.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
NPC	Non-Player Character
LSTM	Long Short-Term Memory
VAE	Variational Autoencoder
LSTM-VAE	Long Short-Term Memory Variational Autoencoder
OCEAN	Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism
CI	Confidence Interval

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