





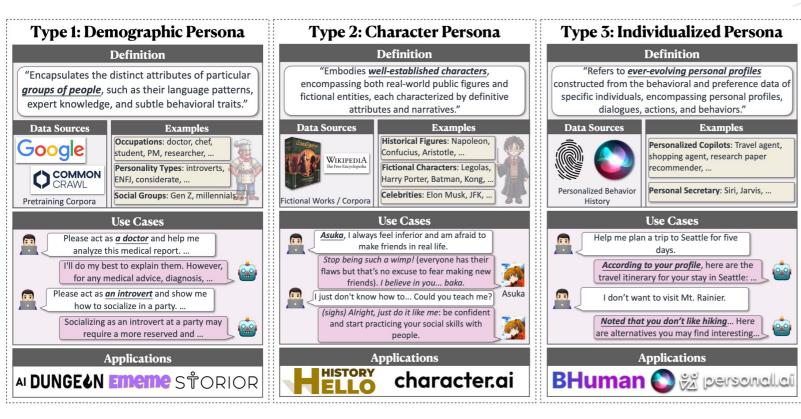
# MMRole: A Comprehensive Framework for Developing and Evaluating Multimodal Role-Playing Agents

Yanqi Dai, Huanran Hu, Lei Wang, Shengjie Jin, Xu Chen, Zhiwu Lu Gaoling School of Artificial Intelligence, Renmin University of China yanqidai@ruc.edu.cn



# **Motivation**





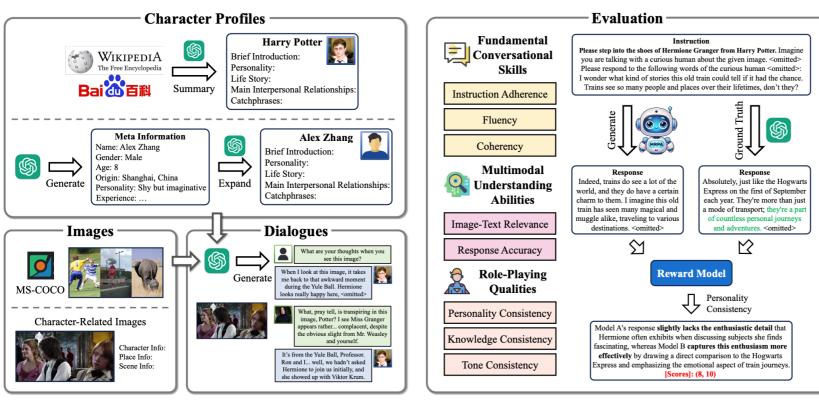
However, exsiting Role-Playing Agents (RPAs) are primarily confined to the textual modality, unable to simulate humans' multimodal perceptual capabilities.

Figure 1: An overview of various persona types for RPLAs. In this survey, we categorize personas into three types: 1) Demographic Persona, 2) Character Persona, and 3) Individualized Persona. We showcase their definition, data sources, examples, use cases and corresponding applications.



# **Overview**





We propose MMRole, a comprehensive framework for developing and evaluating of Multimodal Role-Playing Agents (MRPAs), which comprises a personalized multimodal dataset and a robust evaluation approach.

(a) Dataset Construction

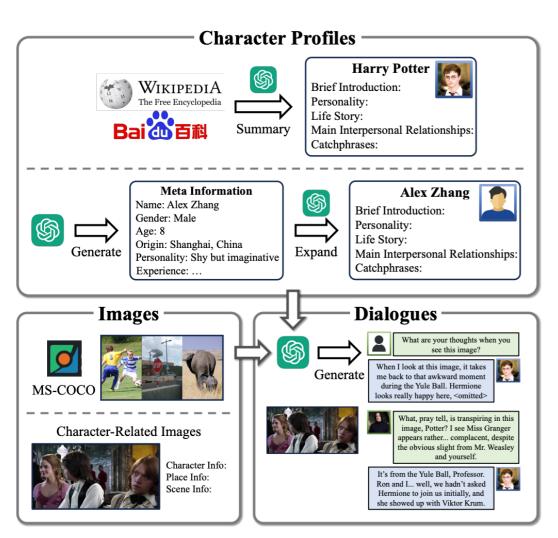
(b) Performance Evaluation

Figure 1: An overview of the *MMRole* framework. (a) *MMRole-Data* includes character profiles, images, and dialogues centered around images. (b) *MMRole-Eval* comprises eight evaluation metrics across three dimensions. For each metric, the reward model scores MRPAs with the constructed ground-truth data for comparison.



## **Dataset Construction**





**Statistics of MMRole-Data** 

85 characters, 11K images, and 14K dialogues, yielding 85K training samples and 294 test samples.

Table 1: The statistics of *MMRole-Data*. 'CR Images' represents character-related images. 'In-Test' denotes the in-distribution test set, while 'Out-Test' signifies the out-of-distribution test set.

	Train	In-Test	Out-Test	Overall
Characters	7	2	13	85
Generic Images	10,	800	39	10,839
CR Images	1'	75	18	193
Dialogues	14,052	216	78	14,346
Samples	85,456	216	78	85,750

Table 2: The statistics for the three types of dialogue scenarios in MMRole-Data.

	Comment.	Human-Role.	Inter-Role.	Overall
Dialogues	4893	4617	4836	14346
Turns / Dlg.	1.00	5.80	5.75	4.15
Tokens / Dlg.	236.00	446.91	429.54	369.12

(a) Dataset Construction



# **Performance Evaluation**



## **Evaluation**



**Fundamental** Conversational **Skills** 

Instruction Adherence

Fluency

Coherency



Multimodal Understanding **Abilities** 

Image-Text Relevance

Response Accuracy



**Role-Playing Qualities** 

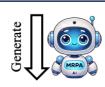
Personality Consistency

Knowledge Consistency

**Tone Consistency** 

#### Instruction

Please step into the shoes of Hermione Granger from Harry Potter. Imagine you are talking with a curious human about the given image. <omitted> Please respond to the following words of the curious human <omitted>: I wonder what kind of stories this old train could tell if it had the chance. Trains see so many people and places over their lifetimes, don't they?





#### Response

Indeed, trains do see a lot of the world, and they do have a certain charm to them. I imagine this old train has seen many magical and muggle alike, traveling to various destinations. <omitted>

#### Response

Absolutely, just like the Hogwarts Express on the first of September each year. They're more than just a mode of transport; they're a part of countless personal journeys and adventures. <omitted>





**Reward Model** 

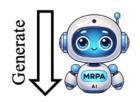


Model A's response slightly lacks the enthusiastic detail that Hermione often exhibits when discussing subjects she finds fascinating, whereas Model B captures this enthusiasm more effectively by drawing a direct comparison to the Hogwarts Express and emphasizing the emotional aspect of train journeys. [Scores]: (8, 10)

## (b) Performance Evaluation

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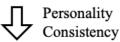
## Response

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**Reward Model** 



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[Scores]: (8, 10)



# **Experiments**



## **Evaluation of Reward Model**

These results indicate that our specialized reward model effectively learns the evaluation abilities of GPT-4 and aligns closely with human evaluators

Table 4: The validation mean absolute error (MAE) results for the effectiveness of the reward model. 'QWen-VL-Chat (GPT-4)' and 'Reward Model (GPT-4)' denote the scores evaluated by QWen-VL-Chat and the reward model compared to those evaluated by GPT-4. 'QWen-VL-Chat (humans)', 'GPT-4 (humans)', and 'Reward Model (humans)' signify the score gaps provided by QWen-VL-Chat, GPT-4, and the reward model compared to the ground-truth score gaps provided by humans.

Evaluators (Ground Truth)	IA	Flu	Coh	ITR	RA	PC	KC	TC	Overall
QWen-VL-Chat (GPT-4)	0.3776	0.3718	0.3218	0.3561	0.3528	0.4091	0.3794	0.4558	0.3780
Reward Model (GPT-4)	0.0708	0.0387	0.0526	0.0568	0.0584	0.1165	0.0815	0.1154	0.0738
QWen-VL-Chat (humans)	0.2469	0.1870	0.2720	0.2574	0.2608	0.2368	0.2243	0.2658	0.2439
GPT-4 (humans)	0.1526	0.1150	0.0772	0.0922	0.1463	0.1475	0.1279	0.1442	0.1254
Reward Model (humans)	0.0993	0.0815	0.1006	0.1225	0.1412	0.1669	0.1438	0.1507	0.1258

Table 9: The root mean squared error (RMSE) results. 'Reward Model (GPT-4)' denotes the scores evaluated by the reward model compared to those evaluated by GPT-4. 'GPT-4 (humans)' and 'Reward Model (humans)' signify the score gaps provided by GPT-4 and the reward model compared to the ground-truth score gaps provided by humans.

Evaluators (Ground Truth)	IA	Flu	Coh	ITR	RA	PC	KC	TC Overall
Reward Model (GPT-4)	0.1585	0.1076	0.1228	0.1334	0.1145	0.1564	0.1172	0.1778   0.1381
GPT-4 (humans) Reward Model (humans)	0.1794	0.1421	0.1050	0.1253	0.1837	0.1826	0.1515	0.1946   0.1609 0.2010   0.1695

Table 10: The Pearson correlation coefficient (Pearson) results. 'Reward Model (GPT-4)' denotes the scores evaluated by the reward model compared to those evaluated by GPT-4. 'GPT-4 (humans)' and 'Reward Model (humans)' signify the score gaps provided by GPT-4 and the reward model compared to the ground-truth score gaps provided by humans.

Evaluators (Ground Truth)	IA	Flu	Coh	ITR	RA	PC	KC	TC	Overall
Reward Model (GPT-4)	0.7497	0.7344	0.7610	0.7955	0.8186	0.8167	0.8237	0.8129	0.8129
GPT-4 (humans) Reward Model (humans)	0.6130	0.6736 0.3123	0.9199 0.8033	0.8184 0.8709	0.7247 0.7321	0.6997 0.7268	0.7924 0.5832	0.6985 0.5443	0.7269 0.6502



# **Experiments**



## **Evaluation of MMRole-Agent and Various General-Dialogue LMMs**

Table 5: The average results across all test samples for each evaluated MRPA, along with the detailed results for our *MMRole-Agent* on both the in-distribution test set (In-Test) and the out-of-distribution test set (Out-Test). In each group categorized by parameter scale, the best overall result is **bolded**, while the second-best one is underlined.

MRPAs	IA	Flu	Coh	ITR	RA	PC	KC	TC	Overall
GPT-4 Turbo	1.055	1.032	1.084	1.097	1.092	1.168	1.103	1.161	1.099
Gemini Pro Vision	0.999	1.007	1.028	1.009	1.013	1.052	1.013	1.050	1.021
Claude 3 Opus	1.127	1.070	1.149	1.167	1.146	1.219	1.168	1.213	1.157
QWen-VL-Max	1.014	1.012	1.035	1.034	1.029	1.042	1.021	1.041	1.028
LLaVA-NeXT-34B	1.002	1.007	1.021	1.033	1.035	1.053	1.030	1.038	1.027
Yi-VL-34B	0.895	0.968	0.910	0.875	0.863	0.844	0.869	0.845	0.884
InternVL-Chat-V1.5	0.988	0.996	0.997	0.977	0.984	0.967	0.972	0.960	0.980
QWen-VL-Chat	0.844	0.954	0.879	0.850	0.829	0.778	0.827	0.785	0.843
LLaVA-NeXT-Mistral-7B	0.948	0.986	0.964	0.938	0.933	0.924	0.940	0.921	0.944
Yi-VL-6B	0.844	0.919	0.859	0.828	0.811	0.776	0.820	0.774	0.829
MMRole-Agent	0.998	1.000	0.997	0.993	0.987	1.000	0.992	0.988	0.994
MMRole-Agent (In-Test)	1.000	1.000	0.999	0.997	0.989	1.012	0.997	0.997	0.999
MMRole-Agent (Out-Test)	0.992	0.999	0.993	0.979	0.981	0.963	0.977	0.962	0.981

- ➤ In the MRPA group with over 100 billion parameters, Claude 3 Opus exhibits superior performance.
- ➤ In the MRPA group with tens of billions of parameters, LLaVA-NeXT-34B achieves the highest performance.
- ➤ In the MRPA group with billions of parameters, MMRole-Agent is the best.
- ➤ LLaVA-NeXT-34B outperforms Gemini Pro Vision
- ➤ LLaVA-NeXT-7B and MMRole-Agent surpass Yi-VL-34B

Both the training methods and training data are important for enhancing LMMs, rather than merely expanding the model size.

MMRole-Agent has strong generalization capabilities for characters and images that are not seen in the training set.





Yanqi Dai's Homepage



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