Towards a Design Guideline for RPA Evaluation: A Survey of Large Language Model-Based Role-Playing Agents

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Abstract

Role-Playing Agent (RPA) is an increasingly popular type of LLM Agent that simulates human-like behaviors in a variety of tasks. However, evaluating RPAs is challenging due to diverse task requirements and agent designs. This paper proposes an evidence-based, actionable, and generalizable evaluation design guideline for LLM-based RPA by systematically reviewing 1,676 papers published between Jan. 2021 and Dec. 2024. Our analysis identifies six agent attributes, seven task attributes, and seven evaluation metrics from existing literature. Based on these findings, we present an RPA evaluation design guideline to help researchers develop more systematic and consistent evaluation methods.

1 Introduction

LLMs have yielded human-like performance in various cognitive tasks (e.g., memorization (Schwarzschild et al., 2025), reasoning (Wang et al., 2023; Plaat et al., 2024), and planning (Song et al., 2023; Huang et al., 2024)). These emergent capabilities have fueled growing research interest on **Role-Playing Agent** (RPA) (Chen et al., 2024d; Tseng et al., 2024): RPAs are digital intelligent agent systems powered by LLMs, where users provide human-like **agent attributes** (e.g., personas) and **task attributes** (e.g., task descriptions) as input, and prompt the LLM to generate human-like behaviors and the reasoning process. The potential of RPAs is promising and far-reaching, as illustrated by the early results of the massive interdisciplinary studies in social science (Park et al., 2022, 2023), network science (Chen et al., 2024b), psychology(Jiang et al., 2024) and juridical science (He et al., 2024b).

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Github repository: `https://github.com/CRChenND/LLM_roleplay_agent_eval_survey`

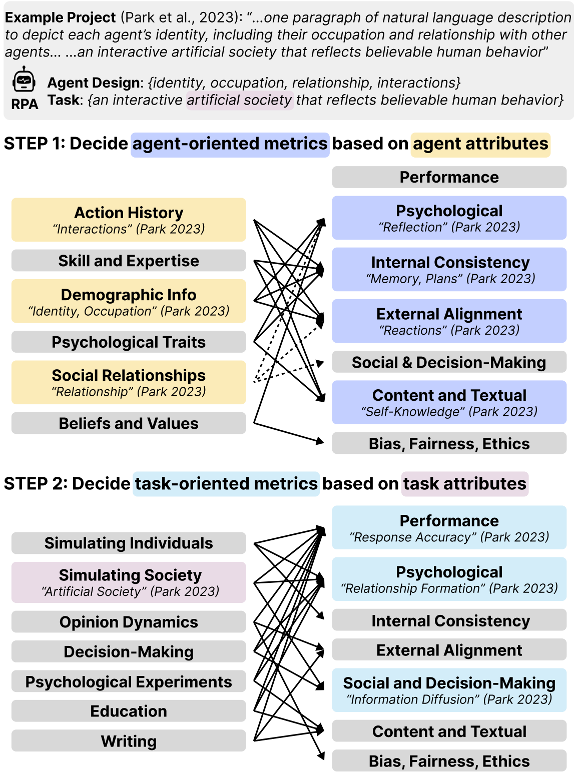

Figure 1: RPA evaluation design guideline. To illustrate how to use it in practice, we pretended we were selecting the evaluation metrics for the "Stanford Agent Village" (Park et al., 2023) given agent attributes (yellow) and task attributes (pink). The original authors' selection of evaluation metrics (purple and blue) perfectly aligns with our RPA design guideline, which echoes their work's robustness. More details in Sec 5.1 and a bad example in Sec 5.2.

Despite growing interest in RPAs, a fundamental question remains: **how can we systematically and consistently evaluate an RPA?** How should we select the evaluation metrics, so that the evaluation results can be comparable or generalizable from one task to another task? Addressing these challenges is difficult (Dai et al., 2024; Tu et al., 2024; Wang et al., 2024c). due to the vast diversity of tasks (e.g., simulating an individual's online browser behavior (Chen et al., 2024b) or simulating a hospital (Li et al., 2024c)), and the high flexibility in RPA design (e.g., an agent persona can be one sentence or 2-hours of interview log (Park et al., 2024)). Another challenge is the inconsistent and often arbitrary selection of evaluation methods and metrics for RPAs, raising concerns about the validity and reliability of evaluation results (Wang et al., 2025b; Zhang et al., 2025). As a result, the research community finds it difficult to compare the performance across multiple RPAs in similar tasks reliably and systematically.

To address this gap, we propose an evidence-based, actionable, and generalizable design guideline for evaluating LLM-based RPAs. We conducted **a systematic literature review** of $1,676$ papers on the LLM Agent topic and identified 122 papers describing its evaluation details. Through expert coding, we found that agent attribute design interacts with task characteristics (e.g., simulating an individual or simulating a society requires a diverse set of agent attributes). Furthermore, we synthesized common patterns in how prior research successfully (or unsuccessfully) designed their evaluation metrics to correspond to the RPA's agent attributes and task attributes. Building on these insights, we propose an RPA evaluation design guideline (Fig. 1) and illustrate its generalizability through two case studies.

2 Related Work

Existing surveys on the evaluation of RPAs (Gao et al., 2024; Chen et al., 2024d; Tseng et al., 2024; Chen et al., 2024e; Mou et al., 2024a) provide a unified classification of RPA evaluation metrics from the perspective of evaluation approaches. However, they lack a comprehensive and consistent taxonomy for versatile evaluation metrics, leading to arbitrary metrics selection in practices.

Prior works (Gao et al., 2024; Mou et al., 2024a) categorize RPA evaluations into three types: automatic evaluations, human-based evaluations, and LLM-based assessments. Automatic evaluations are efficient and objective, but lack context sensitivity, failing to capture nuances like persona consistency. Human-based evaluations provide deep insight into character alignment and engagement, but they are costly, less scalable, and prone to subjectivity. LLM-based evaluations are automatic and offer scalability and speed, but may not always align with human judgments.

The classification of evaluation metrics in prior works varies significantly, leading to inconsistency and ambiguity. For instance, Gao et al. (2024) focuses on realness validation and ethics evaluation, whereas Chen et al. (2024d) differentiates between character persona and individualized persona. Furthermore, Chen et al. (2024e) classifies evaluation into conversation ability, role-persona consistency, role-behavior consistency, and role-playing attractiveness, which partially overlap with Mou et al. (2024a)'s individual simulation and scenario evaluation. These discrepancies indicate a lack of standardized taxonomy, making it difficult to compare results across studies and select appropriate evaluation metrics for specific applications.

While existing surveys offer different taxonomies of RPA evaluation, they do not provide concrete evaluation design guidelines. Our work addresses this gap by proposing a structured framework that systematically links evaluation metrics to RPA attributes and real-world applications.

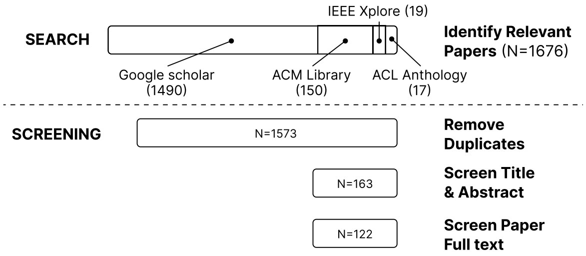

Figure 2: Screening process of literature review. We initially retrieved $1,676$ papers published between 2021 and 2024, and narrowed down to 122 final selections.

3 Method

We conduct a systematic literature review to address our research question. Following prior method (Nightingale, 2009), we aim to identify relevant research papers on RPAs and provide a comprehensive summary of the literature. We selected four widely used academic databases: Google Scholar, ACM Digital Library, IEEE Xplore, and ACL Anthology. These databases encompass a broad spectrum of research across AI, human-computer interaction, and computational linguistics. Given the rapid advancements in LLM research, we included both peer-reviewed and preprint studies (e.g., from arXiv) to capture the latest developments. Below, we detail our paper selection and annotation process.

3.1 Literature Search and Screening Method

Our literature review focuses on LLM agents that role-play human behaviors, such as decision-

Table 1: Definition and examples of six agent attributes.

Agent attributes	Definition	Examples
Activity History	A record of past actions, behaviors, and engagements, including schedules, browsing history, and lifestyle choices.	Backstory, plot, weekly schedule, browsing history, social media posts, lifestyle
Belief and Value	The principles, attitudes, and ideological stances that shape an individual's perspectives and decisions.	Stances, beliefs, attitudes, values, political leaning, religion
Demographic Information	Personal identifying details such as name, age, education, career, and location.	Name, appearance, gender, age, date of birth, education, location, career, household income
Psychological Traits	Characteristics related to personality, emotions, interests, and cognitive tendencies.	Personality, hobby and interest, emotional
Skill and Expertise	The knowledge level, proficiency, and capability in specific domains or technologies.	Knowledge level, technology proficiency, skills
Social Relationships	The nature and dynamics of interactions with others, including roles, connections, and communication styles.	Parenting styles, interactions with players

making, reasoning, and deliberate actions. We specifically focus on studies where LLM agents demonstrate the ability to simulate human-like cognitive processes in their objectives, methodologies, or evaluation techniques. To ensure methodological rigor, we define explicit inclusion and exclusion criteria (Tab. 6 in Appendix A).

The inclusion criteria require that an LLM agent in the study exhibits human-like behavior, engages in cognitive activities such as decision-making or reasoning, and operates in an open-ended task environment. We excluded studies where LLM agents primarily serve as chatbots, task-specific assistants, evaluators, or agents operating within predefined and finite action spaces. Additionally, studies focusing solely on perception-based tasks (e.g., computer vision or sensor-based autonomous driving) without cognitive simulation were also excluded.

Using this scope, we searched four databases using the query string provided in Appendix B, retrieving $1,676$ papers published between January 2021 to December 2024. After removing duplicates, $1,573$ unique papers remained. Two authors independently screened the paper titles and abstracts based on the inclusion criteria. If at least one author deemed a paper relevant, it proceeded to full-text screening, where two authors reviewed the paper in detail and resolved any disagreements through discussion (Fig. 2). The final set of selected studies comprised 122 publications.

3.2 Paper Annotation Method

Our team followed established open coding procedures (Brod et al., 2009) to conduct an inductive coding process to identify key themes. Three coauthors with extensive experience in LLM agents ("annotators," hereinafter) collaboratively annotated the papers on three dimensions: **agent attributes**, **task attributes**, and **evaluation metrics**.

To ensure consistency, two annotators independently annotated the same 20% of articles and then held a meeting to discuss and refine an initial set of categories for the three dimensions. After reaching a consensus, each annotator annotated half of the remaining papers and cross-validated the other half annotated by the other annotator. Once the annotations were completed, a third annotator reviewed the coded data and identified potential discrepancies. Any discrepancies were discussed among the annotators to ensure consistency until disagreements were resolved, ensuring reliability and validity through an iterative refinement process.

4 Survey Findings

Building on the annotated data, we systematically categorized agent attributes, task attributes, and evaluation metrics. We then present a structured RPA evaluation design guideline, outlining how to select appropriate evaluation metrics based on agent and task attributes.

4.1 Agent Attributes

We identified six categories of agent attributes, as shown in Tab. 1. *Activity history* refers to an agent's longitudinal behaviors, such as browsing history (Chen et al., 2024b) or social media activity (Navarro et al., 2024). *Belief and value* encompass the principles, attitudes, and ideological stances that shape an agent's perspectives, including political leanings (Mou et al., 2024c) or religious affiliations (Lv et al., 2024). *Demographic information* includes personal details such as name, age, education, location, career status, and household income. *Psychological traits* include an agent's personality (Jiang et al., 2023a), emotions, and cognitive tendencies (Castricato et al.,

Table 2: Definition of seven task attributes.

Task attributes	Definition
Simulated Individuals	Simulating specific individuals or groups, such as users and participants.
Simulated Society	Simulating social interactions, such as cooperation, competition, and communication.
Opinion Dynamics	Simulating political views, legal perspectives, and social media content.
Decision Making	Simulating decision-making of stakeholders in investment, public policies, or games.
Psychological Experiments	Simulating human traits, including personality, ethics, emotions, and mental health.
Educational Training	Simulating teachers and learners to enable personalized teaching and accommodate learner needs.
Writing	Simulating readers or characters to support character development and audience understanding.

Table 3: Definitions and examples of seven evaluation metric categories.

Evaluation Metrics	Definitions	Examples
Performance	Assess RPAs' effectiveness in task execution and outcomes.	Prediction accuracy
Psychological	Measure human psychological responses to RPAs and the agents' self-awareness and emotional state.	Big Five Invertory
External Alignment	Evaluate how closely RPAs align with external ground truth or human behavior and judgments.	Alignment between model and human
Internal Consistency	Assess coherence between an RPA's predefined traits (e.g., personality), contextual expectations, and behavior.	Personality-behavior alignment
Social and Decision-Making	Analyze RPAs' social interactions and decision-making, including their effects on negotiation, societal welfare, markets, and social dynamics.	Social Conflict Count
Content and Textual	Evaluate the quality, coherence, and diversity of RPAs' text, including semantic understanding, linguistic style, and engagement.	Content similarity
Bias, Fairness, and Ethics	Assess biases, extreme or unbalanced content, or stereotyping behavior.	Factual error rate

2024). *Skill and expertise* describe an agent's knowledge and proficiency in specific domains, such as technology proficiency or specialized professional skills. Lastly, *social relationships* define the social interactions, roles, and communication styles between agents, including aspects like parenting styles (Ye and Gao, 2024) or relationships between players (Ge et al., 2024).

4.2 Task Attributes

We identified seven key types of RPA downstream task attributes (Tab. 2). These tasks fall into two broad categories: those that use simulation as a research goal and those that use simulation as a tool to support specific research domains.

Among them, simulated individuals and simulated society primarily use simulation as the research goal. *Simulated individuals* involve modeling specific individuals or groups, such as end-users (Chen et al., 2024a), to study their behaviors and interactions in a controlled setting. *Simulated Society* focuses on social interactions, including cooperation (Bouzekri et al., 2024), competition (Wu et al., 2024), and communication (Mishra et al., 2023), aiming to explore emergent social dynamics.

In contrast, the other task attributes employ simulation as a means to serve specific research domains. *Opinion dynamics* entails simulating political views (Neuberger et al., 2024), legal perspectives (Chen et al., 2024c), and social media discourse (Liu et al., 2024c) to analyze the formation and evolution of opinions. *Decision making* addresses the decision-making processes of stakeholders in investment (Sreedhar and Chilton, 2024) and public policy (Ji et al., 2024), providing insights into strategic behaviors. *Psychological experiments* explore human traits such as personality (Bose et al., 2024), ethics (Lei et al., 2024), emotions (Zhao et al., 2024), and mental health (De Duro et al., 2025), using simulated scenarios to study cognitive and behavioral responses. *Educational training* supports personalized learning by simulating teachers and learners, enhancing pedagogical approaches and adaptive education systems (Liu et al., 2024d). Finally, *writing* involves modeling readers or characters to facilitate character development (Benharrak et al., 2024) and audience engagement (Choi et al., 2024), contributing to storytelling and content generation research.

4.3 Agent- and Task-Oriented Metrics

We derived seven categories of evaluation metrics (Tab. 3) that are shared by agent- and task-oriented metrics despite differences in the specific metrics.

Agent-oriented metrics focus on intrinsic, task-agnostic properties that define an RPA's essential ability, such as underlying reasoning, consistency,

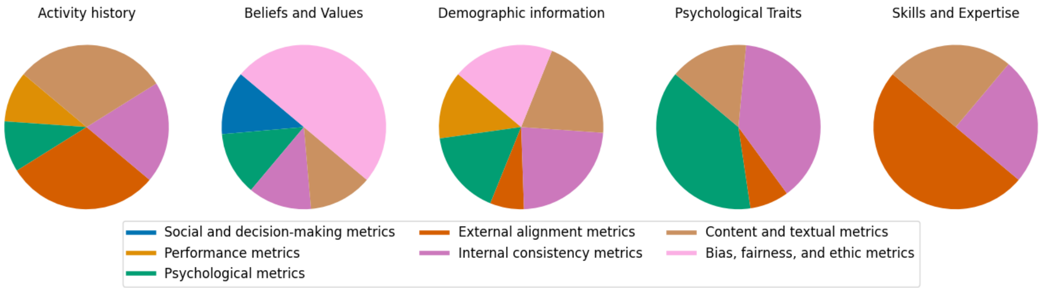

Figure 3: Proportional distribution of agent-oriented metrics across different agent attributes.

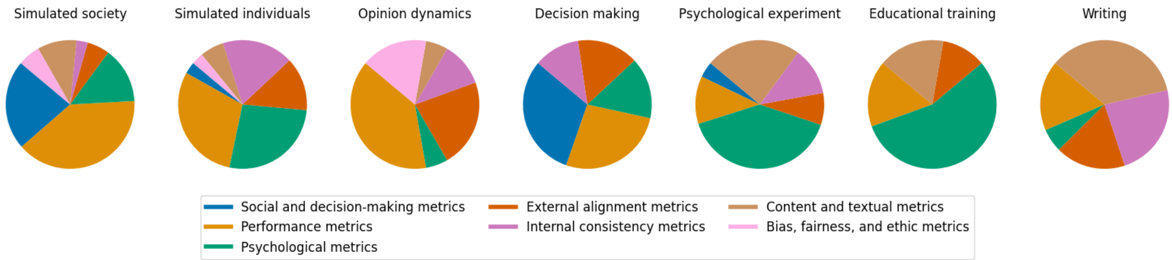

Figure 4: Proportional distribution of task-oriented metrics across different task attributes.

Agent Attributes	**Top 3 Agent-Oriented Metrics**
Activity History	External alignment metrics, internal consistency metrics, content and textual metrics
Belief and Value	Psychological metrics, bias, fairness, and ethics metrics
Demographic Info.	Psychological metrics, internal consistency metrics, external alignment metrics
Psychological Traits	Psychological metrics, internal consistency metrics, content and textual metrics
Skill and Expertise	External alignment metrics, internal consistency metrics, content and textual metrics
Social Relationship	Psychological metrics, external alignment metrics, social and decision-making metrics

Table 4: Top 3 frequently used agent-oriented metrics for each agent attribute

and adaptability. These include *performance* metrics like memorization, *psychological* metrics such as emotional responses measured via entropy of valence and arousal, and *social and decision-making* metrics like social value orientation. Additionally, agent-oriented evaluations emphasize *internal consistency* metrics (e.g., consistency of information across interactions), *external alignment* metrics (e.g., hallucination detection), and *content and textual* metrics such as clarity. These evaluations ensure logical coherence, factual accuracy, and alignment with expected behavioral and cognitive frameworks, independent of any specific task.

Task-oriented metrics evaluate an RPA's effectiveness in performing specific downstream tasks, focusing on task-related aspects such as accuracy, consistency, social impact, and ethical considerations. *Performance* measures how well RPAs execute designated tasks, such as prediction accuracy. *Psychological* metrics assess human psychological responses to RPAs, including self-awareness and emotional states; for example, the Big Five Inventory. *External alignment* evaluates how closely RPAs align with external ground truth or human behavior; for instance, alignment between model and human. *Internal consistency* ensures coherence between an RPA's predefined traits, contextual expectations, and behavior; for example, personality-behavior alignment. *Social and decision-making* metrics analyze RPAs' influence on negotiation, societal welfare, and social dynamics; for instance, the social conflict count. *Content and textual qual-*

Task Attributes	**Top 3 Task-Oriented Metrics**
Simulated Individuals	Psychological, performance, and internal consistency metrics
Simulated Society	Social and decision-making metrics, performance metrics, and psychological metrics
Opinion Dynamics	Performance metrics, external alignment metrics, and bias, fairness, and ethics metrics
Decision Making	Social and decision-making, performance, and psychological metrics
Psychological Experiment	Psychological, content and textual, and performance metrics
Educational Training	Psychological, performance, and content and textual metrics
Writing	Content and textual, psychological, and performance metrics

Table 5: Top 3 frequently used task-oriented metrics for each task attribute

ity focuses on the coherence, linguistic style, and engagement of RPAs' generated text, such as content similarity. Lastly, *bias, fairness, and ethics* metrics examine biases, extreme content, or stereotypes; for instance, the factual error rate. Together, these seven metrics provide a comprehensive framework for evaluating RPAs' task performance and broader impact.

4.4 RPA Evaluation Design Guideline

Building on our previous classification of agent attributes, task attributes, and evaluation metrics, we observed that both agent design and evaluation can be broadly divided into two categories: **agent-oriented** and **task-oriented**. This distinction led us to investigate patterns between agent design and evaluation, aiming to develop systematic guidelines for selecting evaluation metrics in future research.

Step 1. Selecting Agent-Oriented Metrics Based on Agent Attributes We analyzed the distribution of agent attributes and agent-oriented metrics, as illustrated in Fig. 3. Our analysis reveals that, for each agent attribute, the top three categories of agent-oriented metrics account for the majority of all metric types. Based on this observation, our first guideline recommends selecting agent-oriented metrics according to agent attributes. Specifically, we suggest referring to Tab. 4 to identify the top three corresponding metrics. For instance, for Activity History, the recommended metrics are external alignment, internal consistency, and content and textual metrics. Likewise, for Beliefs and Values, the most relevant choices are psychological metrics and bias, fairness, and ethics metrics. In particular, there are no established agent-oriented evaluation metrics for social relationships. Based on Social Exchange Theory (Cropanzano and Mitchell, 2005), which explains relationship formation through reciprocal interactions and resource exchanges, we propose assessing social relationships with psychological metrics, external alignment metrics, and social and decision-making metrics.

Step 2: Selecting Task-Oriented Metrics Based on Task Attributes Additionally, we analyzed the distribution of task attributes and task-oriented metrics, as shown in Fig. 4. Consistent with our previous findings, we observed that for each category of task attributes, the top three task-oriented metrics account for the vast majority of all metrics. Based on this, our second guideline recommends selecting task-oriented metrics according to task attributes. Specifically, we suggest referring to Tab. 5 to identify the top three corresponding metrics. For instance, for the *Simulated Society* task, the recommended metrics are social and decision-making, performance, and psychological metrics. Similarly, for the *Opinion Dynamics* task, the most relevant choices are performance, external alignment, bias, fairness, and ethics metrics.

However, these two steps should not be treated as one-time decisions. As the agent design process evolves, evaluation results may prompt adjustments to the attributes of the agent and the task, thereby influencing the selection of evaluation metrics. Therefore, this two-step evaluation guideline should be used iteratively to ensure that the evaluation remains adaptive to changing agent capabilities and task requirements. This iterative approach enhances the reliability, relevance, and robustness of RPA evaluation experiments.

5 Case Study: How to Use RPA Design Guideline to Select Evaluation Metrics

We present **two case studies** to illustrate how following our evaluation guidelines leads to the selection of a comprehensive set of evaluation metrics, while significant deviations may result in incomplete evaluation. By adopting the perspective of the original authors, we compare the evaluation outcomes resulting from adhering to or deviating from the RPA evaluation guidelines.

5.1 A Good Example: *Generative Agents: Interactive Simulacra of Human Behavior*

As shown in Fig. 1, Park et al. (2023) designed agents with demographic information, action history, and social relationships to create an interactive artificial society. Their evaluation methods are in line with the structured selection process proposed in our survey. Since no established agent-oriented evaluation metrics exist for social relationships, they focused on demographic information and action history. Referring to Fig. 3, they identified four relevant metric categories: Content and textual metrics, Internal consistency metrics, External alignment metrics, and Psychological metrics. Based on Tab. 7 in Appendix E, they selected five specific evaluation metrics: Self-knowledge (Content and textual, Internal consistency), Memory and Plans (Internal consistency), Reactions (External alignment), and Reflections (Psychological).

For task-oriented metrics, they determined that the agents' downstream tasks aligned with *simulated society* and designed the evaluation metrics that are aligned with the top three most relevant metric types reported in Fig. 4. As shown in Tab. 8 in Appendix E, they selected four evaluation metrics: Response accuracy (Performance), Relationship formation (Psychological), Information diffusion and Coordination (Social and decision-making). By systematically aligning evaluation metrics with agent attributes and task objectives, this approach ensured a comprehensive and meaningful assessment.

5.2 A Flawed Example: *A Generative Social World for Embodied AI*

A flawed example is presented in Appendix D Fig. 8, which is an ICLR submission, and the reviews are publicly available on OpenReview. The authors developed agents with demographic attributes, action history, psychological traits, and social relations for route planning and election campaigns. However, their evaluation deviated significantly from our RPA evaluation design guidelines.

Despite designing agents with clear attributes, they did not include any agent-oriented evaluation metrics. For task-oriented metrics, they identified tasks related to Opinion Dynamics and Decision-Making, which should have been evaluated using five key categories: Performance metrics, Psychological metrics, External alignment metrics, Social and decision-making metrics, and Bias, fairness, and ethics metrics. Instead, their evaluation relied solely on Arrival rate, Time, and Alignment between campaign strategies, leading to an incomplete assessment. This omission resulted in criticism from reviewers, as one noted: *"The paper performs almost no quantitative experiments... This actually shows that the benchmark cannot cover too many current research methods, which is the biggest weakness of the paper."*

6 Relationships Between Agent Attributes and Downstream Tasks

Both agent attributes and downstream task attributes play a crucial role in selecting appropriate RPA evaluation metrics. Researchers predefine these factors when designing and evaluating RPAs, yet their interrelation remains an open question. In this section, we analyze how agent attributes correspond to different downstream tasks, uncovering several recurring patterns (Fig. 5).

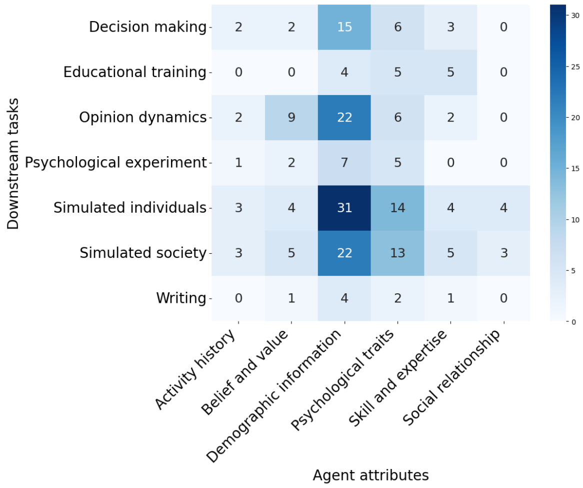

Figure 5: Relationships between agent attributes and downstream tasks. The numbers in the heatmap represent the paper counts.

Demographic information and psychological traits are fundamental across all downstream tasks. Whether in decision-making, opinion dynamics, or simulated environments, these attributes consistently shape RPA design. As shown in Fig. 5, they are the most frequently incorporated factors, underscoring their central role in modeling agent behavior across diverse applications.

For tasks where simulation itself is the primary objective, such as Simulated Individuals and Simulated Society, the selection of agent attributes becomes broader. In addition to demographic and psychological factors, these tasks frequently incorporate skills, expertise, and social relationships, reflecting the need for richer agent representations to capture complex social and individual interactions. By contrast, tasks that use simulation as a means to study specific research fields tend to prioritize certain agent attributes. For instance, in Opinion Dynamics, beliefs and values play a distinctive role, as they directly influence how agents interact and form opinions. Similarly, tasks related to Educational Training and Writing exhibit a different pattern, emphasizing skills and expertise over broad demographic or psychological considerations.

In contrast, attributes such as activity history and social relationships receive significantly less emphasis across tasks. This raises a question: is their impact inherently limited, or are they simply underexplored in current RPA applications?

Overall, these findings highlight the nuanced interplay between agent attributes and downstream tasks. While demographic information and psychological traits are universally relevant, attributes like beliefs and values gain importance in specific contexts. At the same time, the relative absence of activity history and social relationships in current evaluations presents an open research question, particularly in scenarios requiring long-term modeling and complex social interactions.

7 Discussion

7.1 RPA: an Algorithm v.s. a System

Unlike traditional algorithmic innovations in NLP, the design of RPAs can not only support technical innovations to improve LLMs' humanoid capabilities but also enable RPA-based simulation systems for practical benefits. For instance, from the perspective of psychology, RPAs support the exploration of human cognitive and behavioral activities in controlled yet highly scalable experiments, even in hypothetical scenarios. In social science, RPAs can deployed as proxies or pilot experiments to analyze and audit social systems, power dynamics, and human societal behaviors at scale. For the machine learning community, RPAs shed light on dynamic and human-centered model evaluations that are aligned with real-world scenarios by incorporating human and societal factors into consideration. Last but not least, HCI researchers are particularly intrigued by the implications of RPA systems that can provide personalized assistance with human-centered applications in various sectors, such as medicine, healthcare, and education.

Nevertheless, RPAs' capability and flexibility are a double-edged sword; they not only have the potential to bring benefits to stakeholders but also expose potential risks and even harm if not responsibly designed. To what extent do RPAs' responses align with genuine human cognitive activities, whether the cultural, linguistic, and contextual biases learned from the training data of LLMs impact predicted behaviors, and how to ensure RPAs' robustness and consistency under different scenarios, are critical but under-explored challenges for both technical developers and system designers.

As a result, the design of RPAs should incorporate system design considerations while advancing technical explorations. For instance, RPA design should focus on target users from the very beginning of system design, emphasize the diversity of user backgrounds and perspectives, and iteratively refine the system, as suggested by Gould and Lewis (1985) and Shneiderman and Plaisant (2010) in established design guidelines for system usability. Nevertheless, differences in cultural norms, linguistic subtleties, and domain-specific knowledge can introduce variability in how RPAs are designed and perceived. Designers and developers must focus on a balance between generalization and specificity to ensure RPAs are both adaptable and effective across a wide range of scenarios.

7.2 The Design of RPA Persona

One of RPAs' key strengths is their ability to adapt to diverse personas, tasks, and environments. But how can RPA personas be designed to ensure that LLMs faithfully and believably reflect the agents' cognitive behaviors within a given task? Persona descriptions must strike a careful balance between intrinsic agent characteristics and contextual factors, ensuring thoughtful consideration of both the agents' intrinsic characteristics and the contextual information of the specific environments for which the agents are designed.

The *intrinsic characteristics* of RPAs, such as their personal characteristics, education experience, domain expertise, emotional expressiveness, and decision-making processes, must be *aligned with the purpose* of the applications of RPAs. For example, an RPA designed for psychological experiments should prioritize cognitive characteristics like personality and empathy ability, whereas an RPA developed for economic simulations might emphasize negotiation tactics, competitive reasoning, and adaptability to changing conditions.

On the other hand, *contextual information*, such as task- and scenario-specific details, factors, and specifications, is equally critical in shaping the behaviors of RPAs. In healthcare applications, for instance, RPAs may simulate caregivers' emotional responses to patients' changing health status but still operate under clinical protocols, such as the ICU visitor rules. The granularity and fidelity of contextual information heavily influence the believability and effectiveness of the agents' behaviors.

7.3 The Challenges of RPA Evaluation

The versatility of RPAs, which allows them to function in diverse roles and contexts, makes it infeasible to have a "one-solution-fits-all" evaluation metric for systematically evaluate RPAs both within and across tasks and user scenarios. One major difficulty lies in designing and determining task-oriented and agent-oriented evaluation metrics. Despite our work recommending an RPA evaluation design guideline based on a comprehensive review of the literature, existing evaluation metrics may not be sufficient to measure the performance of RPAs for different domain-specific applications.

The diversity of user scenarios further exacerbates the evaluation challenge. Different tasks may prioritize different aspects of RPAs, making it difficult to develop a one-size-fits-all evaluation framework. For instance, RPAs designed for psychological research focus on believable emotional responses, whereas RPAs for policymaking simulations underscore robustness to policy changes.

Moreover, cross-task evaluations pose significant challenges due to inconsistencies in how metrics are designed and applied across studies. The lack of standardized evaluation criteria complicates systematic benchmarking in RPA development and impedes interdisciplinary collaboration.

Addressing these challenges will require the development of systematic, multi-faceted evaluation frameworks that can accommodate the diverse applications and capabilities of RPAs while providing consistency and comparability across studies.

8 Conclusion

RPA evaluation lacks consistency due to varying tasks, domains, and agent attributes. Our systematic review of $1,676$ papers reveals that task-specific requirements shape agent attributes, while both task characteristics and agent design influence evaluation metrics. By identifying these interdependencies, we propose guidelines to enhance RPA assessment reliability, contributing to a more structured and systematic evaluation framework.

Limitations

RPAs are rapidly evolving and have widespread applications across various domains. While we aim to comprehensively review existing literature, we acknowledge certain limitations in our scope. First, our review may not encompass all variations of RPA evaluation approaches across different application domains. Second, new research published after December 2024 is not included in our analysis. As a result, our work does not claim to exhaustively cover all potential evaluation metrics. Instead, our goal is to provide a structured framework and actionable guidelines to help future researchers design more systematic and consistent RPA evaluations, even as the field continues to evolve.

Ethics Statement

Our work focuses on summarizing and analyzing the evaluation of RPAs, which we believe will be valuable to researchers in AI, HCI, and related fields such as psychological simulation, educational simulation, and economic simulation. We have taken care to ensure that this survey remains objective and balanced, neither overestimating nor underestimating trends. We do not anticipate any ethical concerns that arise from the research presented in this paper.

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Table 6: Inclusion and exclusion criteria.

Inclusion Criteria (IC)	
IC-1	The LLM agents in the paper simulate humanoid behavior with implicit personality (e.g., preference and behavior pattern) or explicit personality (e.g., emotion or characteristics).
IC-2	The LLM agents in the paper have cognitive activities such as decision-making, reasoning, and planning.
IC-3	The LLM agents in the paper are capable of completing complicated and general tasks.
IC-4	The LLM agents' action set in the paper is neither predefined nor finite.
Exclusion Criteria (EC)	
EC-1	The study does not employ LLM agents for simulation purposes but rather uses them as chatbots, task-specific agents, or evaluators.
EC-2	The paper's research objectives, methodologies, and evaluations are not focused on simulating human-like behavior with LLM agents, but rather on optimizing LLM algorithms.
EC-3	The study primarily investigates the perception or action capabilities of LLM agents without simulating the cognitive process.
EC-4	The LLM agents are restricted to handling specific, close-ended tasks.
EC-5	The LLM agents' actions are either predefined or limited.

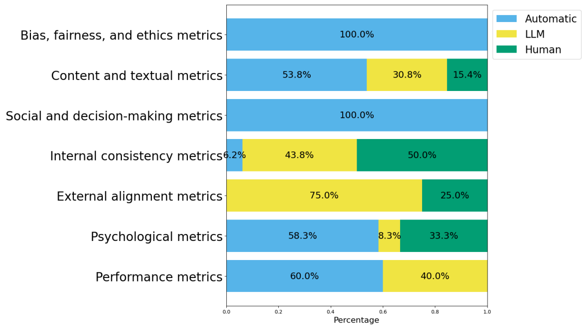

Figure 6: Usage ratio of evaluation approaches for each category of agent-oriented metrics.

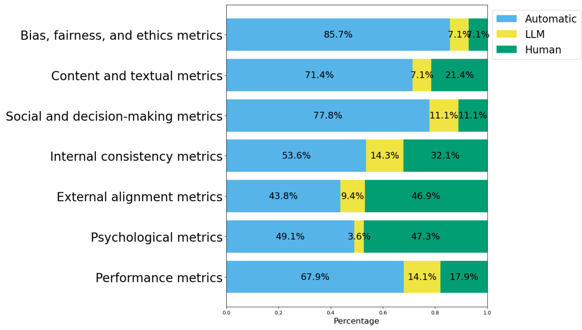

Figure 7: Usage ratio of evaluation approaches for each category of task-oriented metrics.

A Inclusion and Exclusion Criteria

We summarize the inclusion and exclusion criteria in Table 6. Briefly, the **Inclusion Criteria (IC)** ensure that the reviewed studies focus on LLM agents exhibiting human-like behavior—either implicitly (e.g., preference or behavioral patterns) or explicitly (e.g., emotions or personality)—along with key cognitive processes such as reasoning and decision-making. Moreover, an open-ended action space and the capacity to tackle multifaceted tasks are essential attributes for inclusion.

By contrast, the **Exclusion Criteria (EC)** eliminate studies employing LLMs purely as chatbots, single-purpose systems, or evaluation tools, rather than as agents mimicking human cognition. Likewise, if the LLM agents are restricted to fixed, close-ended tasks or limited to algorithmic optimization without simulating cognitive processes, they fall outside the scope of this work.

B Query String

We employed the following query to guide our literature retrieval process:

```
("large language model" OR LLM)
AND (agent OR persona OR "human
digital twin" OR simulacra) AND
(simulat* OR generat* OR eval*)
AND "human behavior" AND cognit*
```

This query was designed to capture a broad spectrum of studies on large language models that simulate or replicate human-like behavior. It combines keywords related to LLM agents (*LLM*, *persona*, *simulacra*), their capabilities (*simulat**, *generat**, *eval**), and the focus on cognitively grounded human behavior (*cognit**). This ensures that the resulting literature is relevant to our exploration of how LLM-based systems can mimic or exhibit human-like cognition and behavior patterns.

C Evaluation Approach Usage for Agent- and Task-Oriented Metrics

We present a breakdown of evaluation approach usage by agent-oriented metrics (Fig. 6) and task-oriented metrics (Fig. 7).

D Case Study: Flawed Example

Fig. 8 visualized how the authors in the flawed example selected their evaluation metrics how further evaluation metrics could be uncovered through our proposed guideline.

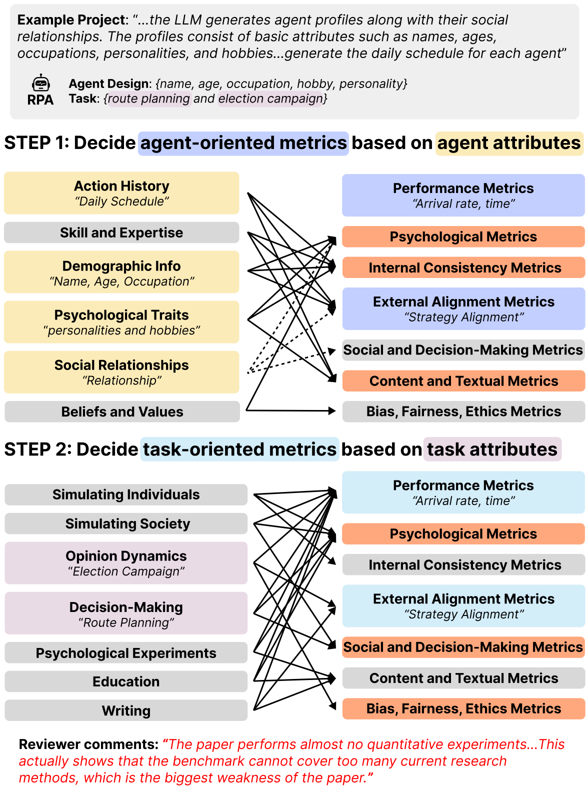

Figure 8: Case study of a flawed example in Section 5.2. Given agent attributes (yellow) and task attributes (pink). The original authors' selection of evaluation metrics (purple and blue). The missing metrics that are recommended by our proposed guideline (orange) align with the reviewer's criticism in red text.

E Metrics Glossary

We present two glossary tables for referencing the source of agent-oriented metrics (Tab. 7) and task-oriented metrics (Tab. 8).

Table 7: Agent-oriented evaluation metrics glossary.

Attribute	Category	Agent-oriented Metrics	Approach Source
Belief & Value	Bias, fairness, ethics metrics	Exaggeration (normalized average cosine similarity)	Automatic (Cheng et al., 2023)
Belief & Value	Bias, fairness, ethics metrics	Individuation (classification accuracy)	Automatic (Cheng et al., 2023)
Belief & Value	Bias, fairness, ethics metrics	Bias (performance disparity, prevalence, magnitude, variation, attitude shift)	Automatic (Gupta et al., 2024)
Belief & Value	Bias, fairness, ethics metrics	Bias (performance disparity, prevalence, magnitude, variation, attitude shift)	Automatic (Taubenfeld et al., 2024)
Demographic Information	Bias, fairness, ethics metrics	Exaggeration (normalized average cosine similarity)	Automatic (Cheng et al., 2023)
Demographic Information	Bias, fairness, ethics metrics	Individuation (classification accuracy)	Automatic (Cheng et al., 2023)
Demographic Information	Bias, fairness, ethics metrics	Bias (performance disparity, prevalence, magnitude, variation, attitude shift)	Automatic (Gupta et al., 2024)
Demographic Information	Bias, fairness, ethics metrics	Bias (performance disparity, prevalence, magnitude, variation, attitude shift)	Automatic (Neuberger et al., 2024)
Demographic Information	Bias, fairness, ethics metrics	Bias (performance disparity, prevalence, magnitude, variation, attitude shift)	Automatic (Taubenfeld et al., 2024)
Demographic Information	Bias, fairness, ethics metrics	Message toxicity	Automatic (Fang et al., 2024)
Activity History	Content and textual metrics	Coherence	LLM (Li et al., 2024e)
Activity History	Content and textual metrics	Clarity	Human (Chen et al., 2024b)
Activity History	Content and textual metrics	Diversity of dialog (Shannon entropy, intra-remote-clique, inter-remote-clique, semantic similarity, longest common subsequence similarity)	Automatic (Ha et al., 2024)
Belief & Value	Content and textual metrics	Diversity of dialog (Shannon entropy, intra-remote-clique, inter-remote-clique, semantic similarity, longest common subsequence similarity)	Automatic (Gu et al., 2024)
Demographic Information	Content and textual metrics	Coherence	LLM (Li et al., 2024e)
Demographic Information	Content and textual metrics	Attitudes (topic term frequency)	Automatic (Fang et al., 2024)
Demographic Information	Content and textual metrics	Diversity of dialog (Shannon entropy, intra-remote-clique, inter-remote-clique, semantic similarity, longest common subsequence similarity)	Automatic (Fang et al., 2024)
Demographic Information	Content and textual metrics	Clarity	Human (Chen et al., 2024b)
Demographic Information	Content and textual metrics	Diversity of dialog (Shannon entropy, intra-remote-clique, inter-remote-clique, semantic similarity, longest common subsequence similarity)	Automatic (Ha et al., 2024)
Demographic Information	Content and textual metrics	Linguistic complexity (utterance length, Kolmogorov complexity)	Automatic (Milička et al., 2024)
Psychological Traits	Content and textual metrics	Text similarity (BLEU, ROUGE)	Automatic (Zeng et al., 2024)
Psychological Traits	Content and textual metrics	Tone Alignment	LLM (Zeng et al., 2024)
Skills and Expertise	Content and textual metrics	Coherence	LLM (Li et al., 2024e)
Activity History	External alignment metrics	Hallucination	LLM (Shao et al., 2023)
Activity History	External alignment metrics	Entailment	LLM (Li et al., 2024e)
Activity History	External alignment metrics	Believability/Credibility(self-knowledge, memory, plans, reactions, reflections)	Human (Park et al., 2023)

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Attribute	Category	Agent-oriented Metrics	Approach	Source
Demographic Information	External alignment metrics	Entailment	LLM	(Li et al., 2024e)
Demographic Information	External alignment metrics	Believability/Credibility(self-knowledge, memory, plans, reactions, reflections)	Human	(Park et al., 2023)
Psychological Traits	External alignment metrics	Fact Accuracy	LLM	(Zeng et al., 2024)
Skills and Expertise	External alignment metrics	Hallucination	LLM	(Shao et al., 2023)
Skills and Expertise	External alignment metrics	Entailment	LLM	(Li et al., 2024e)
Activity History	Internal consistency metrics	Stability	LLM	(Shao et al., 2023)
Activity History	Internal consistency metrics	Consistency of information	Human	(Chen et al., 2024b)
Belief & Value	Internal consistency metrics	Attitude shift	LLM	(Wang et al., 2024e)
Demographic Information	Internal consistency metrics	Stability	LLM	(Shao et al., 2023)
Demographic Information	Internal consistency metrics	Attitude shift	LLM	(Neuberger et al., 2024)
Demographic Information	Internal consistency metrics	Attitude shift	LLM	(Taubenfeld et al., 2024)
Demographic Information	Internal consistency metrics	Behavior stability (mean, standard deviation)	Automatic	(Wang et al., 2024g)
Demographic Information	Internal consistency metrics	Consistency of information	Human	(Chen et al., 2024b)
Demographic Information	Internal consistency metrics	Consistency of psychological state / personalities	Human	(Chen et al., 2024b)
Demographic Information	Internal consistency metrics	Consistency of information	Human	(Zeng et al., 2024)
Psychological Traits	Internal consistency metrics	Stability	LLM	(Shao et al., 2023)
Psychological Traits	Internal consistency metrics	Consistency of information	Human	(Zeng et al., 2024)
Psychological Traits	Internal consistency metrics	Consistency of psychological state / personalities	Human	(Zeng et al., 2024)
Psychological Traits	Internal consistency metrics	Consistency of information	Human	(Cai et al., 2024)
Psychological Traits	Internal consistency metrics	Consistency of psychological state / personalities	Human	(Cai et al., 2024)
Skills and Expertise	Internal consistency metrics	Stability	LLM	(Shao et al., 2023)
Activity History	Performance metrics	Memorization	LLM	(Shao et al., 2023)
Demographic Information	Performance metrics	Memorization	LLM	(Chen et al., 2024b)
Demographic Information	Performance metrics	Communication ability (win rates)	Automatic	(Liu et al., 2024a)
Demographic Information	Performance metrics	Reaction (accuracy)	Automatic	(Liu et al., 2024a)
Demographic Information	Performance metrics	Self-knowledge (accuracy)	Automatic	(Liu et al., 2024a)
Activity History	Psychological metrics	Empathy	Human	(Chen et al., 2024b)
Belief & Value	Psychological metrics	Value	LLM	(Shao et al., 2023)
Demographic Information	Psychological metrics	Personality consistency	Automatic	(Wang et al., 2024c)
Demographic Information	Psychological metrics	Measured alignment for personality	Human	(Wang et al., 2024c)
Demographic Information	Psychological metrics	Sentiment	Automatic	(Fang et al., 2024)
Demographic Information	Psychological metrics	Empathy	Human	(Chen et al., 2024b)
Demographic Information	Psychological metrics	Belief (stability, evolution, correlation with behavior)	Automatic	(Lei et al., 2024)

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Attribute	Category	Agent-oriented Metrics	Approach	Source
Psychological Traits	Psychological metrics	Personality	Automatic	(Shao et al., 2023)
Psychological Traits	Psychological metrics	Belief (stability, evolution, correlation with behavior)	Automatic	(Shao et al., 2023)
Psychological Traits	Psychological metrics	Emotion responses (entropy of valence and arousal)	Automatic	(Shao et al., 2023)
Psychological Traits	Psychological metrics	Personality (Machine Personality Inventory, PsychoBench)	Automatic	(Jiang et al., 2023a)
Psychological Traits	Psychological metrics	Personality (vignette tests)	Human	(Jiang et al., 2023a)
Belief & Value	Social and decision-making metrics	Social value orientation (SVO-based Value Rationality Measurement)	Automatic	(Zhang et al., 2023b)

Table 8: Task-oriented evaluation metrics glossary.

Task	Category	Task-oriented Metrics	Approach Source
Decision Making	Social and economic metrics	Negotiation (Concession Rate, Negotiation Success Rate, Average Negotiation Round)	Automatic (Huang and Hadfi, 2024)
Decision Making	Social and economic metrics	Societal Satisfaction (average per-capita living area size, average waiting time, social welfare)	Automatic (Ji et al., 2024)
Decision Making	Social and economic metrics	Societal Fairness (variance in per capita living area size, number of inverse order pairs in house allocation, Gini coefficient)	Automatic (Ji et al., 2024)
Decision Making	Social and economic metrics	Macroeconomic (Inflation rate, Unemployment rate, Nominal GDP, Nominal GDP growth, Wage inflation, Real GDP growth, Expected monthly income, Consumption)	Automatic (Li et al., 2024d)
Decision Making	Social and economic metrics	Market and Consumer (Purchase probability, Expected competing product price, Customer counts, Price consistency between competitors)	Automatic (Gui and Toubia, 2023)
Decision Making	Social and economic metrics	Market and Consumer (Purchase probability, Expected competing product price, Customer counts, Price consistency between competitors)	Automatic (Zhao et al., 2023)
Decision Making	Social and economic metrics	Probability weighting	Automatic (Jia et al., 2024)
Decision Making	Social and economic metrics	Utility (Intrinsic Utility, Joint Utility)	Automatic (Huang and Hadfi, 2024)
Decision Making	Psychological metrics	Level of trust (distribution of amounts sent, trust rate)	Automatic (Xie et al., 2024a)
Decision Making	Psychological metrics	Risk preference	Automatic (Jia et al., 2024)
Decision Making	Psychological metrics	Loss aversion	Automatic (Jia et al., 2024)
Decision Making	Psychological metrics	Selfishness (Selfishness Index, Difference Index)	Automatic (Kim et al., 2024)
Decision Making	Performance metrics	Frequency (distribution of expert type)	Automatic (Wang et al., 2024b)
Decision Making	Performance metrics	Valid response rate	Automatic (Xie et al., 2024a)
Decision Making	Performance metrics	Web search quality (Mean reciprocal rank, Mean reciprocal rank)	Automatic (Ren et al., 2024a)
Decision Making	Performance metrics	Performance deviations/alignment from the baseline (accuracy, Jaccard Index, Cohen's Kappa Coefficient, Percentage Agreement, overlapping ratio between prediction and targets)	Automatic (Kim et al., 2024)
Decision Making	Performance metrics	Performance deviations/alignment from the baseline (accuracy, Jaccard Index, Cohen's Kappa Coefficient, Percentage Agreement, overlapping ratio between prediction and targets)	Automatic (Jin et al., 2024)
Decision Making	Performance metrics	Performance deviations/alignment from the baseline (accuracy, Jaccard Index, Cohen's Kappa Coefficient, Percentage Agreement, overlapping ratio between prediction and targets)	Automatic (Wang et al., 2024b)
Decision Making	Performance metrics	Performance deviations/alignment from the baseline (accuracy, Jaccard Index, Cohen's Kappa Coefficient, Percentage Agreement, overlapping ratio between prediction and targets)	Automatic (Wang et al., 2024f)
Decision Making	Internal consistency metrics	Behavioral alignment (lottery rate, behavior dynamic, Imitation and differentiation behavior, Proportion of similar and different dishes)	Automatic (Xie et al., 2024a)

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Task	Category	Task-oriented Metrics	Approach	Source
Decision Making	Internal consistency metrics	Behavioral alignment (lottery rate, behavior dynamic, Imitation and differentiation behavior, Proportion of similar and different dishes)	Automatic	(Zhao et al., 2023)
Decision Making	Internal consistency metrics	Cultural appropriateness (Alignment between persona information and its assigned nationality)	LLM	(Li et al., 2024e)
Decision Making	External alignment metrics	Factual hallucinations (String matching overlap ratio)	Automatic	(Wang et al., 2024f)
Decision Making	External alignment metrics	Simulation capability (Turing test)	Human	(Ji et al., 2024)
Decision Making	External alignment metrics	Entailment	LLM	(Li et al., 2024e)
Decision Making	External alignment metrics	Realism	LLM	(Li et al., 2024e)
Educational Training	Psychological metrics	Perceived reflection on the development of essential non-cognitive skills	Human	(Yan et al., 2024)
Educational Training	Psychological metrics	Non-cognitive skill scale	Automatic	(Yan et al., 2024)
Educational Training	Psychological metrics	Sense of immersion / Perceived immersion	Human	(Lee et al., 2023)
Educational Training	Psychological metrics	Perceived intelligence	Human	(Cheng et al., 2024)
Educational Training	Psychological metrics	Perceived enjoyment	Human	(Cheng et al., 2024)
Educational Training	Psychological metrics	Perceived trust	Human	(Cheng et al., 2024)
Educational Training	Psychological metrics	Perceived sense of connection	Human	(Cheng et al., 2024)
Educational Training	Psychological metrics	Personality (Big Five Invertory, MBTI score, SD3 score, Linguistic Inquiry and Word Count framework, HEXACO)	Automatic	(Sonlu et al., 2024)
Educational Training	Psychological metrics	Personality (Big Five Invertory, MBTI score, SD3 score, Linguistic Inquiry and Word Count framework, HEXACO)	Automatic	(Liu et al., 2024d)
Educational Training	Psychological metrics	Perceived usefulness	Human	(Cheng et al., 2024)
Educational Training	Performance metrics	Density of knowledge-building	Automatic	(Jin et al., 2023)
Educational Training	Performance metrics	Effectiveness of questioning	Human	(Shi et al., 2023)
Educational Training	Performance metrics	Success criterion function outputs before operation and after operation	Human	(Li et al., 2023a)
Educational Training	External alignment metrics	Knowledge level (reconfigurability, persistence, and adaptability)	Automatic	(Jin et al., 2023)
Educational Training	External alignment metrics	Perceived human-likeness	Human	(Cheng et al., 2024)
Educational Training	Content and textual metrics	Story Content Generation (narratives staging score)	Automatic	(Yan et al., 2024)
Educational Training	Content and textual metrics	Willingness to speak	Human	(Shi et al., 2023)
Educational Training	Content and textual metrics	Authenticity	Human	(Lee et al., 2023)
Opinion Dynamics	Psychological metrics	Opinion change	Human	(Triem and Ding, 2024)
Opinion Dynamics	Psychological metrics	Emotional density	Automatic	(Gao et al., 2023)
Opinion Dynamics	Performance metrics	Prediction accuracy (F1 score, AUC, MSE, MAE, depression risk prediction accuracy, suicide risk prediction accuracy)	Automatic	(Gao et al., 2023)

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Task	Category	Task-oriented Metrics	Approach Source
Opinion Dynamics	Performance metrics	Prediction accuracy (F1 score, AUC, MSE, MAE, depression risk prediction accuracy, suicide risk prediction accuracy)	Automatic (Mou et al., 2024c)
Opinion Dynamics	Performance metrics	Prediction accuracy (F1 score, AUC, MSE, MAE, depression risk prediction accuracy, suicide risk prediction accuracy)	Automatic (Yu et al., 2024)
Opinion Dynamics	Performance metrics	Classification accuracy	Human (Chan et al., 2023)
Opinion Dynamics	Performance metrics	Rephrase accuracy	Automatic (Ju et al., 2024)
Opinion Dynamics	Performance metrics	Legal articles evaluation (precision, recall, F1)	Automatic (He et al., 2024a)
Opinion Dynamics	Performance metrics	Judgment evaluation for civil and administrative cases (precision, recall, F1)	Automatic (He et al., 2024a)
Opinion Dynamics	Performance metrics	Judgment evaluation for criminal cases (accuracy)	Automatic (He et al., 2024a)
Opinion Dynamics	Performance metrics	Prediction error rate	Automatic (Gao et al., 2023)
Opinion Dynamics	Performance metrics	Locality accuracy	Automatic (Ju et al., 2024)
Opinion Dynamics	Performance metrics	Decision probability	Human (Triem and Ding, 2024)
Opinion Dynamics	Performance metrics	Decision volatility	Human (Triem and Ding, 2024)
Opinion Dynamics	Performance metrics	Case complexity	Human (Triem and Ding, 2024)
Opinion Dynamics	Performance metrics	Alignment (compare simulation results with actual social outcomes)	Automatic (Wang et al., 2024g)
Opinion Dynamics	Internal consistency metrics	Alignment (stance, content, behavior, static attitude distribution, time series of the average attitude)	Automatic (Mou et al., 2024c)
Opinion Dynamics	Internal consistency metrics	Personality-behavior alignment	Human (Navarro et al., 2024)
Opinion Dynamics	Internal consistency metrics	Similarity between initial and post preference (KL-divergence, RMSE)	Automatic (Namikoshi et al., 2024)
Opinion Dynamics	Internal consistency metrics	Role playing	Human (Lv et al., 2024)
Opinion Dynamics	External alignment metrics	Correctness	Human (He et al., 2024a)
Opinion Dynamics	External alignment metrics	Accuracy (correctness)	Automatic (Ju et al., 2024)
Opinion Dynamics	External alignment metrics	Logicality	Human (He et al., 2024a)
Opinion Dynamics	External alignment metrics	Concision	Human (He et al., 2024a)
Opinion Dynamics	External alignment metrics	Human likeness index	Automatic (Chuang et al., 2023b)
Opinion Dynamics	External alignment metrics	Alignment between model and human (Kappa correlation coefficient, MAE), Authenticity (alignment of ratings between the agent and human annotators)	Human (Chan et al., 2023)
Opinion Dynamics	External alignment metrics	Alignment between model and human (Kappa correlation coefficient, MAE), Authenticity (alignment of ratings between the agent and human annotators)	Human (Triem and Ding, 2024)
Opinion Dynamics	External alignment metrics	Alignment between model and human (Kappa correlation coefficient, MAE), Authenticity (alignment of ratings between the agent and human annotators)	Human (Lv et al., 2024)
Opinion Dynamics	Content and textual metrics	Turn-level Kendall-Tau correlation (naturalness, coherence, engagingness and groundedness)	Automatic (Chan et al., 2023)

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Task	Category	Task-oriented Metrics	Approach Source
Opinion Dynamics	Content and textual metrics	Turn-level Spearman correlation (naturalness, coherence, engagingness and groundedness)	Automatic (Chan et al., 2023)
Opinion Dynamics	Bias, fairness, and ethic metrics	Partisan bias	Automatic (Chuang et al., 2023b)
Opinion Dynamics	Bias, fairness, and ethic metrics	Bias (cultural, linguistic, economic, demographic, ideological)	Automatic (Qu and Wang, 2024)
Opinion Dynamics	Bias, fairness, and ethic metrics	Bias (mean)	Automatic (Chuang et al., 2023a)
Opinion Dynamics	Bias, fairness, and ethic metrics	Extreme values	Automatic (Chuang et al., 2023b)
Opinion Dynamics	Bias, fairness, and ethic metrics	Wisdom of Partisan Crowds effect	Automatic (Chuang et al., 2023b)
Opinion Dynamics	Bias, fairness, and ethic metrics	Opinion diversity	Automatic (Chuang et al., 2023a)
Psychological Experiment	Social and economic metrics	Money allocation	Automatic (Lei et al., 2024)
Psychological Experiment	Psychological metrics	Attitude change	Automatic (Wang et al., 2025a)
Psychological Experiment	Psychological metrics	Average happiness value per time step	Automatic (He and Zhang, 2024)
Psychological Experiment	Psychological metrics	Belief value	Automatic (Lei et al., 2024)
Psychological Experiment	Psychological metrics	Personality (Big Five Invertory, MBTI score, SD3 score, Linguistic Inquiry and Word Count framework, HEXACO)	Automatic (He and Zhang, 2024)
Psychological Experiment	Psychological metrics	Personality (Big Five Invertory, MBTI score, SD3 score, Linguistic Inquiry and Word Count framework, HEXACO)	Automatic (de Winter et al., 2024)
Psychological Experiment	Psychological metrics	Personality (Big Five Invertory, MBTI score, SD3 score, Linguistic Inquiry and Word Count framework, HEXACO)	Automatic (Bose et al., 2024)
Psychological Experiment	Psychological metrics	Personality (Big Five Invertory, MBTI score, SD3 score, Linguistic Inquiry and Word Count framework, HEXACO)	Automatic (Jiang et al., 2023b)
Psychological Experiment	Psychological metrics	Longitudinal trajectories of emotions	Automatic (De Duro et al., 2025)
Psychological Experiment	Psychological metrics	Valence entropy	Automatic (Lei et al., 2024)
Psychological Experiment	Psychological metrics	Arousal entropy	Automatic (Lei et al., 2024)
Psychological Experiment	Performance metrics	Precision of item recommendation	Automatic (Wang et al., 2025a)
Psychological Experiment	Performance metrics	Missing rate	Automatic (Lei et al., 2024)
Psychological Experiment	Performance metrics	Rejection rate	Automatic (Lei et al., 2024)
Psychological Experiment	Internal consistency metrics	Correlation between social dilemma game outcome and agent personality	Automatic (Bose et al., 2024)
Psychological Experiment	Internal consistency metrics	Behavioral similarity	Automatic (Li et al., 2024b)
Psychological Experiment	Internal consistency metrics	Perception consistency (agent perceived safety, agent perceived liveliness)	LLM (Verma et al., 2023)
Psychological Experiment	External alignment metrics	Rationality of the agent memory	Automatic (Wang et al., 2025a)
Psychological Experiment	External alignment metrics	Believability of behavior	Automatic (Wang et al., 2025a)
Psychological Experiment	Content and textual metrics	Salience of individual words	Automatic (De Duro et al., 2025)
Psychological Experiment	Content and textual metrics	Absolutist words	Automatic (De Duro et al., 2025)

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Task	Category	Task-oriented Metrics	Approach	Source
Psychological Experiment	Content and textual metrics	Personal pronouns or emotions	Automatic	(De Duro et al., 2025)
Psychological Experiment	Content and textual metrics	Information entropy	Automatic	(Wang et al., 2025a)
Psychological Experiment	Content and textual metrics	Story (readability, personalness, redundancy, cohesiveness, likeability, believability)	Human	(Jiang et al., 2023b)
Psychological Experiment	Content and textual metrics	Story (readability, personalness, redundancy, cohesiveness, likeability, believability)	LLM	(Jiang et al., 2023b)
Simulated Individual	Social and economic metrics	Numbers of generated peer support strategies	Automatic	(Liu et al., 2024b)
Simulated Individual	Social and economic metrics	Perceived social support questionnaire	Human	(Liu et al., 2024b)
Simulated Individual	Psychological metrics	Emotions	Human	(Pataranutaporn et al., 2024)
Simulated Individual	Psychological metrics	Agency	Human	(Pataranutaporn et al., 2024)
Simulated Individual	Psychological metrics	Future consideration	Human	(Pataranutaporn et al., 2024)
Simulated Individual	Psychological metrics	Self-reflection	Human	(Pataranutaporn et al., 2024)
Simulated Individual	Psychological metrics	Insight	Human	(Pataranutaporn et al., 2024)
Simulated Individual	Psychological metrics	Persona Perception Scale	Human	(Salminen et al., 2024)
Simulated Individual	Psychological metrics	Persona Perception Scale	Human	(Shin et al., 2024)
Simulated Individual	Psychological metrics	Persona Perception Scale	Human	(Ha et al., 2024)
Simulated Individual	Psychological metrics	Persona Perception Scale	Human	(Chen et al., 2024b)
Simulated Individual	Psychological metrics	Engagement	Human	(Zhang et al., 2024a)
Simulated Individual	Psychological metrics	Safety	Human	(Zhang et al., 2024a)
Simulated Individual	Psychological metrics	Sensitivity to personalization	Automatic	(Giorgi et al., 2024)
Simulated Individual	Psychological metrics	Agent self-awareness	LLM	(Xie et al., 2024b)
Simulated Individual	Psychological metrics	Personality (Big Five Invertory rated by LLM)	LLM	(Jiang et al., 2023a)
Simulated Individual	Psychological metrics	Positively mention rate	Automatic	(Kamruzzaman and Kim, 2024)
Simulated Individual	Psychological metrics	Optimism	Human	(Pataranutaporn et al., 2024)
Simulated Individual	Psychological metrics	Self-esteem	Human	(Pataranutaporn et al., 2024)
Simulated Individual	Psychological metrics	Pressure perceived scale	Human	(Liu et al., 2024b)
Simulated Individual	Performance metrics	Error rates (error of average, error of dispersion)	Automatic	(Lin et al., 2024)
Simulated Individual	Performance metrics	Model fit indices (Chi-square to degrees of freedom ratio, Comparative Fit Index, Tucker-Lewis Index, Root Mean Square Error of Approximation)	Automatic	(Ke and Ng, 2024)
Simulated Individual	Performance metrics	Knowledge accuracy (WikiRoleEval with human evaluators)	Human	(Tang et al., 2024)
Simulated Individual	Performance metrics	Knowledge accuracy (WikiRoleEval)	LLM	(Tang et al., 2024)
Simulated Individual	Performance metrics	Win rates	Automatic	(Chi et al., 2024)
Simulated Individual	Performance metrics	Comprehension	Automatic	(Shin et al., 2024)
Simulated Individual	Performance metrics	Completeness	Automatic	(Shin et al., 2024)

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Task	Category	Task-oriented Metrics	Approach Source
Simulated Individual	Performance metrics	Validity (average variance extracted, inter-construct correlations)	Automatic (Ke and Ng, 2024)
Simulated Individual	Performance metrics	Composite reliability	Automatic (Ke and Ng, 2024)
Simulated Individual	Performance metrics	Rated statement quality	Human (Liu et al., 2023)
Simulated Individual	Performance metrics	Rated statement quality	LLM (Liu et al., 2023)
Simulated Individual	Performance metrics	Conversational ability (CharacterEval)	LLM (Tang et al., 2024)
Simulated Individual	Performance metrics	Roleplay subset of MT-Bench	LLM (Tang et al., 2024)
Simulated Individual	Performance metrics	Professional scale (accuracy in replicating profession-specific knowledge)	LLM (Sun et al., 2024)
Simulated Individual	Performance metrics	Language quality	LLM (Zhang et al., 2024a)
Simulated Individual	Performance metrics	Prediction accuracy between real data and generated data (Replication success rate, Kullback-Leibler divergence)	Automatic (Assaf and Lynar, 2024)
Simulated Individual	Performance metrics	Prediction accuracy between real data and generated data (Replication success rate, Kullback-Leibler divergence)	Automatic (Tamaki and Littvay, 2024)
Simulated Individual	Performance metrics	Prediction accuracy between real data and generated data (Replication success rate, Kullback-Leibler divergence)	Automatic (Park et al., 2024)
Simulated Individual	Performance metrics	Prediction accuracy between real data and generated data (Replication success rate, Kullback-Leibler divergence)	Automatic (Yeykelis et al., 2024)
Simulated Individual	Performance metrics	Accuracy of distinguishing between AI-generated and human-built solutions	Automatic (Schuller et al., 2024)
Simulated Individual	Internal consistency metrics	Accuracy of reaction based on social relationship	Automatic (Liu et al., 2024a)
Simulated Individual	Internal consistency metrics	Perceived connection between personas and system outcomes	Human (Chen et al., 2024b)
Simulated Individual	Internal consistency metrics	Representativeness (Wasserstein distance, respond with similar answers to individual survey questions), Consistency (Frobenius norm, the correlation across responses to a set of questions in each survey)	Automatic (Moon et al., 2024)
Simulated Individual	Internal consistency metrics	Role consistency (WikiRoleEval with human evaluators)	Human (Tang et al., 2024)
Simulated Individual	Internal consistency metrics	Role consistency/attractiveness (WikiRoleEval, CharacterEval)	LLM (Tang et al., 2024)
Simulated Individual	Internal consistency metrics	Consistency	Human (Zhang et al., 2024a)
Simulated Individual	Internal consistency metrics	Consistency	Human (Mishra et al., 2023)
Simulated Individual	Internal consistency metrics	Future self-continuity	Human (Pataranutaporn et al., 2024)
Simulated Individual	Internal consistency metrics	Agreement between a synthetic annotator both with and without a leave-one-out attribute (Cohen's Kappa)	Automatic (Castricato et al., 2024)
Simulated Individual	Internal consistency metrics	Consistency with the scenario and characters	Automatic (Zhang et al., 2024a)
Simulated Individual	Internal consistency metrics	Quality and logical coherence of the script content	Automatic (Zhang et al., 2024a)
Simulated Individual	Internal consistency metrics	Nation-related response percentage	Automatic (Kamruzzaman and Kim, 2024)

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Task	Category	Task-oriented Metrics	Approach	Source
Simulated Individual	External alignment metrics	Unknown question rejection (WikiRoleEval with human evaluators)	Human	(Tang et al., 2024)
Simulated Individual	External alignment metrics	Unknown question rejection (WikiRoleEval)	LLM	(Tang et al., 2024)
Simulated Individual	External alignment metrics	Accuracy of self-knowledge	Automatic	(Liu et al., 2024a)
Simulated Individual	External alignment metrics	Correctness	Human	(Zhang et al., 2024a)
Simulated Individual	External alignment metrics	Correctness	Human	(Milička et al., 2024)
Simulated Individual	External alignment metrics	Agreement score between human raters and LLM,	Automatic	(Liu et al., 2023)
Simulated Individual	External alignment metrics	Agreement score between human raters and LLM,	Automatic	(Jiang et al., 2023a)
Simulated Individual	External alignment metrics	Agreement score between human raters and LLM,	Automatic	(Liu et al., 2024a)
Simulated Individual	External alignment metrics	Human-likeness	Human	(Zhang et al., 2024a)
Simulated Individual	Content and textual metrics	Content similarity (ROUGE-L, BERTScore, GPT-based-similarity, G-eval)	Automatic	(Shin et al., 2024)
Simulated Individual	Content and textual metrics	Entity density of summarization	Automatic	(Liu et al., 2024a)
Simulated Individual	Content and textual metrics	Entity recall of summarization	Automatic	(Liu et al., 2024a)
Simulated Individual	Content and textual metrics	Dialog diversity	Automatic	(Lin et al., 2024)
Simulated Individual	Bias, fairness, and ethic metrics	Hate speech detection accuracy	Automatic	(Giorgi et al., 2024)
Simulated Individual	Bias, fairness, and ethic metrics	Population heterogeneity	Automatic	(Murthy et al., 2024)
Simulated Society	Social and economic metrics	Social Conflict Count	Automatic	(Ren et al., 2024b)
Simulated Society	Social and economic metrics	Social Rules	Human	(Zhou et al., 2024b)
Simulated Society	Social and economic metrics	Social Rules	LLM	(Zhou et al., 2024b)
Simulated Society	Social and economic metrics	Financial and Material Benefits	Human	(Zhou et al., 2024b)
Simulated Society	Social and economic metrics	Financial and Material Benefits	LLM	(Zhou et al., 2024b)
Simulated Society	Social and economic metrics	Converged price	Automatic	(Toledo-Zucco et al., 2024)
Simulated Society	Social and economic metrics	Information diffusion	Automatic	(Park et al., 2023)
Simulated Society	Social and economic metrics	Relationship formation	Automatic	(Park et al., 2023)
Simulated Society	Social and economic metrics	Relationship	LLM	(Zhou et al., 2024b)
Simulated Society	Social and economic metrics	Coordination within other agents	Automatic	(Park et al., 2023)
Simulated Society	Social and economic metrics	Probability of social connection formation	Automatic	(Leng and Yuan, 2024)
Simulated Society	Social and economic metrics	Percent of social welfare maximization choices	Automatic	(Leng and Yuan, 2024)
Simulated Society	Social and economic metrics	Persuasion (distribution of persuasion outcomes, odds ratios)	Automatic	(Campedelli et al., 2024)
Simulated Society	Social and economic metrics	Anti-social behavior (effect on toxic messages)	Automatic	(Campedelli et al., 2024)
Simulated Society	Social and economic metrics	Norm Internalization Rate	Automatic	(Ren et al., 2024b)
Simulated Society	Social and economic metrics	Norm Compliance Rate	Automatic	(Ren et al., 2024b)
Simulated Society	Psychological metrics	NASA-TLX Scores	Human	(Zhang et al., 2024c)

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Task	Category	Task-oriented Metrics	Approach	Source
Simulated Society	Psychological metrics	Helpfulness rating	Human	(Zhang et al., 2024c)
Simulated Society	Psychological metrics	Personality (Big Five Invertory, MBTI score, SD3 score, Linguistic Inquiry and Word Count framework, HEXACO)	Automatic	(Frisch and Giulianelli, 2024)
Simulated Society	Psychological metrics	Personality (Big Five Invertory, MBTI score, SD3 score, Linguistic Inquiry and Word Count framework, HEXACO)	Automatic	(Li et al., 2024b)
Simulated Society	Psychological metrics	Degree of reciprocity	Automatic	(Leng and Yuan, 2024)
Simulated Society	Psychological metrics	Pleasure rating	Human	(Zhang et al., 2024c)
Simulated Society	Psychological metrics	Trend of Favorability Decline	Automatic	(Gu et al., 2024)
Simulated Society	Psychological metrics	Negative Favorability Achievement	Automatic	(Gu et al., 2024)
Simulated Society	Psychological metrics	Trend of Favorability Decline	Automatic	(Gu et al., 2024)
Simulated Society	Psychological metrics	Negative Favorability Achievement	Automatic	(Gu et al., 2024)
Simulated Society	Performance metrics	Abstention accuracy	Automatic	(Ashkinaze et al., 2024)
Simulated Society	Performance metrics	Accuracy of information gathering	Automatic	(Kaiya et al., 2023)
Simulated Society	Performance metrics	Implicit reasoning accuracy	Automatic	(Mou et al., 2024b)
Simulated Society	Performance metrics	Prediction accuracy (F1 score, AUC, MSE, MAE, depression risk prediction accuracy, suicide risk prediction accuracy)	Automatic	(Lan et al., 2024)
Simulated Society	Performance metrics	Guess accuracy	Automatic	(Leng and Yuan, 2024)
Simulated Society	Performance metrics	Classification accuracy	Automatic	(Li et al., 2024a)
Simulated Society	Performance metrics	Success rate	Automatic	(Kaiya et al., 2023)
Simulated Society	Performance metrics	Success rate	Automatic	(Li et al., 2023b)
Simulated Society	Performance metrics	Success rate	Automatic	(Li et al., 2023b)
Simulated Society	Performance metrics	Success rate for coordination (identification accuracy, workflow correctness, alignment between job and agent's skill)	Automatic	(Li et al., 2023a)
Simulated Society	Performance metrics	Success rate for coordination (identification accuracy, workflow correctness, alignment between job and agent's skill)	Automatic	(Li et al., 2023a)
Simulated Society	Performance metrics	Task Accuracy	Automatic	(Zhang et al., 2023a)
Simulated Society	Performance metrics	Task Accuracy	Automatic	(Lan et al., 2024)
Simulated Society	Performance metrics	Errors in the prompting sequence	Human	(Antunes et al., 2023)
Simulated Society	Performance metrics	Error-free execution	Automatic	(Wang et al., 2024a)
Simulated Society	Performance metrics	Goal completion	Human	(Mou et al., 2024b)
Simulated Society	Performance metrics	Goal completion	LLM	(Zhou et al., 2024a)
Simulated Society	Performance metrics	Goal completion	LLM	(Mou et al., 2024b)
Simulated Society	Performance metrics	Goal completion	LLM	(Zhou et al., 2024b)

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Task	Category	Task-oriented Metrics	Approach	Source
Simulated Society	Performance metrics	Efficacy	Human	(Ashkinaze et al., 2024)
Simulated Society	Performance metrics	Knowledge	Human	(Zhou et al., 2024b)
Simulated Society	Performance metrics	Knowledge	LLM	(Zhou et al., 2024b)
Simulated Society	Performance metrics	Reasoning abilities	Automatic	(Chen et al., 2023)
Simulated Society	Performance metrics	Reasoning abilities	Human	(Chen et al., 2023)
Simulated Society	Performance metrics	Efficiency	Automatic	(Piatti et al., 2024)
Simulated Society	Performance metrics	Text understanding and creative writing abilities (Dialogue response dataset, Commongen Challenge)	LLM	(Chen et al., 2023)
Simulated Society	Performance metrics	Probabilities of receiving, storing, and retrieving the key information across the population	Automatic	(Kaiya et al., 2023)
Simulated Society	Performance metrics	Correlation between predicted and real results	Automatic	(Mitsopoulos et al., 2024)
Simulated Society	Internal consistency metrics	Behavioral similarity	Automatic	(Li et al., 2024b)
Simulated Society	Internal consistency metrics	Semantic consistency (cosine similarity)	Automatic	(Qiu and Lan, 2024)
Simulated Society	External alignment metrics	Alignment (Environmental understanding and response accuracy, adherence to predefined settings)	Automatic	(Gu et al., 2024)
Simulated Society	External alignment metrics	Strategy accuracy (strategies provided by the models vs. by human experts and evaluate the accuracy)	Automatic	(Zhang et al., 2024b)
Simulated Society	External alignment metrics	Believability of behavior	Human	(Zhou et al., 2024b)
Simulated Society	External alignment metrics	Believability of behavior	Human	(Park et al., 2023)
Simulated Society	Content and textual metrics	Content similarity (ROUGE-L, BERTScore, GPT-based-similarity, G-eval, BLEU-4)	Automatic	(Li et al., 2024a)
Simulated Society	Content and textual metrics	Content similarity (ROUGE-L, BERTScore, GPT-based-similarity, G-eval)	Automatic	(Chen et al., 2024f)
Simulated Society	Content and textual metrics	Content similarity (ROUGE-L, BERTScore, GPT-based-similarity, G-eval)	Automatic	(Mishra et al., 2023)
Simulated Society	Content and textual metrics	Semantic understanding	Automatic	(Gu et al., 2024)
Simulated Society	Content and textual metrics	Complexity of generated content	Automatic	(Antunes et al., 2023)
Simulated Society	Content and textual metrics	Dialogue generation quality	Automatic	(Antunes et al., 2023)
Simulated Society	Content and textual metrics	Number of conversation rounds	Automatic	(Zhang et al., 2024c)
Simulated Society	Bias, fairness, and ethic metrics	Bias rate (herd effect, authority effect, ban franklin effect, rumor chain effect, gambler's fallacy, confirmation bias, halo effect)	Human	(Liu et al., 2025)
Simulated Society	Bias, fairness, and ethic metrics	Bias rate (herd effect, authority effect, ban franklin effect, rumor chain effect, gambler's fallacy, confirmation bias, halo effect)	LLM	(Liu et al., 2025)
Simulated Society	Bias, fairness, and ethic metrics	Bias rate (herd effect, authority effect, ban franklin effect, rumor chain effect, gambler's fallacy, confirmation bias, halo effect)	Automatic	(Liu et al., 2025)
Simulated Society	Bias, fairness, and ethic metrics	Equality	Automatic	(Piatti et al., 2024)

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Task	Category	Task-oriented Metrics	Approach	Source
Writing	Psychological metrics	Qualitative feedback (expertise, social relation, valence, level of involvement)	Human	(Benharrak et al., 2024)
Writing	Performance metrics	Prediction accuracy (F1 score, AUC, MSE, MAE, depression risk prediction accuracy, suicide risk prediction accuracy)	Automatic	(Wang et al., 2024f)
Writing	Performance metrics	Success rate	Automatic	(Wang et al., 2024d)
Writing	Performance metrics	Behavioral patterns	Human	(Zhang et al., 2024c)
Writing	Internal consistency metrics	Consistency (user profile, psychotherapeutic approach)	Automatic	(Mishra et al., 2023)
Writing	Internal consistency metrics	Motivational consistency	LLM	(Wang et al., 2024d)
Writing	Internal consistency metrics	Audience similarity	Human	(Choi et al., 2024)
Writing	Internal consistency metrics	Quality of generated dimension & values (relevance, mutual exclusiveness)	Human	(Choi et al., 2024)
Writing	External alignment metrics	Factual error rate	Automatic	(Wang et al., 2024f)
Writing	External alignment metrics	Correctness (politeness, interpersonal behaviour)	Automatic	(Mishra et al., 2023)
Writing	External alignment metrics	Hallucination (groundedness of the chat responses)	Human	(Choi et al., 2024)
Writing	Content and textual metrics	Linguistic similarity	Human	(Choi et al., 2024)
Writing	Content and textual metrics	Fluency	Human	(Mishra et al., 2023)
Writing	Content and textual metrics	Perplexity	Automatic	(Mishra et al., 2023)
Writing	Content and textual metrics	Non-Repetitiveness	Human	(Mishra et al., 2023)
Writing	Content and textual metrics	response generation quality	Automatic	(Li et al., 2024a)
Writing	Content and textual metrics	Coherency	LLM	(Wang et al., 2024d)