Evaluating General-Purpose AI with Psychometrics

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Abstract

Artificial intelligence (AI) has witnessed an evolution from task-specific to general-purpose systems that
trend toward human versatility. As AI systems begin to play pivotal roles in society, it is important
to ensure that they are adequately evaluated. Current AI benchmarks typically assess performance on
collections of specific tasks. This has drawbacks when used for assessing general-purpose AI systems.
First, it is difficult to predict whether AI systems could complete a new task it has never seen or that did
not previously exist. Second, these benchmarks often focus on overall performance metrics, potentially
overlooking the finer details crucial for making informed decisions. Lastly, there are growing concerns
about the reliability of existing benchmarks and questions about what is being measured. To solve these
challenges, this paper suggests that psychometrics, the science of psychological measurement, should be
placed at the core of evaluating general-purpose AI. Psychometrics provides a rigorous methodology for
identifying and measuring the latent constructs that underlie performance across multiple tasks. We
discuss its merits, warn against potential pitfalls, and propose a framework for putting it into practice.
Finally, we explore future opportunities to integrate psychometrics with AI.

1 Introduction

Artificial intelligence (AI) is transitioning from specialized tools tailored for specific tasks to general-
purpose systems that can handle a diverse set of challenges, edging toward human versatility. It is playing
an increasingly important role in society, amplifying productivity and enhancing societal well-being. For
example, general-purpose AI systems\textsuperscript{*} have significantly improved productivity in professional writing\textsuperscript{[1]},
have been successfully utilized in coding\textsuperscript{[2,3]}, and offer potentially transformative applications in sectors
such as medicine, law, business, and education\textsuperscript{[4,5]}.

As the significance of AI systems in society grows, obtaining an accurate understanding of their
capabilities becomes essential. AI systems must undergo rigorous evaluation to ensure their readiness for
real-world applications. Such evaluation serves a dual purpose. Firstly, it examines whether AI systems
are capable of completing their intended duties, thereby reducing operational risks. For example, before
deploying a generalist medical AI system\textsuperscript{[4]} that could be widely used across diverse medical applications
to serve patients, we need to ensure that the AI outputs are correct and safe given various patient
inputs. Secondly, the evaluation forms the foundation for continuous improvement, identifying areas
for improvement and allowing developers to pinpoint system vulnerabilities, biases, and inaccuracies.
Scientifically grounded evaluation acts as our compass in this transformative era, guiding the development
and integration of AI systems into our society.

\textsuperscript{*}We use “AI systems” to cover various AI technologies, such as AI models, agents, and future AI paradigms.
Evaluating general-purpose AI systems is particularly challenging. While task-specific AI systems are evaluated based on the tasks they were built to solve, such as translation or chess playing, general-purpose AI systems are designed to operate in complex scenarios where tasks are unknown beforehand. Take ChatGPT [6] as an example: it can generate human-like responses to innumerable tasks, ranging from standard ones such as translation and grammar error correction to novel tasks such as writing a mathematical proof in the style of a Shakespeare play [7]. As a result, it is difficult to foresee how users would use the AI systems. This type of broad applicability is not exclusive to ChatGPT. Systems that are tailored to a specific sector, such as generalist medical AI models, might be employed to carry out unanticipated tasks proposed by an end user for the first time [4].

In this paper, we suggest that the key to solving the challenges in evaluating general-purpose AI systems is to learn from psychometrics, a science that has been developed over a century to measure the psychological constructs of humans. We show why the integration of psychometrics into general-purpose AI systems evaluation is now becoming urgent and delve into the essential considerations for how to implement it. Specifically, we examine how studies that directly use psychometric tests developed for humans to evaluate general-purpose AI systems might be misleading. We present a framework grounded in psychometric principles, highlight useful psychometric techniques, and discuss open questions that warrant further investigation. We also explore the opportunities that psychometrics brings to AI, for example, transforming the AI development pipeline.

2 The Time for Psychometrics in AI Evaluation

Many benchmarks have been developed to evaluate AI systems in multiple domains [8]. To better evaluate the versatility of general-purpose AI systems, big benchmarks that combine collections of disparate tasks and tests [9] [10] [11] have been proposed. For example, BIG-Bench [9] includes a collection of over 200 tasks contributed by over 450 authors from 132 institutions.

Unfortunately, even big benchmarks cannot effectively address the complexities of evaluating general-purpose AI systems. Fundamentally, they are task-oriented: They are only able to evaluate an AI system’s performance on predefined tasks, such as translation, summarization, and sentiment analysis [8]. As summarized in Figure 1 this task-oriented paradigm was originally designed for assessing narrow, task-specific instead of general-purpose AI systems [12]. Below, we present three limitations inherent in the task-oriented paradigm and explain how psychometrics, with a focus on latent constructs, provides a potential solution.

2.1 Predictiveness

When evaluating general-purpose AI systems, the current task-oriented paradigm is unable to handle tasks that are unknown beforehand. For instance, BIG-Bench contains several tasks related to biology or medicine, but they are insufficient to predict the performance of an AI system acting as a general medical assistant due to the variety of potential situations that could arise and the associated requirements. The assumption that the performance of an AI system tested on a limited number of benchmarks can anticipate performance in a practically infinite range of applicable tasks is wrong [12] [13].

In psychometrics, predictiveness is achieved by capitalizing on construct-oriented evaluation. Constructs, such as personality traits, cognitive abilities, and values, are latent attributes that psychologists hypothesize underlie a range of behaviors [14]. Especially, our focus is to measure constructs that cannot be directly observed such as intelligence. Such constructs are interpreted as causes or descriptors for
performances across multiple tasks and scenarios, offering a holistic understanding of individuals and maintaining relevance over extended periods [15]. Imagine a student who exhibits high conscientiousness (personality), strong logical reasoning (cognitive ability), and a commitment to ethical medical practice (value), all of which are essential constructs in the medical profession. Without testing the student on specific tasks, we are able to predict that their performance as a doctor would be outstanding, even on medical procedures yet to be developed.

It has long been acknowledged that important latent constructs are useful for predicting future performance. For example, a longitudinal study shows that academic grades can be predicted by cognitive ability and thinking characteristics such as self-esteem, hope, and attributional style [16]. In hypermedia learning settings, academic achievement can be predicted using thinking styles after controlling for personality and achievement motivation [17]. Research has also indicated that shifts in personality from adolescence to young adulthood can be predictive of initial career outcomes such as degree attainment, income, occupational prestige, and job satisfaction [18]. By focusing on latent constructs, psychometrics is able to predict human performance on a wide range of tasks and real-life outcomes.

2.2 Informativeness

Current benchmarks predominantly rely on aggregate performance metrics, which tend to conceal key information, undermining the resolution that is crucial for informed decisions [19]. For example, an AI system that achieves a classification accuracy of 90% may appear to be highly competent and mask significant vulnerabilities. The system may fail to accurately classify a small group of important test cases, raising concerns in safety and fairness [19].

In comparison to task-oriented evaluation, psychometrics offers much richer information by operationalizing the definition of a given construct and specifying a clear structure for its assessment [20]. For example, creativity, a multifaceted concept, can be broadly defined as the generation of products or ideas that are both novel and appropriate [21]. Its measurement revolves around latent variables such as fluency (generating many ideas), flexibility (creating diverse thought categories), originality (coming up with unique concepts), and elaboration (consistent addition of details to creations) [22]. Well-being is another extensively studied psychological construct. Psychometric research has suggested a hierarchical structure of well-being that is built upon three second-order constructs including hedonic (related to pleasure and happiness), eudaimonic (associated with purpose and meaning), and social well-being [23]. Based on these structures that draw upon relationships among observable indicators, psychometric tests are designed to be discriminative and informative in the estimation of latent constructs. Therefore, we can both obtain an overall assessment of the targeted construct and delve deeper into nuanced individual differences. This type of in-depth evaluation offers greater resolution, providing the information that is crucial for comprehensive understanding.

2.3 Quality Assurance

Serious concerns have been raised about the reliability of AI evaluation and what is actually being measured [24]. It has been frequently reported that the performance of general-purpose AI systems is affected by factors such as input prompts and specific configurations [25, 26, 27]. This type of sensitivity makes it challenging to assess whether a benchmark can generate a reliable measure and whether the system can consistently perform well in the real world. Moreover, it is unclear what is (not) being measured by a benchmark. For example, a 95% success rate on a particular BIG-Bench task may not translate into high performance in a real-world task. It could simply be an indication of overfitting [12, 13].

Psychometrics has developed a systematic approach to examining test quality, focusing on both the reliability and validity of the measurement. Reliability demands stable and consistent results across multiple assessments. This concept is related to “replicability” or “robustness” in computer science. Validity indicates how well a test measures what it is designed to measure [28]. For example, a numerical reasoning test should tap into the ability of numerical reasoning rather than irrelevant constructs such as language proficiency. Only with reliable and valid tests can we put confidence in the test results and derive meaningful interpretations.

3 Leveraging Psychometrics for AI Evaluation

Given the advantages of construct-oriented evaluation over task-oriented evaluation, we will demonstrate how to integrate psychometrics into the evaluation of general-purpose AI systems. We will first discuss
issues in existing studies and identify common misconceptions. Subsequently, we will propose a framework guided by psychometric principles, followed by key considerations in each stage of the framework. We will end with a set of open questions that warrant further investigation in the future. For brevity, we will use “AI” to refer to “general-purpose AI” in subsequent sections of this paper.

3.1 The Perils of a Simplistic Application of Psychometrics

Recent literature suggests treating AI systems as participants in psychology experiments designed for humans [29]. In accordance with this idea, some existing psychometric tests have been directly applied to AI evaluation, from general intelligence using IQ tests [30, 31] to theory of mind [32] and personality [33]. While an individual’s performance on a test reflects their underlying construct [33], it remains a question whether tests designed for humans could be applied to AI without considering the unique features of AI systems that might undermine the reliability and validity of the tests [12].

For example, several studies have applied self-report personality scales that were originally developed for humans to AI systems [34]. Given slightly altered phrasing in the scale questions without introducing actual semantic changes, human responses tend to consistently reflect their personality traits. However, when applied to AI systems, a minor change in the input that is negligible to humans (such as reversing the order of the questions) may result in a substantial change in an AI system’s response [34]. This raises doubts about whether the AI system responses to self-report scales reflect a true understanding of personality traits or are merely probabilistic selections based on the AI system’s training data distribution.

Furthermore, it is problematic to assume that the relationship between a certain latent construct and its indicators identified in humans remains intact for AI systems. For instance, researchers have found processing speed an important indicator of intelligence in humans [35]. For humans, rapid thinking and response are often associated with higher cognitive abilities [36]. However, for AI systems, processing speed might not be relevant to intelligence or cognitive abilities. Smaller models that have fewer parameters typically process faster than larger models, but this does not necessarily mean that smaller models are more intelligent than larger models, which, on the contrary, are usually capable of handling more complex tasks.

When integrating psychometrics into the evaluation of AI systems, it is vital to scrutinize the assumptions behind each psychometric test to determine its applicability [33]. In addition to adapting human tests, it is sometimes necessary to develop new tests specifically tailored for the latent constructs of AI systems, leveraging the principles of psychometrics.

3.2 A More Rigorous Framework: Key Considerations

Here, we suggest a framework for construct-oriented evaluation of AI systems. We also introduce psychometric theories and techniques that could be employed to facilitate evaluation. As shown in Figure 2, our framework for evaluating AI systems includes three stages: construct identification, construct measurement, and test validation.

3.2.1 Construct Identification

In the first stage, we need to identify the latent constructs to be measured. In psychometrics, construct identification often involves expert discussions, interviews, and questionnaires [37]. To identify the construct for the AI evaluation, one could employ the Delphi method, which is known for its effectiveness in achieving consensus on intricate constructs [38]. It starts with an initial questionnaire to experts, followed by the summarization of their feedback and subsequent refinement of the questions as needed. In later rounds, experts would revisit previous summaries and may modify their responses. This iterative process persists until a consensus emerges. The method encourages independent thinking, ensures anonymity, and circumvents group influence [39]. AI systems are increasingly being used in real-world services, requiring essential constructs such as communication, creative thinking, and problem-solving. These constructs may sound similar to those in humans, but AI systems and humans are inherently different in terms of their working mechanisms. Drawing inspiration from how psychometricians approach human evaluations, we suggest identifying constructs specific to AI systems based on the impact these constructs have on real-world performance. Specifically, we can consult domain experts familiar with AI deployment using techniques such as the Delphi methods or interviews to identify the most significant latent constructs. For instance, if an AI system is to be utilized for career counseling, experts might
Stage 1. Construct Identification
Identify the latent constructs to be measured

**Example:** For career counseling, domain experts identify important constructs as emotional intelligence and problem solving. They clarify the former as the ability to recognize, interpret, and respond to human emotions.

**Methods:** Use Delphi method with questionnaires or interviews to efficiently achieve consensus among experts, ensure independent thinking and anonymity, and assure the correctness of construct identification.

Stage 2. Construct Measurement
Design the test scenarios and items, then establish scoring criteria

**Example:** Measure emotional intelligence by designing test items based on real-world application scenarios (e.g., a user expressing sadness about losing a job), and compute the score.

**Methods:** Develop a test based on Evidence-Centered Design and apply Item Response Theory during scoring to obtain accurate and comprehensive estimation of the construct.

Stage 3. Test Validation
Verify whether the evaluation is reliable and valid based on responses of test subjects (AI)

**Example:** Verify that the measurement of emotional intelligence is consistent (reliable) and is able to predict relevant outcomes like user satisfaction (valid).

**Methods:** Compute the quality of the test with indices like test-retest reliability, internal consistency reliability, convergent validity, and predictive validity.

Figure 2: A framework for evaluating AI systems using psychometrics, illustrated by an example of assessing chatbots in career counseling, with exemplary psychometrics methods provided for each stage.

highlight the necessity for the AI system to possess emotional intelligence and define the emotional intelligence of the AI system as the ability to recognize, interpret, and respond to human emotions. In contrast, human emotional intelligence also involves recognizing, understanding, and managing one’s own emotions, which is not applicable to AI systems, which lack genuine emotions [40]. Such insights are pivotal when laying the groundwork for subsequent construct measurement.

We should bear in mind that the concepts of latent constructs are constantly evolving. For instance, when the concept of self-esteem was initially introduced, it was primarily viewed as a single dimension, representing an individual’s overall evaluation or feelings of self-worth [41]. As research progressed, psychologists began to recognize that self-esteem encompasses multiple facets and then differentiated between state self-esteem (which relates to one’s perception of self-worth in specific instances or situations) and trait self-esteem (which indicates a person’s consistent or long-lasting level of self-worth) [42]. This evolution in the understanding of latent constructs in psychology is also expected in AI evaluation. Newly identified constructs are likely to be partial or biased. With enriched knowledge derived from empirical evidence, we should expect to continuously refine the definition of the constructs as well as their measurements.

3.2.2 Construct Measurement

After identifying a construct, psychometricians design tests to measure it. This encompasses processes such as developing the test items and establishing the scoring criteria [43].

Test items can be abstract and bear little resemblance to real-world situations. For instance, to assess reasoning ability, the number-series test [44] asks test-takers to discover the pattern in a sequence of numbers and select the choice that gives the missing number. Other examples of abstract items are verbal logic test [45] and graphical reasoning test [46]. Such tests frequently use highly abstract symbols or graphics to measure a construct in a standard format without the interference of complex real-world situations. The resulting test items tend to be less susceptible to constructs that we do not intend to measure, which helps ensure test validity.

Unlike abstract test items, some tests such as simulation-based assessment [47] employ real-world situations as context so as to improve ecological validity. This type of test is more similar to current AI benchmarks in that the test items could take the form of real-world applications. For example, we may measure emotional intelligence using test items that ask test-takers to help someone experiencing sadness over losing a job. To ensure that the test items effectively measure the target construct, psychometricians have proposed Evidence-Centered Design (ECD) [47]. This framework helps test developers identify observable behaviors that are indicative of specific constructs and design the situations to elicit these behaviors [48, 49]. For example, in assessing emotional intelligence with simulation-based tests, we may...
look at evidence or behaviors including responsiveness to emotional cues or expression of empathetic responses. To elicit such behaviors, we can simulate specific situations, such as when a person expresses sadness about losing a job. By systematically linking observable behaviors in certain situations to latent constructs, ECD provides effective guidance for construct-oriented evaluation based on real-life situations.

After selecting the most appropriate test item formats, psychometricians follow item-writing guidelines to craft the test items. Moreover, scoring rules are established to quantify the level of the construct given the obtained responses. Item Response Theory (IRT), also known as latent trait theory, is an advanced psychometric paradigm used for the design, analysis, and scoring of construct-based tests. IRT is founded on the notion that the probability of a correct response to an item is a mathematical function of person parameters (e.g., the level of the construct for a person) and item parameters (e.g., item difficulty and discrimination) and it allows the person parameters and item difficulty to be estimated on a unified scale. The application of IRT in AI evaluation is particularly useful, mainly reflected in the following two points. Firstly, given the rapid development of AI systems, frequent evaluation becomes imperative. Yet, using a fixed set of test items has been criticized due to the potential exposure of items in the training data. IRT enables comparisons across varying test formats or item sets. This makes it possible to present AI systems with different sets of items while ensuring comparable estimated constructs. For instance, when assessing the emotional intelligence of AI systems using IRT, the results can be compared with different tests, whether they are abstract or simulation-based. Secondly, IRT lays the groundwork for Computerized Adaptive Testing (CAT), which enables the selection of optimal items tailored for evaluating AI systems with different levels of certain constructs. This results in a more targeted assessment of specific AI systems and is especially helpful when researchers decide to focus on high-performing systems. Notably, CAT has already seen applications in several evaluations of AI systems.

Some IRT models are starting to be used in AI evaluation. We expect more insights to be gained from recent IRT advancements, for example, IRT-based cognitive diagnostic models that aim at pinpointing specific facets of strengths or weaknesses in the construct and IRT-based latent class models that combine the strengths of IRT with the idea of identifying the hidden groups that test takers belong to. These techniques may result in a more fine-grained measurement of the targeted construct, allowing a more accurate and comprehensive evaluation of AI systems.

3.2.3 Test Validation

Imagine that we have created a test to measure a certain construct. Before collecting any response data from the AI systems, it is crucial to evaluate the quality of the test. For instance, is the measurement free of error? What does the measurement indicate in real life? For this purpose, psychometrics provides a systematic and rigorous methodology that focuses particularly on indicators of reliability and validity in the measurement.

**Reliability** refers to the consistency or stability of a measure or test. In psychometrics, there are several reliability indicators. For instance, test-retest reliability involves giving the same test to the same group of test takers multiple times to evaluate the consistency in the measurements. In practice, one could administer the test to an AI system multiple times to gauge its performance consistency (i.e., replicability). If a test is designed to measure the emotional intelligence of an AI system, we should expect a consistent level of emotional intelligence without significant fluctuations each time the test is administered. Another reliability indicator is internal consistency reliability. It is a measure of the consistency of results across items within a test. Taking the example of measuring the emotional intelligence of an AI system, strong internal consistency reliability indicates that an AI system with advanced emotional intelligence should consistently exhibit good performance across all test items or scenarios. Considering the characteristics of AI systems, we can measure the internal consistency in terms of robustness, for instance, by comparing the performance of an AI system when using different prompt phrasings.

**Validity** indicates the extent to which a test measures the specific construct that it claims to measure. There are different validity indicators in psychometrics: Construct validity measures how well the test reflects the latent construct. A prominent method used to evaluate construct validity is factor analysis, which conceptualizes the constructs as latent factors underlying test items. By examining the fit of the specified structural model with empirical data, we can quantitatively understand the construct validity of the test. Recent research endeavors have already applied this method within the context of AI evaluation.

Construct validity can be further categorized into two primary subtypes. Specifically, convergent
validity reflects the extent to which two measures of constructs, which are theoretically expected to be related, are related. Conversely, discriminant validity evaluates if measurements that are supposed to be unrelated are, in fact, unrelated [59, 60]. For instance, when evaluating the emotional intelligence of an AI system, we would expect its performance on the emotional intelligence test to be (more) correlated with measures of its understanding and management of emotions and not (or less) correlated with measures of unrelated constructs such as creativity.

Predictive validity is another form of validity that is concerned with the extent to which a score on a test predicts performance on a certain criterion measure [59]. The criterion measure can be real-life performance or future outcomes. For example, individuals with higher intelligence are expected to achieve higher SAT scores [64]. Both construct validity and predictive validity are important indicators of validity for AI systems since they ensure that the construct being measured by the test can be related to the actual use of the AI systems in real life. With adequate test validity (and reliability), we would be able to trust the test results and interpret them to answer questions such as: “Does a higher score in emotional intelligence tests for GPT-4 relative to GPT-3 mean a real increase of satisfaction among users when used for career counseling?”

3.3 Open Questions

Leveraging psychometric theories and techniques to evaluate AI systems brings forth many challenges and open questions. Traditional psychometrics is designed for humans. Given the remarkable differences between AI systems and humans, there is a need to recalibrate some fundamental principles when evaluating AI systems.

Redefining “population” and “person” in psychometrics. For humans, the distinction between a person and a population is clear. When evaluating an AI system, it is crucial to determine whether it is being treated as a person or a population since this distinction would determine the research methods and affect the conclusions and interpretations. However, the notion of “person” and “population” becomes ambiguous for AI systems. For example, if we create different personas in the prompts [65], would this generate different persons? Is a fine-tuned AI model the “same person” as the previous model? If we consider different versions of models (e.g., GPT-3.5 and GPT-4) as “multiple persons”, do they belong to the same population?

One possible perspective to determine whether AI systems are a “population” or multiple data points of one “person” is to examine the variance. When a test is taken by a population, the variance (between-person variance) is relatively large, as it reflects the diverse abilities among individuals. However, when the same person takes a test multiple times, the variance in the responses (within-person variance), which is potentially caused by factors such as mood, is considerably smaller. Accordingly, we may consider an AI system with different settings as a single person giving repeated responses if the variance is small, and treat them as a population if the variance is sufficiently large. However, this brings about the question of what is considered sufficiently large. One potential approach is to use the within-person and between-person variance observed in human test results as a reference. Further research is required to determine the effectiveness of this approach and to explore other potential solutions.

Handling prompt sensitivity. The pronounced sensitivity of AI systems to prompts [26] highlights the relevance of prompt engineering. This raises questions about the necessity of prompt engineering in AI evaluation. For instance, when evaluating the AI systems, can we use the same prompts that are designed for humans, or should we make adjustments based on the characteristics of the AI systems? Should the prompts be carefully tuned to ensure optimal performance of AI systems? If so, how would we choose the most appropriate prompt from a large number of potential options? Addressing these questions may require the development of a more standardized evaluation protocol.

A related question is how we interpret the performance variations in AI systems caused by prompt engineering. Some prompts may have a consistent impact on the performance of AI systems. For example, prompts that create a certain persona may result in a consistent gain in the performance of AI systems. This is a systematic effect that could indicate that a second construct that we did not intend to measure may have been activated. This impacts the validity of the test. Other prompts, for instance, created by paraphrasing, may lead to a random increase or decrease in performance but have no influence on the level of average performance among multiple tests. This is a random effect and impacts the reliability of the test. Currently, it is hard to tell which prompts would induce systematic or random effects. Moreover, systematic effects and random effects may vary between different constructs and tests. In the future, we may better categorize the prompts based on their effects on AI systems.

Prompt sensitivity also raises concerns about the inherent reliability of AI systems. Are AI systems
too unstable for tests to ever be reliable? A more practically important question is: if we tried a set of test items on the AI systems and found out that their responses were unreliable, how can we change the test items in order to be more reliable? Should the lack of reliability be addressed by improving AI systems? Addressing these questions requires collaborative efforts from researchers in both the AI and psychometric fields.

**AI vs. humans: a comparative exploration.** When evaluating AI systems, especially when aiming to compare them with humans, researchers often draw upon constructs that have been proposed for humans. Unfortunately, there are fundamental differences between AI and humans, which raises questions about how comparable human constructs are with AI systems. For example, do AI systems exhibit emotional intelligence, creativity, and empathy, just like humans? AI systems might have a unique way of thinking that is entirely different from humans but equally effective. It is critical to consider the unique nature of AI systems to identify new constructs instead of simply choosing constructs from the existing list of human constructs. This requires the assistance of psychometrics, which helps researchers to identify and measure constructs and further allow meaning interpretations based on test results [36].

In some cases, we may want to develop tests that are applicable to both humans and AI systems for comparison. When conducting such an assessment, it is important to ascertain the appropriateness and fairness of the items for both humans and AI systems. One potential approach to address this challenge is the application of Differential Item Functioning (DIF) [69] from psychometrics. DIF identifies instances where an item is biased against certain groups, after controlling for their level of constructs [69]. DIF may offer a method for comparing item performance between humans and AI systems, as well as among diverse AI systems. However, the practical application of DIF in this context remains challenging, and interpreting its results can be complex. For instance, if an item displays DIF between humans and AI systems, does it imply that it is probing an aspect of the construct that the AI system lacks? Alternatively, could the AI system be interpreting the item in a manner different from humans?

### 4 Opportunities

In this section, we discuss opportunities that possess the potential to shape the frontier of AI research.

#### 4.1 Evaluation of AI-Human Teaming

Given the demonstrated enhancements in human productivity facilitated by AI systems [4], it is increasingly clear that AI-human teaming may play a pivotal role in the future. However, the evaluation of this hybrid form of intelligence is significantly lacking. The human-AI teaming depends on the capacities of both the humans and the AI to work in a complex and dynamic context [67]. While there have been initial studies in this area, such as those on Human-AI Decision Making [68], there is still much to uncover. We can explore methods to disentangle the contributions of different types of intelligence or the collaborative process when tasks are performed together. Humans assisted by AI might be regarded as a new population and we can adapt the principles and methods mentioned in the previous section to develop assessments to achieve accurate and efficient evaluation of their performance. In this process, the collaboration and interaction among humans form the crucial foundation for studying cooperation and interaction between humans and AI systems [69, 70].

#### 4.2 Transforming the AI Pipeline

Figure 3 shows our vision of a future in which psychometrics helps redefine every step in the AI pipeline with its advantages in predictiveness, informativeness, and test quality assurance.

When identifying the goals of AI in the initial stages, psychometrics can help move beyond targeting a single task or a combination of tasks, from playing chess and classifying images to requiring latent constructs that are useful in complex scenarios with unforeseen tasks. For instance, imagine an AI system designed to assist judges in court decisions. Instead of merely summarizing the presented evidence against a predefined legal database (a single task), with the aid of psychometrics, the system could be designed to understand and prioritize latent constructs such as the principle of justice (value) and critical thinking (ability). This holistic perspective can ensure that the AI does not just mechanically assess evidence based on a specific distribution, but also aligns itself with broader societal values and abilities that remain useful even in dynamic, complex scenarios.

In the training and refinement stage, psychometrics helps identify AI systems with potential for future use before they are extensively trained. For example, psychometrics may help select a few AI systems
that have the greatest potential for being a good assistant to a judge before they have been trained with a large legal dataset. This could be achieved by seeking AI systems with preferred abilities (e.g., critical thinking) and values (e.g., justice), and rigorously ensuring that these constructs are predictive of being a good judge in the future. Compared to training all available AI systems and evaluating them in terms of the final performance, this prospective AI selection saves a great amount of training effort and helps allocate the most valuable resources to the most high-potential AI systems. With the help of psychometrics and its advantage of informativeness, we may also identify fundamental limitations (e.g., lack of creativity when encountering new lawsuits), prioritize and make better plans for the training, and determine whether the AI system is really improving over targeted latent constructs (e.g., improving creativity), as opposed to merely overfitting to a specific dataset (e.g., memorizing answers to some cases).

In the validation and integration stage, psychometrics helps develop quality-assured tests for AI systems by using indices such as internal consistency reliability. By ensuring that the tests are reliable and valid, we can verify that an AI system really possesses the abilities and values that are required for handling uncertain real-world challenges and for responsible integration into society.

5 Conclusion

As AI systems evolve from being task-specific to general-purpose, evaluation has become vital to ensure the readiness of AI for society. Current benchmarks, which are primarily task-oriented, fall short in key aspects such as predictiveness, informativeness, and quality assurance in evaluating general-purpose AI systems. Our proposed framework addresses these limitations by placing psychometrics at the core of AI evaluation and focusing on the latent constructs. Through a three-stage process, we have demonstrated how psychometrics can be applied, which overcomes the limitations of current benchmarks while guarding against the potential pitfalls of oversimplified psychometric application. In addition, we have explored open questions and potential opportunities for future research. By emphasizing the importance of evaluating the latent constructs, we aim to shape the evaluation of AI research, as well as ensure that we harness the potential of general-purpose AI systems in ways that benefit society as a whole.

Acknowledgments and Declarations

The authors would like to thank Jinyan Fan, Marija Slavkovik, Clemens Stachl, Meng Li, Li Dong, Jingdong Wang, and Lidong Zhou for the insightful discussions. This work was supported by the National Natural Science Foundation of China (Grant No. 62377003) and the Microsoft Research Asia Collaborative Research Program (FY23-Research-Sponsorship-422, “The convergence of assessing human and big model capabilities”). This work was also funded by the EU (FEDER) and Spanish grant RTI2018-094403-B-C32 funded by MCIN/AEI/10.13039/501100011033, CIPROM/2022/6 funded by Generalitat Valenciana, EU’s Horizon 2020 research and innovation program under grant agreement No. 952215 (TAILOR), US DARPA HR00112120007 (RECoG-AI) and Spanish grant PID2021-1228300B-C42 (SFERA) funded by MCIN/AEI/10.13039/501100011033 and “ERDF A way of making Europe”. LS and DS gratefully acknowledge financial support from Invesco through their philanthropic donation to Cambridge Judge Business School.
The authors declare no conflict of interest. All the icons and images in the paper are generated by using Image Creator in Bing.

References


