Challenges in Collective Intelligence: A Survey

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***Abstract*—Collective Intelligence (CI) has been gaining significant attention as an effective method for decision-making and forecasting. Prediction Markets (PMs), as a subset of CI, aim to aggregate participants' diverse opinions and knowledge to produce more accurate predictions than any individual could make alone. The unique market-based mechanism of PMs incentivizes participants to reveal their information truthfully, leading to a collectively superior prediction. However, CI and PMs have challenges, including manipulation, fallacies, and group polarization. This paper provides an overview of the challenges facing CI and PMs as tools for collective knowledge aggregation and examines the role of machine learning (ML) models as tools for amplification and hybridization in the future development of CI. Furthermore, the importance of continued research in this field is emphasized.**

Keywords*—*collective intelligence, prediction markets, artificial cognition, challenges

I. Introduction

Collective Intelligence (CI) refers to the collective behavior of a group of individuals that results in intelligent outcomes. While the concept of CI has been around for a long time, the advent of the global network and the ability to connect people and intelligent bots has led to new and innovative developments [1].

Determining collective knowledge, i.e., reaching a consensus of the collective, is the most important part of properly functioning CI. One of the ways for a collective to reach a consensus is through Prediction Markets (PMs). PMs are defined as virtual markets created to aggregate collective thoughts that operate in a way similar to the stock market [2], [3]. The proof of the effectiveness of PMs is in their widespread usage for sharing knowledge, making a prediction, and solving problems [4], [5].

Despite the many benefits of PMs, they are not immune to challenges and limitations that can negatively impact the accuracy of the predictions. This article will provide a comprehensive overview of PMs, their advantages, and their limitations. In particular, we will delve into the various challenges PMs face, such as manipulations, fallacies, and group polarization. Through this examination, we hope to shed light on the strengths and weaknesses of PMs and how they can be improved for more accurate and reliable predictions.

In this survey paper, we provide a comprehensive overview of the challenges associated with CI from the perspective of PMs. Our main contributions include the following::

- A taxonomy of CI aspects based on interactions and types of agents, with a special focus on the role of Artificial Intelligence (AI) in CI. A clear definition of PMs and a mathematical formulation for future experiments are also discussed.
- A thorough examination of the main challenges in realizing CI and PMs, supported by a review of related literature.
- An exploration of the role of Machine Learning (ML) models and future developments in this field.

The rest of the paper is organized as follows. In Section II, we begin by presenting the definitions and taxonomy of CI. Section III highlights the significance of PMs for decision-making and provides a detailed mathematical model. In Section IV, we provide an overview of the main concepts and challenges involved in achieving CI. Section V provides a detailed analysis of the challenges in PMs, such as fallacies and group polarization. In Section VI we discuss future developments in the field. Finally, conclusions are drawn in Section VII.

II. Overview and Applications of Collective Intelligence

In this section, we first briefly overview the CI definitions and taxonomy and then explain how CI can help solve problems by aggregating peripheral knowledge.

A. *Definitions and Taxonomy*

CI is a multi-disciplinary concept encompassing various domains, including agent-based models, swarm optimization, artificial intelligence, and human interactions. CI can be categorized into three aspects: *cooperation*, *cognition*, and *coordination* [6]. All three aspects are depicted in Figure 1.

1) Cooperation: When discussing cooperation, primitive agents such as bees and ants acting intelligently are denoted by the term Swarm Intelligence. On the other hand, intelligent agents (i.e., humans) are denoted by the term Wisdom of the Crowds (WoC). WoC refers to a form of CI in which individuals with diverse perspectives and self-interests interact at a macro level to produce more accurate predictions than those made by a single individual [7]. A similar approach for aggregating individual predictions of multiple ML models was introduced in *ensemble learning* [8].

2) Cognition: The cognition type of CI refers to the system of agents with learning abilities. In this case, an agent can be people and artificially intelligent bots interacting with each other [9], [10].

3) Coordination: In the coordination aspect of the CI, each individual solves a small portion of a global problem where their efforts are combined through the system design of the coordination platform [1]. A typical example of coordination is PMs, where traders, motivated by a profit, sell or buy shares in the outcome of a future event. Through the continuous process of buying/selling, prices are constantly aggregated and updated, yielding a good estimation of future event outcomes [11].

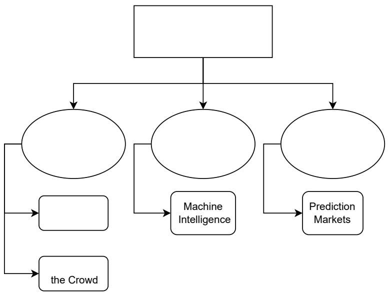

Fig. 1: Categories of Collective Intelligence

Combining the results of individual actions and behaviors achieves a collective outcome. The level of interaction between individuals and the feedback mechanisms used during the aggregation process play a critical role in determining the outcome of CI systems. In order to better understand interactions between the agent in collective, He *et al.* in [12] proposed three main paradigms of CI, namely *isolation*, *collaboration*, and *feedback*. These paradigms reflect the extent to which individuals interact and the role of feedback mechanisms in the aggregation process, thus providing a framework for exploring the properties of CI systems. The paradigms are illustrated in Figure 2.

4) Isolation: In the isolation paradigm, individuals work in isolation, without any interactions or feedback from the environment or other group members. This paradigm can be used for simple statistics (e.g., mean, median), but the results are point estimates, which do not necessarily represent the accurate output like a probability distribution.

5) Collaboration: In the collaboration paradigm, individuals engage in direct interactions and exchange of information without receiving feedback from the environment. Through trial and error, the best-performing agents and collaborative practices emerge. This evolutionary process has led to the development of efficient collaborative techniques and establishment of ethical norms in human societies [13]. In this paradigm, the level of diversity and the impact of social influence (e.g., herding effect) on the decision remains an open research question.

6) Feedback: In the feedback paradigm, individuals engage in both direct interactions with each other and indirect interactions through feedback from the environment [12]. This paradigm is beneficial for solving complex problems and analyzing complex systems, as it facilitates self-organization and synergistic problem-solving [14]. Present studies focus on feedback paradigms with simple rules due to mathematical simplicity, but in reality, such a model encapsulates complex behaviors of human interactions.

This paper focuses on CI involving intelligent agents, such as humans and intelligent bots, as described in [1] following the feedback paradigm, i.e., prediction markets.

B. Finding Solutions by Aggregation

Successful CI aggregates peripheral knowledge to find a solution. *Peripheral knowledge* can be defined as knowledge in the outsourced activity, i.e., core to the specialist that provides an activity but peripheral to the specialist that requires such activity [15]. Therefore, for successful CI following elements must be present [16]:

1) The crowd should comprise a diverse group of individuals to ensure the generation of a rich diversity of information.
2) Individual independence is crucial, both from within the group and from external sources.
3) Each group member should possess specialized knowledge to solve specific subproblems, like in the "divide and conquer" paradigm, to promote a decentralized problem-solving approach. This approach is also used in linear programming by dividing problems into substructures [17].
4) An efficient aggregation mechanism is required to combine local solutions to subproblems and deliver a comprehensive solution to the main problem.

An approach similar to the one proposed for CI has been utilized in machine learning by OpenAI. The Iterated Amplification training strategy was proposed, which incrementally builds training signals for complex problems by aggregating solutions to simpler subproblems. This approach results in a fully automated AI system capable of solving complex tasks without direct training on those tasks, as described in [18].

III. Prediction Markets

This section provides a comprehensive overview of PMs as a subfield of CI. We begin by defining PMs and then proceed to outline their mathematical formulation.

A. Definitions

Collective decision-making has been recognized as an effective method for solving complex problems and predicting future events [19]. While AI techniques have been proposed as an alternative, human intuition and creativity remain challenging to replicate, which has led to the emergence of the concept of hybrid intelligence [20]. This approach combines both intending to achieve superior performance in decision-making and problem-solving tasks.

PMs are a form of CI that leverages the collective wisdom of a group by allowing participants to buy or sell contracts that represent predictions about future events.

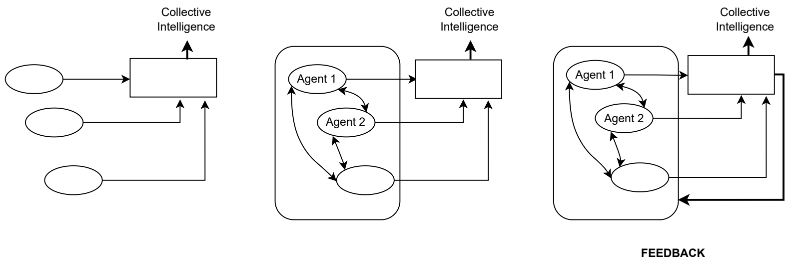

Fig. 2: Three paradigms of Collective Intelligence based on interaction: isolation, collaboration, and feedback

The contract's market price reflects the group's aggregate belief and can be used for a wide range of applications, such as election result forecasting, predicting the launch date of a new product, and more [18].

The mechanism of PMs incentivizes participants to act truthfully and share their knowledge and insights. By buying or selling shares in the outcome, participants are motivated to reveal their genuine beliefs as this strategy is expected to yield the most profit in the long run, [21].

PMs leverage the CI of a group of participants through incentivized interactions in the market. Adhering to the principle of WoC, the PMs enable the aggregation of diverse perspectives and sources of information, thus reducing biases and increasing the accuracy of predictions. This approach is similar to the Random Forest algorithm, which combines multiple decision trees to enhance predictions. [22]. Another technique, boosting algorithms, trains weak models through an iterative process to create a strong learner. Authors [23] demonstrated the effectiveness of these algorithms in creating more accurate predictive models.

Participants are incentivized to be truthful and to share their knowledge and insights by buying or selling shares in the outcome, thereby leading to an effective aggregation of the knowledge. Moreover, the PMs provide opportunities for participants to share knowledge, leading to the continuous improvement of their predictions over time [1].

B. Mathematical Model

Multiple mathematical models have been developed to describe the behavior of PMs, as demonstrated in previous studies such as [24]–[27]. However, due to the complexities inherent in social interactions, a model should encompass all aspects of PMs to provide a comprehensive representation. To model multiple agent interactions, stochastic games are often used. In light of this, we propose the use of a Partially Observable Stochastic Game (POSG) as a model for PMs with unknown environment, as previously demonstrated in [28]–[30]. PMs in POSG are defined as a tuple $\langle N, S, \{b^0\}_{i \in N}, \{A_i\}_{i \in N}, T, \{R_i\}_{i \in N}, \{O_i\}_{i \in N}, \Omega, \{I_i\}_{i \in N} \rangle$. Where

- N represents the finite set of all agents
- S represents the finite non empty set of all states – a quantity of shares being held by trading agent
- b^0 represents the initial distribution of beliefs about the current state of agent i where $b^0 \in B = \Delta(S)$
- A_i represents a final non-empty action space of agent i – a quantity of shares an agent i sells or buys
- O_i represents an observation agent i receives in state k where $k \in S$ joint observation $\overline{o} = \langle o_1, \ldots, o_{|N|} \rangle$
- $T : T(s, \overline{a}, s') = P(s'|s, \overline{a})$ represents the state transition probability of moving from state s to state s' on joint action $\overline{a} = \langle a_1, \ldots, a_{|N|} \rangle$.
- R_i represents the reward for an agent i in state k
- $\Omega : \Omega(s_k, I_{i,k}, o_{i,k}) = P(o_{i,k}|s_k, I_{i,k})$ is the observation probability of agent i receiving observation $o_{i,k}$ in state s_k when information $I_{i,k}$ is received
- $I_i = \bigcup_k I_{i,k}$ is the information agent i receives in state k

The market goes through a set of states duration of a trading period, i.e., how long the market is open. The actual market state at the time is unknown to participating agents. However, each agent has its interpretation of the state, i.e., belief probability distribution $B_{i,t} = \langle b_{1,t}, \ldots b_{|S|,t} \rangle$ where the $b_{s,t}, s \in S, t \in T$ represents the probability of market being in state s at the time t. Belief probabilities are updated using *belief update function* that takes past action past, belief state, and the observation.

Each trading agent aims to make the most profitable decision by choosing the action with the highest expected reward. This objective is often achieved through the truthful revelation of information, as highlighted in [29].

IV. Collective Intelligence Challenges

The realization of CI faces several challenges, which are primarily related to its core components: *diversity*, *independence*, *decentralization*, and *aggregation*. The importance of diversity as a component of CI was emphasized in a study of enterprises, where the authors of [31] found that diversity in answers, such as ideas and creativity, was more crucial than diversity in terms of the individuals themselves.

The challenge of promoting diversity in CI is complex, as diversity encompasses more than just demographic factors such as gender or ethnicity. According to a study [32], diversity in CI is composed of four main elements:

1) diverse perspective – representing problems in a different way
2) diverse interpretation – categorizing problems differently
3) diverse heuristic – solving problems differently

4) diverse predictive methods – a different way to infer cause and effect

Those same principles of diversity can be applied not only in human CI but in AI systems. One typical example of such is *ensamble learning*. Here, we combine diverse classifier systems that train and combine multiple learners to solve a learning problem [8].

Maintaining independence among individuals is crucial for the accuracy of CI but can be challenged by the influence of peer pressure, conformist cultures, and deference to leaders. Peer pressure can lead to group bias or polarization when individuals are asked to provide their opinions in the presence of others. Conformist cultures can result in individuals withholding their genuine opinions to avoid conflict. Deference to leaders, where individuals refrain from sharing negative information to avoid disappointing them, can also undermine the independence and limit the information available to leaders [32].

The decentralization of decision-making processes can pose a challenge, particularly in cultures where centralization is the norm. This can result in neglecting valuable insights and perspectives from individuals at the periphery, who may have different areas of expertise and bring a fresh perspective to problem-solving [32]. The decentralization of decision-making is crucial in leveraging the CI of a group, as it allows for the incorporation of diverse perspectives and expertise, leading to more creative and effective solutions.

Moreover, aggregation methods play a crucial role in CI, as they allow the conversion of individual responses into a single collective response. Currently, the available aggregation methods are limited, and more research is needed to explore different approaches and their impact on individual and group responses. Price mechanisms, as used in prediction markets, have been touted as one of the most effective ways of aggregating dispersed and asymmetrical information sources [33].

V. Prediction Market Challenges

PM results can be manipulated when individuals or groups strategically choose to provide false information, often for personal gain. This can result in biased predictions not representative of the true CI. Moreover, various fallacies can also impact the validity of PMs. Lastly, group polarization can occur when group members become more extreme in their opinions, leading to an increased likelihood of bias in predictions [7]. The challenges associated with aggregation are illustrated in Figure 3.

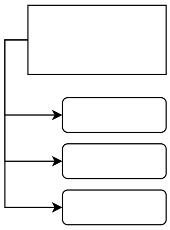

Fig. 3: Collective intelligence challenges

A. Manipulations

The validity of PMs is vulnerable to various challenges, including manipulation by malicious participants, the influence of biased individuals, and the problem of insider information. These challenges can undermine the accuracy of PMs by distorting information, altering incentives, and manipulating the aggregation mechanism.

As a result, it is critical to developing robust mechanisms for detecting and mitigating manipulation and bias in PMs. This can be achieved through technical solutions, such as secure aggregation algorithms, and social solutions, such as transparency, accountability, and community-driven moderation [34], [35]. Additionally, mapping adversarial ML techniques and their defense mechanisms [36], [37] to PMs could provide valuable insights into the systematic classification of manipulations, thereby facilitating their neutralization.

PMs possess a unique ability to self-correct when faced with potential attacks, as demonstrated in [38]. They investigated the effects of manipulations in PMs and found that the market could recover from them independently. However, it took some time for other traders to respond and counteract the manipulation, which created a window for further manipulation closer to the market closing time. This highlights the need for efficient mechanisms to detect and mitigate manipulations in PMs to improve their accuracy and validity.

Additionally, authors [24] found that PMs can be more resilient to manipulation when participants have a high stake in the outcome or when the costs of manipulating the market are high. On the other hand, when incentives are low, or manipulation costs are low, PMs can be more vulnerable. The results of this study emphasize the importance of understanding participants' incentives and designing PMs to align these incentives to obtain accurate predictions. The findings also highlight the need for robust mechanisms to detect and mitigate manipulation in PMs, particularly in cases where manipulation incentives are high and manipulation costs are low [24].

Designing the PMs to mitigate possible manipulations can be achieved through *mechanism design*. Mechanism design, as a subfield of game theory, focuses on designing rules for multi-agent systems to achieve desired outcomes through incentivizing individuals to behave in desired manner [13]. Mechanisms used in PMs are *incentive compatible* where the best strategy is to report truthfully, regardless of other agent's signals [39].

B. Fallacies

The presence of cognitive biases in event forecasting in PMs was explored by authors in a study published in [21]. They discovered that even experienced traders are susceptible to probabilistic fallacies, such as the conjunction fallacy, which can result in missed trading opportunities and affect the outcome of PMs. The authors emphasized the need to account for these biases in PMs, as they persist despite large trading volumes.

The issue of testimonial injustice in PMs has been the subject of much concern. According to Fricker [40], testimonial injustice occurs when an individual's credibility and the value of their information are unfairly impacted by prejudice related to their social identity. This epistemic injustice can have severe consequences when aggregated in PMs [41]. It is, therefore, crucial to address this challenge to ensure the accuracy and fairness of PMs. One way to achieve that is by implementing solid ethics policies into such systems [13].

The authors in [42] examined the effect of social influence on election forecasting through voting in PMs. Their findings revealed that the influence of various voting groups could result in inaccuracies in prediction outcomes. To mitigate this challenge, the authors suggested implementing a prediction model incorporating social factors' influence.

C. Group polarization

The authors of [43] conducted a study on group polarization in PMs and found that it can significantly impact accuracy. Group polarization occurs when group members become increasingly extreme in their opinions, leading to a biased collective prediction influenced by internal or external factors. This highlights the need to consider social dynamics' impact on PMs and address this challenge to enhance their accuracy and reliability.

To mitigate the harmful effects of group polarization, researchers [44] found that larger groups tend to exhibit lower levels of polarization. Additionally, implementing sequential actions between polarized and non-polarized individuals can produce less polarized outcomes.

The impact of the order of participant entry on the outcome in PMs was explored in a study by Othman *et al.* [25]. The authors discovered that when individuals with firmly held opinions join PMs near the end of the market, they can significantly impact the prices, potentially leading to arbitrary results. However, this study only focused on the influence of changing belief values. It did not consider other factors affecting PMs outcomes, such as information exchange, intrinsic motivation, and multiple groups with extreme views [25].

VI. Future Developments and the AI

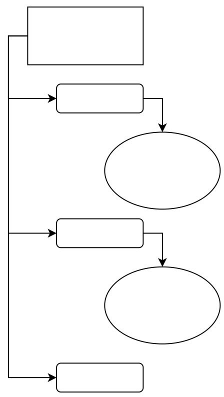

Fig. 4: Categorization of Prediction Markets challenges

PMs can often be underlooked despite their potential to perform as well or better than hyped ML models, according to Cotton's study of PMs for the M6 Financial Forecasting contest [45]. The PMs outperformed 96.5% of ML models used by other contestants, according to [46], highlighting the value of PMs as an alternative to traditional ML models [47]. The superiority of PMs over ML models in prediction contests can be attributed to the distributed nature of human knowledge [47]. While ML models are trained on limited data, human participants in PMs have access to a broader range of information and diverse private data sources, giving them a more comprehensive understanding of the problem. This allows them to make more accurate predictions and reflect the current market conditions.

Future developments in this area could include the integration of AI into PMs, creating a hybrid approach that combines human intuition and creativity with the analytical reasoning of AI. This integration would enable more accurate predictions and better decisions by leveraging the strengths of both humans and machines [20].

In addition, there is a need for research on new techniques of knowledge aggregation using AI to mitigate the effects of manipulations, fallacies, and group polarization. Such research is crucial for the sustainability and prevalence of PMs. The PMs could be further enhanced by developing techniques that can reduce the negative effects of these challenges. Therefore, future studies should focus on these areas to improve the effectiveness and reliability of PMs. In this regard, utilizing mitigation techniques from adversarial ML attacks to prevent manipulations in PMs, such as those used in [36], [37], might be a promising research direction.

VII. Conclusion

This paper explored the potential challenges faced in implementing Collective Intelligence (CI) through Prediction Markets (PMs). PMs offer a valuable tool for collective decision-making, as participants are incentivized to report accurate information, leading to more reliable predictions. However, like all implementations of CI, PMs are subject to potential manipulations, biases, and polarization due to human nature. Despite these limitations, PMs have been shown to outperform Machine Learning (ML) models due to the broader access to information [47] and human intuition and creativity that severely lacks in analytically oriented Artificial Intelligence (AI). To further enhance the capabilities of CI, integrating human input with ML models to address limitations inherent in human nature could be a promising direction for future research and development.

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