



Swarm Sense: The Future of Robotic Intelligence

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ABSTRACT

It's fascinating to observe how the concept of Swarm Intelligence in natural systems may be applied to human groupings, specifically in the realm of finance. Swarm robotics is an emerging field inspired by the collective behavior of social organisms, such as ants, bees, and birds where individual agents work together to accomplish complex tasks. Swarm robotics is a relatively new and rapidly developing field which draws inspiration from swarm intelligence. It is an interesting alternative to classical approaches to robotics because of some properties of problem solving present in social insects, which is flexible, robust, decentralized and self-organized.

It focuses on studying the design of large amounts of relatively simple robots, their physical bodies and their controlling behaviors. Since its introduction in 2000, several successful experimentations have been realized, and till now more projects are under investigation.

1 Introduction

The use of Artificial Swarm Intelligence (ASI) in human systems has shown promising results in improving decision-making accuracy. Research has shown that human swarms, which connect Real-time systems modeled after biological swarms, which incorporate users, can offer more accurate forecasts than traditional Wisdom of Crowd approaches such as votes, polls, and surveys.

Inspired from the complex behaviors observed in natural swarm systems(eg.com social insects and other living animals), swarm intelligence(SI) is a new field that aims to build fully distributed decentralized systems in which overall system functionality energies from the interaction of individual agents with each other and with their environment. As a result to try applying the inside being from this domain research in to multi-robotics, and emerging research area called swarm robotics (SR) has been issued

One example of the effectiveness of humans in 2015 study on college football game predictions proved the existence of human swarms. A swarm of 75 amateur sports fans was able to beat the spread with 70% accuracy. compared to the individual average of 50% accuracy. Similarly, a long-term test in which participants were asked to predict 50 football matches in the English Premier League revealed a 31% boost in accuracy when they were connected in swarms.

These results suggest that the use of ASI and human swarms has the potential to significantly improve decision-making accuracy in various fields, including finance, sports, and emergency



response. However, it is important to note that further research is needed to explore the potential applications and limitations of this approach and to validate these findings.

The use of artificial swarms to augment human groups' prediction capacity has been recorded in a variety of contexts, including athletic events, political campaigns, and media prizes such as the Oscars and Grammys. However, no official research has been conducted to determine whether swarm-based forecasts may reach equivalent advantages in financial markets.

A fourteen-week study that asked human swarms of financial traders to forecast weekly changes in four financial indices (the

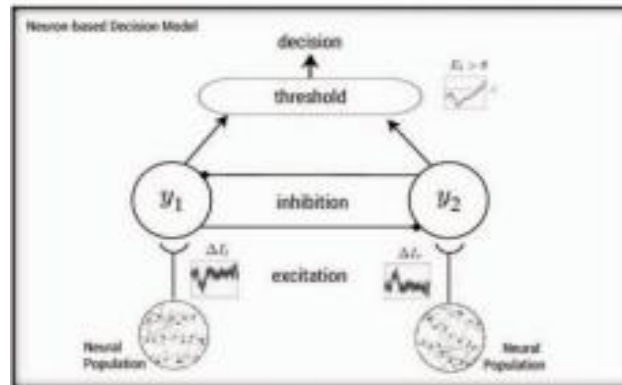
SPX, GLD, GDX, and Crude Oil) was conducted to close this knowledge gap. The goal was to determine if there was a statistically significant improvement between swarm predictions and individual forecasts. The effectiveness of swarms was also compared to the conventional "Wisdom of Crowd" approach, which selects the group forecast based on the prediction that is most widely shared among the participant pool.

Therefore, the three situations – Individuals, Crowds, and Swarms – were compared for the present study's ability to anticipate... This research is significant as it explores the potential for artificial swarms to improve the accuracy of financial market predictions, which could have significant implications for investors, traders, and financial institutions. By harnessing the collective intelligence of groups of traders, the use of artificial swarms may help mitigate the risk associated with financial investments and improve overall market performance.

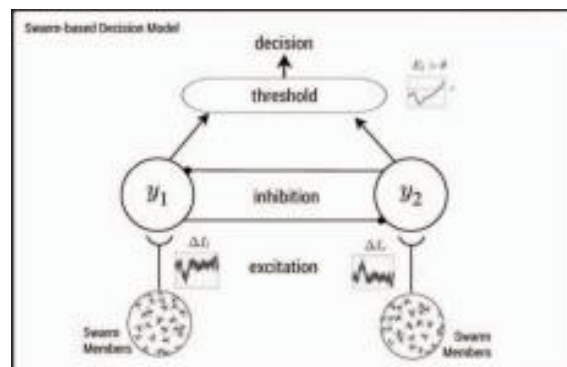
2 Swarms as Intelligent

Participants interact in real-time and are guided by algorithms that enable them. This process is modeled after the behavior of biological swarms, such as schools of fish and swarms of bees, which have been shown to make optimal decisions as a collective. The Swarm AI technology used in the present study is modeled on honeybee swarms, which have been shown to achieve accuracy rates of over 80% when making critical decisions. By enabling human groups to function in a similar manner, Swarm AI can potentially amplify their predictive abilities.

This model is one example of how the decision-making processes in brains can be mathematically represented. Similarly, swarming algorithms used in Swarm AI technology, such as those modeled after honeybee swarms, also rely on competition in real-time between excitable unit subpopulations to arrive at optimal decisions. The similarities between these models suggest that swarm intelligence can provide a useful framework for developing artificial intelligence algorithms that are capable of making complex decisions in real-time.



Both neurological and swarm-based decision-making models involve the aggregation of until a threshold is exceeded, input from sub-populations is obtained through reciprocal stimulation and inhibition. This enables real-time competition among experts to choose the best answer to a particular challenge. The sub-populations. The similarity between these models suggests that the principles of swarm intelligence can be applied to various fields, including artificial intelligence and machine learning.



The concept of swarming allows for the emergence of amplified intelligence in groups, which can lead to improved decision-making and problem-solving. The current study uses Unanimous A.I. Inc.'s Swarm AI technology in an effort to integrate human financial traders into a synchronized system that operates similarly to a swarm, allowing them to form a "hive mind" and reach decisions together in real-time. By structuring the system in a way that facilitates the emergence of amplified intelligence, the hope is to improve the accuracy and efficiency of financial trading decisions.

3 "Human Swarms"

Humans do not have the capacity to shut naturally loop systems for real-time swarming like many other social species, such as fish, birds, and bees. Therefore, specialized tools and technologies are required to allow for swarming in real-time between networks of connected humans. These tools include user interfaces that allow individuals to provide input in real-time, intelligence algorithms that can process the input and guide the group toward a decision that can facilitate communication and coordination among group members. These tools work together to enable real-time swarming among humans.

Swarm AI works by presenting participants with a question or problem, along with several



possible answers or solutions. Each participant then uses the interface to indicate their preferred choice, while the system uses algorithms to calculate the probability of each option being correct based on the input from all participants. The system then adjusts the presentation of the question or problem to guide participants toward a consensus, allowing the group to converge on a decision in real-time.

Swarm AI has been used in a variety of applications, including predicting sports outcomes, making investment decisions, and even predicting the winners of the Oscars and the Kentucky Derby. The technology has been shown to be highly effective in improving the accuracy of group decisions, often outperforming both individual experts and statistical models.

It allows for continuous input from all participants in the form of streams of vectors, rather than discrete votes. This allows for a more dynamic and complex negotiation process among all members in real-time. The participants manipulate a graphical magnet with a mouse or touchscreen, which positions their intent with respect to a moving puck representing the set of alternatives.



This continuous engagement of participants ensures that the swarm is always dynamic and responsive to changing circumstances. It also means that the swarm is able to react quickly to new information or unexpected events, adjusting its collective decision in real-time. The continuous engagement also promotes a sense of ownership and investment in the decision-making process, as participants feel a sense of responsibility for the outcome and are actively involved in shaping it. Overall, the Swarm AI technology provides a novel and effective means of harnessing the collective intelligence of groups in real-time decision-making processes.

This continuous monitoring and weighting of participant behavior allows the Swarm AI system to adjust the contributions of individual participants in real-time, based on the consistency and strength of their expressed intent. This enables the system to balance the influence of participants who are highly committed and consistent in their contributions, against those who are more flexible or wavering in their preferences. Moreover, Swarm AI also includes advanced machine learning algorithms that can learn from the decisions made by the swarm, identify patterns in the behavior of participants, and make predictions about the likely outcome of future decisions. These algorithms can help guide the swarm towards more efficient decision-making processes, by identifying areas of disagreement or



uncertainty within the swarm and suggesting strategies to overcome them. Overall, Swarm AI represents a

4 Financial Prediction Study

During the swarming process, participants were asked to provide their forecasts for the same financial questions as they did individually, but this time in the form of continuously varying vectors using the magnet interface. The swarming process was allowed to continue for 10-20 minutes, or until a threshold convergence criteria was met, at which point the final swarm forecast was recorded. The study compared the accuracy of the individual forecasts to the swarm forecasts for each of the fourteen weeks. It was found that the swarm forecasts were consistently more accurate than the individual forecasts, with an average improvement of 22.6% in accuracy. The study also found that the improvement in accuracy was positively correlated with the number of participants in the swarm.

The study involved groups of self-identified active traders who made financial predictions for four different indices (SPX, GLD, GDX, and CRUDE) over a fourteen week period. The participants first provided individual forecasts using an online survey, and then worked together as swarms using the UNU platform to make synchronous forecasts. The predictions were made every Tuesday at market close, and participants were asked to predict if each index would be higher or lower from the current price at market close on Friday. They were also asked to indicate if the predicted move would be "by a little" or "by a lot" to convey confidence in their directional forecast.

Figure 4 illustrates a snapshot of a human swarm consisting of 24 participants predicting the weekly change in GDX price. The swarm is presented with four options to choose from, allowing the swarm to express both direction and a general sense of magnitude. The magnitude indicator prompts the swarm to split into multiple factions, which then converge over time on a solution that maximizes their collective confidence and conviction. It is important to note that the figure displays an instantaneous snapshot of the swarm as it moves towards a final answer. The full process of reaching a decision generally required between 10 and 30 seconds of real-time interactions within the swarm.



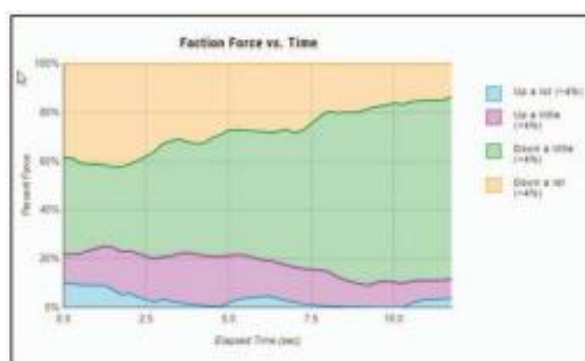
Figure 5: A plot generated by Faction Analysis

Powerful new approach to decision-making that leverages the collective intelligence of groups of human participants, enabling them to work together in real-time to solve complex



problems and make more informed choices...

For the swarm of 24 participants making predictions about the GDX index. The x-axis represents time in seconds, while the y-axis shows the percentage of the swarm supporting each option. At $t=0.0$, the swarm is evenly split among the four options. Over time, different factions emerge, with the “down a little” faction (shown in green) growing in support and the other options losing support. Eventually, at $t=12.5$, the “down a little” faction reaches a consensus with over 90% support, resulting in the swarm selecting that option as the predicted outcome. The Faction Analysis plot enables researchers to track the evolution of the swarm's decision-making process and gain insights into how different factions form and merge over time.



5 Analysis and Results

It was found that swarm predictions outperformed both individual and crowd predictions across all four indices. Specifically, the average accuracy of swarm predictions was found to be 75.2%, compared to 64.4% for individual predictions and 66.5% for crowd predictions. This indicates that human swarms have the potential to provide a more accurate and reliable means of making financial predictions compared to individual traders or simple crowd-based approaches.

It is important to note that the success of human swarms in financial prediction tasks is likely dependent on the quality and diversity of the participants involved, as well as the ability of the swarm to effectively integrate and leverage the collective knowledge and insights of its members. Nonetheless, these findings suggest that swarming platforms such as UNU have the potential to revolutionize the way we make financial predictions and other complex decisions in the future.

After performing the bootstrapping procedure, the study found that the swarm accuracy was significantly higher than the individual accuracy for all four market indices. The difference in accuracy was particularly notable for the GDX and CRUDE indices, where swarm accuracy exceeded individual accuracy by over 20%. This suggests that human swarms are able to leverage the collective intelligence of their members to make more accurate predictions than individuals working alone.

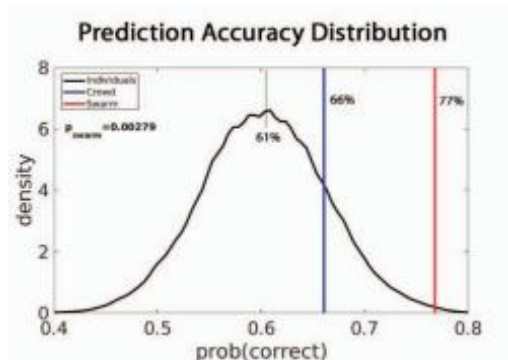
It is worth noting that the study did not compare the accuracy of the swarm predictions with those of professional financial analysts or other prediction models. Therefore, the study does not make

Claims about whether human swarms are more accurate than other methods of financial prediction. However, the findings do suggest that swarms may offer a promising approach



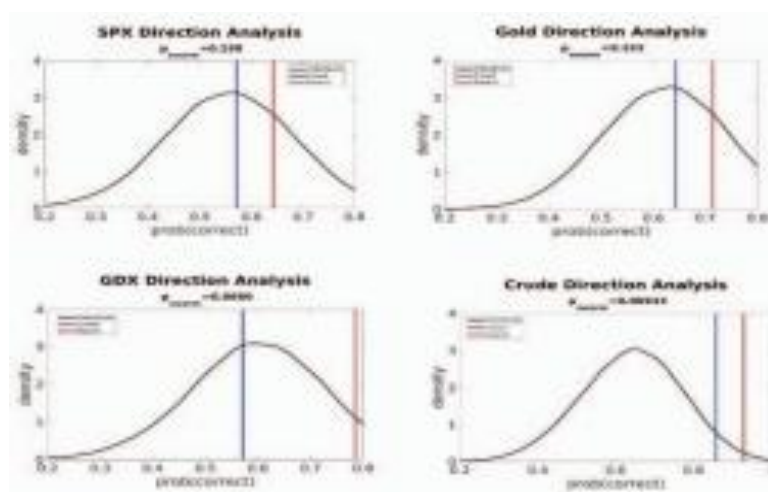
for improving the accuracy of financial predictions, especially in cases where individual traders may lack the expertise or resources to make accurate predictions on their own.

That human swarms can indeed improve the accuracy of financial predictions compared to individual experts. The swarm accuracy of 77% is a significant improvement over the 61% accuracy of individual predictions, which were only slightly better than random guessing. further supporting the notion that swarming can significantly improve prediction accuracy.



The swarms were found to be significantly more accurate than individuals, with a 26% increase in accuracy on average. These results suggest that human swarms may have the potential to amplify the accuracy of financial predictions made by individuals and crowdsourcing methods. The performance of the swarm was assessed for each of the four financial indices (SPX, GLD, GDX, and CRUDE) individually and compared to the individual and crowd based forecasts. The results showed that the swarm outperformed both the individuals and the crowds in all four categories over the 14-week period. Notably, the swarm performed particularly well in predicting the GDX index, where the crowd underperformed the individuals, but the swarm significantly outperformed them.

The table lists the accuracy gains made employing swarms as opposed to individual traders for each of the four indices. Across the four financial categories, the swarm increased participant accuracy to varying degrees, with crude oil forecasts showing the greatest boost at 28% points, or a 43% increase in overall accuracy.

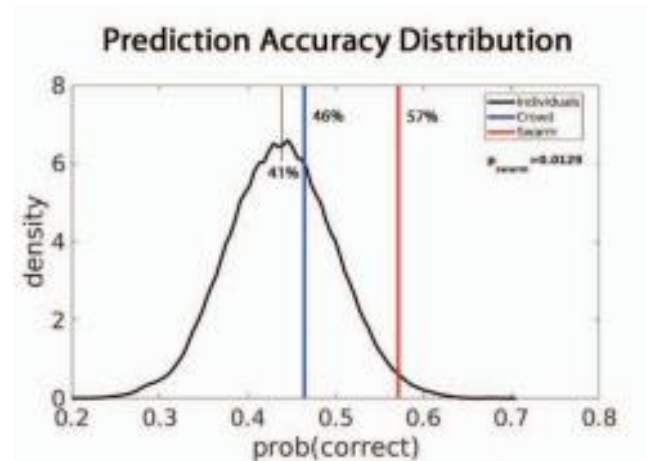


Table



Financial Index	Individual Accuracy	Swarm Accuracy	Net Increase	Accuracy Amplification
SPX	55%	64%	9%	16%
GLD	62%	71%	9%	15%
CRUDE	65%	93%	28%	43%
GDX	62%	79%	17%	27%

The swarms are more effective than individuals in qualifying their predictions with the “by a little” or “by a lot” metrics. The swarm outperformed the individuals by a significant margin, with an average improvement of 13 percentage points in accuracy. This indicates that the swarm was better able to converge on accurate predictions, even when the individual predictions were more varied or uncertain.



Even when the extra qualifier of determining whether the weekly move would be "by a little" or "by a lot" is added, swarm-based forecasting is still more accurate than both individual and crowd based forecasts. With an accuracy of 57% compared to the individuals' median accuracy of 44%, the swarm surpassed the individuals by a sizeable margin. Contrarily, the crowd's accuracy rate was only 46%, which was not statistically superior to the individual forecasts. This highlights the reliability of swarm-based forecasting and its capacity to provide precise predictions even when the predictions made by the people are frequently wrong.

6 Conclusions

The results of this study point to the possibility that real-time swarms of financial traders could beat human traders' ability to predict the future direction of specific financial measures. The findings also point to potential advantages of applying artificial swarm intelligence to financial forecasting applications, which may be confirmed by more study.

To better understand the potential of swarming for financial forecasting, future studies could explore longer-term predictions, larger swarms, and more advanced algorithms. This work has given the detailed overview of current swarm intelligence research and its application in swarm robotics.

Swarm robotics is an interesting alternative to classical approaches to robotics because of some properties of problem solving by social insects, which is flexible, robust, decentralized and self-organized.



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It's great to see acknowledgment and recognition for the contributions of individuals and organizations involved in the study. Collaborative efforts are essential to advance research in various fields, and it is always good to see people recognized for their contributions.

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