Amplifying the Collective Intelligence of Teams with Swarm AI

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1. INTRODUCTION

Group decision-making is strengthened by the varied knowledge and perspectives that each member brings, yet teams often fail to capitalize on their diversity. This paper describes how Swarm AI, a novel collaborative intelligence technology modeled on the decision-making process of honey bee swarms, enables networked human groups to more effectively leverage their combined insights. Through an empirical study conducted on 60 small teams, each of 3 to 6 members, we demonstrate the capacity of Swarm AI to significantly amplify the collective intelligence of human groups. A well-known testing instrument—the Reading the Mind in the Eyes (RME) test —was used to measure the social intelligence of each team—a key indicator of collective intelligence. The study compares the RME performance of (i) individuals, (ii) teams working by majority vote, and (iii) teams using an interactive software platform that employs Swarm AI technology.

1.1 Augmenting Human Intelligence Through Swarming

The collective decision-making process found in honey bee swarms provides a powerful example of how groups, working together in closed-loop systems, can significantly amplify their combined intellect [Marshall et al. 2009] and inspired the development of Swarm AI—a collaborative intelligence technology that enables networked human groups to make decisions by working together in systems modeled on natural swarms. Using the Swarm AI platform, each participant contributes their unique knowledge and perspectives in parallel until the group converges upon optimized decision [Rosenberg 2015]. By enabling human groups to converge synchronously on solutions in real-time, Swarm AI has been shown to amplify the combined intelligence of teams so that they produce more accurate forecasts [Rosenberg et al. 2016], generate better informed market research and human resource decisions, and surpass machine learning approaches to diagnosing medical conditions [Halabi 2018, Rosenberg et al. 2018].

As shown in Figure 1, participants provide input by manipulating a small, U-shaped graphical magnet with a mouse, touchpad, or touchscreen. Participants use their magnets to guide the puck away from alternatives they do not support and toward more favorable alternatives. User manipulation of the magnets is continuous throughout the decision-making process (i.e. not discrete votes) and thereby produces a stream of behavioral signals that are processed by the AI Engine in real-time to guide the motion of the puck. In this way, a feedback loop is created between the participants and the AI engine, enabling the system to converge on solutions that amplify benefits and suppress errors common to group collaboration [Zamfirescu and Filip, 2010, Heylighen 2016].

In prior studies, Swarm AI has been shown to produce more accurate predictions and higher quality decisions than experts, crowds, and markets. Swarm AI was used at Stanford Medical School in 2018 to amplify the accuracy of radiologists, enabling them to more accurately diagnose pneumonia from x-ray images compared to individuals, and to cutting edge deep learning algorithms [Halabi 2018, Rosenberg et al. 2018]. In another 2018 study, researchers showed that Swarm AI technology enabled groups of sports fans to out-predict Las Vegas sports betting markets: after 20 weeks the Vegas model generated a 41% loss, while the swarms generated a 170% gain (Rosenberg and Willcox 2018]. The accuracy of these predictions can be explained, in part, by Swarm AI's ability to elicit each individual's tacit knowledge, which refers to the experience, intuition, and feelings possessed by an individual that are often challenging to verbalize [Polanyi 1966].

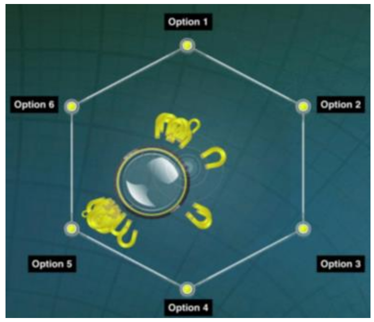

Fig 1: Networked Team Making a Real-Time Decision using Swarm AI Platform

1.2 Empirical Study of Team Intelligence using RME Test

A group's social intelligence strongly predicts its collective intelligence and performance [Woolley et al. 2010]. Groups high in social intelligence tend to have higher collective intelligence and are better able to collaborate effectively. Social intelligence is measured through the Reading the Mind in the Eyes (RME) assessment, which involves making subjective judgements about what emotion a face is displaying by viewing only the area around the eyes. Individuals who score high on social intelligence can perceive and respond to subtle nonverbal emotional and interpersonal cues, which facilitates collaboration in group settings. Social intelligence equally predicts a group's collective intelligence whether members interact face-to-face or in online contexts where communication is limited to textual messages [Engel et al. 2014], which makes use of the RME assessment a compelling way to examine the degree to which Swarm AI can augment the social intelligence of a group.

2. METHOD, ANALYSIS, AND FINDINGS

To explore the degree to which a group's social intelligence could be amplified through human swarming, the social intelligence of 63 real work groups, consisting of 3-5 team members, was measured twice. First, members of each group completed the RME assessment individually. Second, each group completed the RME assessment collectively as a swarm using the Swarm AI platform.

We hypothesized:

H1: Swarms will score higher on social intelligence than the group's average.
H2: Swarms will score higher on social intelligence than the group's majority vote.
H3: Swarms will score higher on social intelligence than the highest performing individual in a group.

- *Team Mean Social Intelligence (SI)*: The average of each member's score on the RME. This method of computing a team's social intelligence score was used by Woolley et al. [2015a].
- *Team Majority SI*: The most frequently answered response for a question among the individuals in the group. Team Majority Social Intelligence represents the responses the team would have selected for each RME question if deciding by majority vote.
- *Team Max SI*. Each team's highest scoring member represents the Team Max Social Intelligence score for that group. The maximum score is another frequently used measure of determining the intelligence of a group [Malone 2018].

- *Swarm SI*: Each team's single score form completing the RME assessment as a swarm.

Swarming produced the not only the highest mean score (*Swarm SI* mean = 29.48) on the RME but also the highest *Team Max SI* score. The *Swarm SI* scores were observed to be 4.06% higher than the *Team Max SI* scores, 12.17% higher than the *Team Majority SI* score, and 14.23% higher than the *Team Mean SI* score.

Testing Method	**Mean**	**Min**	**Max**	**Range**	**Std Err**	**SD**	**Var**
Team Mean SI	24.50	18.67	28.67	10	.23	1.85	3.42
Team Majority SI	25.22	13	34	21	.57	4.55	20.69
Team Max SI	28.06	24	33	9	.24	1.87	3.48
Swarm SI	29.48	23	35	12	.34	2.69	7.25

Hypothesis 1 states that human swarms will score higher on social intelligence than the group's average. A paired-samples t-test revealed a statistically significant difference in the *Team Mean SI* scores (M = 24.50, SD= 1.8) and *Swarm SI* scores (M=29.41, SD=2.65) on the RME assessment; $t(62)=15.01$, $p < .001$. These results suggest that human swarms making subjective decisions outperform the average scores of the group.

Hypothesis 2 states that human swarms will score higher on social intelligence than the team's majority vote. A paired-samples t-test shows a statistically significant difference in the *Team Majority SI* scores (M = 25.22, SD= 4.55) and *Swarm SI* scores (M=29.41, SD=2.65) on the RME assessment; $t(62)=7.53$, $p < .001$. These results suggest that human swarms making subjective decisions outperform the majority vote of the group.

Hypothesis 3 states that human swarms will score higher on social intelligence than the team's max score. A paired-samples t-test reveals a statistically significant difference in the *Team Max SI* scores (M = 28.06, SD= 2.65) and *Swarm SI* scores (M=29.41, SD=2.65) on the RME assessment; $t(62)=4.44$, $p < .001$. These results suggest that human swarms making subjective decisions outperform the highest performing individual in that group.

The results indicate that teams collaborating as swarms outperformed the group average, the group's majority vote decision, as well as the group maximum and suggest that swarms augment the collective intelligence of human groups. Since social perceptiveness is the greatest predictor of collective intelligence, these results suggest that swarms can perform better than individuals on a wide range of tasks and decisions. Perhaps the most notable finding is that swarms outperform even the highest performing individual (Team Max SI). This suggests that the swarming process enables effective synergy to occur among participants, not that the crowd simply follows a dominant voice in the group. That the swarm outperforms majority rule is interesting and points toward the potential of Swarm AI to enlist the unique knowledge of all individuals in the group. A majority vote assumes that the majority is smarter than a single individual with unique knowledge, whereas a swarm encourages a group to find the places where they agree [Paynter 2017]. Prior research has shown that social intelligence does not depend on face-to-face communication and generalizes to online groups that communicate only by text [Engel et al. 2014]. The research presented here confirms these findings and contributes to the literature by adding that human swarms can exhibit social intelligence in an environment that permits limited linguistic interaction.

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