Review of: "Collaborative Intelligence: A scoping review of current applications"

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Title: Collaborative Intelligence: A Scoping Review of Current Applications

General Comments

In this paper, the authors apply rigorous methods for searching academic and "grey" publications that meet 3 robust criteria for collaborative intelligence (CI). Their key word guided search for articles from 2012 – 2021 yielded 1,250 English language documents of which 16 (1.28%) met criteria. Applications (mostly prototypes) from these selected articles in a diverse range of domains are examined, and the types of work/range of benefits are discussed in detail (Table 1). In these applications, artificial intelligence (AI) either had a virtual reality (8/16 in VR, cyberspace) presence or occurred physical formats (8/16 with robots/cobots, UAVs/drones).

The overarching premise of the paper is the evolution of the AI technology trend from narrow task-based applications that are carried out to augment human efficiency ("Industry 5.0"), to achieve a higher level of AI-human interaction that is "collaborative", allowing intelligent agents to do more together that alone (complementarity). The authors note that this level-up is often discussed, but that it largely remains aspirational. In doing this study, the authors set out to prove that collaborative intelligence is more than a theoretical concept. In carrying out their study, their yield of CI meeting criteria is low (1.28% of all candidates), but the early applications (mostly prototypes) are diverse and interesting.

The 3 chosen CI criteria, complementarity, shared objective and sustained interaction (i.e., reciprocal communication), are robustly defined, and appropriately exclude independent AI, testing teamwork feasibility, divisions of labor and static Q&A interactions. The decision to avoid a laissez-faire set of CI inclusion criteria reduces the yield, but also reduces the hype associated with AI technologies (the "promise" of AI exceeding the reality of AI). The authors also are careful to acknowledge the limits of AI vis-à-vis human capabilities, and that what AI generally learns, it learns from brilliant and/or biased humans.

Specific Comments

1. Introduction – provides an overview of "the field" of CI, circa 2010 - 2021. It is good to see the variety of investigators and efforts in this area of AI research & development. It is surprising that large language model (LLM) technologies (circa 2017 – present) were not specifically touched upon, given their current combination of human interactions and AI

hyping. One wonders what a LLM (Chat GPT 3.5 – 4.0) query might have produced (a possible future project?).

2. General Methods – the artificial intelligence acronyms & synonyms sought in the search are discussed. Most of what is covered in this article is the type of advanced AI typically called deep learning (DL). The likelihood that narrower machine learning (ML) algorithms would be able to participate in CI is low.
3. Google Search – the “odd thing” about AI academic research and corporate R&D is that it is often unpublished, either presented at meetings & symposia or held proprietary (as intellectual property). Did the search for full text articles miss out on some of the information that is not actually citable. In this regard, what are “grey” literature publications? What were the sources of the final 16 papers (“grey” versus not grey)? Could we see the impact factors of these journals?
4. Table 1 – this large text table is helpful. Could the type of AI tech powering each of the 16 applications also be specified (Evolver = generative AI, Story Drawer = generative AI, Robot Dancer = robotics + computer vision, Creative Agents = generative AI, Complement = multi-sensor detection + decision-support, ARMAR-6 = sensori-motor inputs + NLU, etc.)? There is a range, but it appears that many of the applications are based on generative AI tech.
5. SAGE – physician often made decisions in real time with partial information. This machine-doctor interaction within a shared (clinical) data context is a prototype of a decision support tool. While truly explainable AI for real-time decision support is next generation AI, this is an interesting start. The challenges (among many) are the quality of clinical data (often poor), the dynamic nature of data flows in the clinical setting (need for resets), the variability of ground truths for care planning (guidelines), the persistent reliance by doctors on mental short cuts (heuristics), etc. I would expect SAGE to be helpful in simple clinical settings only. Of note, there is no published evidence that explainable AI enhances decision-making over “black box” AI. The “safety” of SAGE would likely be to reduce major medical errors; doctors don’t really want help making a diagnosis.
6. Stage of Development – the time frame for this cohort publication (2012-2021) and their applications (2017-forward) is interesting. As stated above, in addition to rapid LLM emergence (after BERT in 2017), the overall DL tech field has made tremendous progress over this decade. As such, the search is a ‘lagging indicator’ of what has happened in this field, which since 2021, could be out of date. This would represent another “study limitation” which is alluded to in that section (beyond under sampling).