Exploring the Role of Adaptive Hybrid Intelligent Systems on Competitive Advantage Using a Case From the STM Publishing Industry

Semester Paper

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Abstract: @todo: write the abstract once the paper is ready...

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1 Introduction

As enterprises face universally accelerating change (Eliazar & Shlesinger, 2018), it is crucial for their artificial intelligence (AI) systems to be dynamic and adaptable. Adaptive and hybrid intelligent (HI) systems that learn from new data, from the interaction with human agents and work synergistically with humans can provide a competitive advantage to enterprises. This study explored the competitive advantage for enterprises adopting adaptive hybrid intelligent systems using the case of a typical editorial process in the scientific, medical and technical (STM) publishing industry. The study answers the following research question: *How can AI systems learn from and adapt to humans and their environment for the competitive advantage of enterprises?*

A mixed-methods approach was used, consisting of a literature review and qualitative data collection from a focus group of graduate students in information systems ($n = 25$). The literature review identified how adaptive hybrid intelligent systems contribute to competitive advantages and was used to derive hypotheses using the case of the scientific, medical and technical (STM) publishing industry. The hypotheses were tested through qualitative feedback from the focus group.

@todo: after the workshop, add a short summary of the main hypotheses, findings, discussions and conclusion…

The remainder of the paper is structured as follows. Section 2 presents a literature review on hybrid intelligent systems and their competitive advantage for enterprises. Section 3 describes the methodological approach of the study. Section 4 presents the findings. The paper concludes in Section 5 with a discussion of the findings and limitations of the study.

2 Literature Review

This section provides an overview of artificial intelligence (AI), including hybrid intelligence, adaptive AI, design patterns for hybrid intelligent systems, and how the use of such systems in enterprises can create a competitive advantage.

2.1 Overview of Artificial Intelligence

AI involves the creation of computer programs and algorithms that allow machines to replicate human cognition and behavior, which includes the capabilities of perception, learning, reasoning, solving problems, and making decisions. AI can be broadly subdivided into symbolic and sub-symbolic approaches, see e.g., Eliasmith and Bechtel (2006). Symbolic approaches involve the use of explicit symbols and rules to represent knowledge and reason in a way that is easily understood and explainable by humans, while sub-symbolic (or *connectionist*) approaches aim to learn complex patterns from vast amounts of data using neural networks (Ilkou & Koutraki, 2020). Hybrid AI refers to systems combining symbolic and sub-symbolic approaches. Hybrid AI systems can be anywhere from loosely coupled to tightly integrated (d'Avila Garcez & Lamb, 2023).

Loosely coupled hybrid AI systems typically involve a human, which is also known as *human in the loop* (HITL) computing. In such systems the humans and AI work together towards common goals, augmenting the human intellect and overcoming human limitations and cognitive biases (Akata et al., 2020). Akata et al. (2020) refer to this combination of human and machine intelligence as *hybrid intelligence*. The concept is also known as intelligence augmentation and amplification, see e.g., Schmidt (2017) and Zhou et al. (2021). The idea of hybrid intelligence can be traced back to Joseph Licklider's "man-computer symbiosis" and Douglas Engelbart's vision of increasing human capabilities trough better and faster machine understanding (Schmidt, 2017, and references cited therein). With the advanced and ubiquitous digital technologies now available, hybrid intelligent systems show the potential for improving the outcomes of AI systems, hence *augmenting* rather than replacing human intelligence (Akata et al., 2020; Schmidt, 2017). Hybrid intelligent systems have recently received attention from the leaders in the field as a response to an ever increased focus on sub-symbolic approaches and deep learning in particular: Kambhampati (2020) demanded that AI researchers build human-aware AI systems that work synergistically with humans, including considering the human mental state, recognizing desires and intentions, and providing proactive support to humans. In particular, AI researchers should aim at systems that show the capabilities of *explicability* (AI agents should show behavior that is expected by humans) and *explainability* (AI agents – if behaving unexpectedly – should be able to provide an explanation) (Kambhampati, 2020). Such human-aware AI systems act as a human collaborator and must *"sense, understand, and react to a wide range of complex human behavioral qualities, like attention, motivation, emotion, creativity, planning, or argumentation"* (Korteling, van de Boer-Visschedijk, Blankendaal, Boonekamp, & Eikelboom, 2021).

To reach human-level intelligence, some argued that AI systems would need to be *degraded* at some point due to the dissimilar nature of human and machine intelligence (Korteling et al., 2021). The physical substrate (biological, respectively digital) determines the cognitive abilities and limitations of human *versus* artificial intelligence, with human cognitive faculties being limited by the biological and evolutionary origin of intelligence (Korteling et al., 2021). Further, Korteling et al. (2021) argue that the pursuit of Artificial General Intelligence (AGI), i.e., machines reaching human-level intelligence, may be a misleading goal due to these limitations of human intelligence. They conclude that (hybrid intelligent) AI systems supporting human decision-making appear to be the best way forward for implementing better solutions, even if this means that we stick to narrow AI applications for the foreseeable future (Korteling et al., 2021).

The concept of narrow AI refers to AI applications that have been trained with specific data for narrowly defined use cases, typically yielding good performances on a single, predefined task. Hence, narrow AI applications typically lack versatility: due to the limited amount and variety of training data, changing the use case of the AI typically requires re-training a new model with different training data. On the other side, narrow AI application require fewer data points and compute time for training and may thus be re-trained more frequently or continuously trained on new data (i.e., online training). Further, narrow AI models have a smaller number of parameters (i.e., weights, biases) and thus also require less compute time and resources at inference time.

In contrast, broad AI applications such as large language models (LLMs) are sophisticated systems that successfully adapt to different cognitive tasks by virtue of their sensory perception, computational learning, and previous experience (Hochreiter, 2022). LLMs were originally designed as large neural networks trained on vast amounts of textual data collected from the Internet. Recently a number of such large models were trained with multimodal data, including text, images, speech, and video (Bommasani et al., 2022). The resulting broad AI models are good at a wide variety of tasks with the performance being often close to that of specialized narrow AI models (Bommasani et al., 2022). Surprisingly, as LLMs became larger, they also exhibited an increasing number of emergent capabilities that were unpredictable and absent in smaller models (Wei et al., 2022). This has sparked enormous interest in LLMs as potentially a single AI model can be adapted to a wide variety of use cases.

However, even the broadest of current LLMs show severe limitations, such as hallucination (Ji et al., 2023), shortcomings in their capability to reason (Bang et al., 2023), or biases (Tamkin, Brundage, Clark, & Ganguli, 2021). Thus, the term *foundation model* was proposed by researchers at the Human-centered AI (HAI) institute of the Stanford University to better reflect the nature of the multimodal training data and the severe limitations that remain in these models (Bommasani et al., 2022). One famous example of a foundation model is GPT, which has been popularized through a chatbot user interface as ChatGPT. ChatGPT is arguably highly interactive, as the user has to prompt the AI model. Additionally, ChatGPT and other foundation model exhibit the emerging capability of *in-context learning*, meaning they can learn from a small set of examples in the prompt, and apply that context to generate more precise and succinct responses to user's prompt (Bommasani et al., 2022). The capability of in-context learning further reduces adoption obstacles for humans and enables the use of generative AI models in diverse downstream tasks (Bommasani et al., 2022).

2.2 Adaptive Artificial Intelligence

There are several aspects of adaptability of AI. First, AI systems may need to adapt to various tasks. Second, AI systems may need to adapt to a human teammate in the course of completing a task that is jointly performed by an AI-human team. Third, AI systems may need to adapt to varying needs of different users. Fourth, AI systems may need to adapt to other autonomous or human agents in the environment. Finally, AI systems may need to adapt to changes of the environment.

Various Tasks:

Joint Task Completion: As AI becomes ubiquitous, teams are exploring ways to integrate AI agents and robots in their work towards achieving common goals. Zhao, Simmons, and Admoni (2022) distinguish four ways how the AI agents may need to adapt in the context of a team: (1) adaption to goals and intentions of the human teammates; (2) adaptation to cognitive features of the human; (3) adaptation to physical factors of the human in robot-human interactions (e.g., fatigue of the human); and (4) adaptation of learned human models to transfer a learned model to the interaction with another human.

Hauptman, Schelble, McNeese, and Madathil (2023) propose that the role and contribution of AI agents

Different User Needs: Kabudi, Pappas, and Olsen (2021) reviewed the literature regarding learning systems used in education that utilize some form of AI that adapts to the user.

Interactions with Agents: Madeira, Corruble, and Ramalho (2006) have researched the adaptability of AI systems as part of strategy games: the reward functions in reinforcement learning algorithms can be designed to consider the effect of their behavior on other participating agents (Madeira et al., 2006). In a single-agent reinforcement learning setting, the agent is trained based on its actions and the state of the environment. In a multiagent reinforcement learning (MARL) setting, the agent is trained based on the effect of its actions on the environment while consider potential (re)actions of the other agents (Canese et al., 2021). AI models trained through MARL thus show a high adaptability to other agents in the environment. However, MARL applications face challenges which make them hard to use in real-world applications, including limitations in the scalability to settings with large numbers of agents, and the non-stationarity of the environment (Canese et al., 2021). Further, AI in hybrid intelligent systems may also need to adapt to a variety of temporal changes occurring in the environment and in the composition of the group of agents (Akata et al., 2020). Nevertheless, strategy games with a multitude of agents working towards a common goal are an interesting subject as they share some commonalities with enterprises: a group of agents is interacting, and each agent is taking decisions towards reaching a common goal.

Changing Environment: changes in the environment that requires adaptation of an AI system could include societal trends, political or legal changes, etc. To adapt to such changes an AI system can be retrained with newer training data. A common problem observed with machine learning algorithms subject to periodic or continuous retraining (i.e., online training) is model drift: the quality of new data may worsen over time or the distribution of the new data may shift over time, slowly degrading the performance of the machine learning model (Nelson et al., 2015). Thus, while retraining is needed to adapt the AI system to changes in the environment, great care has to be taken to train and evaluate the model with current and high quality data.

Adaptive AI: AI can adapt to user's specific needs. This can be part of a recommender system or a decision support system that adapts according to the input received by users. As such, hybrid AI systems that are loosely coupled can be seen as adaptive AI systems. On the other hand, adaptive AI can also mean that the AI adapts to changes in the environment, be it new data (adapting the AI to new data, i.e., retraining with new or more data or continuous online learning of the AI model) or new use cases (adapting the task of the AI model).

Safety of adaptive AI: it may learn and apply wrong strategies, quality of the incoming data stream may degrade over time, hence degrading the model's performance. Such degrading can be slowly happening over time, so that it is difficult to detect.

Further, highly adaptive systems pose a threat to the explainability of the system, as today's decision from the system might be totally different from the yesterday's decisions, making it hard for humans to understand how the system works.

2.2.1 Hybrid Intelligent Approaches Involving Foundation Models

- Agents
- Mixed architecture, e.g., MRKL (**?**)
- Using the model as IR agent

2.3 Design Principles for Hybrid Intelligent Systems

Hybrid AI systems can be represented by a boxology notation with common design patterns (van Bekkum, de Boer, van Harmelen, Meyer-Vitali, & ten Teije, 2021; van Harmelen & ten Teije, 2019; Witschel, Pande, Martin, Laurenzi, & Hinkelmann, 2021).

Ostheimer, Chowdhury, and Iqbal (2021) developed a framework of eight principles for the design of human-in-the-loop (HITL) computing. They argue that such hybrid systems achieve higher accuracy and reliability of machine learning algorithms. Using a case in the manufacturing industry, they showed that the efficiency of operational processes could be increased by applying an algorithm that followed these design principles (Ostheimer et al., 2021).

Box 1. HITL Computing Design principles (Ostheimer et al., 2021).

1. Principle of client-designer relationship: designers should aim for mutual knowledge exchange with clients to foster the understanding of which aspects of a system are influenced by human or artificial intelligence.
2. Principle of sustainable design: designers should keep up to date with the latest progress in the field of AI and apply the latest and lasting AI techniques.
3. Principle of extended vision
4. Principle of AI-readiness
5. Principle of hybrid intelligence
6. Principle of use-case marketing
7. Principle of power relationship
8. Principle of human-AI trust

2.4 Types of Hybrid Intelligent Systems

- Expert systems
- Decision support systems
- Recommender algorithms with human decision-making
- Case-based reason systems

2.5 Enterprise Competitiveness

@todo: what are the aspects of and factors increasing the competitiveness of enterprises?

2.6 Competitive Advantage Through AI

Xu, Guo, and Huang (2021) found that post COVID-19 companies using AI in their products grew faster than their peers. However, they could not observe evidence of the same effect before COVID-19, indicating that this development is either very recent or was fueled by the COVID crisis. More recently Ho, Gan, Jin, and Le (2022) reviewed the potential benefits of AI for enterprises as reported by selected previous studies published between 2016 and 2021:

- reduced costs
- improved performance
- better decision-making
- higher customer satisfaction
- better customer segmentation
- improved customer experience
- better products & services
- business innovation

Further, Ho et al. (2022) identified several empirical studies that reported a positive, neutral or negative effect of AI on enterprise performance. In particular one study by ...liu et al. (2022)... and cited in Ho et al. (2022) reported negative performance of AI-related adoption announcements on firm market value for 62 listed US companies between 2015-2019.

3 Methodology

The study aimed to investigate the competitive advantage that can arise for an enterprise through the adoption of hybrid intelligent systems. Specifically, the study explored the aspect of adaptability of such hybrid intelligent systems. The study used a mixed-methods approach consisting of a literature review (secondary data) and qualitative data collection from a focus group of 25 graduate students in the FHNW Business Information Systems master program (primary data).

The literature review was conducted to identify factors that contribute to the competitive advantage of enterprises using AI systems in general, and adaptable hybrid intelligent systems in particular. The literature search was mainly conducted on Elicit [1] and Google Scholar [2] using different query terms, including "competitive advantage of AI", "hybrid intelligent system", "expert system", "decision support system", "human-in-the-loop", "competitive advantage and AI", etc. Additionally, a forward and backward search was applied on relevant papers that were identified from the initial literature searches.

The findings from the literature review were used to establish hypotheses on the competitive advantage of adaptable hybrid intelligent systems for enterprises using the example of one industry. Given the background knowledge of the author, the hypotheses were applied to the scientific, technical and medical (STM) publishing industry. To test the derived hypotheses, a focus group of students ($n = 25$) was selected based on their educational background in business information systems. As part of a workshop the focus group was presented with the hypotheses and asked to discuss and provided qualitative feedback for each hypothesis. Participants were encouraged to provide detailed feedback on their experiences and perceptions related to the application of the hypotheses in the industry case. The qualitative data was analyzed using thematic analysis and common themes identified.

4 Results

4.1 Hypotheses

Hypotheses from the literature:

- *"[Humans] overestimate the range of expertise of an automated system and deploy it for tasks at which it is not competent"* (Akata et al., 2020, p. 19)
- *"AI systems [...] were not designed with societal values such as fairness, accountability, and transparency in mind"* (Akata et al., 2020, p. 19)

4.2 Typical Editorial Process

The typical editorial process for a manuscript submitted to a scholarly journal looks like the following:

- Reviewer reads the manuscript.
- Editor makes decision.

4.3 Potential Use Cases For (Hybrid) AI in the Editorial Process

A simplified, typical editorial process – from writing to the final decision – for a manuscript submitted to a scholarly journal is shown in Figure 1. The process includes at least three parties: the author who writes the manuscript, the editor of the journal or conference chair that coordinates the peer-review process, and the peer-reviewers that review and comment on a manuscript. Towards the end of the writing process,

[1] elicit.org
[2] scholar.google.com

the author will start to think about the journal (or conference) where he/she wants to submit the paper to. Once the author identified a journal, the manuscript has to be formatted to meet the submission requirements of the journal.

Table 1 shows an overview of the use cases for hybrid AI systems for each step in the typical editorial process.

@todo: then we can pick those areas where adaptive hybrid AI could be interesting and reason why so...

@todo: then we can pick exactly one adaptive hybrid AI use case, draw 1-2 hypotheses that we can research during the workshop...

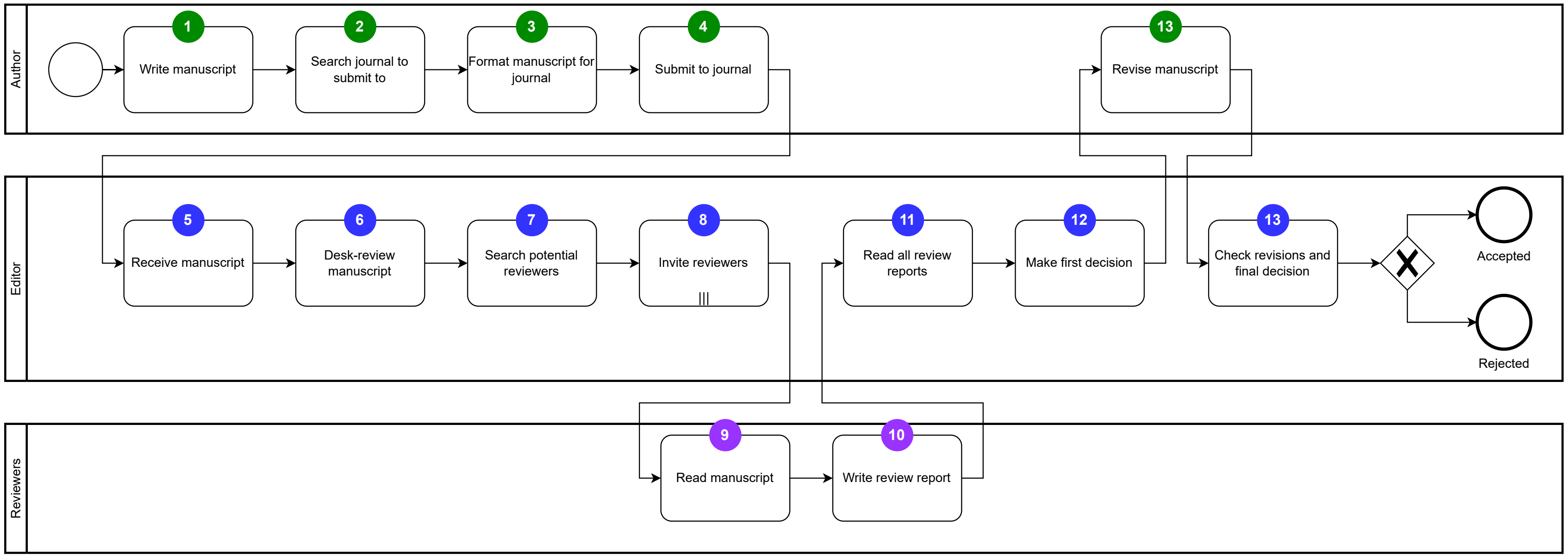

Figure 1: A simplified, typical editorial process from writing the manuscript to the final decision of acceptance or rejection for publication (in BPMN 2.0). For better understanding, the process steps performed by outside parties are also modelled and the process starts with the outside party (author) writing the manuscript. The numbers indicate the sequence flow of the process.

Table 1: Typical editorial processing steps and use cases for (hybrid) AI for a scholarly journal.

Step	**Role**	**Task**	**Use Cases for Hybrid AI**
1	Author	Writes manuscript	AI-aided writing, translating, grammar and spell-checking, AI-aided literature search and literature review
2	Author	Searches for journals to submit to	Decision support system with AI-guided journal recommendation based on word embeddings of the manuscript and knowledge engineering using the academic graph
3	Author	Formats paper to meet journal's requirements	AI-assisted conversion and formatting of manuscript and references, knowledge engineering-based completion of references metadata
4	Author	Submits paper to a journal	AI-aided extraction of metadata from the manuscript file
5	Editor	Receives manuscript submission	AI-generated summary of the manuscript
6	Editor	Conducts desk review of the manuscript	Decision support system with AI-assisted checks of the manuscript, including detecting plagiarism, tortured phrases ("paraphrased plagiarism"), biased or inappropriate language, off-topic references, fabricated or manipulated images, potentially inappropriate authorship, controversial topics, etc. Manuscripts are flagged by problem type, ideally by providing examples from within the manuscript, for the editor to investigate.
7	Editor	Searches for potential reviewers	Decision support system, semantic text similarity search (in vector space using document embeddings), graph embeddings, review assignment algorithms using e.g., knowledge graph to exclude potential reviewers with conflicts of interest
8	Editor	Invites potential reviewers to review	AI-assisted email writing, AI-generated summary of the manuscript
9	Reviewer	Reads the manuscript	AI-assisted summarization of key findings, AI-assisted checking of the content of cited references
10	Reviewer	Writes review report	AI-assisted writing of qualitative review reports (help reviewer to avoid biases, inappropriate feedback, lack of specificity)
11	Editor	Reads all review reports	AI-assisted checking of the quality of the peer-review reports
12	Editor	Makes decision on manuscript	AI-assisted summarization of peer-review outcome for decision letter to author
13	Author	Revises manuscript	AI-assisted checking that reviewer concerns are being addressed, AI-assisted writing of a rebuttal letter to the reviewers & editors

5 Discussion

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Appendix

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