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

Semester Paper

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

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 scholarly 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 scholarly 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 the theoretical background on hybrid intelligent systems and the competitive advantage from AI 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 Theoretical Background

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

2.1 AI and Hybrid 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). This combination of human and machine intelligence is known as *hybrid intelligence*, *augemented intelligence* or *amplified intelligence* (Akata et al., 2020; Schmidt, 2017; L. Zhou et al., 2021). 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). 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). Human-aware AI systems are designed to work alongside humans and must possess the ability to detect, comprehend, and respond to a broad spectrum of human behavioral traits, including but not limited to *"attention, motivation, emotion, creativity, planning, or argumentation."* (Korteling, van de Boer-Visschedijk, Blankendaal, Boonekamp, & Eikelboom, 2021). As the cognitive abilities of human intelligence are limited by the biological substrate as well as the biological and evolutionary origin of intelligence, Korteling et al. (2021) argue the best approach to improve outcomes of AI system is to develop human-aware AI systems that support human decision-making rather than pursuing the goal of Artificial General Intelligence (AGI). This could mean that we continue to stick to *narrow* AI models to develop human-aware AI systems for the foreseeable future (Korteling et al., 2021).

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 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: it is highly interactive, as the user has to prompt for an answer from the AI model and may further interact with the AI model until reaching satisfaction. 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 AI models in a wider spectrum of downstream tasks. In particular, the paradigm shift from *pre-train then fine-tune* towards *prompt-based learning* allows for overcoming the severe limitation of narrow AI applications that often lack sufficient high quality training data (Y. Zhou, Zhao, Shumailov, Mullins, & Gal, 2023). Although foundation models seem to be highly adaptable, they lack to meet the criteria of *explicability* and *explainability* and may thus not meet the definition of a human-aware AI system.

2.2 Adaptive AI

There are several aspects to adaptability of AI systems in the context of human-AI interaction. AI systems may require: adaptation to different users' needs; adaptation to various user tasks; adaptation to human teammates for human-AI joint task completion; adaptation to other autonomous (or human agents); or adaptation to a changing environment.

2.2.1 Different Users' Needs

Different users may want to use an AI system in different ways. As an example, a recommender system should provide recommendations that are pertinent to a particular user. Further, such recommender systems may learn additional feedback from each user by tracking if recommendations that were given to a particular user were followed. Thus, such an AI system may learn and adapt to the needs of each individual user. In particular, recommender systems can leverage graph-based learning techniques by using a graph representation of user-related data (Zhang, Liu, & Gulla, 2023). According to Deng (2022), data in graph representations may include *user-item interactions* (clicks, browsing, views), *side information* (connections to other users, such as followed and following users) and *knowledge*. Such graph learning recommender systems (GLRS) can overcome the cold-start and data sparsity problems commonly observed in recommender systems (Zhang et al., 2023). However, Liao, Sundar, and B. Walther (2022) found that user had more trust in recommender system based on collaborative filtering, regardless of the system's performance.

2.2.2 Various User Tasks

An AI system may need to adapt to different tasks that the user wants to perform. The ability of in-context learning makes foundation model highly adaptable as they do not need task-specific fine-tuning (Brown et al., 2020). This opens the possibility to use foundation models in a wide variety of tasks where only little task-specific training data is available. Yet, the user may have to learn how to effectively prompt a foundation model to obtain the desired results. Dang, Mecke, Lehmann, Goller, and Buschek (2022) have identified *lack of guidance* leading to a trial and error approach, *lack of representation* and *time delays* due to the computational costs as the main challenges for users to effectively prompt generative AI models. Also, users may need to learn completely new strategies such as *chain of thought* prompting (Wei et al., 2023) and *least-to-most* prompting (D. Zhou et al., 2023) to effectively adopt foundation models.

2.2.3 Joint Task Completion

An AI system may adapt to the user in the context of a joint task completion. As AI becomes ubiquitous, teams are exploring ways to integrate AI-based agents and robots in their work towards achieving common goals. Zhao, Simmons, and Admoni (2022) distinguish four ways how such AI agents may need to adapt in the context of a team: adaption to goals and intentions of the human teammates; adaptation to cognitive features of the human; adaptation to physical factors of the human in robot-human interactions (e.g., fatigue of the human); and adaptation of learned human models to transfer a learned model to the interaction with another human. According to Hauptman, Schelble, McNeese, and Madathil (2023) humans were more comfortable with autonomous AI agents during initial phases of the joint work cycle, which has defined work processes and predictable outcomes, while they expressed more concerns in later phases of the work cycle, which deals with more uncertainty and permanent change.

2.2.4 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.

2.2.5 Changing Environment

Societal trends, political or legal changes, etc. can lead to changes in the objectives that AI models were designed for (*concept drift*) or changes in the data distribution (*data drift*) (Lu, Liu, Song, & Zhang, 2020). To adapt to such changes in the environment an AI model can be retrained with training data that reflects the new reality. Another common problem that arises when periodically or continuously retraining (i.e., online training) models is *model drift*: as the quality or distribution of the new data may shift over time, the performance of the model might be slowly degrading (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 detect model drift while accounting for concept drift and data drift by retraining and evaluating models periodically with current *and* high quality data.

2.3 Competitive Advantage Through AI

AI fuels new business models and entire new companies are running on AI (Iansiti & Lakhani, 2020). Traditionally, AI has been used primarily by large enterprises, technology companies and specialized AI start-ups (Davenport, 2018, p. 30-31). While AI is democratizing, e.g., through foundation models such as ChatGPT, it is important for any enterprise to develop AI-related capabilities. Three AI capabilities can be nurtured by enterprises to achieve greater performance: automation of business processes and repetitive tasks through robotics and robotic process automation (RPA); gaining insights from vast amounts of data through machine learning; and AI-based engagement with employees and customers through, e.g., chatbots or intelligent agents (Davenport, 2018, p. 41). Through developing these AI capabilities into AI-based business model innovations, companies can envisage to gain sustained competitive advantage (Sjödin, Parida, Palmié, & Wincent, 2021). To develop AI-based business model innovation, Reim, Åström, and Eriksson (2020) proposed a four-stepped roadmap, where enterprises: first aim to understand AI and capabilities required for digital transformation; second understand their current business model, its potential for innovation and the ecosystem; third develop the AI-related capabilities; and fourth promote organizational acceptance.

As enterprises develop and productionize AI-related capabilities, benefits emerge. Ho, Gan, Jin, and Le (2022) identified the different types of 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; and business innovation. Empirical evidence suggests that companies that adopted AI in their offerings post COVID-19 grew faster than their peers (Xu, Guo, & Huang, 2021). However, in the same study researchers could not observe evidence of the same effect before COVID-19, indicating that this development is fairly recent or was fueled by the COVID crisis (Xu et al., 2021). 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 Lui, Lee, and Ngai (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. According to this study, the stock price dropped 1.77% in average on the day of announcement, while enterprises with weak IT capabilities, low credit score, and operating in non-manufacturing sectors were more heavily affected (Lui et al., 2022). These results suggest that – while AI can boost competitiveness of enterprises – the development of AI-related capabilities might be a lengthy and costly process and that for most companies adopting AI benefits emerged only recently. Enterprises might thus be well advised to have a strategy and action plan in place and start to effectively nurture AI capabilities towards productionizing them into and scaling them as part of the business model.

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 scholarly 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

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

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

This section first gives an overview of a typical editorial process in the setting of scholarly communication. Then, the potential for hybrid intelligent systems (with a focus on adaptability) as part of the editorial process is discussed. Finally, we derive two hypotheses and subject them to qualitative feedback from a group of students in business information systems ($n = 25$).

4.1 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, 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. @todo: textual description of process steps . . .

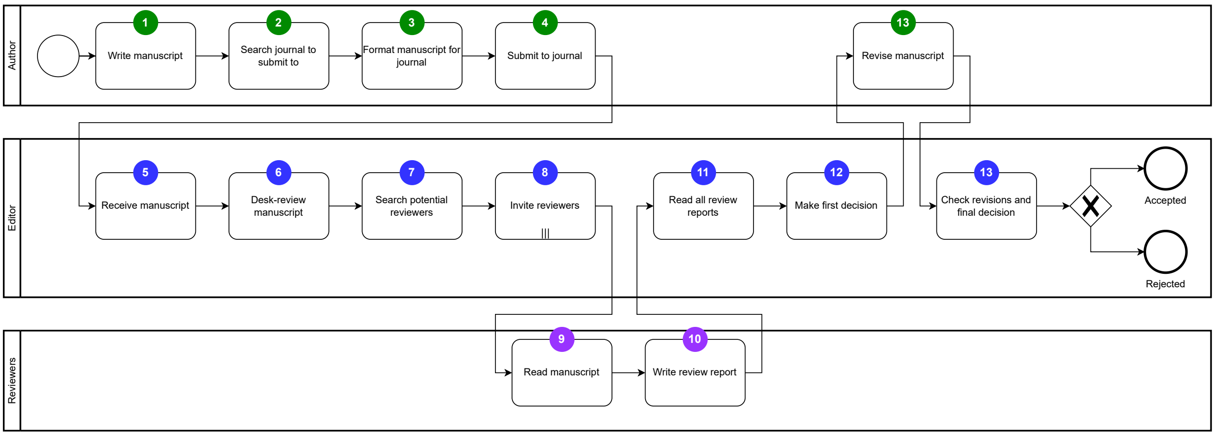

Figure 1: A simplified, typical editorial process from writing the manuscript to the final decision of acceptance or rejection for publication (in BPMN 2.0). For better understanding, the process steps performed by outside parties are also modelled and the process starts with the outside party (author)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

4.2 Use Cases For AI in the Editorial Process

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. . .

4.3 Step XY

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

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

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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