Exploring the Role of Adaptive Hybrid Intelligent Systems on Competitive Advantage Using The Example of Scholarly Publishing

Semester Paper

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Declaration of Authenticity

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I have used some help of a generative AI tool to write this paper. However, the use of the AI tool has been strictly limited to the generation of ideas for sentence completion, aiding at properly paraphrasing cited sources, rewriting sentences for better readability, avoiding grammatical errors, and writing boilerplate LaTeX code. Any generated content has been manually and diligently reviewed and edited by the author to conform to the standards of scholarly communication, and to conceptually fit into the paper and the narrative.

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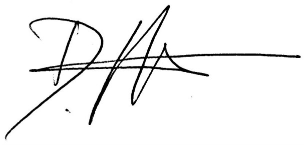


Dietrich Rordorf

Source code and versioning (not yet public):
`https://github.com/rordi/emerging-2023`

Contents

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 types of competitive advantage arising for enterprises that adopt adaptive hybrid intelligent systems using the case of one industry. It answers the following research question: *What types of competitive advantages can arise out of using adaptive, hybrid AI systems in the editorial process of academic publishers?* The paper contributes to the literature by conceptually exploring the research question using the case of the scholarly publishing industry. This could guide future research on competitive advantages of AI involving real-world implementations of adaptive hybrid intelligent systems.

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 ($n = 27$). The literature review identified how adaptive hybrid intelligent systems contribute to competitive advantage of enterprises. This was used to create a categorization of competitive advantages of AI. The focus group was split in 4 subgroups and each presented with a scenario involving an adaptive hybrid intelligent system within the editorial process in scholarly publishing. After being introduced to adaptive and hybrid intelligence and types of competitive advantages of AI, the subgroups were asked to discuss which type of competitive advantage was relevant in the scenario using the categorization.

The findings of this study are fourfold. Firstly, as part of writing research manuscripts, we identified "Improved performance" and "Improved customer experience" as the two main types of competitive advantage. Secondly, as part of finding appropriate journals and formatting a paper according to the journal's style, we identified "Improved performance" and "Reduced costs" as the relevant types of competitive advantage. Thirdly, as part of @todo ... Finally, as part of @todo ... Based on the conceptual nature of this paper, more research is needed to validate the findings in a real-world setting. The findings of this study can be used as a basis to guide further research in the area of competitive advantages that result from the use of adaptive and hybrid intelligent information systems.

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. Further, the editorial process is presented.

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*, *augmented intelligence* or *amplified intelligence* (Akata et al., 2020; Schmidt, 2017; L. Zhou et al., 2021). The tradition 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). Further, 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. Akata et al. (2020) argue that the AI in hybrid intelligence should follow 4 guiding principles, namely that AI in such hybrid systems need to be collaborative, adaptive, responsible, and explainable (CARE). In the next subsection, we will specifically discuss the aspect of adaptability of AI.

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.

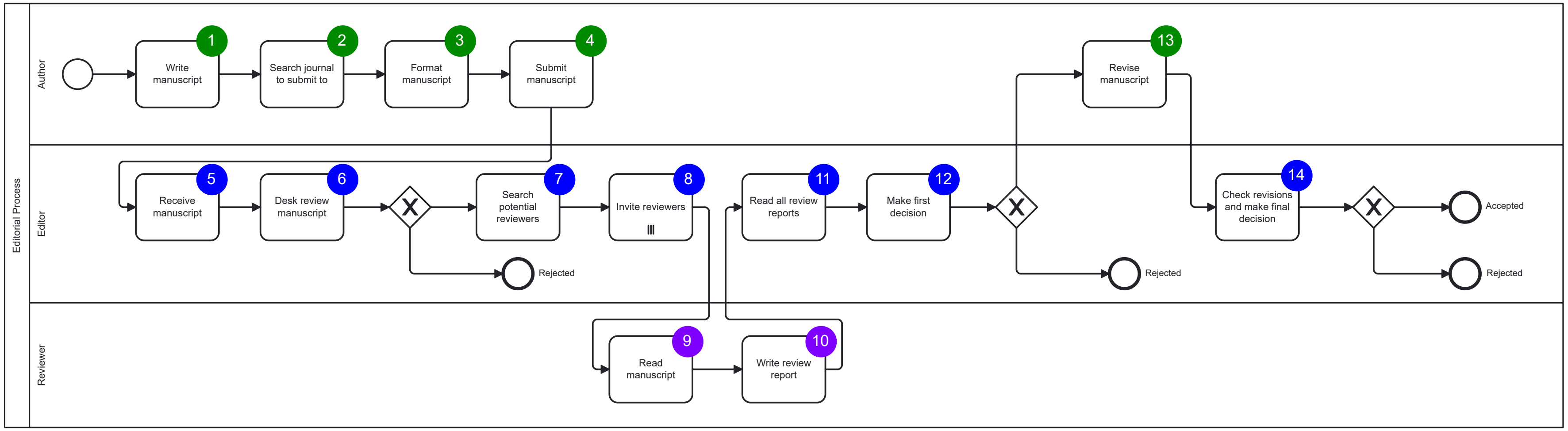
2.4 The Editorial Process

The typical editorial process was described before, e.g., in Faggion (2016). Figure 1 shows a simplified, typical editorial process for a manuscript submitted to a journal, from writing the manuscript to the final decision of acceptance or rejection. 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. For some journals the editor could be two persons: an academic editor, such as an *Editor-in-Chief*, taking the decisions on manuscripts after peer-review, and an internal editorial staff coordinating the editorial process. The typical editorial process involves several steps that must be completed in a particular order. First, the author writes the manuscript with the research results. Once the manuscript is complete, the author searches for an appropriate journal to submit it to. Next, the author formats the manuscript according to the specific instructions of the chosen journal (i.e., as a Microsoft Word or LaTeX document). The author then submits the manuscript files to the journal for consideration and peer-review.

Once the journal receives the manuscript, the editor performs a desk review to assess whether the manuscript meets the journal's requirements and stated scope. If the editor finds that the manuscript could be a good fit for the journal, they will search for potential reviewers who have expertise in the manuscript's subject. Depending on the journal and publisher, this task could be performed by the editorial staff of the journal or by an external academic editor. In cases where the editor is an academic editor, they will typically search for reviewers themselves. In cases where the editor is an internal editorial staff, they will typically use a reviewer recommendation system to search for potential reviewers. Reviewer candidates are typically selected based on their expertise, previous publications, and after checking their conflicts of interests (e.g., if they have co-authored a paper with the author in the past). The editor will then invite reviewers that passed the screening to evaluate the manuscript, i.e., invite them to peer-review the manuscript. If the reviewers accept the invitation, they will be granted access to the manuscript, read it and write a review report that details their feedback and recommendations (typically split into a part addressed to authors, and another part addressed to the editors of the journal).

After all review reports have been received, the editor will read and assess each one. Based on the reviews, the editor will make a first decision on whether to accept, reject, or request revisions to the manuscript. If revisions are required, the author will revise the manuscript according to the review reports and asked to resubmit the revised version to the journal. The editor will then check the revised manuscript and make a final decision on whether to accept it for publication in the journal.

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.



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 27 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 types of 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 ($n = 27$) was selected based on their educational background in business information systems. As part of a workshop the group was split into 4 subgroups and each subgroup was presented with one scenario (see Appendix A.1). The participants were first introduced to the concepts of hybrid intelligent systems, adaptability of AI, and the competitive advantage of AI. Then, they were asked to discuss and provided qualitative feedback for their scenario. In particular, they were asked to discuss which type of competitive advantage was relevant in the scenario. Participants were encouraged to provide detailed feedback on their experiences and perceptions.

4 Results

This section presents the results. Based on the findings from the literature review in Section 2, mostly based on Ho et al. (2022); Iansiti and Lakhani (2020), we define the following dimensions for assessing the competitive advantage of AI systems:

1. Reduced costs: AI streamlines processes and reduces the costs of performing processes.
2. Improved performance: AI improves the performance of the processes.
3. Better decision-making: AI helps with data-driven decision-making.
4. Higher customer satisfaction: AI contributes to higher customer satisfaction.
5. Better customer segmentation: AI helps to better segment and better target customers.
6. Improved customer experience: AI improves the customer experience.
7. Better products & services: AI enables product and service innovations.
8. Business innovation: AI enables new business models.

The types of competitive advantages are subsequently used to assess the potential of adaptive hybrid AI systems. Table 1 shows an overview of potential use cases for hybrid AI for each step in the typical editorial process introduced previously in Section 2. In the following we will focus on 4 areas of use cases,

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

which correspond to the 4 scenarios presented in Appendix A.1. The 4 use cases of AI are focused on the following topics: how can adaptive and hybrid AI contribute to the competitive advantage of an enterprise by (1) facilitating the process of writing a manuscript; (2) helping authors to find appropriate journals to submit to and format the paper according to the journal's style; (3) improving the desk review process; and (4) improving the process of finding peer-reviewers. Each of these 4 domains is discussed in more detail in the following subsections, including presenting the use cases, discussing the competitive advantage for a scholarly publisher of implementing the use case, and contrasting with the qualitative feedback from the focus group participants.

4.1 Writing a Manuscript

Adaptive and Hybrid AI Use Cases

Writing a scholarly manuscript involves several tasks, such as literature search, summarization of key findings, and writing-up the literature review. This is a time-consuming task that requires a lot of effort from the author. Hybrid AI could help to automate aspects of the literature search process. For example, AI could recommend relevant papers based on the authors' previous publications and search history. Whenever the author reads a paper, the author could classify it according to some user-defined criteria, e.g., "relevant", "not relevant", "method", "result" and categorized by topics. Humans would thus steer the classification scheme, while the AI could learn to adapt to the user by identifying relevant papers and classifying them according to the user's preferences. Such an adaptive AI could automatically screen new recent literature to expand the author's collection while continuously collecting additional feedback from the author to refine the recommendations. Finally, when the user writes its manuscript, the AI can recommend relevant papers from the collection based on the context and narrative in the author's manuscript.

Further, the system could remind authors on particular manuscript sections to include, the order of sections, and automatically formatting the manuscript according to the journal's style. Some sections, such as funding, conflict of interest, and data availability statements, could be automatically adjusted to the journal's preferred wording. In case of doubt, the LLM could offer a chatbot interface to answer questions that the author may have about specific format and style issues. The author could thus receive pertinent feedback based on the context of the manuscript and the journal it is being written for.

Another frequent problem in writing the manuscript are language issues. Many scholars are not native English speakers but have to communicate their results in that language, especially in the natural and social sciences. An adaptive AI could help to improve the writing and language quality of manuscripts by providing suggestions for (re)writing sentences. Because the author may have his own preferred style of writing, the AI learns to adapt to the author's style and provide suggestions that are improving the clarity and grammatical correctness of the text, while still following the author's style.

Competitive Advantages

A writing assistant system based on a LLM that helps authors in writing their manuscript could constitute a competitive advantage for publishers as authors could write papers faster. Submission processes for journals could be integrated into the writing process, thereby increasing the process efficiency. A recent study cited in *Nature* estimated that time authors spent on formatting manuscripts could be worth 230 million USD annually (Clotworthy et al., 2023; Kozlov, 2023). A writing assistant system could help to reduce this time and hence increase the efficiency of the writing process. This would also translate into a better customer experience for the author. Using an LLM as a writing assistant could also streamline later peer-review and production processes. As papers that will be submitted to the publisher are in a clearer language, efficient peer-review and decision-making is facilitated. This translates into faster turnaround times and better cost efficiency in the peer-review and subsequent production process (i.e., copy-editing, typesetting, proofreading).

Findings

A group of 6 participants was presented with the first scenario of writing a manuscript and asked to discuss the competitive advantages of such a system based on adaptive hybrid AI. As part of their discussion, the participants mentioned better decision-making (arguing in the perspective of an author): if the literature review is automated by an AI system that can adapt to the users' preferences, the system could help authors to make better decisions on which papers to cite. This would further free up time for authors to focus on the actual content of the paper. This finding does not directly explain a competitive advantage for the publisher. However, as the process is more effective for the author, the author may write more papers and hence submit more manuscripts to the publisher. We could therefore categorize this finding as "Improved performance". Similarly, the participants mentioned that an AI system could act as a writing assistant for foreign language authors by offering automated translations, which they considered to be of type "Improved customer experience".

4.2 Finding Appropriate Journals & Formatting

Adaptive and Hybrid AI Use Cases

When an author has finished writing the manuscript, the next step is to find an appropriate journal to submit the manuscript to. Authors may typically have some journals that they regularly read in mind to potentially submit their paper to. However, given that manuscripts are often rejected after peer-review, an AI system that adapts to the user's preferred journals—yet has the capability to predict which journal is most likely to accept the manuscript—could be a valuable tool for authors to reduce the time to publication. The AI system could learn the author's preferred journals from its previous publications but also from journals typically cited by the author in its previous paper. Additionally, the author could provide input data, such as if the journal needs to be covered in a specific index or if the journal needs to be open access. Further, the AI system can learn patterns of acceptance and rejection of manuscripts in different journals. While data on rejections are not publicly available, the AI system could learn from the author's own previous submissions and rejections. The acceptance, however, can be learned from public data as the accepted manuscripts end up being published, i.e., constitute publicly available data. The AI system could then present a ranking of journals that match with the user's preferences and are most likely to accept the manuscript.

Competitive Advantages

A publisher offering such a journal finder and ranking system to guide authors in finding appropriate journals could have a competitive advantage due to faster publication times and higher customer satisfaction. The faster publication time is due to lower overall probability of rejection, while higher satisfaction is due to fewer rejections and fast time to publication. The AI system could also be used to recommend journals that are not yet on the author's radar. This could be a competitive advantage for the publisher as it could increase the total number of submissions to the publisher's journals, including smaller and more specialized journals. Publishers may also recommend that authors publish their significant or very novel papers in more prestigious journals with higher publication charges (assuming an open access publisher that charges authors for publication).

Findings

A group of 8 participants was presented with the second scenario of finding appropriate journals and adjusting the manuscript to the journal's style. The participants discussed the potential competitive advantages of such a system using adaptive hybrid AI. The group argued that most benefits would be of type "Improved performance" as the system would help authors to find better suited journals and hence reduce rejections. Further, For publishers, this would translate to less editorial work (reduced workload) for peer-reviewing papers that finally get rejected. Further, as the system would format manuscripts according to the journal's style, the publisher has less editing efforts. This was seen as a competitive advantage of both types, "Reduced costs" and "Improved performance". This finding also links back to the writing assistant in scenario 1, as the writing assistant could already format the manuscript according to the journal's style.

4.3 Editor Desk Review

Adaptive and Hybrid AI Use Cases

We now leave the author's perspective and move to the editor's perspectives. After the author has submitted the manuscript, an editor will perform the initial desk review of the manuscript. The editor will check if the manuscript is within the scope of the journal, if it is of sufficient quality, and formatted according to the journal's style. Desk review is an important step as it allows filtering out unsuitable manuscripts early in the process. This saves time and resources for peer-reviewing and editing of manuscripts that will be likely rejected anyway.

Competitive Advantages

Findings

4.4 Finding Peer-Reviewers

Adaptive and Hybrid AI Use Cases

Competitive Advantages

Findings

Table 1: Typical editorial processing steps for a journal manuscript and use cases for adaptive hybrid AI.

Step	**Role / Task**	**AI Use Cases**	**Adaptability Aspect**
1	Author writes manuscript	Literature search, literature recommendation, summarization of key findings, writing (auto-completion), translating, grammar and spell-checking	AI adapts to user by learning what papers are relevant, recommends more similar papers, and expands to related concepts. AI suggests auto-completions and corrections based on the *user's writing style* and the context of the manuscript.
2	Author searches journal to submit to	Journal recommendation	AI adapts to user by learning what journals are relevant to the user (journals read, cited, previously published in) and recommends more similar journals.
3	Author formats paper to meet journal requirements	Manuscript conversion and styling	AI learns styles of journals and adapts its output to the journal selected by user
4	Author submits paper	Extraction of metadata	(Adaptability not required)
5	Editor receives submission	Summarization of key findings	(Adaptability not required)
6	Editor conducts desk review	Checks of the manuscript: detecting plagiarism, tortured phrases, generated papers, bias, inappropriate language, off-topic references, manipulated images, inappropriate authorship, etc.	AI needs to adapt to recent literature (e.g., plagiarism check needs to account for latest literature) and detecting new methods of generating papers.
7	Editor searches potential reviewers	Semantic search (in vector space using word embeddings), graph embeddings, review assignment algorithms using e.g., knowledge graph to exclude potential reviewers with conflicts of interest	AI needs to adapt to recent literature and previous reviewer preferences of the editor
8	Editor invites potential reviewers	E-mail writing, generate summary of the manuscript	AI should learn the user's writing style and typical wording from previous examples.
9	Reviewer reads manuscript	Summarization of key findings, checking of the content of cited references	AI needs to adapt to recent cited literature.
10	Reviewer writes review report	Writing (auto-completion) of qualitative review report: help reviewer to avoid biases, inappropriate feedback, lack of specificity	(Adaptability not required)
11	Editor reads review reports	Checking of the quality of the peer-review report: detect biases, inappropriate language, generic / non-specific feedback, ad hominem criticism, off-topic comments, etc.	(Adaptability not required)
12	Editor makes decision	Summarization of peer-review outcome for decision letter to author	AI should learn the user's writing style and typical wording from previous examples.
13	Author revises manuscript	Checking that reviewer concerns are being addressed, writing (auto-completion) of rebuttal letter to the reviewers & editors	AI should learn the user's writing style and typical wording from previous examples.

5 Discussion

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A Appendix

A.1 Scenarios and Raw Data

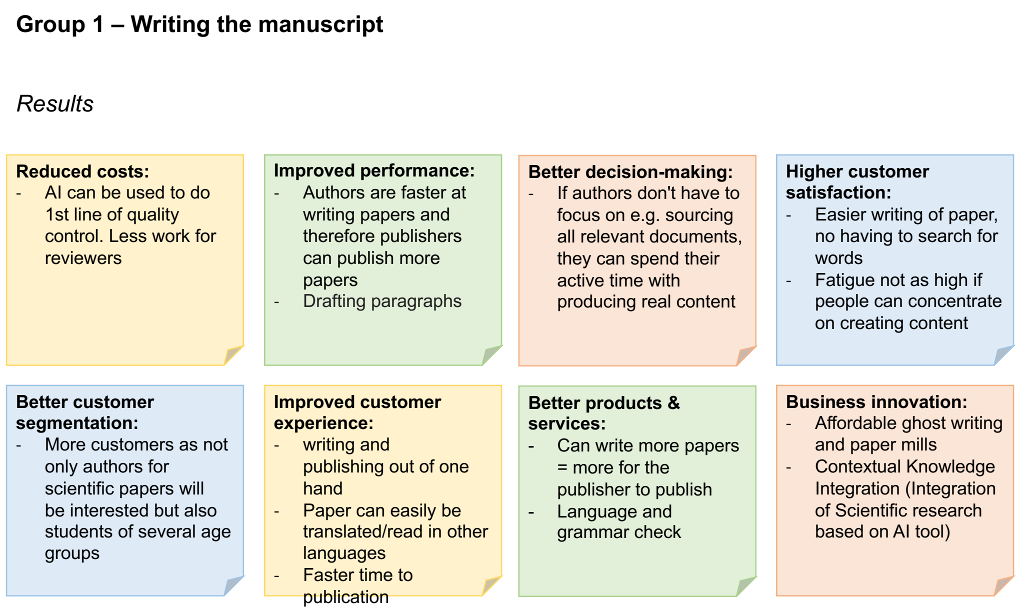
The following scenarios were presented to information systems students to evaluate the types of competitive advantages that could arise from using adaptive hybrid intelligence in the context of the described scenario. The students were first introduced to adaptive hybrid intelligence and competitive advantages for enterprises from using AI. Then, they were asked to discuss the following scenarios in groups of 6-7 students and to record their thoughts

A.1.1 Scenario 1: Writing Manuscripts

Scenario: Web-based platforms for authors to write their manuscript is typically not part of the offering of publishers. Let's now assume that a publisher would launch a tooling that allows authors to write their papers on the publisher's platform. The publisher could support authors by deploying adaptive AI tools—similar to GitHub Copilot for coding—to write the scientific manuscript. How and why should the tool be a hybrid AI that adapts to the author? How can it adapt to the author? How would such a system bring a competitive advantage to publishers?

Results: The results for this scenario are shown in Figure 2.

Figure 2: Scenario 1: Writing Manuscripts

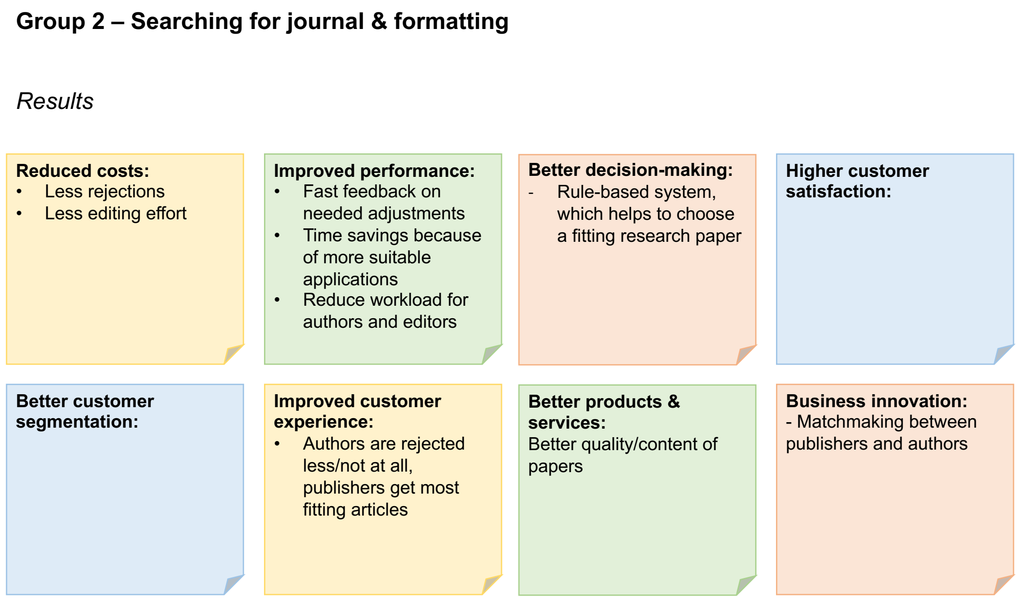


A.1.2 Scenario 2: Finding Journals & Formatting Manuscripts

Scenario: There are 1000s of journals—alone 260 journals contain "information systems" in the title. Imagine you are an author and just finished writing your manuscript. You are now looking at options where you could publish your manuscript. How and why could an adaptive, hybrid AI system support you as the author in recommending suitable journals—considering that you may have specific wishes (maybe a journal in information system that accept more technical contributions, or with authors predominantly from the D-A-CH region, or a journal published in German). As an author you will typically also be asked to comply with the style of the journal that you chose. How can it adapt to or learn from the author (e.g., history of previous recommendations)? How would such a system bring a competitive advantage to publishers? Think of reformatting the manuscript, if the author was rejected in another journal and now resubmits to your journal.

Results: The results for this scenario are shown in Figure 3.

Figure 3: Scenario 2: Finding Journals & Formatting Manuscripts



A.1.3 Scenario 3: Desk Review of Manuscripts

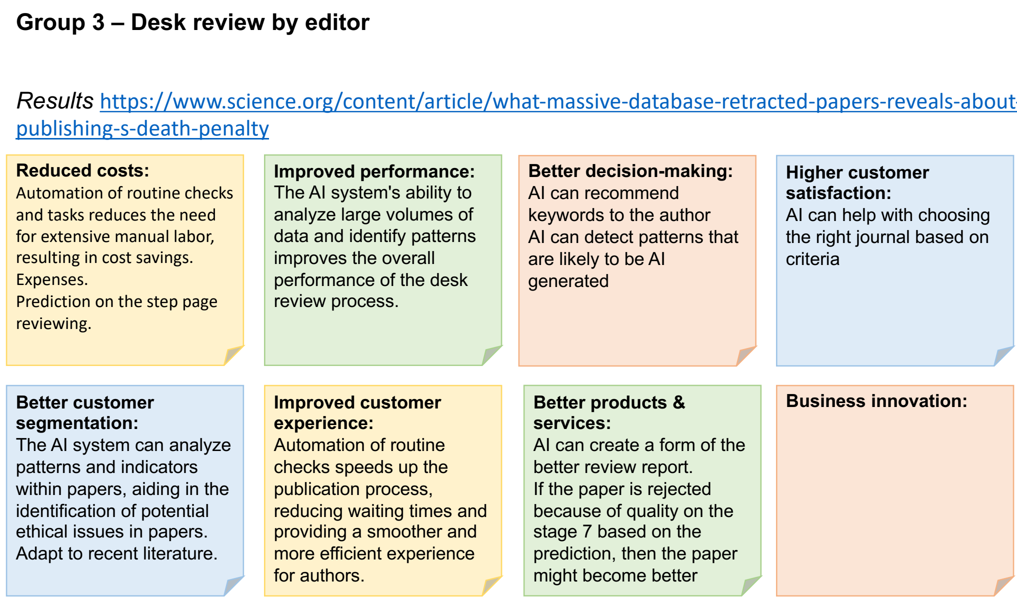
Scenario: As part of desk review, editors are confronted with an increasing number of ethical problems. This could be completely fake (AI generated) papers, authorship issues (adding authors that did not contribute to the manuscript), fabricated images and data, citation to references that are irrelevant to the work, etc. Doing these checks manually is laborious. Yet, automating with narrow AI is difficult as there are only few data examples (there are may be few hundred papers known for each of the ethical cases). How could a hybrid, adaptive AI system support the editor in this task of desk review? To what does the AI need to adapt and why? How would such an adaptive, hybrid AI system contribute to the competitive advantage of the company?

Results: The results for this scenario are shown in Figure 4.

A.1.4 Scenario 4: Finding Reviewers

Scenario: Once a manuscript passes desk review, the editors will send it to peer-review. To effectively peer-review a manuscript, the editor will need to find subject experts that have previous experience with the type of research reported in the manuscript. A hybrid, adaptive AI system could be employed to recommend suitable reviewers. The editor may have additional rules for the selection of candidate reviewers (i.e., rules engineering or symbolic AI). How could a hybrid AI combine sub-symbolic (e.g., word embeddings in vector space) and symbolic approaches (rules), and how does such a system need

Figure 4: Scenario 3: Desk Review of Manuscripts



to adapt? Hints: think of ca. November 2019 and early 2020 when the COVID pandemic hit. Think of someone retiring. Think of a user that rejects certain recommendations. How would such a system help the company to gain a competitive advantage?

Results: The results for this scenario are shown in Figure 5.

Figure 5: Scenario 4: Finding Reviewers