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Procedia Computer Science 280 (2026) 320–326

Procedia Computer Science

www.elsevier.com/locate/procedia

The 17th International Conference on Ambient Systems, Networks and Technologies (ANT)
April 14-16, 2026, Istanbul, Türkiye

On the creation of value achieved by harnessing large language models

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Abstract

With the emergence of ChatGPT, large language models (LLMs) have gotten considerable attention from industry and academia alike. While there are numerous publications that describe the use of LLMs in different scenarios, the discussion regarding its actual utility from an organizational perspective is currently rather limited. Yet, for a technology to strive long-term and justify its utilization, it needs to provide tangible benefits to its users or their organizations. To bridge this gap, the publication at hand discusses how the harnessing of LLMs can create value for organizations and what is necessary to better support decision makers in assessing whether they want to integrate LLMs into their organization's processes and, if so, in which capacity and to which extent. Further, a case study approach to analyze the economic impact of LLMs is suggested.

Keywords: Large language model; LLM; Value creation; Organizational value; Case study

1. Introduction

Since ChatGPT emerged in 2022 [1], large language models (LLMs) have gotten considerable attention by researchers and practitioners [2, 3] and across many domains and tasks [4–9], ranging from office-work to manufacturing. Their ability to create complex and high-quality texts based on provided inputs positions them as a

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potentially valuable tool to support in numerous tasks or even to automatically carry them out. Hereby, they can, for instance, help in creating texts, summarizing data from different sources, cleaning and transforming data, translating texts, annotating data, or facilitate the interaction with data by providing a user-friendly chat interface [10]. Nevertheless, despite these positives, a considerable challenge with LLMs is the user's trust in them, respectively the results they produce [11]. While many factors (can) play into this, two important ones are their black-box nature [12] and their tendency to produce so-called hallucinations, where they create and confidently present statements that are not based on facts and, instead, made-up [13, 14]. This, in turn, constitutes an issue for many use cases for LLMs, where outputting truthful information is required to make such a tool beneficial. However, the issue can be addressed through retrieval augmented generation (RAG), where the LLM is supplemented with additional information that can be curated beforehand, thus, basing the outputs on a reliable knowledge-base [15]. Together with LLMs' ability to create texts whose quality is perceived as human-like [16] as well as their inherent flexibility [7], since they do not necessarily require specifically structured inputs or specific commands, especially RAG-based LLMs promise significant value to those organizations that meaningfully integrate them into their suitable operations.

Therefore, the publication at hand is dedicated to the relation between organizations' use of LLMs and their productivity. This, in turn, can support decision makers in their assessment, whether they want to integrate LLMs into their organization's processes and, if so, in which capacity and to which extent, thereby, supporting a more informed decision making.

2. LLMs and their impact on organizational value creation

Due to their capabilities, LLMs can support organizations' operations in many different ways. While it is neither intended nor possible to give a comprehensive overview of all possible application areas in the scope of this work (and the references given are also only exemplary and by no means exhaustive), in the following, at least a somewhat representative outline of ways shall be given, how the use of LLMs can create value for organizations.

A very popular use of them is as chatbots, where they excel with their versatility and are frequently employed to interact with external clients [3, 7, 17–19] or for the communication with patients in the healthcare sector [3, 7, 17, 18]. Hereby, they can on the one hand relieve existing employees such as personnel in product support or doctors and nurses in a medical setting by answering standard requests, thus freeing them up for other tasks, since they only need to be consulted for more complicated cases. On the other hand, LLM chatbots can also be used to provide new contact opportunities that were previously not offered and that are available around the clock regardless of weekends or public holidays.

Another use is as a personal assistant to draft emails and schedule appointments to save some time that can be spent more productively in other areas [17–19]. Yet, besides just reducing the time expenditure, the support for emails can also unlock new capabilities because a well-designed setup can enable a higher degree of customization for use cases such as crafting marketing emails. Instead of sending everyone the same text, available background information can be used to make them more personal, in hopes of increasing their appeal [19]. While this would be, theoretically, also be possible in a manual way, the associated time expenditure would usually be prohibitive.

Similarly, LLMs are highly suited for crafting (drafts for) documents (e.g., reports that draw from widespread information) and presentations, formulate well-articulated product descriptions from provided details, or for creating contents for social media and websites, thus reducing the involved manual effort [3, 7, 17–19]. Besides creating documents and other content, LLMs also have a role in their translation [3, 17], which can oftentimes be a very time-consuming task, especially when multiple languages are involved. Further, in the latter case, the manual way potentially also requires the involvement and coordination of numerous employees for covering all required languages, which can be circumvented through automation, saving time and resources.

Another big application area is in software development [17–22]. Here, numerous tasks can be handled or supported through LLMs. These are, for instance, code and test generation, code auto-completion, the detection of errors, code smells and duplicates, refactoring, the translation of code from one programming language in another one, or the creation of documentation for existing or newly created code. Besides the immediate increase in productivity that is sought after, especially the latter capabilities can also increase maintainability and help to avoid and counteract the emergence of legacy systems with their inherent challenges and issues [23].

Due to their characteristics, LLMs are also used for numerous tasks when it comes to the processing of data. They are used as an easily usable interface to access data [24–28], eliminating the need to know how to deal with specific tools (e.g., SQL databases) in favor of a natural-language-based approach. Further, they can create analyses and summarizations of data [3, 7, 17–19] that would otherwise take a long time and a lot of effort to compile as well as high-quality annotations of data and information [16, 29], increasing their accessibility. Besides that, they also find use for providing predictions based on the available information [3, 7]. Therefore, they can be valuable tools across a plethora of organizational processes and are often harnessed in the context of decision support systems [17, 18, 30]. Hereby, LLMs can not only impact the processes themselves but indirectly also the employees that are performing them, since they also find use in human resources departments and recruitment processes, where they can help to deal with massive amounts of employee and applicant data as well as with other tasks that relieve the department's employees [18].

Also in the realm of the workforce is the use of LLMs when it comes to training the employees [3, 17, 19, 22, 31]. The tools can, for instance, help learners by answering questions, creating tasks and corresponding solutions, providing feedback, and acting as personal tutors but they can also be harnessed for preparing training materials (e.g., exercises or presentations). As for other use cases, this can on the one hand help to relieve the personnel responsible, allowing them to focus on other tasks, and on the other hand, it enables the creation of additional offerings as well as the expansion of service times. While the use for training purposes is, naturally, more common in the actual educational sector, especially in the context of universities [32–36], companies and other organizations can also greatly benefit from these capabilities when it comes to upskilling their workforce.

Further, and especially interesting for manufacturing companies, LLMs can not only be used to access different systems to query data, but also to steer machinery and robots via natural language [8]. This, in turn, can potentially greatly increase accessibility, making their use generally easier and more intuitive. It can also help avoiding the need to familiarize oneself with various steering schemes if a single worker is required to operate multiple different machines that might even be from several different brands. Thus, the need for training could be reduced while enlarging the available pool of eligible workers and increasing the general flexibility of the staff. Additionally, the importance of a machine's ease of use could be reduced, which allows for the prioritization of other aspects during the planning of factories and the procurement of machines.

3. Proposed case study approach

Through a case study, one could conduct a detailed analysis of the economic impact that LLMs have on business operations. The foundation for our proposed experimental approach is a comprehensive structural model of the respective enterprise architecture, as exemplarily shown in Fig. 1 [37–39]. The integration of LLM services into existing business processes will allow to pinpoint which business activities are directly or indirectly influenced by LLMs, such as decision-making, customer support, and data processing. This step involves mapping LLM capabilities to relevant business activities and assessing potential improvements in efficiency, accuracy, and cost. It is not entirely feasible to identify all potential LLM use cases at the outset, given the technology's evolving nature and the complexity of business processes. Therefore, we propose an iterative approach that regularly reviews current LLM deployments, solicits stakeholder feedback, and continuously scans for new LLM applications as they emerge within the enterprise. In the beginning, the most promising and applicable initial instance of LLM services for integration into specific business processes are selected. These pilot implementations will serve both as models for further adoptions and as opportunities to measure concrete economic outcomes, allowing to refine our approach based on the lessons learned from these initial cases.

In the following section, we elaborate on the iterative approach to integrating LLM applications within enterprise business processes. The initial step entails a comprehensive identification and meticulous documentation of all existing business processes encompassed by the enterprise architecture. This ensures that each process is thoroughly delineated and its objectives, workflows, and stakeholders are fully understood. Subsequently, the focus shifts to systematically identifying and analyzing potential use cases in which LLM technology could be embedded within the mapped business processes. This involves evaluating and prioritizing processes that stand to gain the greatest value from LLM integration, with an emphasis placed on articulating the functional roles and specific integration points for the technology within each process.

At this stage, it is essential to assess the organization's technological and operational landscape to determine the feasibility of implementing controlled experimental interventions. These interventions involve running targeted business processes both with and without the LLM service, thus allowing for a comparative analysis. The experimental design requires a clear demarcation of the experimental and control groups and the establishment of standardized experimental conditions, thereby minimizing bias and ensuring the validity and reliability of benchmarking outcomes. Implementation follows, wherein LLM applications are judiciously integrated into the designated business processes in accordance with the experimental plan. Parallel to this, a comprehensive approach to performance measurement must be formulated, encompassing the selection of relevant Key Performance Indicators (KPIs) and the institution of rigorous data collection protocols to secure data integrity and accuracy. After conducting the experiments, collected quantitative and qualitative data should be analyzed to compare the efficacy of LLM-integrated processes against traditional workflows. Both statistical and thematic analyses may be employed to elucidate the impact and value added by the LLM services.

Based on a critical evaluation of experimental results, a well-substantiated determination can be made regarding the further adoption, expansion, or refinement of LLM services within future business process management strategies, thereby fostering evidence-based decision-making and continuous organizational improvement.

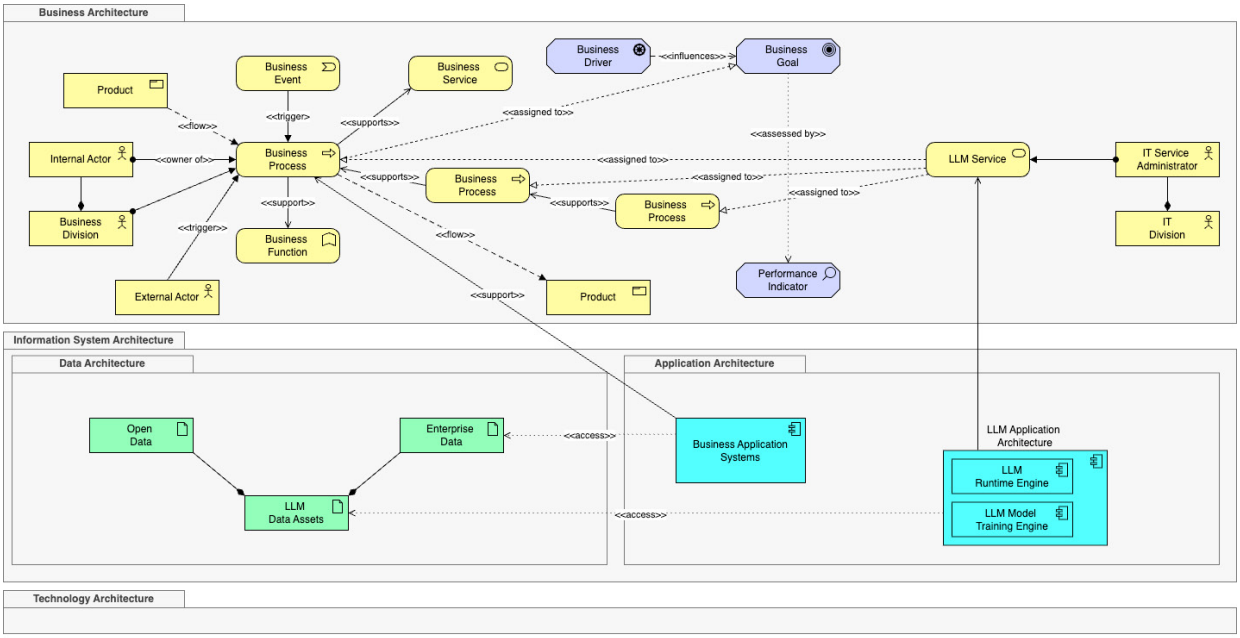

Fig. 1. An exemplary structural model of an enterprise architecture.

4. Discussion

While the overview provided above is explicitly non-exhaustive and neither covers all conceivable use cases nor the entirety of the related literature, it provides a general overview of the domain that provides some insights. As evidenced by the reports, even though LLMs still have significant weaknesses [17, 18], their ability to process and generate texts can be harnessed in numerous use cases [18, 22]. Hereby, especially those, where absolute correctness is not required or where humans check the results before further processing are positioned to benefit from LLMs [18], since their use can significantly free up the employees' time, allowing them to invest it in other places, potentially creating additional value. Thus, they can also help to address a lack of qualified experts for certain tasks by relieving the available ones [40]. Further, LLMs also enable the creation of new products and services [19, 41] or the development of new target groups and markets [25–27]. However, across the publications, the reporting of these benefits comes with a significant limitation.

Based on the high interest in their adoption and anecdotal reports [18, 42–46], it can be assumed that the purposeful use of LLMs is beneficial for organizations. Yet, while some studies address the general topic [3, 18], comprehensive studies determining concrete numbers for, for instance, organizational productivity increases, as they exist for other domains such as big data [47] are still missing. These would, however, greatly support decision makers in determining in which settings and for which use cases the adoption of LLMs should be promoted to obtain maximum benefits for their organization.

Therefore, in addition to conducting company specific analyses as outlined in Section 3, in general, future publications should, whenever possible, aim to provide as many objective economic and productivity measures as possible. These could for instance include but are not necessarily limited to implementation and operational costs, percentual productivity increases, concrete cost savings through effects of LLM-use on costs, impacts on revenue or profit, or the impact on training times. Moreover, interview and survey studies exploring these aspects could also help to further the understanding of the implications of employing LLMs. Subsequently, all these findings should, as far as possible, be integrated into a comprehensive analysis of the effects based on factors such as application domain, type of task, geographical region, characteristics of the users, type of LLM and similar aspects that might potentially be relevant. This, in turn, could help decision makers to better understand the impact that LLMs can have on organizations under different circumstances, thereby allowing for more informed decisions when it comes to the corresponding strategy crafting. Further, this added knowledge can also support researchers in steering their work towards the most meaningful directions, increasing the impact of their work.

5. Conclusion

The emergence of ChatGPT and the following developments in the realm of LLMs provided organizations with a new and versatile tool to enhance their processes in many ways. Consequently, there is a huge number of scientific publications dedicated to the field. Without claiming exhaustiveness, the paper at hand provided an overview of tasks, for which LLMs can be incorporated into organizations' operations. Hereby, a multitude of domains and environments were covered, further emphasizing LLMs' far-reaching utility. However, while several papers address the benefits that LLMs can provide, which is already valuable in its own, to help decision makers and potential users to inform themselves of the possibilities, a more comprehensive and quantified perspective on the matter is still mostly missing. Therefore, it was also outlined why providing it would be significant to practitioners and researchers alike, and how the pathway for doing so could look like.

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