Towards Enhanced E-Learning Within MOOCs: Exploring the Capabilities of Generative Artificial Intelligence

Completed Research Paper

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Abstract

Massive open online courses (MOOCs) have significantly transformed e-learning by providing global accessibility, collaborative learning opportunities, and high-quality educational content. However, MOOCs face limitations such as limited social interaction, delayed feedback, and linguistic barriers. To overcome these challenges, there is a growing interest in research to leverage artificial intelligence (AI) technologies. In this study, we conduct a systematic literature review examining the capabilities of generative AI (GenAI) and its implications for e-learning in MOOCs. We identify ten capabilities of GenAI, including analytical processing, generative, (personalized) assistant, support, feedback, assessment, communication, reflection, adaptivity, and accessibility. The findings highlight GenAI's potential to overcome challenges in MOOCs by providing insightful and contextually relevant responses, generating new content, facilitating multilingual interactions, and enhancing the overall e-learning experience. We therefore contribute to the broader understanding of GenAI's impact on e-learning and suggest avenues for future research on GenAI and its integration in MOOCs.

Keywords: E-Learning, Massive Open Online Courses, Generative Artificial Intelligence, Capabilities

Introduction

The advent of the World Wide Web and technological advancement has led to the establishment of e-learning as a way of teaching people skills online (Kooli, 2023). Consequently, e-learning has witnessed a gradual shift towards massive open online courses (MOOCs) as a prominent educational platform (Mutiga, 2023; Sadhasivam, 2014) owing to their ubiquitous accessibility, collaborative learning opportunities, and the ability to provide high-quality educational content to globally dispersed learners (Hew & Cheung, 2014; Topali et al., 2021). Due to increased demand for cost-effective education and training in business and academia (Cornejo-Velazquez, 2020), renowned international organizations and companies have partially switched their course offering to MOOCs. Thus platforms, such as Udemy, Coursera, and Udacity, are successfully building up millions of enrollments (Hermawan, 2021). Besides several advantages, such as the availability to a large group of learners at the same time and the reduction of personnel for the actual delivery of course concepts, there are also several disadvantages (Hassan, 2022) originating from MOOCs' characteristics: a huge diversity and an impersonal nature (Borras-Gene et al., 2016; Topali et al., 2021). In conventional educational settings, interpersonal engagements occur between instructors and students, facilitating feedback provision and assistance, as well as fostering reflective processes on acquired knowledge (e.g., McPherson & Nunes, 2004; Roepnack, 2020). Conversely, MOOCs exhibit deficiencies in social interactions, as noted by various studies (Jung et al., 2019; J. Lin, 2023; McCarthy et al., 2021; Wei & Taecharungroj, 2022). Another limitation of e-learning within MOOCs originates in the absence of immediate and direct feedback (Jung et al., 2019). Learners are confronted with either automated assessments or delayed responses to their inputs, necessitating patience for feedback from instructors. This delay not only impedes the learning process but also has the potential to undermine learners' motivation

(Islam et al., 2015). Nevertheless, these automated assessments apply solely to multiple-choice tasks, while free-form texts mark a major issue (Bai & Stede, 2023). Additionally, linguistic barriers pose a challenge in MOOCs, particularly in the context of non-native English-speaking tutors delivering content swiftly (Khalaf & Al Athali, 2020). This challenge further complicates the interaction between tutors and multilingual learners, impacting the effectiveness of the learning experience. Consequently, this creates difficulties in comprehension as learners may struggle to understand taught course concepts (Khalaf & Al Athali, 2020).

To mitigate those challenges within MOOCs, research introduced diverse solutions, encompassing gamification (e.g., Borras-Gene et al., 2016), machine learning (ML) for dropout prediction (e.g., Jin, 2023), chatbot-assisted tutoring systems (e.g., Tauqeer et al., 2021), and multimedia educational strategies to decrease cognitive load (e.g., Mutlu-Bayraktar et al., 2019). Furthermore, the personalized learning approach has been increasingly highlighted as a crucial area of focus to accommodate individual learning preferences (Sharef et al., 2021). Nowadays, due to recent technological developments in the realm of natural language processing (NLP), there is a growing interest in leveraging (generative) artificial intelligence (AI) technologies to enhance the e-learning environment within MOOCs. One promising generative AI (GenAI) technology that has gained significant attention in the last years is ChatGPT, a Large Language Model (LLM) based on the GPT-3.5 architecture developed by OpenAI (2022). ChatGPT utilizes advanced NLP and natural language understanding (NLU) techniques, powered by generative pre-trained transformer (GPT) models, to analyze complex information in user prompts and to provide human-like responses to learners' inquiries (Bender, 2023; Brown et al., 2020; Geerling et al., 2023). It accepts requests in natural language and responds in a way that gives the user the feeling of communicating with a real person (Iskender, 2023; Shoufan, 2023). Recent research has shown that challenges of e-learning in MOOCs can be (partially) solved with the help of generative NLP (Farrokhnia et al., 2024; Fergus et al., 2023; Singh & Singh, 2023). For instance, Bai & Stede (2023) illustrate the efficacy of advanced NLP technologies in automating the assessment of free-form texts, a notably more complex and time-consuming task compared to multiple-choice evaluations. From an educational standpoint, free-form text tasks are particularly valuable as they promote deeper learning by requiring students to construct their own responses and articulate their problem-solving processes (Rasul et al., 2023). Despite the large body of recent research on GenAI and LLMs, particularly regarding the application of ChatGPT in e-learning, there remains a notable gap in the literature concerning a holistic conceptualization of GenAI's visible and invisible capabilities. Current studies tend to concentrate on distinct e-learning areas such as assessment (e.g., Hsiao et al., 2023; Rai et al., 2023), feedback mechanisms (e.g., Dai et al., 2023; Katz et al., 2023), or AI-facilitated content creation (e.g., Bozkurt & Sharma, 2023; B. Li et al., 2023). Moreover, current research often focuses on GenAI as the primary object of study rather than as a representation of broader, underlying phenomena (Flanagin, 2020). This approach, however, overlooks the essential "capabilities that span technologies" (Flanagin, 2020, p. 23), underscoring the need for a comprehensive framework that encapsulates both the visible and invisible capabilities to guide researchers and practitioners in the integration and optimization of GenAI to enhance e-learning contexts. Shoufan (2023) reinforces this gap, emphasizing the significant impact that a well-rounded understanding of GenAI's capabilities could have on enhancing e-learning environments. As experts predict, AI technologies are poised to become a fundamental component of educational systems shortly (Motlagh et al., 2023), further underscoring the urgency for a conceptual exploration of underlying capabilities. We address this research gap by means of a systematic literature review (SLR) to identify and inductively derive the visible and invisible capabilities of GenAI and its implications for enhanced e-learning in MOOCs. We strive to answer the following research question (RQ):

RQ: Which specific capabilities characterize GenAI and how can they be harnessed to mitigate existing challenges in MOOCs to enhance e-learning?

To answer the RQ and respond to recent calls on how GenAI's "unique capabilities [...] can be exploited" (Dwivedi et al., 2023, p. 56) to facilitate an "enhanced student learning experience" (Dwivedi et al., 2023, p. 54), we conducted an SLR and identified 86 relevant articles from five academic databases. Based on this corpus, we applied knowledge-building activities (Schryen et al., 2020), including synthesizing, aggregating evidence, and identifying research gaps to inductively derive overarching capabilities of GenAI in the realm of e-learning and to identify avenues for future research. This study's contribution is two-fold: First, we provide a state-of-the-art literature review that contributes to the development of a shared body of knowledge on GenAI and its disruptive impact on e-learning (Singh & Singh, 2023). In doing so, we identify and theorize the broader implications of GenAI in fostering an adaptive and interactive learning environment that goes beyond the conventional use-cases and develop a capability-driven framework. Second, we propose avenues for future research, especially related to the integration of LLMs into MOOCs. We therefore contribute to the literature on e-learning and Information Systems (IS) by highlighting key capabilities of GenAI and their potential improvements toward enhanced e-learning experiences in MOOCs.

Theoretical Foundations

E-learning is a common approach to imparting knowledge electronically (Hammad et al., 2018). Even though a universally accepted definition of e-learning is still elusive, it is understood as the provision of learning materials by means of digital multimedia use and the Internet (European Commission, 2001). Especially in the last decade, the use of digital media has increased (Steinbeck et al., 2019). Within these digital learning offerings, there are several ways of imparting knowledge, e.g., by providing videos, audio transcripts, or slides (Çakiroğlu et al., 2020; Mayer & Moreno, 2003). Various studies have shown that e-learning leads to higher learning success among participants than traditional face-to-face methods (Mastour et al., 2023). This can be traced back to the fact, that the provision of learning formats in multimedia formats is claimed to support the learning processes in the human brain[i] (Mutlu-Bayraktar et al., 2019; Sweller, 2016, 2020). Thus, e-learning formats provide several benefits for learning design. A great advantage of e-learning offerings is the flexibility they offer, as the participants can work self-contained, where and whenever they want (Jung et al., 2019; Tîrziu & Vrabie, 2015). Furthermore, e-learning offers the possibility to individualize learning, as in terms of adaptive environments the courses can be adapted according to the knowledge level or learning types of participants (Holliman et al., 2018; Jung et al., 2019). Additionally, e-learning offerings help to overcome the constraints of traditional classroom teaching concepts, as there are no (or at least just a few) limits for participation (Jung et al., 2019; Shah et al., 2021). This is particularly true for MOOCs (García Fernández et al., 2018; Yang & Wei, 2023), which have been conceptualized to democratize education and thus aim at proposing learning content to a large number of learners via online platforms (Moreno-Marcos et al., 2019; Oh et al., 2020). As a huge number of learners enter MOOCs, there is a vast amount of information to be obtained regarding their behavior within the MOOC (J. Lin, 2023; Moreno-Marcos et al., 2019). These huge amounts of data that are collected and stored offer the possibility to be utilized and analyzed within the context of AI, whose models need to be trained on large data sets (Brown et al., 2020; Lund & Ting, 2023; Moreno-Marcos et al., 2019). Despite the advantages inherent in MOOCs, low completion rates of between six to ten percent imply (Sümer & Aydın, 2022), at least in part, a prevailing existence of shortcomings. These shortcomings comprise the lack of teaching aid (Jin, 2023), feedback (Jung et al., 2019), and the lack of interaction with other learners (Jung et al., 2019; Wei & Taecharungroj, 2022). Recent research has pinpointed several areas for AI-enabled enhancement within MOOCs, categorized across three dimensions: instructor, course, and learner (Wei & Taecharungroj, 2022). At the instructor level, the focus is on enhancing support, delivery quality, and student-instructor interactions. For instructors in MOOCs, repetitive and administrative tasks are time-consuming and block the capacity for more fruitful interaction with learners (Motlagh et al., 2023; Tonbuloğlu, 2023). To address this, research has explored the utilization of GenAI to augment or even replace the instructor's role with virtual instructors in asynchronous MOOCs (e.g., X. Lin, 2023; Pataranutaporn et al., 2022). This includes employing GenAI to improve instructor-student interactions (e.g., Su & Yang, 2023), which is positively related to the perceived usability of MOOCs and which might lead to higher completion rates (Tao et al., 2022), simulating student interactions for instructor training (e.g., Markel et al., 2023), and providing automated recommendations to instructors on student performance and potential dropout risks (e.g., Ahmad et al., 2024; Sharef et al., 2021). At the course level, the emphasis lays on enhancing course content, structure, and assessment in MOOCs. Developing and structuring online courses, along with effectively integrating multimedia, are notable challenges (Tonbuloğlu, 2023). To address these issues, research has investigated the use of GenAI for preparing and creating course materials such as videos, questions, and assessments (e.g., Bozkurt & Sharma, 2023; Ruiz-Rojas et al., 2023; Santhosh et al., 2023), managing course administration tasks such as automated forum postings (e.g., Balaji et al., 2023; Yee et al., 2023), and revising course syllabi (e.g., Al-Zoubi & Aldmour, 2023). At the learner level, the focus lays on enhancing learners' motivation, personalization, and student-student interactions. Research has investigated how GenAI can be employed to create virtual students that engage with learners in a human-like manner (e.g., Santhosh et al., 2023), facilitating peer-to-peer feedback (e.g., Bauer et al., 2023), and assisting in the completion of tasks, management of information, or composition of essays (e.g., Su & Yang, 2023). Additionally, GenAI aids learners in idea generation (e.g., Al-Zoubi & Aldmour, 2023), and personalizes feedback and assessments through implemented chatbots (e.g., Jeon et al., 2023; Jiang & Cheong, 2023), as well as serving as conversational partners in language learning (e.g., Belda-Medina & Calvo-Ferrer, 2022). Pataranutaporn et al. (2022) found that while GenAI can significantly enhance learner motivation, it does not necessarily translate into better test scores. In sum, research on GenAI across all three levels remains fragmented and underexplored (Jeon & Lee, 2023). While GenAI offers substantial potential for enhancing MOOCs, it also introduces new risks, including potential biases, hallucination, and an overreliance on AI, which could compromise educational integrity and privacy (Ifelebuegu et al., 2023).

Method

To disclose IS research on the capabilities of GenAI and its application in e-learning contexts, we report on an SLR in reference to vom Brocke et al. (2009) and Tranfield et al. (2003). An SLR seeks to identify all relevant empirical evidence that satisfies prior specified inclusion criteria to retrieve, evaluate, and synthesize reliable information on a topic of interest (Snyder, 2019; vom Brocke et al., 2009). Furthermore, SLRs minimize bias by following well-defined processes (Kitchenham & Brereton, 2013), enhance credibility (Paré et al., 2016), and seek to ensure rigor through quality criteria, such as transparency, traceability, and reproducibility (Cram et al., 2020; Templier & Paré, 2018). A rigorous methodology allows researchers to decode, replicate, and build upon a review's findings, essential for future research given the anticipated pivotal role of AI, particularly GenAI, in e-learning academia and practice. Following Paré et al. (2016), our overarching goal in this review is to summarize previous knowledge on GenAI in the e-learning context, as well as to inductively derive and outline its inherent capabilities through a comprehensive analysis of previous research. We thereby draw on an exploratory and interpretive approach grounded in the philosophy of interpretivism, as we grasp to achieve knowledge and understanding through observation and interpretation of the phenomena, that is the application of GenAI in e-learning contexts (Creswell & Creswell, 2022; Kooli, 2023). To attain our overarching goal and address the RQ (see Section 1), we meticulously adapted the literature extraction and analysis guidelines proposed by Keding (2021), Tranfield et al. (2003), and vom Brocke et al. (2009), to suit the specific scope and focus of our study.

Planning the Review

After establishing the overarching goal of the SLR, several pilot searches in leading IS and e-learning journals (i.e., journals within the Senior Scholars' Basket, e-learning journals according to the 2022th SCImago Journal Rank indicator (SJRi) rated 1.5 or above) were conducted to acquire "a broad conception [...] about the topic" (Torraco, 2005, p. 359) as well as to identify relevant sources and search terms (vom Brocke et al., 2009). To address the multidisciplinary e-learning field and diversify our sources, we focused on incorporating a wide range of literature from the fields of IS and e-learning research. Consequently and following Gusenbauer & Haddaway's (2020) assessment, we selected the following well-suited sources: (a) Scopus, (b) EBSCOhost (Business Source Premier), (c) Web of Science Core Collection, (d) IEEE Xplore, and (e) Education Resources Information Center (ERIC) with no lower time limit and up to October 2023. Moreover, these sources were classified as well-suited due to their ability to provide access to leading IS and e-learning journals and conferences, therefore "ensuring that all the top-tier sources are included in the review" (vom Brocke et al., 2009, p. 9). In terms of search strategy, we initially conceptualized both areas – GenAI and MOOCs – and integrated them afterward within our search string. Since MOOCs are a distinct subset of online education diverging considerably in aspects such as scale, accessibility, structure, and scope, we encompassed the broader realm of e-learning in our search string as well, to capture a wider array of capabilities applicable to MOOCs (e.g., Oh et al., 2020). In detail, we considered terms, such as "MOOC*" and "e-learning." Regarding GenAI, we considered general terms, such as "generative artificial intelligence," "pretrained transformer," or "large language model" and their abbreviations (e.g., "LLM" or "generative AI"). Furthermore, we considered specific terms, such as "chatgpt" or "gpt," thereby acknowledging the disruptive impact of ChatGPT in both academia and practice. We argue that its emergence has disrupted existing paradigms and subsequently sparked significant scholarly interest, rendering it a prevailing and noteworthy topic of discussion in the context of MOOCs. To ensure coverage of the entire research fields across different sub-disciplines, synonyms and homonyms were identified in an iterative review approach and incorporated into the search strategy (Tranfield et al., 2003).

Conducting the Review

We carried out the SLR in January 2024 consisting of four steps. In step one, we applied our search strings to five well-suited academic databases (e.g., Gusenbauer & Haddaway, 2020), leading to a total sample of 165 articles, as shown in Figure 1. In a second step, we included English articles following Keding (2021), that were published in peer-reviewed academic journals and conference proceedings, as it is recommended to focus on high-quality publications (vom Brocke et al., 2009; Webster & Watson, 2002). Hence, further source types (e.g., books, commentaries) were excluded, due to their nonexistent, inconsistent, or nontransparent peer-review process. After the removal of duplicates, we proceeded with step three and assessed the suitability of the remaining 93 articles in a two-step content-screening process, as proposed by Kitchenham & Brereton (2013). In detail, a double-screening approach of titles and abstracts was performed by two authors independently from each other. In this step, we divided the articles into three categories: A – articles relevant to the RQ and the scope of the SLR, B – articles whose relevance to the SLR was unclear, and C – non-relevant articles (e.g., Bettinelli et al., 2022). In detail, we excluded C-articles with the following characteristics: articles employing search terms with incorrect meanings (e.g., LLM as an abbreviation for logit leaf model (Coussement et al., 2020), purely technical/mathematical articles (i.e., articles focusing solely on AI or algorithms neglecting the e-learning perspective), articles solely focused on conventional learning, articles solely centered on e-learning (i.e., articles that exclusively focus on e-learning without acknowledging the perspective of generative AI). We included articles in category A, if they were related to the application of GenAI in e-learning contexts (Bandara et al., 2015). We did not discriminate based on the methodological approach; thus, we incorporated studies employing quantitative, qualitative, and design science methodologies. This led to 49 A-articles, 13 B-articles, and 24 C-articles. Following this, the authors double-checked A- and C-articles followed by an in-depth analysis of articles in categories B and C, where the full-texts were read and discussed regarding their inclusion. Thus, we were able to identify 56 relevant articles. In step four, we conducted a backward and forward search in reference to Webster & Watson (2002) and identified an additional 30 relevant articles (i.e., category A), resulting in a final sample of 86 relevant articles.

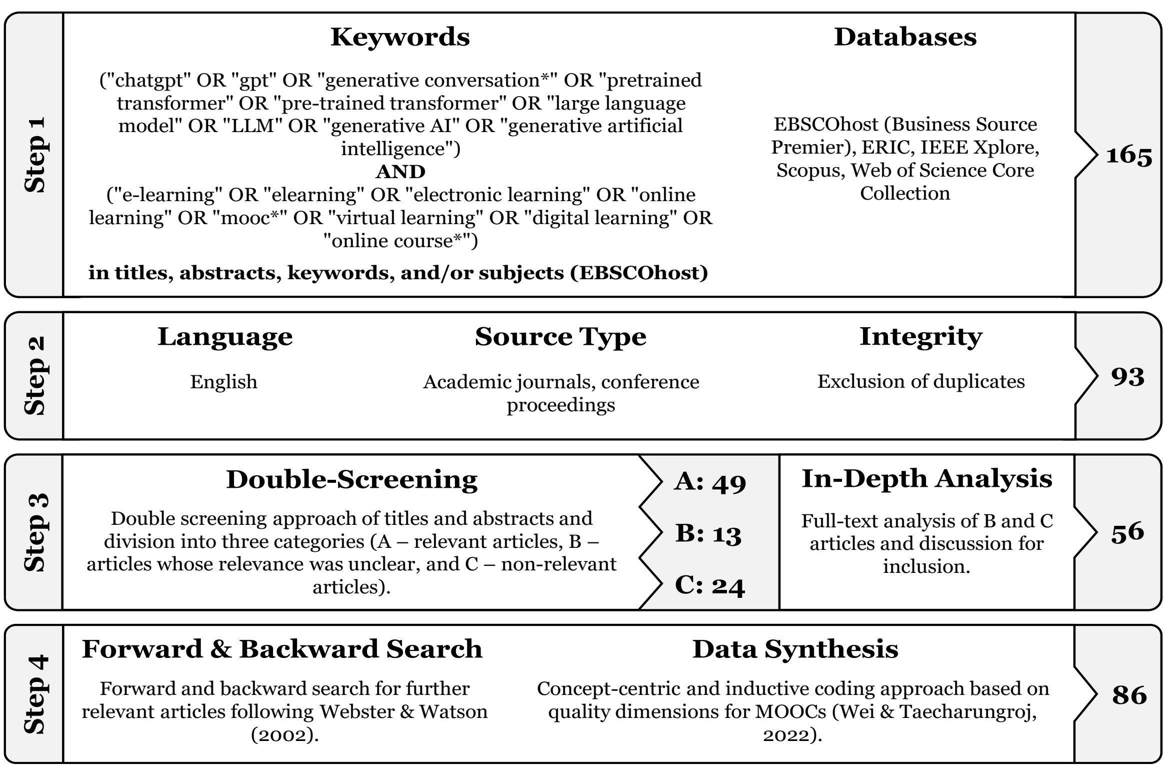

Figure 1. Systematic Approach to Article Selection

Coding and Presentation of Results

After corpus retrieval, the next phase involved managing and coding the collected literature based on a mixed approach to conceptualize the capabilities of GenAI. First, we adopted a deductive approach to analyze the application of GenAI in the identified publications, thereby assessing whether these publications addressed MOOCs at the level of the instructor, course, learner, or a combination of these dimensions. This analysis was guided by the MOOC dimensions proposed by Wei & Taecharungroj (2022). Results were stored in a concept-matrix (Webster & Watson, 2002). After that, we adopted an inductive approach that involved deriving categories, themes, and patterns from the publications during the analysis (Bandara et al., 2015), rather than imposing pre-existing concepts or theories. We first focused on the scope for which GenAI is applied in respective publications, followed by an examination of its role in e-learning contexts. In detail, we focused on coding text fragments from publications in an explorative manner, which enabled us to collect and discuss derived insights to ensure a shared understanding. Both visible and invisible high-level capabilities were derived by discussion within selective coding steps, whereby separate notes and memos supplemented our thought process to systematically capture emerging thoughts. Each of the 86 articles was coded independently by two different authors in three iterations, ultimately leading to the following agreements per code: instructor 28.3%; course 29.2%; learner 45.5%. To mitigate bias and reinforce inter-rater reliability (Pérez et al., 2020), we computed Cohen's Kappa values, which ranged between 0.86 and 0.93 for the three dimensions, indicating almost perfect agreement (Landis & Koch, 1977). To present our results and provide a clear picture of the coverage in predominant literature, we calculated dyads and created a heatmap (see Table 1).

Table 1. Capabilities of GenAI: A Dyad Heatmap

	Analytical Processing Capability	Generative Capability	(Personalized) Assistant Capability	Support	Feedback	Assessment	Communi-cation	Reflection	Adaptivity	Accessibility
Instructor	86	86	40	4	15	4	12	8	10	3
Course	86	86	23	4	4	7	22	10	29	3
Learner	86	86	46	6	33	28	36	21	34	21

>61 articles	*31-60 articles*	*21-30 articles*	*10-20 articles*	*0-9 articles*

Examining the dyads reveals that analytical processing and generative capabilities are consistently addressed in all identified publications across all levels. Additionally, the (personalized) assistant capability is extensively covered across the instructor, course, and learner levels. Notably, on the learner level, these capabilities are predominant, suggesting a recent literature focus on utilizing GenAI for learner support.

Capabilities of GenAI for enhancing MOOCs

The introduction of ChatGPT in 2022 as a focal example of GenAI significantly disrupted the e-learning domain, as evidenced by our data. We observed a significant upward trend in relevant publications over the years: 2019 (1), 2020 (3), 2021 (6), 2022 (11), and 2023 (65). More than three-quarters (75.6%) of the identified publications were published in 2023. 34 (39.5%) publications of our sample have been published in conference proceedings, while 52 (60.5%) appeared in journals. Publications predominantly come from social science (47), computer science (41), engineering (10), psychology (4), and medicine (4), with an additional sixteen spanning various other disciplines (multiple disciplines per publication were possible). In our sample, publications employed conceptual/design science (30), qualitative (25), quantitative (21), and mixed method (10) approaches. Our analysis revealed a diverse array of research methods employed across the publications, mostly literature reviews, but also encompassing bibliometric analyses, surveys (primarily targeting instructors and students), experiments, case studies, and document analyses. Drawing on this sample, we synthesized ten capabilities of GenAI, identifying two foundational systemic functions—analytical processing capability and generative capability—as the bottom layer. These capabilities underpin the (personalized) assistant capability, forming the second layer. This second layer, in turn, encapsulates seven sub-capabilities, which include assessment, communication, reflection, adaptivity, accessibility, support, and feedback (see Figure 2). Each of these sub-capabilities is deeply intertwined, deriving their functionality and interrelation from the foundational analytical processing and generative capabilities, and collectively contributing to the multifaceted (personalized) assistant capability. These capabilities aim to enhance MOOCs by providing support across three dimensions: instructor level, course level, and learner level (Wei & Taecharungroj, 2022).[1] Whilst it might be argued that the single sub-capabilities are already covered by other technologies, GenAI comprises all of them in an intelligent solution.

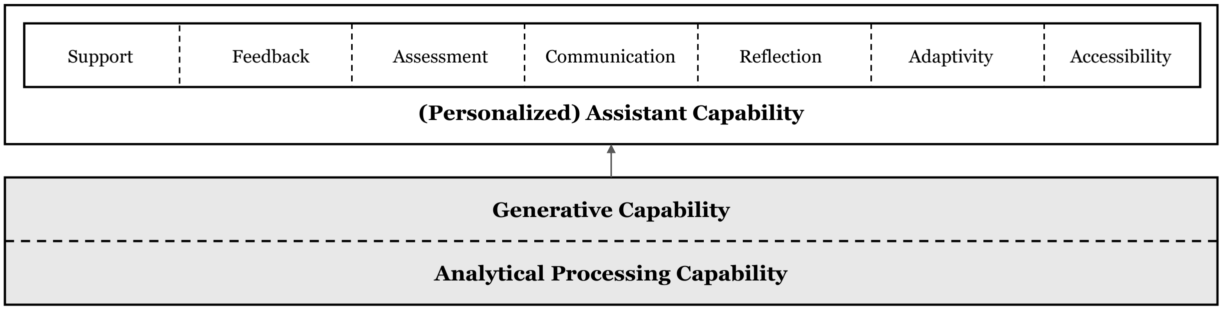

Figure 2. A Framework of Capabilities of GenAI in MOOCs

Analytical Processing Capability

The large amount of learners within MOOCs causes large data sets (Morris et al., 2023; Yee et al., 2023), which bear the potential to serve as a foundation for training ML or deep learning (DL) models. RQs encompassed comparing the analytical processing capabilities of various generative AI models to other ML algorithms (e.g., Savelka et al., 2023), evaluating their effectiveness in specific tasks such as tagging and assessing the quality of forum posts (e.g., Yee et al., 2023), and exploring enhancements through fine-tuning existing LLMs (e.g., Bulathwela et al., 2023). By leveraging ML and DL techniques, GenAI is capable of processing large amounts of textual data in real-time and analyzing them to identify interconnections (Tonbuloğlu, 2023), learner's sentiments (Rasul et al., 2023), and emotions (Santhosh et al., 2023). Further, with the advancements of NLP and NLU in GPT models (Kasneci et al., 2023), GenAI is capable of effectively analyzing complex information in user prompts and reasoning logically (Farrokhnia et al., 2024), hence, demonstrating analytical processing capabilities. This capability of GenAI to analyze and process data serves as a foundation for being able to generate new data and content bearing the capacity of being an assistant to instructors, course content creators, and learners. We understand the analytical processing capability as a presumption in GenAI context, thus application examples can be found in the subsequent capabilities. Nevertheless, the utilization of GenAI models is constrained by the specificity of the datasets on which they are trained, limiting their application to particular domains (Latif et al., 2023). Given the interdependence and sequential nature of their capabilities, it becomes clear that critiques applicable to one aspect of these models also extend to the other (sub-)capabilities.

Generative Capability

Based on recognized patterns resulting from analysis, GenAI is capable of generating new data (Dwivedi et al., 2023). Typically, RQs focus on assessing the effectiveness of GenAI in generating substantive educational interactions and course materials. This might include content creation or the translation of texts (Labadze et al., 2023). For instance, Mishra et al. (2021) demonstrated that GenAI can produce syntactic and semantically correct titles for course content. Du et al. (2023) employed GenAI for emotional and community support in MOOC forums, showcasing that GenAI outperforms other ML algorithms. Moreover, training on extensive datasets enables the generation of realistic, original, and coherent texts and responses in different domains (Cotton et al., 2023; Karadağ, 2023; Kasneci et al., 2023; Labadze et

[1] We assume that the instructor does not necessarily need to be the creator of the MOOCs. Thus, we differentiate between these three levels.

al., 2023; Tauqeer et al., 2021; Yee et al., 2023). Thus, GenAI can respond to a broad array of text-based prompts that can be formatted with text alone and thus can answer learners' questions, or provide instructors with hints for giving students guidance or feedback (Belda-Medina & Calvo-Ferrer, 2022; Sharef et al., 2021; Tauqeer et al., 2021). However, it needs to be stated, that the quality of the generated contents strongly depends on the quality of the dataset on which the GenAI model has been trained (Yee et al., 2023).

(Personalized) Assistant Capability

Based on the analytical processing and the generative capability, GenAI can work as an intelligent and adaptable (personalized) assistant (Kasneci et al., 2023; Sharef et al., 2021; Szczepaniak et al., 2023) for both, instructors and learners within MOOCs, and for creating course content. GenAI can shift the learning method in MOOCs from search-based learning to traditional dialogue-based learning and thus improve the learning experience, as the processing of information is fostered (Saindane et al., 2023; Yinping & Yongxin, 2023). In research, a focus has been laid on (intelligent) tutoring bots (Labadze et al., 2023). On the instructor level GenAI can support generating exercises tailored to learners' individual needs and levels of proficiency (Bahroun et al., 2023; Motlagh et al., 2023; Yee et al., 2023) and automatically assess grammar and spelling in solutions submitted by students (Belda-Medina & Calvo-Ferrer, 2022; Cotton et al., 2023; Kasneci et al., 2023). Furthermore, GenAI can provide aid in administrative tasks (Dwivedi et al., 2023), and automate certain aspects of instructional support, such as providing timely feedback, answering common queries, and facilitating interactive discussions, thereby freeing up instructor's time for more personalized interactions with learners (Motlagh et al., 2023). On the course level GenAI can support the automatic creation of multiple-choice tests (Hoch et al., 2023), the production of learning materials and recommendations (Jeon & Lee, 2023), or tailored solutions to exercises (Karaali, 2023). On the learner level, GenAI bears the capability to generate individualized learning plans, feedback, or guidance through complex problems (Labadze et al., 2023; Sharef et al., 2021). Furthermore, by using GenAI learners are provided with the essential skills and resources to exert control over their writing (Bahroun et al., 2023; Motlagh et al., 2023), which promotes deep engagement in the learning process, frees cognitive resources, and results in maintaining focus on the desired outcome to attain a state of flow (Muñoz et al., 2023). Furthermore, prompts created by GenAI might stimulate critical thinking and could therefore deepen the learning experience (Cotton et al., 2023; Motlagh et al., 2023). By nurturing learners' autonomy, competence, and relatedness, which are crucial psychological needs (Baidoo-Anu & Owusu Ansah, 2023), GenAI contributes to fostering self-determination and improving both, learner's motivation (Muñoz et al., 2023) and performance (Kasneci et al., 2023) within the context of MOOCs. In the long-term, an interactive and personalized approach has the potential to improve emotional support in MOOCs, learner engagement, skill development, comprehension, and retention of course contents and skills (Dwivedi et al., 2023). The traits of the (personalized) assistant capability are further defined by the following sub-capabilities.

Support

Contributing to the (personalized) assistant capability, the sub-capability support is inherent in GenAI. Typical RQs aim at investigating how to implement GenAI to support learners, course creation, or instructors, e.g., by being implemented in discussion forums (C. Li & Xing, 2021). On the instructor level, GenAI can support generating teaching material (Prather et al., 2023), creating domain-specific dialogues (Chang & Mengshoel, 2023), or supporting teachers in identifying educational gaps in students (Ahmad et al., 2024). On the course level, the usage of GenAI in MOOCs can support the creation of course content (Prather et al., 2023). On the learners' level, GenAI can provide individualized support by responding to specific individual problems and stimulating problem-solving (Ruiz-Rojas et al., 2023). Furthermore, GenAI may support providing overviews or individualized evaluations to learners to support their understanding of course content (Bauer et al., 2023).

Feedback

To obtain decreasing dropout rates, timely feedback for learner engagement has been reported as necessary (Belda-Medina & Calvo-Ferrer, 2022; Bozkurt, 2023). Aiming at investigating how to enhance feedback in MOOCs with GenAI, typical RQs focus on how GenAI enables interactive and personalized feedback in real-time (Cotton et al., 2023; Ilieva et al., 2023; Kasneci et al., 2023), allowing for a critical conversation to improve learning outcomes and learner's engagement (Dwivedi et al., 2023). GenAI can provide targeted feedback on specific tasks, such as coding assignments in programming courses, to enhance their quality (Savelka et al., 2023). On the instructor level, GenAI can provide valuable domain-specific feedback to instructors (Tlili et al., 2023). On the course level, GenAI can help to perform sentiment analysis on feedback data from students to inform the instructor and to provide suggestions for revising course content (Qiao et al., 2023). On the learner level, learners can practice course-related tasks and receive immediate guidance and corrective feedback based on their individual needs and skills (Latif et al., 2023).

Assessment

To track the learning progress within MOOCs, various assessment tasks such as multiple-choice questionnaires and essays are employed, which learners are required to complete. Until recently, assessments have been graded automatically by following static pre-defined rules or by using peer-assessments. RQs in this field focus on how GenAI can leverage automated grading by making them sound more natural. Furthermore, there is research on enhancing peer-assessments (Morris et al., 2023). At the instructor level, GenAI facilitates the automation of scoring and assessment processes, thus aiding instructors in efficiently evaluating student submissions (Beerepoot, 2023; Latif et al., 2023). For course level evaluation, GenAI contributes to assessing the overall quality of course content, ensuring that educational materials meet predetermined standards while also providing suggestions for enhancement (Kasneci et al., 2023). At the learner level, GenAI supports the assessment of learners' explanations by supporting learners to understand and apply the critique with the aim of improving their submissions (Lawrie, 2023; Rai et al., 2023).

Communication

Even though communication is considered relevant for learning, MOOCs often lack personalized communication. GenAI can offer assistance by enabling near-human-like communication (Ifelebuegu et al., 2023). Research endeavors aim at investigating how GenAI can be used to enhance communication, e.g., by implementing chatbots (Ahmed & Sharo, 2023; Ifelebuegu et al., 2023; Sharma et al., 2021). GenAI can provide assistance at the instructor level in research endeavors (B. Li et al., 2023) or provide support in addressing learners' queries (Su & Yang, 2023). On the course level, GenAI provides inspiration and guidance for creating learning sessions (Lawrie, 2023). On the learner level, GenAI supports learners' motivation by providing interactive conversational experiences (Muñoz et al., 2023). This has profound implications for learners' experience in MOOCs, as it enables learners to engage in realistic and practical conversational scenarios, enhancing their understanding of course contents and their ability to apply them in real-world situations (Bahroun et al., 2023; Ilieva et al., 2023). Thus, active learning (e.g., Ilieva et al., 2023; Muñoz et al., 2023) and knowledge retention are enabled (Labadze et al., 2023), as learners can engage in meaningful discussions, seek clarifications, and receive personalized feedback, thereby deepening their understanding and mastery of course contents (Kasneci et al., 2023; Sharef et al., 2021).

Reflection

GenAI can reject inappropriate requests, challenge responses, and maintain coherence with the learner's previous prompts (Bahroun et al., 2023). Typical RQs in this category focus on GenAI's ability to engage in self-reflection and challenge self-generated responses, prompts, or assumptions in MOOCs (Dwivedi et al., 2023). On the instructor level, GenAI can thus support reflecting learning contents and media use (Lo, 2023; Su & Yang, 2023). At the course level, this sub-capability can support the reflection of course content and didactical methods (Tauqeer et al., 2021). On the learners' level, the reflection capability can support promoting learners' self-awareness and critical thinking (Cotton et al., 2023; Muñoz et al., 2023). Thus, the learning experience in MOOCs can be enhanced by encouraging critical thinking, maintaining relevance, and providing personalized and critical stimuli to course contents (Ahmed & Sharo, 2023; Beerepoot, 2023; X. Lin, 2023).

Adaptivity

GenAI can be fine-tuned and enhanced towards specific application scenarios (Bahroun et al., 2023; Dwivedi et al., 2023). Furthermore, it self-improves and adapts responses through human interaction, leveraging prompts and feedback (Cotton et al., 2023). RQs addressing this strive to investigate how GenAI can be implemented to create more accurate and individual responses to specific topics of interest within MOOCs (Mastropaolo et al., 2023). On the instructor level, GenAI can adapt to the instructor's level of knowledge and thus give hints, inform, and keep instructors up to date, to improve their confidence (Latif et al., 2023). Furthermore, there can be guidance to adapt teaching methods based on the learner's progress and performance (Baidoo-Anu & Owusu Ansah, 2023). On the course level, GenAI can support by adapting and personalizing course material based on learners' preferences (B. Li et al., 2023; Ruiz-Rojas et al., 2023), or recent developments (Latif et al., 2023). On the learner's level, GenAI helps create personalized learning experiences (Bozkurt, 2023; Ilieva et al., 2023; Labadze et al., 2023). This is done by creating more engaging and meaningful interactions within MOOCs, adapting to situational tasks (Jeon & Lee, 2023), and adjusting to learners' cognitive skills and comprehension of topics at hand (Bahroun et al., 2023; Bozkurt, 2023; Cotton et al., 2023). Hence, GenAI facilitates the potential to improve the learning experience in MOOCs (Bozkurt, 2023; Kasneci et al., 2023) and overall satisfaction with course content (Bahroun et al., 2023; Latif et al., 2023; Pereira et al., 2019).

Accessibility

GenAI has the potential to enhance the accessibility of MOOCs to a globally dispersed audience, and thus to follow the idea of democratizing education (Ifelebuegu et al., 2023; Latif et al., 2023; Tonbuloğlu, 2023). On the instructor level, GenAI can facilitate this by aiding in the translation of educational materials (Baidoo-Anu & Owusu Ansah, 2023) and assisting in translating inquiries and responses to overcome language barriers and improve cross-cultural communication (Lo, 2023). On the course level, GenAI can also support by translating course material in order to make it available to a wider audience (Baidoo-Anu & Owusu Ansah, 2023). At the learner level, GenAI promotes inclusivity by facilitating the participation of individuals from diverse linguistic backgrounds, thereby eliminating language barriers and creating an inclusive learning environment (Dwivedi et al., 2023). Additionally, GenAI supports special-needs learners by transforming written or visual material into natural language, ensuring accessibility to course content (Lo, 2023). Furthermore, by providing guidance and adapting course contents to their needs, GenAI can lead to a more inclusive MOOC design and thus to a more holistic learning experience (Ahmad et al., 2024; Chaka, 2023).

Discussion and Conclusion

Since recent advancements in AI and NLP have become publicly available by means of GenAI (OpenAI, 2022), McKinsey gave insight into the economic potential of GenAI which can increase individual productivity (Chui et al., 2023). The disruptive potential on e-learning concepts becomes visible in practice and research (Singh & Singh, 2023; Sohail et al., 2023), thus, there is a growing need to explore and leverage the capabilities of GenAI to enhance e-learning within MOOCs. Therefore, we conducted an SLR and derived ten underlying capabilities of GenAI and their implications for enhanced e-learning in MOOCs to answer our RQ: "*Which specific capabilities characterize GenAI and how can they be harnessed to mitigate existing challenges in MOOCs to enhance e-learning?"* We posit that the derived capabilities of GenAI have the potential to improve MOOCs across all levels—instructor, course, and learner. This, in turn, could address the limitations of MOOCs that contribute to low completion rates (Sümer & Aydın, 2022). On the instructor's level, these shortcomings comprise—amongst others—the time-consuming administrative tasks, like grading assessments or creating course syllabi. By using GenAI, these administrative assessments can be automated and thus, the instructor gains more time for more valuable tasks with the course participants (Motlagh et al., 2023; Tonbuloğlu, 2023). On the course level, the creation of a comprehensive structure or the orchestration of didactical elements can be quite challenging. GenAI can support the creation of course contents and course structures and can assist in the selection of didactical measures (Qiao et al., 2023; Tonbuloğlu, 2023). On the learner's level, the lack of feedback, instructors' aid, and social interaction might cause an unsatisfying learning experience leading to insufficient learning success (Jung et al., 2019; J. Lin, 2023; Wei & Taecharungroj, 2022). By enabling meaningful discussions, offering real-time feedback, and providing personalized guidance to learners, GenAI promotes learners' engagement and knowledge retention, allowing learners to deepen their understanding of course content. Another appealing aspect of GenAI is its adaptability, which allows it to be fine-tuned toward diverse course topics and its ability to be easily integrated into existing MOOCs, as shown by J. Lin (2023). Despite the obvious advantages the identified (sub-)capabilities offer, several points can be criticized when using GenAI in an educational context. There is an ethical challenge regarding data privacy and security, as for training the

GenAI model, personal data about learners needs to be accessed (Bauer et al., 2023; Kooli, 2023; Santhosh et al., 2023; Sonderegger, 2022). Moreover, it is asserted that potential sources of bias may be present in the trained model, inherited from the bias present in the training data (Ahmad et al., 2024; Ahmed & Sharo, 2023; Bauer et al., 2023; Sharma et al., 2021). Even though it is claimed, that GenAI might be able to give guidance in complex tasks, the efficiency in this context is not yet proven (Su & Yang, 2023). Apart from these ethical concerns, there are observable drawbacks to GenAI's application. Lack of transparency in GenAI may result in a lack of understanding among both, learners and instructors (Ahmed & Sharo, 2023). Moreover, it is essential to note that while GenAI can improve and broaden the learning experience, it cannot replace the inherent learning process of the individual learner (Crawford et al., 2023). Additionally, GenAI cannot match the emotional support and engagement of a human instructor (Labadze et al., 2023). Furthermore, the quality of responses and generated content may suffer, if the model is trained on an unsuitable dataset (Su & Yang, 2023). Nevertheless, we argue that integrating GenAI into MOOCs can lead to an improved overall learning experience and higher levels of satisfaction. Furthermore, GenAI as a virtual tutor in MOOCs can address existing challenges posed by geographically dispersed learners by accommodating individuals from diverse linguistic backgrounds. However, it is important to note that our study adopted an optimistic perspective regarding the potential of GenAI in enhancing e-learning in MOOCs, partially overlooking existing challenges and ethical concerns highlighted in previous research (e.g., Dwivedi et al., 2023; Farrokhnia et al., 2024; J. Lin, 2023). Moreover, our study primarily focused on identifying the capabilities of GenAI by utilizing an SLR and synthesizing theoretical implications for e-learning, without quantitatively validating these findings. Since the identified publications focus on various application areas (e.g., programming classes (e.g., Savelka et al., 2023), language learning (e.g., Belda-Medina & Calvo-Ferrer, 2022), or medical education (e.g., Tauqeer et al., 2021)), it can be argued that our identified capabilities lack comprehensiveness (Schryen et al., 2020). Hence, future research should focus on a practical investigation of GenAI in MOOCs in specific application areas, especially in the context of IS research. As this field of research is rather new (see section 3), the effectiveness of GenAI in MOOCs has not yet been investigated thoroughly. Therefore, future research should focus on how GenAI in MOOCs is affecting learning outcomes. In concordance with this, only a few researchers (e.g., Ifelebuegu et al., 2023) investigated negative aspects that can be induced by the application of GenAI in MOOC contexts. Thus, future research should aim at investigating these thoroughly.

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[i] This refers to the hypothesis, that different types of information are processed in different parts of the working memory, which is responsible for promoting learned information to the long-term memory, where it can be stored and recalled (Sweller, 2016).