Review Article

The Psychology of Generative AI in Higher Education: Mapping Benefits and Risks

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In this review, we discuss the psychological aspects of using generative AI and Large Language Models (LLMs) in higher education. Although these technologies may appear unprecedented, we argue that they align with the recurring *Sisyphean Cycle of Technology Panic*: a well-documented phenomenon characterized by fear and skepticism toward major technological changes. Our primary focus is on the psychological dimensions of LLM accessibility for educators and students, which are often overlooked in favor of technological, legal, or economic considerations. We identify and examine ten key psychological areas relevant to the use of generative AI in academia: accessibility, ethical judgments, determinants of trust in AI, cognitive offloading, cognitive biases, creativity, social relationships, educational motivation, well-being, and potential clinical risks. We provide a balanced analysis for each of these areas, considering the potential benefits and risks associated with integrating AI algorithms into academic practices. We emphasize the necessity of addressing both perspectives when implementing technological solutions in education and suggest directions for future research. We believe this review offers a comprehensive overview of the psychological implications of generative AI in academic contexts.

Generative AI and Large Language Models in Higher Education: A Psychological Perspective

Since the triumphant debut of GPT-3[1], the media landscape has been intensely filled with statements highlighting the exceptional nature of the technological changes we are currently witnessing. Without prejudging the actual state of affairs, it is worth noting that such statements – concerning the ever-increasing pace of change and the exceptional scale of technological progress – have accompanied us continuously since the beginning of the Industrial Revolution. Equally constant elements of the intellectual landscape of successive eras are the recurring self-reflections of academic communities and attempts to find the most appropriate responses to these changes[2]. These reflections often take on ritualized repetitive forms while, at the same time, encompassing a surprisingly constant spectrum of attitudes: from conservative positions describing cultural and social transformations (including technological ones) as degrading forces toward the essential academic formation to techno-enthusiasm and its utopian promises.

The same logic applies to the current reactions to the rapid emergence of generative AI and large language models (LLMs) like ChatGPT by OpenAI, Copilot by Microsoft, or Claude by Anthropic. That is precisely why, in this article, we try to adopt a different perspective and focus on the psychological underpinnings of AI-evoked changes in academia. How will these technologies affect students' cognitive processes, motivation, and emotional well-being? What are the potential benefits and risks to mental health? Furthermore, how might AI reshape the fundamental social and interpersonal aspects of the learning experience?

As we grapple with these questions, we must recognize that concerns about technological disruption in education are neither new nor surprising. This debate replicates previously existing schemes and positions, moving between well-known poles of utopian visions and technocratic realism, opportunities and threats, resistance and hope. This consistency of rhetorical gestures repeated against the backdrop of a changing technological landscape is well established in this field of study. Amy Orben has described this phenomenon as the Sisyphean Cycle of Technology Panic[3]. She showed how, over the decades, the same pattern has been repeated in which successive technological breakthroughs or inventions (from the emergence of writing to social media) are accompanied by the same cycle of growing anxiety or even panic, hastily formulated policies, and a lack of actual knowledge accumulation. One of the consequences of this repetitive pattern is that the attention of public opinion and researchers constantly shifts towards the latest (and thus most disturbing) phenomena, abandoning previous topics and hindering the development of reasonable long-term solutions. This model explains well what happens when the pace of change is so rapid that it hinders the achievement of a scientific consensus based on reliable data: discussions lose their empirical character and turn into rhetorical, political, or ideological disputes. The field of AI research seems prone to similar difficulties due to the perceived nature of the changes taking place and the objective speed of the technological revolution. How can they be avoided?

Certainly, this new and fascinating field of research could benefit from more structure and organization. Therefore, in the following part of the introduction, we will first outline the key questions, which represent significant practical challenges and, at the same time, can greatly benefit from the theories and findings already developed by scientific psychology. Next, we present the assumptions and methodological premises that guided our work.

Based on an analysis of the existing literature[4][5], as well as our continually updated personal experiences, we have decided to outline 10 psychological questions related to the use of AI in academia within this article. We are aware that this selection is largely subjective and likely not exhaustive. However, we hope that it does not overlook any of the most current topics and practical challenges that we face in our everyday teaching practice. The ten key questions are the following:

1. **Accessibility:** What determines the availability of AI tools and the motivation to use them?
2. **Ethics:** Does AI require a new set of guidelines, or is it just a new domain for the application of existing ethical frameworks?
3. **Trust calibration:** How can we manage our level of trust, and what psychological mechanisms contribute to the anthropomorphizing of AI?
4. **Cognitive Load**: Can avoiding the complexity or memory use thanks to the use of AI become a barrier to our development?
5. **Fairness**: How can we ensure that AI becomes a tool for reducing rather than perpetuating biases?
6. **Creativity:** When does the use of AI act as a prosthesis for creativity, and when does it serve as its catalyst?

7. **Social Relationships**: Will AI, by effectively emulating them, create new opportunities for personalization and development in education, or will it introduce a new form of social isolation?
8. **Motivation:** How can we ensure that the convenience offered by AI leads to the building (rather than the erosion) of motivation?
9. **Well-being**: What are the consequences of AI-related changes for the well-being and mental health of both educators and students?
10. **Clinical risks**: How can AI solutions be implemented in a way that addresses, rather than exacerbates, risks and issues in the area of mental health?

By exploring these questions through a psychological lens, we hope to provide a more nuanced understanding of both the opportunities and challenges presented by AI in higher education. Rather than making definitive predictions, our goal is to equip readers with frameworks for critically evaluating the psychological impact of these technologies as they continue to evolve. At the same time, we are aware of the characteristic challenges of the dominant debate described above. That is why, in our article, we adopted a specific methodological perspective based on three main premises.

Firstly, despite the tendency to perceive all the aspects of AI-related changes as novel, surprising, or even revolutionary, we believe that it is equally important to highlight that many of these developments are not entirely new. Rather, they often represent particular or novel instances of already recognized phenomena for which we are familiar with the psychological mechanisms and their determinants. This perspective allows for the use of existing, well-empirically grounded theoretical models. We believe that existing knowledge can enable the streamlining of research activities and optimize the design of interventions in this area. At the same time, it can make the obtained results less susceptible to technological inflation associated with focusing on the (almost daily emerging) innovations.

Secondly, we will endeavor to illustrate that most of these phenomena do not have an unequivocally inherent positive or negative character. Their ultimate impact will depend on a wide range of factors, including implementation details and broader regulatory solutions, and - of course - countless dimensions of individual differences, attitudes, and emotions. This implies that the context (also intrapersonal) in which new technologies are introduced plays a crucial role in determining their overall effect.

Thirdly, building on the previous point, we aim to highlight the complex, multifaceted nature of the environment that shapes the ultimate effects of AI adoption. This means, among other things, that the study of the factors shaping the future of AI in academia (and the future of universities in the age of AI) cannot overlook psychological aspects, nor can it be limited to them. The impact of technology, like that of other powerful social forces, disregards the formal boundaries separating academic disciplines. This topic seems to merit a much more extensive discussion. However, due to space constraints, we only signal here that future considerations could benefit from the use of broader, interdisciplinary approaches. Bronfenbrenner's ecological model or the PESTEL framework[6] might offer valuable perspectives to understand and articulate this complexity more clearly.

In this article, our goal is a bit narrower. We believe that by addressing the complex psychological questions, we can outline the path toward leveraging AI's potential to enhance learning and well-being while proactively addressing potential risks to students' psychological development and academic experiences. This article aims to spark thoughtful discussion and inspire further research into the intricate relationship between artificial intelligence and the human mind in educational settings.

LLMs as a source of (non) equality

One of the great, historically recurring, and perpetually unfulfilled promises associated with technological progress is its potential to transform societies by liberating us from effort, work, and other burdens. These visions are usually accompanied by either utopian hopes or dystopian fears related to societal shifts. Since, at least for now, the changes brought about by AI are more likely to alter the demand for certain professional profiles[7] rather than make work as such entirely redundant, we will begin by addressing a more fundamental issue with significant social implications – equality in access to AI solutions.

The challenge of democratizing access to AI and the entirely new set of digital competencies required for its achievement is currently one of the central topics in discussions concerning the labor market. In academic discourse, which is much more conservative and often emphasizes threats, this problem seems to be less noticeable but equally inevitable. Similar to many topics analyzed in this article, the issue of AI accessibility can only be understood from a systemic perspective. Our ability and willingness to utilize technology – particularly one perceived as cutting edge – are conditioned by various socio-cultural factors: economic, organizational, and legal. Concurrently, research clearly indicates that the decision to adopt new technologies also depends on various psychological mechanisms. These can include relatively stable traits (for example, personality traits such as openness to experience) and more transient events – such as motivational or emotional states (anxiety, technostress, etc.)[8]. Importantly, existing studies also highlight the significant role of technology anxiety not only in adopting tools like ChatGPT but also in the longer-term consequences, such as compulsive usage or reduced life satisfaction[9].

Regardless of how we decide to regulate the principles of use and access to AI, the formulation of effective intervention methods should be based on existing knowledge rooted in established theoretical models concerning the diffusion of innovations and change management[10]. Only such an approach will allow for the creation of effective interventions that will promote greater inclusivity while simultaneously ensuring the well-being and welfare of users[9]. If we do not pay sufficient attention to the broadly defined accessibility of AI, it will simply become another – perhaps even more severe than others – dimension of digital exclusion.

Managing Academic Misconduct

The act of writing is often perceived by academics as crucial: it is the visible, measurable product of our thinking and, therefore, defines our identity as scientists and perhaps even as human beings. Maybe that is why, among all the potential threats related to the use of AI in academic settings, the possibility of unethical use of LLMs to aid writing is mentioned most frequently. The most extreme and problematic scenario, where a chatbot is prompted to produce an entire paper, and this fact is not disclosed during submission[11], is not the only possible context for AI use. Bekker[12] identifies four tiers of (un)ethical use of AI for academic writing (Ban, Proofing, Editing, Co-creating) - which illustrates how complex this problem is.

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AI is a tool that we should be able to use effectively, yet it is also a tool that should not replace us in exercising essential cognitive skills. It is a solution that is both unavoidable and, in certain situations, needs to be avoided (e.g., to prevent our evaluation methods from becoming a caricature). Finally, generative artificial intelligence confronts us directly with fundamental questions (maybe, for the first time in years): What does "to be skilled" mean? What does "to know" mean? What kind of knowledge do we *really* need?

However, an important question arises: has the availability of LLMs influenced the psychology of intentions toward academic dishonesty, creating a new generation of problematic students? Or is it simply a new tool for those already predisposed to violating academic ethics in traditional settings[13]? Answers to this question can be found in the research of psychologists such as Koscielniak and Chudzicka-Czupala[14]. They employed the Theory of Planned Behavior[15], which has frequently been used to determine the psychological foundations of academic misconduct. This model identifies three key psychological determinants of academic dishonesty: attitudes (positive vs. negative evaluations of behavior), subjective norms (social pressure to perform or not perform), and behavioral control (perceived ease or difficulty in engaging in specific behavior). Koscielniak and Chudzicka-Czupala confirmed that the significance of these individual factors in the context of AI-driven academic misconduct is nearly identical to that of traditional academic dishonesty. Moreover, the strongest predictor of intentions to unethically use LLMs in their study was a history of previous dishonesty in high school or college. New technologies were used unethically, especially by those students who had already developed habits of dishonesty. Other studies also confirm the unchanged psychological determinants of academic dishonesty in the AI era, using theories like the fraud triangle[16] or the Dark Triad personality theory and the HEXACO model[17]. In other words, psychologically, students' behaviors are still driven by a similar interplay of rationality and morality as in the pre-ChatGPT period[18].

What shall we do? Certainly, ensuring the ethical use of AI in academia must involve legal regulations and, above all, providing students with reliable knowledge about how they should and should not use these tools. That step might mitigate some of the threats to academic integrity related to mistakes made out of ignorance, such as – for example – using AI to summarize a scientific article under a paid license (accessible through university subscriptions), without realizing that most of the available LLMs store and learn from user data—thus should not have unauthorized access to such content.

Apart from the technical and legal aspects, in light of the studies presented above, it seems that ethical violations related to AI use are merely another facet of the old issue, not a new phenomenon. In line with the perspective adopted in this text, we also want to clearly show that using AI brings many opportunities – including academic integrity. A positive aspect of this phenomenon is the chance to eliminate existing essay mills and traditional contract cheating forms[19]. It might also reduce the motivation leading to various forms of academic dishonesty by eliminating its determinants, such as frustration from insufficient knowledge of a foreign language or anxiety related to academic writing. It is also worth noticing that using LLMs for proofreading, translation, or text editing can be a significant tool for the democratization of science and for reducing language-related gatekeeping[20][21]. Undoubtedly, in contemporary science, which demands publishing in English, using it as a second language or having limited economic resources (necessary for purchasing professional translation or editing services) does not create a level playing field.

(Non)-Human nature of LLMs

LLMs are not humans: this statement seems quite apparent. Interestingly, in psychological terms, the perception of artificial intelligence is ruled by principles surprisingly similar to those applied to perceiving people. "The cat looks so guilty after knocking over the vase!": most people will not find anything strange in this sentence–even though animals are not capable of feeling such self-conscious emotions as guilt or shame. People strongly tend to anthropomorphize non-human agents: animals, objects, or even atmospheric phenomena[22]. We often attribute human desires, emotions, or intentions to their behavior when talking about them. According to the existing research, anthropomorphism is a trait (people differ in intensity) based on three determinants: *Elicited Agent Knowledge*, *Effectance Motivation*, and *Sociality Motivation*[23]. Moreover, it seems clear that the greater the tendency to perceive non-human agents (including AI) as humans – the greater the level of trust we are willing to place in them[24].

The theory of anthropomorphism leads to many paradoxes that determine the nature of AI-human interaction. On the one hand, engineers want to give robots a human-like appearance and human-like capabilities[25] – on the other hand, such forms of contact with AI make the users uneasy and disturbed[26]. Salles et al.[27] vote for a great deal of caution in using words like "knows," "believes," "wants," or "intends" in relation to artificial intelligence – as such terms are culturally mentioned to describe humans and can be misleading if used in the context of algorithms. Simultaneously, the same authors agree that paralleling AI with human emotions and cognition simply reflects an anthropomorphic conception of AI and becomes a new cultural norm. Noting these contradictions – or conversely, similar perceptions of people and AI – should result in asking about the psychological consequences of such mechanisms. The most important of these seems to be the issue of trust: what makes students writing their academic essays blindly copy the information generated – even when they are aware of the well-known instances of LLMs hallucinating, fabricating sources, and producing nonsensical content?

In relations with people, one of the strongest predictors of interpersonal trust, formed in early childhood, is the matter of attachment styles—stemming from the first social relationships with the mother[28]. Surprisingly, it turns out that the established level of security in the attachment style also determines trust in AI-generated data. Researchers[29] have shown that even temporally enhancing attachment anxiety can result in reduced trust in AI – which may be a clue to ways of sensitizing students (and also scientists!) to potentially erroneous or even harmful content generated by LLMs. A recommended strategy for working with AI may be the principle of limited trust in generated content – and cautious, reflective verification of all GenAI-created facts.

In the academic environment, trust in AI is strongly associated with technological self-efficacy and attitudes toward AI, as shown by Obenza and his collaborators[30]. The authors of this study demonstrated that AI trust mediates the relationship between students' self-efficacy in using AI and their overall attitude toward AI, indicating that trust is a crucial factor influencing how confidence in AI capabilities translates into receptiveness toward these technologies in educational contexts. Similar aspects are also underlined by another recent study[31], which notices the popularity of GenAI tools among students—but highlights the significant variation in trust levels towards these tools.

This emerging area of research on the mechanisms shaping our relationship with GenAI clearly indicates the need to develop competencies in trust calibration. Consequently, educators and developers must collaborate to design GenAI interfaces, pedagogies, and learning outcomes that leverage GenAI's educational potential while mitigating risks associated with either overreliance or excessive skepticism.

Cognitive Offloading

While the previously discussed topics had a very clear emotional component, the next one is distinctly situated in a different psychological domain –primarily concerns cognitive processes. One of the main concerns often highlighted in discussions about the role of AI in higher education is the increased dependence on external tools and the significant reduction in personal cognitive engagement. Psychologists refer to this shift as *cognitive offloading*, defined as "the use of physical action to alter the information processing requirements of a task so as to reduce cognitive demand"[32]. Although this mechanism is often cited as fostering mental laziness and a lack of reflection, it is important to ask whether students and educators need to constantly be in a state of cognitive load.

In the last decade of the 20th century, many educational statistical operations were performed manually, often using pen and paper. Today, most students cannot do these calculations independently, as they rely on specialized statistical software. Does this reliance make them academically less capable? Alternatively—is it possible that the cognitive resources saved through such software can be used for more advanced and intellectually demanding tasks, potentially enhancing overall academic performance rather than diminishing it?

Similarly, many cognitive mechanisms may mediate the positive effects of the ability of LLMs to outsource certain mundane or monotonous aspects of cognitive tasks. Reducing cognitive load in education is crucial because it enhances students' ability to process and retain information by freeing up working memory capacity[33]. Simplifying complex tasks and instructional materials can lead to better learning outcomes and reduce the likelihood of students feeling overwhelmed[34]. Additionally, reducing extraneous cognitive load by eliminating unnecessary information can help students focus on the essential elements of the learning task, thus improving their performance and understanding[35]. We must also remember the job market perspective – skills related to using AI tools will increasingly be part of the expected skill set for employees entering the rapidly approaching world of work that integrates humans and machines[7].

However, certain costs associated with excess in cognitive offloading should also be underlined. They are well summarized in the review by Atchley et al.[36], who give examples of impaired memory when the information is gained "too easily"[37] or diminished spatial attention in drivers when GPS is not available[38]. As Lodge et al.[39] conclude, modern GenAI represents algorithms far more advanced when compared to simple calculators used over the last decades – thus, it requires incomparably more nuanced considerations of human-AI interaction.

It is worth noticing that in discussions about this particular aspect of AI application, numerous questions concerning the nature of the educational experience clearly converge. To what extent should studying focus on building specific experiences that require effort and test character? Should we solely concentrate on optimizing the process of producing specific outcomes? Questions of this kind do not have objective or correct answers, as they go beyond the empirical domain. They are questions about the desired shape of future societies.

Psychological Biases

Theoretically, LLMs were designed to facilitate access to more objective and bias-free knowledge. However, it is important to remember how these models are created: based on billions of pages of input material used to train inner algorithms. This material has largely been drawn from internet resources – which constitute such a cognitively biased and stereotype-filled source of knowledge that it is difficult to expect them to generate objective scientific knowledge.

By definition, AI is an algorithmic system created to mimic the way humans process information. However, Atari et al. [40] rhetorically ask in their title: “Which Humans?”. They argue that LLMs copy exactly the same bias, which is one of the major shortcomings of non-AI science: WEIRD bias. This acronym stands for Western, Educated, Industrialized, Rich, and Democratic, describing the populations that are mostly chosen to conduct studies on and generalize obtained results. The problem is that it cannot be generalized – as the majority of the world's citizens are not WEIRD. Moreover, Atari et al. [40] demonstrate that this bias in the academic use of GenAI models affects even their performance on psychological cognitive tasks: LLMs perform quite impressively compared to humans living in Europe or the US, but their performance declines significantly when compared to individuals from other societies.

Apart from the WEIRD bias, it is also well-confirmed that LLMs are politically biased, manifesting a strong preference for left-leaning viewpoints[41]. They often exhibit stereotypical reasoning, such as gender bias[42], or directly mirror multiple human-like behavioral decision-making biases (e.g., risk-aversion or confirmation bias[43]). Finally, they are prone to such psychological effects as priming, size congruity, or SNARC – but (interestingly) not the anchoring effect[44]. It must be noted that this last study was conducted on ChatGPT-3, and a lot could have changed over the last 12 months with newer versions – but still, it is not likely that a new engine working on old data will generate significantly better (less biased) results in the foreseeable future.

Interestingly, the extensive critical literature on the potential problems associated with the massification of algorithmized knowledge predates the widespread adoption of LLMs by a significant margin. Notable titles aimed at the general public, such as *The Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence* [45] and *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy* [46], serve as examples. Unfortunately, it seems that critical reflection on the social consequences of this aspect of technological progress has not been sufficiently assimilated into mainstream discussions. Perhaps the obvious ubiquity of AI-generated content will more strongly motivate both users and regulators to respond appropriately.

GenAI Creativity

Creativity in academic learning fosters critical thinking and problem-solving skills, essential for adapting to complex and dynamic environments. It enhances engagement and motivation by making learning experiences more interactive and enjoyable, thereby improving academic performance. Additionally, integrating creativity into education prepares students for future challenges by encouraging innovative and flexible thinking[47]. Are LLMs likely to change these well-established dependencies?

One of the studies focused on the psychological aspects of ChatGPT in the area of creativity[48] is summarized by the statement that AI has *the potential* to generate creative responses. Based on qualitative and quantitative methodologies, the authors demonstrated that the generated data were similar to the outcomes of human experts in many fields. Nevertheless—it should be emphasized once again that AI is *merely* an algorithm based on already existing data and solutions, so it is unlikely to generate new solutions to complex problems not yet described by humans.

In art, creativity is understood as a language of communicating history and culture—having beneficial effects on both creators and perceivers[49]. If we distinguish the understanding of creativity between its purpose and tools, it limits the nature of AI's creation to tools only (having a conscious aim would require AI to have self-conscientiousness). On the other hand, in the latter context, in several domains, it significantly outperforms humans. It was clearly demonstrated by the computer program AlphaGO, which used several creative and unexpected moves to defeat the best human player in one of the most strategically demanding games in the world: Go[50].

In an academic context, the practical use of LLMs in fostering students' creativity mostly depends on individual skills related to prompt engineering – the art of designing and refining input prompts to elicit creative responses[51]. In other words, the AI's response will be as good and as creative as the operator's question. At present, it seems that the greatest potential for supporting academic creativity through GenAI lies in the completely new environment for using specific and already known human frameworks facilitating creativity, such as SCAMPER (Substitute, Combine, Adapt, Modify, Magnify, Minimize, Put to other use, Eliminate, Reverse, and Rearrange products)[52]. LLMs can become partners in such elaboration, offering an independent view of one's ideas. In a similar way, any GenAI model can be used as a digital support emulating group processes such as brainstorming or Six Thinking Hats[53]. Effective use of prompt engineering to generate ideas or constructively critique existing ones can also be a good response to various forms of student exclusion – those who, due to social rejection or remote location, cannot fully benefit from social support in group educational processes.

When moving from education to academic research, it is clear that the implementation of AI has revolutionized the way scholars approach problem-solving and innovation. AI's capability to process and interpret complex datasets efficiently accelerates the research cycle, allowing researchers to generate new hypotheses and creative solutions more rapidly[54]. This technological advancement not only enhances the quality of academic output but also ensures that researchers can keep pace with the growing demands and complexities of modern scientific reality. Currently, from the perspective of most disciplines, AI tools are seen primarily as a catalyst for creation or a substitute for research assistants. However, extrapolating the current trajectory of development, the issue of AI making bolder inroads into more crucial aspects of the scientific and creative process seems to be only a matter of time.

Social Psychology of LLM-Human Interaction

Albert Bandura's Social Cognitive Theory emphasizes the role of observational learning, imitation, and modeling in behavior. This theory is one of the most crucial in social psychology, justifying one of our fundamental motivations to join social groups. A problem arises when, for various reasons – disabilities, social exclusion, place of residence, etc. – satisfying this affiliation motive becomes difficult or impossible. An example can be seen in the recent context of the COVID-19 pandemic, which in most countries changed crowded lecture halls with hundreds of collaborating students into individual and remote computer stations connected only by the thin thread of the Internet. Is it possible that LLMs will allow us to solve such problems? There is also a range of similar issues that require the utilization of social resources, such as interaction with other people, in the learning process—resources that could not be technically substituted until now.

Large language models like ChatGPT might already be used in such contexts. This applies, for example, to modeling appropriate behaviors during data collection, observing appropriate language structures during academic writing, or receiving feedback after completing tasks. LLMs can be programmed to understand and replicate cultural norms used in diverse academic environments. Moreover, it seems apparent that LLMs can mimic social heuristics related to, e.g., social pressure or limited time[55], promoting expected behaviors like cooperation.

It is perplexing to realize that algorithms that do not exhibit human-like social motives and self-consciousness—have such potential to behave "socially." The answer lies in the enormous technological progress that allows us to extract properties from language data and effectively simulate such qualities as, for example, empathy, which is vital for building interpersonal relationships in humans. Most philosophers of the mind would agree that AI, as a non-human agent, cannot feel anything in the strict sense of the word, but - at the same time - in many contexts, this aspect of their functioning is irrelevant. For example, AI already excels in tasks involving sentiment analysis: identifying the emotions expressed in the analyzed text. Most recent models successfully emulate the Theory of Mind: the ability to attribute mental states to others and use that knowledge in the decision-making process. Recent studies show that in many areas, ChatGPT already surpasses humans in tasks like identifying indirect requests, false beliefs, and misdirection – while still struggling in some others, such as detecting faux pas[56].

The rapid advancement of algorithmic capabilities heralds the possibility of using these technologies even in the most intimate and prototypically "human" contexts—such as the pursuit of romantic relationships[57]. Social changes of this kind naturally raise a number of concerns and controversies, but they also clearly suggest the possibility of effectively using personalized teaching assistants (which seems to be a much less controversial application of the aforementioned technological possibilities). The emergence of LLMs offers a unique opportunity for the personalization of academic education. In addition to traditional teaching methods, each student may have access to an AI-powered assistant that helps them assimilate knowledge in a manner tailored to their individual needs and learning styles. As these technologies continue to evolve, bots gradually assume responsibility for various repetitive and mechanical tasks traditionally performed by educators, such as grading assessments, providing feedback, and assigning tasks to students.

Importantly, the impact of these new solutions is not limited to the cognitive domain but can also have emotional and motivational significance. The presence of an AI assistant throughout the learning journey may also facilitate the realization of social motivation[23]. By providing a constant source of support and engagement, these AI "companions" have the potential to satisfy the fundamental human need for social connection, even in the absence of direct human contact.

Of course, such applications may—rightly—raise a number of concerns, particularly regarding the risk of increased social isolation, erosion of real relationships, and the decline of certain skills (in situations where the majority of our interactions occur not with humans but with machines that do not experience real emotions and are therefore not susceptible to psychological harm). This again suggests the need to seek safe, properly regulated, and empirically validated solutions. It is also important to remember that—from the perspective of many education experts—introducing such technology-supported tutoring can free up resources in teacher-student relationships, allowing that time to be devoted to more qualitative activities rather than investing it in knowledge transfer. Once again, the devil seems to be in the implementation details, not the technology as such.

Motivation

"ChatGPT? It makes me feel lazy!" This candid statement from a student, captured in a qualitative study by[58], encapsulates the complex relationship between artificial intelligence and student motivation in higher education. As with many psychological aspects of AI integration in academia, the effects on motivation and emotions are neither uniformly positive nor negative but rather nuanced and multifaceted.

To better understand the motivational dynamics at play, we can turn to one of the most frequently cited motivational theories: Self-Determination Theory (SDT), proposed by American psychologists Edward Deci and Richard Ryan[59]. SDT posits that human motivation is driven by three fundamental psychological needs: autonomy, competence, and relatedness. The literature suggests that these three basic motivational needs can be directly linked to the opportunities provided to students by AI.

Autonomy, the first pillar of SDT, refers to the sense of control and self-direction in one's actions. In the context of AI-assisted learning, students who feel in control of their learning when using tools like ChatGPT may experience a greater sense of ownership over their educational journey. The accessibility of AI tools allows students to seek clarification, ask questions, and receive guidance on academic subjects at any time, fostering independence in their learning process. This aligns with the concept of autonomous motivation, characterized by self-directed learning behaviors[60].

Competence, the second component of SDT, relates to the feeling of mastery and capability. The ability to effectively utilize AI tools can foster a sense of proficiency, potentially boosting students' confidence in their academic abilities. As students become more adept at leveraging AI for their studies, they may experience increased self-efficacy, which is closely tied to motivation. However, it's crucial to strike a balance between AI assistance and independent problem-solving—to ensure that students develop critical thinking skills alongside their technological competence[61][62].

Relatedness, the third element of SDT, concerns the need for connection and belonging. While AI cannot replace human interaction, it can facilitate connections to the learning process, potentially enhancing students' sense of engagement within their academic community. The conversational nature of tools like ChatGPT allows for dynamic interaction with learning materials, making the process more enjoyable and stimulating. This enjoyment can lead to increased engagement and habitual use of AI tools, aligning with the idea that intrinsic motivation is bolstered when students find the learning process rewarding[61][62].

When these three foundational elements of academic motivation are effectively strengthened through the ethical and rational use of Large Language Models in academic tasks, students may experience increased motivation to learn. However, the integration of AI in education is not without challenges. The initial student quote highlighting feelings of laziness serves as a reminder that AI implementation must be carefully managed to avoid unintended negative consequences. Some students express concern that the ease of access to answers provided by AI might lead to a reduction in effort and engagement in deeper learning processes. This potential downside highlights the importance of balancing the convenience of AI tools with the necessity of active learning and effortful engagement[22][63].

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Furthermore, the perceived value of AI technology in future careers significantly influences students' motivation to engage with these tools. Students who recognize the relevance and importance of AI in their chosen fields are more likely to be motivated to learn about and utilize these technologies. This understanding aligns with the concept of performance expectancy, where students' beliefs about the potential academic and professional benefits of using AI tools drive their motivation to engage with them[62].

In conclusion, while AI presents exciting opportunities for enhancing student motivation through the lens of Self-Determination Theory, it also poses challenges that educators must address. As we continue to explore the integration of AI in higher education, it is crucial to keep in mind the ultimate goal of fostering an environment that promotes genuine learning, critical thinking, and intrinsic motivation among students. Further research is necessary to fully understand the long-term effects of AI tools on students' learning motivation, engagement, and outcomes.

Positive Psychology

The integration of AI in academia has the potential to significantly impact the well-being of both students and faculty members. This impact offers both promising benefits and potential challenges that need to be carefully navigated.

AI-based solutions have the ability to mitigate feelings of isolation and loneliness, particularly in online learning environments, and foster a sense of connection and community among students by facilitating virtual interactions and providing continuous engagement opportunities[64]. Additionally, AI systems can deliver tailored guidance and support, thereby addressing the unique needs of each student. This personalized approach not only enhances the learning experience but also empowers students by making them feel more supported and understood[65].

LLMs can address issues such as academic pressure through personalized counseling, emotional support, and timely intervention. They can function as a virtual academic advisor who is always available for students to discuss their concerns and provide personal guidance. Students can freely share their thoughts without fear of judgment, as AI Chat GPT is a non-judgmental entity. Its relevant and “empathetic” responses can help reduce feelings of loneliness and isolation that students may experience, especially in remote learning environments. Using interactive AI chatbots can improve overall well-being and help reduce stress levels in the student population. This shows the potential of LLMs to provide emotional support and relevant responses to improve students' academic experience[65].

For faculty members, integrating AI can have positive and negative effects on well-being. On the one hand, AI tools can help automate routine tasks such as grading and administrative work, potentially reducing stress and freeing up time for more meaningful interactions with students and research activities[66]. This can lead to increased job satisfaction and a better work-life balance for educators. On the other hand, the rapid adoption of AI technologies may create anxiety and stress for faculty members who feel pressured to quickly adapt their teaching methods and curricula[67]. Also, there are concerns about the potential misuse of AI tools by students for academic dishonesty, which could create additional pressure on faculty to develop new assessment methods.

In conclusion, it is important to highlight that the popularity of LLMs is a relatively new phenomenon, making it difficult to empirically and definitively confirm the potential impact of this technology on the well-being of students and educators. Nevertheless, early research results and existing knowledge about technology-supported human activities provide promising insights. Cognitive offloading and the human-like nature of AI assistants (always present and willing to help) can significantly alleviate the workload of students and educators, improve work-life balance, enhance self-efficacy, and ultimately improve the quality of work and learning. However, it is crucial that institutions provide adequate support and training to help students and faculty members navigate the new era of AI-related opportunities and challenges.

Potential Clinical Challenges

The rapid adoption of large language models (LLMs) in educational settings has transformed how students interact with information and complete academic tasks. This technological advancement brings both exciting opportunities and potential clinical issues. While LLMs offer innovative solutions in the field of clinical psychology, they simultaneously generate new threats to students' mental health. Research on the specific impacts of LLMs is still emerging, but insights from studies on general digital technology use provide valuable perspectives on both the possibilities and challenges associated with their use.

LLMs' ability to detect early warning signs of mental health challenges by analyzing students' interactions can be a game-changer in preventive mental health care. For instance, changes in language patterns or engagement levels can signal distress, allowing for timely interventions (Song, 2023). This proactive approach could revolutionize how educational institutions support student mental health, potentially preventing the escalation of mental health issues before they become severe. However, alongside these promising applications, the use of LLMs also introduces new risks to mental health.

Technostress, a modern form of stress induced by extensive technology use, has become increasingly prevalent among university students. It manifests through physical symptoms, psychological symptoms, and behavioral changes[68][69]. The use of LLMs can significantly increase anxiety levels among students, often linked to the pressure to use these advanced tools for academic purposes effectively. Studies have shown that technostress is associated with higher levels of anxiety, particularly in environments where students must rapidly adapt to new technologies without adequate support[70]. This anxiety can lead to decreased mental health, characterized by persistent worry, restlessness, and difficulty concentrating[71].

While potential addiction to LLMs specifically has not been extensively studied, insights from research on general technology addiction suggest that students may develop compulsive usage patterns. These patterns can detract from their natural cognitive skills and critical thinking abilities, creating a dependency that undermines their overall learning experience[72][73]. The constant pressure to use LLMs effectively can also contribute to depression among students, as they struggle with the continuous demands of technology use in their academic lives. This can manifest as feelings of hopelessness, decreased interest in academic activities, and a general sense of dissatisfaction with their academic performance[74].

Addressing these issues requires a comprehensive approach that balances LLMs' potential benefits with strategies to mitigate their risks. This includes proper education on the healthy use of technology, providing adequate support systems, and promoting a balanced lifestyle that integrates technology use with other essential activities[75].

Final remarks

As we conclude this exploration of the psychological dimensions of AI integration in academia, it is important to revisit the key questions mentioned in the introduction and reflect on the insights gained throughout our discussion. We began by examining the issue of equality in access to AI solutions, highlighting how the democratization of these tools presents both opportunities and challenges. The psychological factors influencing technology adoption, such as personality traits and emotional states, play a significant role in determining who benefits from these advancements. This underscores the importance of addressing digital anxiety and technostress to ensure equitable access and prevent the exacerbation of existing inequalities.

Our analysis of academic misconduct in the AI era revealed that while the tools have changed, the underlying psychological mechanisms driving dishonesty remain largely the same. The discussion on the (non) human nature of LLMs highlighted the complex psychological dynamics at play in human-AI interactions. Our examination of cognitive offloading sheds light on the double-edged nature of AI assistance in learning. The exploration of psychological biases in AI systems revealed the persistence of human biases in these technologies, from WEIRD (Western, Educated, Industrialized, Rich, and Democratic) biases to gender stereotypes. The discussion on AI and creativity highlighted both the potential for AI to enhance creative processes and the enduring importance of human ingenuity. The examination of social psychology in LLM-human interaction revealed the potential for AI to satisfy certain social needs in learning environments while also raising questions about the nature and quality of these interactions. Finally, our analysis of motivation and potential clinical challenges associated with AI use in academia highlighted both the opportunities for personalized, engaging learning experiences and the risks of technostress, addiction, and other mental health concerns.

Undertaking critical reflection on the role of AI in transforming the didactic, scientific, and organizational practices of universities is imperative at the moment. The intensity of the changes we are currently confronted with does not offer us decades for endless deliberations or reflections. It also leaves little room for what we, as representatives of empirical sciences, like the most: research, preferably carefully replicated or integrated in the form of meta-analyses. However, the lack of this luxury does not mean that we should succumb to the simplest or stereotypical reactions in our reflections, which reduce the debate to ritual gestures so well described in the previously mentioned text by Orben[3].

Since the current state of knowledge and research does not justify the creation of "grand syntheses," instead of offering them, we will close our considerations with some recommendations concerning the short-to-mid-term priorities, which, in our opinion, are well justified in the current state of knowledge on the use of LLMs in academia. These will be followed by two more general remarks offering a broader reflection on this field of study.

Based on our review, we consider the following actions as priorities in the responsible implementation of LLM-based solutions in the academic setting:

1. Attention to issues of digital equity, ensuring that the benefits of AI in education are accessible to all members of the academic community.
2. Comprehensive AI training for both students and faculty members, covering technical aspects, ethical considerations, and strategies for mitigating psychological risks.

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3. Continuous development of empirically grounded guidelines and best practices for AI use that implement innovative tools and practices while not neglecting key academic values.
4. Continued research into the long-term psychological impact of AI use in education, with special consideration of issues of mental health and well-being.

Given the rapid pace at which the field of AI is evolving, we recognize that by the time this article reaches its readers, the technological landscape may have already undergone significant changes, possibly making some of our specific examples outdated. However, the underlying psychological principles and ethical considerations discussed here are likely to remain relevant, providing a framework for understanding and navigating future developments.

The caveat just made also serves as an excellent transition to two broader reflections with which we would like to conclude our discussion. First, we are convinced that AI in academia as a field of research needs a good description and understanding rather than easy leaps to the evaluation stage, conclusions, and recommendations. It can only be warranted by continued research efforts. On the one hand, the scale of changes and the necessity of making "here and now" decisions exert strong pressure on us; on the other hand, it is worth remembering that, especially in extreme situations, the quality of reflection undertaken is critically important. We hope that both the examples we have presented and the meta-reflection outlined in the introduction can serve as inspiration for deeper and more conscious debate in this area. If decisions, whether regulatory or implementational, must be made, they should be accompanied by an exceptionally clear awareness of their temporariness and sensitivity to intended and surprising consequences. Using a military metaphor, we are conducting "reconnaissance by fire," and as such, our eyes and ears should be exceptionally wide open and ready for potential changes in tactics and strategy.

At the same time, we would also like to emphasize that the perspective we propose is also a significant source of hope, which is often scarce in the context of debates surrounding the future of academia. In thinking about our relationships with technology, we often behave as if our main role – as social science researchers – was to accurately predict ("foresee"?) the future. The reconstruction of the complex network of dependencies co-determining the fate of relations between our minds, AI, and universities (or – more broadly – education) allows us to realize that the future is rather assigned to us than given. It is not determined by external forces but shaped by research, reflection, and – ultimately – regulation. It gives us a significant amount of freedom and responsibility. Referring to Gibson's famous quote – if "the future is already here, it is just not evenly distributed," it is worth realizing that the future resides not only in server rooms or large technology companies but also in our minds and research agendas.

Integrating AI in academia represents a profound shift in how we approach teaching, learning, and knowledge creation. We believe that by integrating psychological and empirical perspectives into this transformation, we can work towards taking full advantage of AI to enhance the quality of education while mitigating its risks. Hence, the future of AI in academia will be shaped not just by technological advancements but by our collective ability to engage with these tools thoughtfully, ethically, and with a deep understanding of their impact on human psychology and behavior.

Statements and Declarations

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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