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Navigating the Adoption of Artificial Intelligence in Higher Education

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ABSTRACT

With the advent of Education 4.0, the integration of Artificial Intelligence (AI) into higher education has become increasingly prevalent, reflecting the pervasive influence of digital technologies in contemporary educational paradigms. In light of this transformative shift, this conceptual article proposes a comprehensive investigation into the adoption of AI among undergraduate students in higher education institutions. Drawing upon the robust theoretical framework of The Unified Theory of Acceptance and Use of Technology (UTAUT), this study aims to elucidate the intricate interplay between key variables within the UTAUT Model—namely, performance expectation, effort expectation, social influence, and facilitating conditions—on students' attitudes and behavioural intentions toward AI adoption in their educational endeavours. By employing a quantitative research design, this study will leverage Structural Equation Modelling - Partial Least Squares (SEM-PLS) to rigorously analyse the gathered data. Such an inquiry is pivotal as it endeavours to uncover and comprehend the nuanced dynamics of AI adoption tendencies among students, thereby enabling educational institutions to proactively address potential challenges and capitalise on emerging opportunities associated with the integration of AI. Moreover, this study seeks to foster a nuanced discourse on the potential linkages between the aforementioned variables prior to empirical testing, thereby enriching the scholarly discourse surrounding AI adoption in higher education.

Keywords: Artificial Intelligence, Behavioural Intention, Higher Education, UTAUT Model

1. INTRODUCTION

We have seen a significant shift from conventional classrooms to online and hybrid approaches due to the COVID-19 pandemic (Adedoyin & Soykan, 2020). Artificial Intelligence (AI) is a key component of the contemporary digital industrial revolution, commonly referred to as the fourth revolution and its significance is steadily growing in the present era (Araújo, 2020). AI refers to a dialogue system that can analyse and interpret users' linguistic inputs and generate responses through machine-generated or pre-programmed messages in various forms, such as verbal or textual formats (Huang et al., 2022). In the context of education, AI gives students greater chances in out-of-classroom environments and assists them in overcoming certain learning challenges in the new online educational settings after COVID-19 (Fryer et al., 2020). It is indicated that chatbots powered by AI are a distinct category when it comes to educational applications (Lin & Yu, 2023). It is also crucial to use contemporary AI to replace old technologies and manual processes in higher education. This helps institutions adapt and improve education (Razia et al., 2022). Within the domain of educational resources, platforms such as ChatGPT and ChatPDF have emerged as leading tools where it aids students in learning in a variety of ways. Aside from easing academic tasks, such innovation also fosters interactive learning and allows collaboration (Idroes et al., 2023).

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The relevance of addressing the adoption of AI among students lies in the fact that it will better prepare them for a future in which AI technologies will be everywhere. The use of these technologies will help improve critical thinking, problem-solving abilities, and digital literacy, all of which are important qualities in today's rapidly changing labour market (Presbitero & Teng-Calleja, 2023). Notwithstanding the potential advantages, the adoption of AI in the scope of higher education remains constrained (Elhajji et al., 2020). While existing literature reviews have provided an overview of relevant studies in the broader context of technological advancements, limited attention is observed in the applications of AI chatbots with an intermediate focus on education (Lin & Yu, 2023). There could be many factors that contribute to this limitation, which may include issues around data privacy, the need for necessary training, and concerns about the displacement of conventional methods of learning (Ntoutsi et al., 2020). Additionally, there is a concern about the digital divide that needs to be addressed among students (Afzal et al., 2023), in which some may have more access to AI tools than others. As a result, more studies are required to further explore the adoption of AI among students in higher education (Alfarsi et al., 2021; Popenici & Kerr, 2017). Studying and understanding the current level of AI adoption among students will help higher education institutions find effective approaches to enhancing the education and learning process and improving its quality.

Following will be the organisation of this article. We first look at the existing studies and literature reviews on key variables of the Unified Theory of Acceptance and Use of Technology (UTAUT) model namely performance expectation, effort expectation, social influence, and facilitating conditions on attitudes and behavioural intention towards AI adoption in higher education institutions. This will serve as a foundation and groundwork before conducting an empirical study. Then, we describe the methods and analysis that will be used in this study. Finally, we will provide a discussion and conclusion to provide broad implications of the findings and summarise the key insights from the study.

2. LITERATURE REVIEW

2.1 Unified Theory of Acceptance and Use of Technology (UTAUT) Model

According to The UTAUT Model, behavioural intention dictates how technology is being used. In the model itself, the direct influence of four major constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—determines the perceived likelihood of technology adoption (Venkatesh et al., 2003). These four major constructs play a crucial role in an individual's evaluation of technology (Akwang, 2021). The UTAUT model application has seen widespread adoption in the education sector (Raffaghelli et al., 2022; Alowayr & Al-Azawei, 2021). In the context of this study, the UTAUT Model is an important tool for understanding the technology adoption process by users (i.e. students). Hence the model helps to clarify how students' adoption of technology might be further assessed.

2.1.1 Performance Expectation

Performance Expectation (PE) refers to the degree to which individuals believe that using a system or particular technology will help them enhance their jobs (Horodyski, 2023; Venkatesh et al., 2003) and consequently bring positive results (Veiga & Andrade, 2021). In the context of this research, it reflects the perceived usefulness (An et al., 2023) of incorporating AI technology in enhancing learning outcomes for students as well as improving teaching methodologies and experience. Students anticipate that AI-assisted learning environments may increase efficiency, optimise the learning process, and increases their attitude toward learning (Lai, 2021). Meanwhile, by having high-performance expectancy among academicians, they believe that incorporating AI can enhance their teaching effectiveness, leading to improvements in both efficiency and quality (An et al., 2023). They are more likely to be optimistic about AI's potential contributions to their teaching efficiency, the quality of educational delivery, and overall pedagogical effectiveness.

In the current technological landscape, individuals are increasingly prioritising the utilisation of technologies that can offer tangible benefits by streamlining tasks and enhancing overall processes. Emon et al. (2023) mentioned that the possibility of professionals integrating AI into their daily work is directly correlated to their confidence in the technology's capacity to improve their decision-making, tackle complex challenges, and optimise overall performance. It was confirmed by the previous study by Horodyski (2023) and An et al. (2023), where there was a strong positive influence of performance expectancy on the behavioural intention of individuals to incorporate AI. The more they believe that AI can positively benefit the critical aspects of their work, they are more likely to incorporate AI tools into their daily tasks and responsibilities. Thus, the following hypothesis was proposed:

H_1: Performance expectation positively influences behavioural intention to adopt AI in higher education.

2.1.2 Effort Expectation

Horodyski (2023) and Venkatesh et al. (2003) defined Effort Expectation (EE) as the degree of ease associated with the use of the system or particular technology. It speaks to the person's opinion of how simple or complex using the technology would be. It covers aspects such as the individual's experience, IT knowledge, and other factors that may contribute to their perception of the ease of using the technology (Rico-Bautista et al., 2020). If individuals perceive AI technologies as challenging to comprehend or use, they may resist the adoption of AI. On the contrary, they are more likely to embrace or incorporate these technologies into their work processes if the AI systems are designed to be user-friendly, intuitive, and require minimal effort to operate (Emon et al., 2023).

The previous empirical studies conducted on effect expectancy show different results towards the adoption of the technology. An et al. (2023) mentioned that the effect expectancy corresponds with the perceived ease of use, which has significantly affected behavioural intention on particular technologies such as chatbots (Bilquise et al., 2023) and Blackboard learning system (Raza et al., 2022). However, a different result was found by Horodyski (2023) that the effort expectancy was not significantly related to the intention to use AI in recruitment, while An et al. (2023) found that effort expectancy cannot directly predict teachers' behavioural intention to use the AI technologies. The same result has been found by Wang and Chen (2022), where effort expectancy has a negative correlation with acceptance of virtual human technology. Nevertheless, effort expectancy can be considered as the prime determinant influencing the intention (Raza et al., 2022) to adopt AI technology, especially in the higher education context. This positive correlation shows the significance of an individual's experience and ease of use of AI technology. Thus, the following hypothesis was proposed:

H_2: Effort expectation positively influences behavioural intention to adopt AI in higher education.

2.1.3 Social Influence

Venkatesh et al. (2003) interpret Social Influence (SI) as the extent to which an individual believes that influential individuals expect them to adopt the new system. In various theoretical frameworks namely the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and the Combined Technology Acceptance Model and Theory of Planned Behaviour (C-TAM-TPB), SI directly influences behavioural intention and is manifested as the subjective norm. Whereas, in the Model of PC Utilisation (MPCU) this is reflected by social factors and in Innovation Diffusion Theory (IDT) by image. Shortly, individual individual's actions in utilising the technology are shaped by their perception of how others will perceive them in using the same.

SI's operation is mandated, and this can be linked to adherence in obligatory situations. SI exerts a direct linkage on intention, especially during the initial phases when an individual's viewpoints are relatively uninformed. This normative pressure tends to diminish over time as greater experience offers a more pragmatic foundation for the individual's intention to use the system rather than a social one. In mandatory situations, the significance of SI seems to be limited to the initial phases of individual exposure to the technology, diminishing over time and eventually becoming nonsignificant with prolonged use (Venkatesh et al., 2003). Over time, SI is likely to evolve as a result of ongoing social interactions and pedagogical activities (Raffaghelli et al., 2022). Conversely, SI within voluntary settings, operates by shaping perceptions of the technology through internalisation and identification mechanisms (Venkatesh et al., 2003). Hence, SI is intricated and susceptible to various contingent factors and mechanisms - compliance, internalisation, and identification. Internalisation and identification pertain to modifying an individual's belief structure and/or prompting an individual to respond to potential social status gains. In contrast, the compliance mechanism induces an individual to straightforwardly adjust their intention in reaction to social pressure that is the individual intends to comply with the SI (Venkatesh et al., 2003).

In a social development organisation, the environment for SI is shaped by peers, seniors, and management, each playing a role in influencing the utilisation of AI-enabled tools within the organisation (Jain et al., 2022). Venkatesh et al. (2003) theoretical propositions indicate that women tend to be more attuned to others' opinions, making SI more prominent in their decision-making process when forming an intention to adopt new technology. SI is treated as a reliable predictor of acceptance, drawing from literature associated with peer learning, social learning, and students' informal collaboration to assist each other in higher education (Raffaghelli et al., 2022). Notably, social influence emerges as the most influential factor in the adoption of AI-enabled tools within the organisation. Based on the above review, we would like to test the following hypotheses:

H_3: Social influence positively influences behavioural intention to adopt AI in higher education.

2.1.4 Facilitating Conditions

Venkatesh et al. (2003) interpret this as the extent to which an individual perceives the presence of an organisational and technical infrastructure that supports the utilisation of a system. This definition encompasses concepts represented by three distinct constructs: perceived behavioural control (TPB, C-TAM-TPB), facilitating conditions (MPCU), and compatibility (IDT). Each of these constructs is designed to incorporate elements of the technological and/or organisational environment intended to eliminate obstacles to use.

Research has shown that concerns associated with the support infrastructure are predominantly encompassed by the effort expectancy construct. This construct assesses the ease with which a tool can be applied (Venkatesh et al., 2003). Over time, social influence and facilitating conditions are likely to evolve as a result of ongoing social interactions and pedagogical activities (Raffaghelli et al., 2022).

Empirically, it is proposed that the relationships between each of these constructs and intentions exhibit similarities. Venkatesh et al. (2003) found there was a full mediation effect of facilitating conditions on intention by effort expectancy. Clearly, in the presence of effort expectancy, we can anticipate the predictive effect of facilitating conditions on intention as in the case of TPB. In TPB, facilitating conditions are significant in predicting intention. However, in MPCU and IDT, it becomes nonsignificant. Hence, with performance expectation and effort expectation, the facilitating condition would not exhibit a significant relationship with intention. Nonetheless, it does exert a direct influence on usage. Following this, Chatterjee and Bhattacharjee (2020) proposed and concluded in their study that facilitating conditions exert a notable and favourable influence on both effort expectancy and the Attitude (ATT) of stakeholders within higher education institutes regarding the adoption of AI in Pakistan. Facilitating conditions have a positive impact on users' effort expectancy. Besides, it additionally contributes to users displaying a favourable intention to use AI within the higher education system. However, Raza et al. (2022) exhibited a positive but statistically insignificant relationship between facilitating conditions with the Behavioural Intention (BI) of the Learning Management System (LMS). Their result suggests that the availability of timely assistance and the required infrastructure does not significantly impact students' intention to use the LMS for completing their coursework. Raffaghelli et al. (2022) concluded that facilitating conditions were considered highly pertinent, particularly in the context of induced rather than autonomous usage, specifically with the integration of the Early Warning System (EWS) into the virtual learning environment. It is conceivable that students anticipate various forms of support integrated into teaching and tutoring activities. The study of Jain et al. (2022) focused on social development organisations. They discovered that employees received organisational and technical support for adopting and using online technologies powered by AI for their work. To assess the impact of social influence and enabling factors on aversion towards AI, Jain et al. (2022) expanded their investigation. The results showed that both factors had a substantial detrimental effect on AI aversion. This shows that people are more likely to adopt AI in organisations that create a supportive environment where peers, superiors, and subordinates adopt the same technology. Furthermore, there is less opposition to AI when companies provide supporting interventions like facilities, resources, and training.

It could be understood that the previous finding provides inconsistencies of significant linkage between facilitating condition and behavioural intention and usage. Hence, this literature helps us to develop the following hypotheses:

H_4: Facilitating conditions positively influence the behavioural intention to adopt AI in higher education.

2.2 Behavioural Intention and Adoption of Behaviour

The term behavioural intention denotes an individual's inclination or readiness to adopt a specific technology for carrying out various tasks. It reflects the commitment an individual demonstrates to participate in a particular behaviour (Raza et al., 2021). Behavioural intention exerts a substantial and positive influence on the adoption of AI in higher education (Chatterjee & Bhattacharjee, 2020).

Raza et al. (2021) disclosed that students' behavioural intention concerning the adoption of the e-learning system is positively associated with their usage behaviour, leading to improved academic performance. They exhibited a significantly positive correlation between behavioural intention and actual use. Based on their findings, Raza et al. (2021) proposed that since the world is swiftly progressing toward AI, it is recommended to expand the presence of the online environment and diversify activities. Now is the opportune moment to integrate the online environment more extensively into the education system.

Jain et al. (2022) projected the adoption and utilisation of AI-enabled features are completely voluntary, granting employees the freedom to leverage them for team assistance in task completion and the enhancement of team decisions. Nevertheless, despite AI's potential to improve employees' capacity for effective development and bolster team collaboration, certain considerations may impact its widespread implementation. They also suggested that effort expectancy, performance expectancy, facilitating condition, social influence, and algorithmic aversion collectively have a significant impact on the utilisation of AI-enabled tools.

Alzahrani (2023) pioneered a study on the adoption of AI in higher education institutions in Saudi Arabia. In employing the UTAUT model, their result showed the importance of awareness and attitude variables. Attitude was found to have a great influence over students' BI on AI technology. Their result also revealed the influence of EE and PE over ATT, hence suggesting the stakeholders enhance their roles in overcoming technological difficulties. The result impliedly suggested an attentive attention to the serviceability of AI systems on the part of the administrators, designers, developers, and other relevant authorities. Similarly, after conducting an empirical investigation, the study of Li (2023) revealed that the Actual Use (AU) of AI by college students depends largely on the combination of their Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and ATT towards AI. Explicitly, their result suggested that students' PEOU towards AI substantially and positively impacts their PU.

In addition, Roy et al. (2022) showed a positive thought of both teachers and students in adopting AI in universities hence, providing an affirmative answer to their research question, "Do teacher and student attitudes impact the intention to adopt AI-based robots in the education sector?''. The use of AI was found to be helpful and accessible. From the student's perspective, robotic study is indispensable as it illustrates a holistic view of engineering which covers more than just problem-solving on paper but with outcome. Hence, we develop the following hypotheses based on the foregoing literature.

H_5: Behavioural intention positively influences the adoption of AI in higher education.

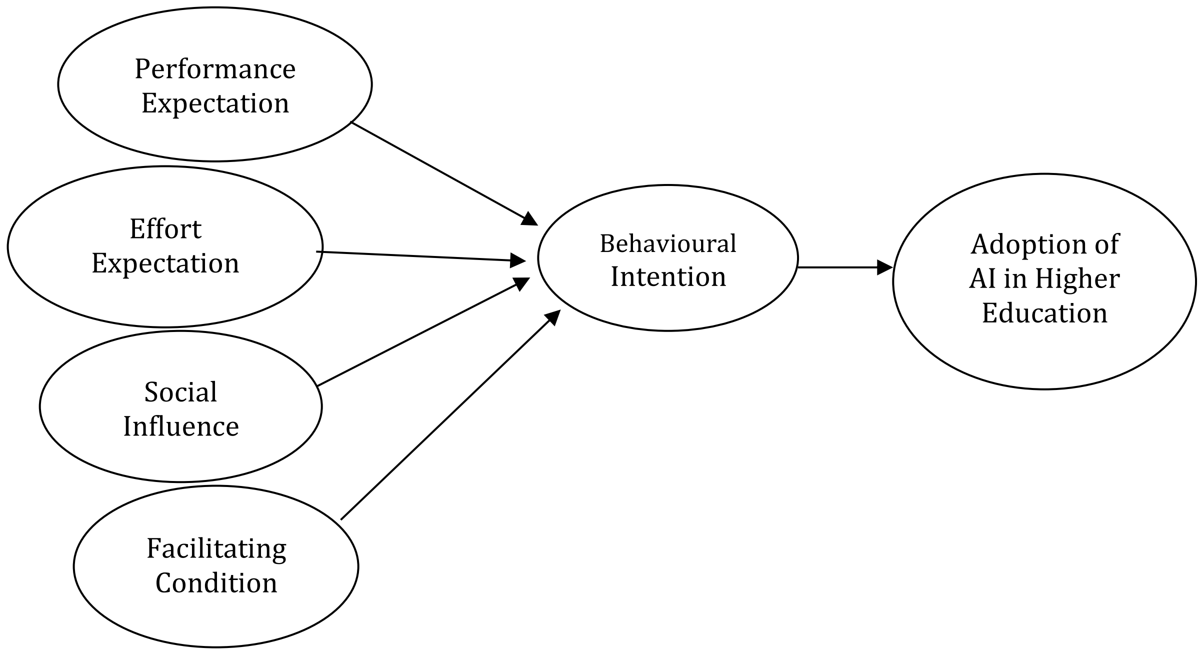

Figure 1. Proposed Research Framework

3. METHODS

The paper aims to examine the current state of AI adoption in higher education, specifically among undergraduate students. The study proposes a conceptual model for adoption by exploring factors such as performance expectation, effort expectation, social influence, and facilitating conditions on behavioural intention.

To analyse the data collected, we will be using two techniques: SPSS and PLS-SEM. PLS-SEM is particularly useful for evaluating relationships between variables in real-time. Our measurement model will be assessed through various methods such as indicator loading, internal consistency reliability, and convergent validity. Any indicators with a score below 0.70 will be excluded from the analysis. Internal consistency reliability will be established through composite reliability and Cronbach alpha, while convergent validity will be measured using the average variance extracted. Lastly, we will use a Heterotrait Monotrait ratio to determine discriminant validity, with a result of less than 0.85 indicating that it is established.

There are altogether four (4) variables used in the current research framework to measure the adoption of AI in Higher Education that were adopted from Venkatesh et al. (2003). Each item was measured using a 5-Likert scale that ranges from strongly disagree (1) to strongly agree (5).

Four (4) performance expectation items were included in the questionnaire such as “AI can help me improve the quality of learning”, “AI can help me improve the efficiency of study” and “I believe AI is very useful in my job”. Effort expectation items encompassed statements such as “AI teaching systems are easy to operate for me”, “I can easily master the skills of using AI study system”, and “The operation of AI learning system is clear”. Facilitating condition were represented by items such as “When I need to use AI in the study, my university will provide help for me”, “There are convenient conditions for me to use AI in the study” and “When using AI in the study, I know where to get technical support. Lastly, three (3) items of social influence items such as “Students around me who are good at using AI will have more respect” “Students who can use AI in teaching will be admired by their teammates” and “My teammate thinks I should use AI to support study”.

4. DISCUSSIONS

The implementation of AI in higher education institutions depends on several important factors that affect people's attitudes and intentions. Four main factors play a significant role in shaping people's perceptions and decisions regarding AI adoption in this context. These factors are performance expectation, effort expectation, social influence, and facilitating conditions.

Performance expectations refer to the anticipated advantages and benefits that stakeholders associate with the adoption of AI in higher education. In this context, AI is perceived as a tool that can enhance teaching efficacy, facilitate personalised learning experiences, and support academic research by providing rapid data analysis and insights (Lescevica et al., 2013). When individuals believe that AI can significantly improve educational outcomes, their positive attitudes and intentions toward its adoption tend to increase. Therefore, it is vital to recognise the potential benefits of AI in higher education to establish a positive perception of its adoption, which is necessary for effective implementation. In another way, effort expectation is a term used to describe the stakeholders' perception of the required level of effort to use AI in higher education settings. If the stakeholders perceive AI implementation as being user-friendly, easy to learn, and seamlessly integrated into the existing educational practices, they are more likely to develop favourable attitudes toward AI adoption. On the other hand, if stakeholders have concerns about the complexity of AI systems or the need for extensive training, they may be less enthusiastic about incorporating it into educational settings. Therefore, educational institutions need to provide user-friendly and easily understandable AI systems that can be easily integrated into existing educational practices to ensure a smooth and successful adoption of AI.

Social influence encompasses the impact of peers, colleagues, and influential figures on an individual's attitudes and intentions toward AI adoption. Within higher education institutions, the endorsement and support of AI by respected educators, administrators, and influential stakeholders can significantly sway opinions. Additionally, peer acceptance and positive experiences shared within professional networks or communities can further encourage or discourage AI adoption in educational practices (Salloum & Shaalan, 2019). When considering the adoption of AI in higher education, facilitation is a key factor. Facilitation refers to the resources, support systems, and infrastructure that are available to individuals. Some factors that contribute to a conducive environment for AI adoption include adequate funding, technological infrastructure, IT support, access to training and development programs, and institutional policies supporting AI integration. When individuals perceive these facilitating conditions as favourable and supportive, they are more likely to have positive attitudes toward and intentions for AI adoption in education (Huang, 2018).

In higher education institutions, the attitudes and intentions toward adopting AI are influenced by factors such as perceived performance benefits, ease of use, social influences, and the presence of facilitating conditions. To increase the stakeholders' willingness to incorporate AI technologies in educational settings, it is important to create an environment that highlights the advantages of AI, minimises perceived effort, leverages social endorsements, and provides necessary resources. By doing so, we can significantly impact the adoption and integration of AI in higher education institutions.

5. CONCLUSION

The integration of AI in higher education has revolutionised the learning environment, leading to numerous positive changes and improvements. The UTAUT model offers a comprehensive framework that helps to comprehend the factors that influence the adoption of AI in higher education settings (Abbad, 2021). By applying the UTAUT model, several critical points can be identified when assessing the impact of AI adoption in higher education. These include factors such as performance expectation, effort expectation, social influence, and facilitating conditions, all of which contribute significantly to the adoption and use of AI in higher education. Additionally, the adoption of AI in higher education has resulted in increased efficiency, improved learning outcomes, personalised learning experiences, and enhanced student engagement (Almaiah et al., 2019). This has been made possible through the use of adaptive learning technologies, intelligent tutoring systems, and chatbots, which have demonstrated their effectiveness in improving learning experiences and outcomes.

The adoption of AI in higher education is accompanied by a plethora of benefits. These benefits include, but are not limited to, enhanced learning experiences, improved efficiency, and innovative research opportunities. However, the introduction of AI also brings to the forefront potential challenges and drawbacks, such as job displacement, ethical concerns, overreliance, accessibility, and interpersonal interactions (Zawacki-Richter et al., 2019). Therefore, a balanced approach is necessary to successfully integrate AI in academia, which maximises the benefits while addressing and mitigating the potential pitfalls. AI must be utilised as a complementary tool to augment rather than replace the human-centric aspects of education. To achieve this, ethical guidelines, thoughtful implementation strategies, and continual assessment of its impact are crucial (Kazoun et al., 2021). Collectively, these studies outline a critical role of adopting AI can be leveraged to its full potential in higher education while also mitigating its potential negative consequences.

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