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Original Article

Exploring Artificial Intelligence as a Remedy to the Heavy Teaching Workloads Caused by Massification of Ugandan Public Universities

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Universities worldwide, particularly public universities in Uganda are facing a dilemma in which their massification has far outstripped the growth of their academic service delivery capacity, especially their actual teaching staff size. Consequently, most lecturers are struggling with heavy teaching workloads resulting from large class sizes of 100 to 300 or more students created by massification per course unit, especially at the undergraduate level. These workloads have overstretched most lecturers' ability to teach effectively and limited their career growth by keeping them too busy to conduct research and participate in community service. The dilemma is faced at the time when Industry 4.0 has developed Artificial Intelligence (AI), which can execute different tasks, including teaching tasks in much the same way as human beings perform them. Drawing on the AI job replacement theory complemented by UTAUT and TOE, this study employed a cross-sectional questionnaire survey involving 325 respondents (deans, heads of department [HODs] and lecturers) randomly selected from five randomly selected public universities to analyse awareness of the teaching tasks AI can execute to reduce faculty members' workload without replacing them, acceptance of AI to perform these tasks, and hindrances to its adoption. Findings from the descriptive analysis indicate that at least 74% of the deans, HODs, and lecturers were highly aware of the teaching tasks AI can perform. Most of these respondents accept AI to perform such teaching tasks that do not involve a human touch as an online search for research and lecture content, lecture dictation, student assessment and evaluation, and grading of marks. They, however, did not accept AI to execute teaching tasks that involve the human touch such as lecture planning, facilitating tutorials and discussions, assessing students' interpersonal weaknesses that affect learning, and feedback provision. These findings allude to a need to adopt AI to execute only the teaching tasks it is accepted to perform and leave to the lecturers all the tasks they do not accept to perform. Adopting AI this way is bound to relieve the teaching workload allocated to lecturers as massification intensifies. The findings indicate, however, that AI adoption is hindered by different factors, including lack of strategic, ethical, and policy guidelines, and lack of funds and skills required to operate it. These findings point to a need for the management of Uganda's public universities to adopt AI by lobbying the government for more funding, mobilizing necessary funds internally, training faculty members in using AI, and encouraging all of them to accept it by explaining the role it is capable of playing in reducing workloads and erasing their fear that AI could replace them.

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INTRODUCTION

Artificial Intelligence (AI) is not a new concept in scholarship. It was coined in the 1950s and as technology transitioned to Industry 4.0, evolved to refer to software and hardware that simulates human intelligence to execute different tasks in much the same way human beings perform them, without receiving any external instruction (Dong *et al.*, 2020; Vrontis *et al.*, 2021). The tasks that AI can perform range over a wide spectrum that includes teaching and instruction at all levels of education, including the university level (Crompton & Burke, 2023; Ghalayini, 2023). However, awareness of the specific teaching tasks that AI can perform, acceptance of this technology by faculty members to execute these tasks as a remedy to the heavy and overstretching teaching workloads allocated to them as a result of the ongoing massification of higher education, and the hindrances to its adoption remain to be analysed, particularly in Ugandan public universities. Yet this analysis is needed as a basis for establishing how AI can be used to ensure that the quality of provided education is not eroded by overstretching faculty members with the heavy teaching workloads allocated as a result of the inevitable ongoing massification.

The concept of massification was coined by Martin Trow in 1973 to refer to a process by which higher education in general and university education, in particular, is made unlimitedly

accessible to all student applicants who meet the minimum entry standards regardless of their numbers (Thambusamy *et al.*, 2019; Mosomi, 2022). Globally, massification started in the late 1960s in the form of establishing as many tertiary institutions and universities to make higher education accessible to as many students as possible (Noui, 2020). Massification was given impetus from the onset of the 21st century following not only higher population growth rates that resulted from improvements in global health standards but also government adoption of cost-free education policies that expanded access to education at lower levels (Eton & Chance, 2022; Ruff *et al.*, 2023). The available global statistics indicate that the result of these factors has been such that the 235 million students who joined higher education in 2021 more than doubled those who had enrolled in 2000, and enrolment is estimated to reach 380 million students by 2030 (Murthi & Bassett, 2022; UNESCO, 2022). In universities alone, massification intensified from less than 60 million students enrolled in 2000 to more than 250 million students enrolled in 2022 worldwide (Gallup, 2023). UNESCO's (2022) enrolment statistics indicate that 9% of university massification, which is equivalent to a rise from less than 10 million students in 2000 to 22.5 million students in 2022, occurred in sub-Saharan Africa.

As one of the sub-Saharan countries, Uganda's universities massified to 198,000 students in 2022, almost four times the enrolment of close to 50,000 students in 2000 (National Council for Higher Education [NCHE], 2022). Uganda has 13 public and 39 private universities, but massification has been far more pronounced in public universities, which include Makerere University, Kyambogo University, Makerere University Business School, Mbarara University of Science and Technology, Uganda Management Institute, Busitema University, Gulu University, Mountains of the Moon University, Kabale University, Lira University, Muni University, Soroti University, and Busoga University (NCHE, 2022). The reasons for the much higher massification of Uganda's public universities include not only the fact that Uganda's population began to grow at a higher rate (from 2% to 3.5%) as a result of government efforts to prevent the six killer diseases, including polio, measles, tuberculosis, whooping cough, diphtheria and tetanus (Kanyesige, 2022). They also include government introduction of Universal Primary and Secondary Education, and privatisation of higher education which increased the number of students who qualify for university education (Musika, 2019; Kamonges, 2021; Otyola *et al.*, 2022). In addition, education is provided by Uganda's public universities at a relatively lower cost compared to its cost in private universities and some of the most massified public universities such as Makerere University have a long-standing national and international reputation that attracts most of the high school leavers (Hand, 2023; Kiconco, 2023). These reasons combine to create a sharp increase in the demand for university education in general and that provided by public universities in particular.

Such demand has created a dilemma in Uganda's public universities because it has resulted in public universities massifying much more in terms of enrolment compared to the growth of their academic service delivery capacity (Kasozi, 2002; Nakimuli & Turyahebwa, 2016; Muriisa & Rwabyoma, 2019; Kibaliwandu & Mwesigye, 2022). University enrolments have far outstripped

the physical instructional infrastructure of public universities such as Makerere University, Kyambogo University and others. These enrolments have also far overstretched the teaching ability of academic staff members. While the available statistics indicate that most of the public universities meet the faculty-student ratio of 1:25 recommended by the NCHE (2022), this ratio applies only when the total of lecturers is compared to the total enrolment. Makerere University, for instance, has an average total enrolment of 30,574 students and 1,274 faculty members, which gives a faculty-to-student ratio of 1:24 (Makerere University Strategic Plan, 2020/2025). However, when the ratio is computed per course unit, it goes far beyond the 25 students per lecturer, especially for course units taught in Arts, Social Sciences, Natural Sciences and Education at the undergraduate level. For most of these course units, lecturers teach large class sizes ranging from 100 to 300 or more students (Johnson *et al.*, 2023). It is in this sense that Waruru (2023, p.1) stated, "Universities in East Africa need to recruit more than 35,500 lecturers to meet the desired student-to-teacher ratio... in various subject areas, and an even higher number of faculty to have the ideal number of teaching staff in their lecturing halls and laboratories." None of the Ugandan public universities has filled its academic staff establishment as planned (Rwothumio *et al.*, 2021).

The excessive class sizes that massification created have overstretched most of Uganda's public university faculty members' ability to teach efficiently and effectively (Tumusiime, 2021). Although the official teaching contact hours are still 48 per month (12 per week) or 60 per month (15 per week) when the paid extra hours are included (NCHE, 2022), the teaching workload allocated within these hours is too heavy for most lecturers to perform given the number of students involved (Mukhayi, 2022). This is exacerbated by the fact that in some of Uganda's public universities, the already heavy teaching workloads are allocated not only within the official working period of 8:00 am to 5:00 pm stipulated in Uganda Public Service Standing

Orders (Ministry of Public Service, 2021). Their allocation also covers morning hours before 8:00 am, evening hours after 5:00 pm and weekends, which are not working days as per the same Orders. These heavy teaching workloads have caused dire consequences for most faculty members of Uganda's public universities.

Indeed, lecturers are struggling with high levels of work-related stress, work-life imbalance, and lack of time for career progression through conducting research and participating in community service as almost all the time is spent on teaching (Tumusiime, 2021). The heavy teaching workloads that cause all these dire health, social and professional effects are allocated in this era when technological advancement has improved AI to a stage at which it can perform some of the teaching tasks, thereby reducing the workloads (Chen *et al.*, 2020; Chu *et al.*, 2022; Crompton & Burke, 2023), but it is not used at all. Different questions arise from this scenario, including Are the faculty deans and department heads who allocate the heavy teaching workloads and the faculty members to whom they are allocated are aware of the teaching tasks that AI can perform to reduce the workload without replacing the lecturers. What is the academic staff's level of AI acceptance to perform these teaching tasks? Are there hindrances to AI adoption in Uganda's public universities? This study sought to answer these questions guided by the theories and gaps identified from the literature reviewed in the next section.

LITERATURE REVIEW

Theoretical Framework

This study was guided by three theories, which include the theory of AI job replacement, the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology-Organisation-Environment (TOE) framework. The theory of AI job replacement posits that AI has an enormous effect of reshaping service by executing different tasks in the same way human beings perform them, and the tasks it accomplishes keep on increasing as technological advances improve its capability, thereby

threatening human jobs (Huang & Rust, 2018). The theory asserts that the effect of AI is more felt at the task level, but not the whole job level because it is programmed to use hard skills to execute specific tasks that do not involve empathy, intuition, adaptability, and creativity (Budhwar *et al.*, 2022). This way, AI can take over routine, programmable, analytical tasks, performing them more predictably, efficiently and accurately, but executing them without a human touch, which makes it supplemental rather than a substitute for human jobs. It is supplemental because it lacks and therefore, leaves the aspects of a job that require soft skills, intuition and empathy to continue being performed by human beings (Huang & Rust, 2018). Only when AI is developed to use soft skills can it threaten human employment (Budhwar & Rust, 2018). The theory of AI job replacement suggests that AI can execute tasks performed by human beings, but currently, it lacks in terms of the human touch. This implies that AI can be applied to perform teaching tasks which do not involve the human touch, leaving those that require a human touch to faculty members. This way, AI can reduce the teaching workload allocated to faculty members by leaving them with only tasks that involve a human touch.

The theory of AI job replacement is, however, about the ability of AI to execute some human tasks; it does not look into the factors that constrain the use of this technology (Budhwar *et al.*, 2022). Therefore, while it was used in this study as a basis for determining the awareness of the teaching tasks that AI can perform, it was complemented by UTAUT, which was proposed by Venkatesh *et al.* (2003) to explain how individuals' subjective beliefs, intentions, behaviour, performance and effort expectation, social influence, and enabling factors influence people's acceptance and use of new technology. This theory was used in this study as a basis for determining faculty members' acceptance of AI to supplement teaching in public universities of Uganda, and whether their beliefs about it were supportive or unsupportive to its adoption. UTAUT is, however, about individual-based

supportive or constraining factors (Venkatesh *et al.*, 2012; Mariqyan & Papagiannidis, 2023). It does not explain the factors that constrain the use of AI at a technical, organisational and environmental level. It was therefore complemented by the TOE framework developed by Tomatzky and Fleischer (1990). TOE explains the influence of the internal and external technical, organisational, and environmental contexts on the use of new technology such as AI (Faqihi & Miah, 2023). In this study, TOE was applied as a guide for identifying contextual factors hindering the adoption of AI to perform teaching tasks with the aim of reducing the heavy teaching workloads allocated to faculty members of Ugandan public universities as a result of massification.

EMPIRICAL REVIEW

Artificial Intelligence

The concept of AI was coined by McCarthy in 1956 based on seminal papers that Turing published in 1937 and 1950 to explain algorithms or software that had been developed by simulating human intelligence and enable machines to operate as intelligent, reasoning and thinking machines referred to as intelligent machines (Crompton & Burke, 2023). As this software got modernised in tandem with technological advancement, AI evolved into a more sophisticated system that could perform different human tasks. These tasks include allowing information inputting, auto-online information searching, processing, analysis, interpreting, learning, memorising and applying the output to prepare plans, solve problems, execute routine activities and guide decision-making (Dong *et al.*, 2020; Tuffaha & Perello-Marin, 2022). Other tasks that AI can perform include adapting, synthesizing, translation, self-correction, communication, and more importantly for this study, teaching and instructional tasks, among others (Al-Tuwayrish, 2016; Popenici *et al.*, 2017; Alajmi, Al-Sharafi & Abuali, 2020; Ayse & Nil, 2022). AI performs these tasks using different types that include reactive machines, robotics, computer vision, natural language processing, AI

for assessment, evaluation and predicting, AI Assistant, Generative AI, Intelligent Tutoring Systems, Managing Student Learning, Pedagogical Conversational Agents and Learning Analytics, and AI-enabled remote learning, digital mentors and interactive virtual tutorials, among other tools that mimic human intelligence activities (Atif *et al.*, 2021; Charlwood & Guenole, 2022; Crompton & Burke, 2023; Konecki *et al.*, 2023). This present study, however, focuses on establishing awareness of only AI that is capable of executing teaching tasks at the higher education level.

Teaching Workload

Teaching workload is a concept used to define the regular teaching tasks allocated to each teacher or faculty member for teaching and instructional activities that should be performed and completed in the given number of hours, days, weeks or months (Creagh *et al.*, 2023). The specific tasks include developing a scheme of work according to the allocated course units, number of lectures and teaching hours and planning and sequencing of allocated course units (Türkoglu & Cansoy, 2020). Workload also includes searching content of planned lectures, developing lecture notes, delivering lecture notes to students, assessing students through coursework, and evaluating students by setting tests and exams, invigilating, marking, grading, compiling marks, advising, and student research supervision (Van Droogenbroeck *et al.*, 2014; Zydziunaite *et al.*, 2020). Workloads are allocated to lecturers in terms of teaching contact hours, preparation, evaluation, and complementary functions the total of which ranges from 44 to 48 hours per week, with hours beyond 44 being considered as paid overtime (Mushabe *et al.*, 2022). Out of these hours, teaching contact hours, which refer to the time a faculty member interacts directly with students as he or she delivers lectures, instructs students, holds lecture room discussions, moderates presentations, provides necessary guidance, and research supervision, tends to range from 12 to maximise of 15 hours per week (Miller, 2019). The remaining hours are allocated to preparation,

which refers to the time (12-15 hours) lecturers should use to prepare for lectures before lecturing, and 12-15 hours of student evaluation (Siswantoa *et al.*, 2019).

Research has shown that as a result of the massification of higher education, workloads allocated to faculty members have been increasing in terms of number of hours worked by faculty members, with a rising number of lecturers being allocated extra and unpaid contact hours (Rasool *et al.*, 2019). Workloads have also been increasing in terms of teaching tasks assigned to lecturers even where working hours have remained the same (Burrow *et al.*, 2020; Amie-Ogan & Fekarurhobo, 2021; Maas *et al.*, 2021; Sandmeier *et al.*, 2022). The tasks have become too heavy and stressful as a result of the large class sizes that massification has created (Tumusiime, 2021). This is because while the standard class size is 30-45 students, massification has resulted in class sizes ranging from 100 to 300 or more students per course unit, especially at the undergraduate level (Tumusiime, 2021). Research has further shown that such class sizes stress and exhaust faculty members by not only increasing contact hours but also causing them to spend extra effort and time to assess students through coursework marking, evaluate them through invigilating and marking exams, compiling and grading marks, and uploading them into the universities' general grading system (García-Arroyo & Segovia, 2019; Khairunesa & Palpanadan, 2020; Ugwuanyi *et al.*, 2021; Hammoudi-Halat *et al.*, 2023; Xu & Wang, 2023). This research has, however, not analysed whether the stressed lecturers and those allocating the stressing teaching workload are aware of and can accept the role of AI in remedying this situation.

Teaching Tasks AI Can Perform

Different studies have explained the role that AI can play in the teaching of higher education students, including university students. In particular, the study of Ghalayini (2023) explains the role of AI in performing repetitive teaching tasks without replacing human skills such as emotional intelligence, adaptability and dealing

with ambiguous situations that characterise the interactive teaching-learning process. Similarly, Benvenuti *et al.* (2023) observed that even when AI currently in use lacks human skills – which these scholars refer to as soft skills – including interpersonal communication skills, empathy, teamwork, collaboration, and leadership, its ability to apply hard skills have been harnessed to teach mathematics, statistics, engineering, chemistry, physics, biology and other course units that can be taught through dictation following underlying scientific principles. AI is also capable of performing the tasks of student assessment and evaluation, intelligent tutoring, and serving as an assistant in facilitating student learning (Suvrat & Roshita, 2019; Mousavinasab *et al.*, 2021; Crompton & Burke, 2023). Mavrikis *et al.* (2019) added that AI plays a vital role in checking and ensuring exam integrity, detecting plagiarism, searching for lecture content, facilitating programmed offline and online discussions, marking, compiling and grading student marks, and facilitating academic research through reviewing academic research. Pedró (2020) summarised well by observing that AI can be used by faculty members to reduce their workload by automating some of the tasks such as administration, assessment, feedback, plagiarism detection, and getting information about students' learning weaknesses so that they can be proactively supported and guided when needed. To note however, is that while these roles of AI can be exploited by any university, their awareness and acceptance by the workload allocators and faculty members is not clear in some higher education institutions such as public universities in Uganda.

Awareness and Acceptance of Teaching Tasks AI Can Perform

The awareness of the teaching role that AI can play has been analysed by different researchers including Shin and Shin (2020) and AlKanaan (2022) who found that this awareness was low among pre-service science teachers. Gaber *et al.*'s (2023) study established that this awareness was moderate among faculty members although it did

not translate into significant acceptance of this role. Rodway and Schepman (2023) found so did Wu *et al.* (2022) that AI acceptance was moderate. In contrast, the study of Al-Darayseh (2023) indicates that despite having awareness of the teaching role of AI, science teachers' acceptance of to use of AI was high and correlated positively with self-efficacy, ease of use, expected benefits, attitudes, and behavioural intentions. Likewise, the findings of Nja *et al.*'s (2023) study indicate high awareness and acceptance of AI utilisation among science teachers. Lozano and Blanco (2023) found high acceptance of AI particularly ChatGPT among teachers pursuing a Primary Education Degree at the University of León (Spain) and this acceptance was among them both as current students and future teachers. These student teachers were of the view that this AI had great potential to ease teaching without posing a threat to their employment because it could cover the entire interactive teaching process because, by its programmed nature, it lacked flexibility and institutions that are vital for effective teaching. Note about these studies is that despite having been conducted in different contexts, none of them was in the context of public universities in Uganda. Secondly, their findings are not consistent, which suggests that the level of AI awareness and acceptance differs from one context to context. It is for this reason that the context of public universities needs to be investigated.

Hindrances to the Adoption of AI as a Teaching Tool at the University Level

Previous research identifies different hindrances to the adoption of AI in higher education in general and university education in particular. One of the identified hindrances is related to the fact that AI is considered unethical in that it violates the moral campus of human beings owing to its inability to judge whether what it is doing is right or wrong, appropriate or inappropriate, and also to be sensitive to the emotional changes and privacy of teachers and students as the teaching-learning session progresses (Gabriel, 2020). Akinwalere and Ivanov (2022) added that the

major constraint to the adoption of AI is the fear of its job-replacement ability which causes most faculty members to oppose it. Research has also shown that even where faculty members may not have this fear, they tend to be unaware of the instructional roles of AI and to lack the skills necessary to use it to complement their workload besides their institutions lack the resources required to purchase and install in this technology (Pedró, 2020). Another hindrance is that instead of focusing on executing tasks that help teachers reduce their workloads, AI seeks to replace teachers by centering on doing the teaching activities that are traditionally meant to be done by teachers (Bartolomé *et al.*, 2018). As a result, another challenge is that teachers appreciate what AI can do, but are reluctant to accept its adoption (Castañeda & Selwyn, 2018). In addition, many educational institutions and countries at large lack policies on how AI can be introduced and used in schools, what teaching tasks it should execute and under what ethical conditions (Ifenthaler & Yau, 2019). Furthermore, when the aim is to reduce teaching workload, using AI to execute some of the teaching tasks requires students to know how to interact with it to perform these tasks without the involvement of teachers, but most of the students do not have the skills they need to activate AI as a tool for enhancing self-directed learning and self-assessment (Suvrat & Roshita, 2019; Alajmi *et al.*, 2020). In general, the literature reveals different factors that hinder the adoption of AI as a tool for teaching in higher education. The factors are identified in different contexts, which, however, do not include that of public universities in Uganda. This study was hence intended to establish hindrances to the adoption of AI as a tool for teaching in the context of these universities.

RESEARCH METHODS

The study employed a cross-sectional descriptive survey and drew on the quantitative approach that could facilitate the collection and analysis of data that was needed to answer the set research questions (Ihudiebube-Splendor & Chikeme, 2020; Labisso *et al.*, 2020). The study population consisted of faculty deans, heads of departments

and faculty members. Faculty deans and heads of departments were included in the population because of the role they play in allocating workloads to faculty members. Faculty members were included in the sample because of their role as implementers of the allocated workloads. The total number of these potential respondents was therefore 12,187 since this is the total of all the academic staff members of the 13 public universities in Uganda (NCHE, 2022). Consequently, the sample size was computed using Sloven's formula given below:

$$n = \frac{N}{1 + N(e^2)}$$

Where n was the required sample size, N was the total population size (given above as 12187), and e was the sampling error. The sample was selected at the confidence level of 95%, implying that e was 5% or 0.05. Using the formula above,

$$n = \frac{12187}{1 + 12187(0.05^2)} = 387.288 = 388$$

The actual sample was however 325 respondents, determined based on the number of returned questionnaires. These included 25 faculty deans, 100 heads of departments (HODs) and 200 faculty members. These respondents were all selected using a simple random sample and were selected from five public universities also selected randomly from the 13 public universities of Uganda. Therefore, the selected universities were 38.5% of all the public universities in Uganda and were therefore statistically representative since they were above the 10% recommended by Andrade (2020). Simple random sampling was used to give each university and each respondent an equal chance of participating in the study, since, by virtual of their respective job titles, they were all in a position to assess their awareness of the role that AI plays in teaching at the universities, their acceptance of AI to reduce the teaching workloads, and hindrances to its adoption. The assessment was provided using a self-administered questionnaire whose content validity index was .898 and Cronbach Alpha coefficient was .863, suggesting that this research instrument had largely valid and reliable measures

of the variables that were being investigated. All the invalid and unreliable were disregarded during the analysis, which was conducted using the descriptive method aided by the SPSS program (Version 25).

FINDINGS AND DISCUSSION

The first research question focused on establishing deans', HODs' and faculty members' awareness of the teaching tasks that AI can perform at the university. These respondents were asked to use a scale ranging from 0 to 5 to assess their awareness. Accordingly, the assessment whose mean was close to zero represented unawareness, that whose mean was close to '1' or '2' represented low awareness, that close to '3' represented moderate awareness and that close to '4' or '5' represented high awareness of these tasks. Results from descriptive analysis are shown in *Table 1*.

The frequency distribution corresponding to the overall row in *Table 1*, the deans (4%), HODs (3%), and faculty members (4%) assessed their level of awareness of the teaching tasks that AI can perform as '0', revealing that they were unaware of the teaching tasks that AI could play. The deans (8% + 8% = 16%), HODs (5% + 10% = 15%) and faculty members (4% + 12% = 16%) who assessed their level of awareness as '1' to '2' showed low awareness of these tasks. The deans (4%), HODs (5%) and faculty members (6%) who assessed their level of awareness as '3' meant that it was moderate. The deans (16% + 60% = 76%), HODs (14% + 63% = 77%) and faculty members (8% + 66% = 74%) who assessed their awareness as '4' and '5' showed that their awareness of these tasks was high. This frequency distribution suggests that the level of awareness of the teaching tasks that AI can perform was high among the selected deans, HODs and faculty members. This high level is also revealed by the mean values corresponding to the overall awareness.

All these means were close to '4' revealing that the selected deans, HODs and faculty members were highly aware that AI could perform the depicted teaching tasks. Moreover, the standard deviations were less than '1', suggesting low dispersion which reveals that individual assessments of this awareness did not deviate much from the average awareness of the sample. Accordingly, the results are consistent with previous research, particularly the studies conducted by Al-Darayseh (2023) and Nja *et al.* (2023) that found that awareness that AI can perform different teaching roles was high among the teachers who participated in these studies. High awareness implies that the selected deans, HODs and faculty members knew that AI could be used to

teach students. There were, however, exceptions to this view. Table 1 indicates the awareness that AI can develop lesson plans and facilitate tutorials was generally low and negligible among most of the deans, HODs and faculty members. This negligible awareness points to a need to raise most of these academic staff members' awareness of how AI executes these teaching tasks.

After establishing respondents' awareness of the different teaching tasks AI can perform, they were asked to assess their acceptance of this technology to execute these tasks as a way of reducing their workloads. Descriptive analysis of their responses produced results shown in *Table 2*.

Table 1: Level of Awareness of the Teaching Tasks Executed by AI

Indicators of teaching tasks AI can perform	Respondents	% of respondents by their level of awareness							
		0	1	2	3	4	5	Mean	Std.
AI can develop lesson plans	Deans (n = 25)	16.0	32.0	36.0	4.0	4.0	8.0	2.30	.986
	HODs (n = 100)	10.0	20.0	30.0	10.0	20.0	10.0	2.02	.883
	Faculty (n = 200)	10.0	10.0	50.0	10.0	10.0	10.0	2.44	.765
AI can search online for lecture content	Deans (n = 25)	0.0	0.0	0.0	4.0	16.0	80.0	4.66	.555
	HODs (n = 100)	0.0	0.0	0.0	5.0	25.0	70.0	4.54	.357
	Faculty (n = 200)	0.0	0.0	4.0	10.0	10.0	76.0	4.57	.489
AI can search online for relevant content for research	Deans (n = 25)	0.0	0.0	0.0	4.0	16.0	80.0	4.66	.565
	HODs (n = 100)	0.0	0.0	0.0	5.0	25.0	70.0	4.54	.657
	Faculty (n = 200)	0.0	0.0	4.0	10.0	10.0	76.0	4.57	.589
AI can deliver lecture notes to students through dictation	Deans (n = 25)	0.0	0.0	0.0	4.0	12.0	84.0	4.76	.775
	HODs (n = 100)	0.0	0.0	0.0	0.0	5.0	95.0	4.84	.887
	Faculty (n = 200)	0.0	0.0	4.0	8.0	8.0	80.0	4.77	.619
AI can deliver lecture notes by interacting with students	Deans (n = 25)	26.0	36.0	26.0	4.0	4.0	4.0	2.22	.406
	HODs (n = 100)	10.0	50.0	20.0	10.0	5.0	5.0	2.12	.313
	Faculty (n = 200)	15.0	50.0	5.0	10.0	10.0	10.0	2.27	.565
AI can facilitate tutorials involving lecturer discussions with students	Deans (n = 25)	16.0	36.0	36.0	4.0	4.0	4.0	2.46	.706
	HODs (n = 100)	10.0	20.0	50.0	10.0	5.0	5.0	2.32	.813
	Faculty (n = 200)	10.0	10.0	50.0	10.0	10.0	10.0	2.24	.465
AI is capable of assessing students through marking coursework	Deans (n = 25)	4.0	4.0	4.0	16.0	32.0	40.0	4.46	.736
	HODs (n = 100)	5.0	5.0	10.0	10.0	10.0	60.0	4.32	.833

Indicators of teaching tasks AI can perform	Respondents	% of respondents by their level of awareness							
		0	1	2	3	4	5	Mean	Std.
AI is capable of evaluating students through marking examinations	Faculty (n = 200)	0.0	0.0	10.0	10.0	10.0	70.0	4.24	.445
	Deans (n = 25)	4.0	4.0	4.0	16.0	36.0	36.0	3.56	.506
	HODs (n = 100)	10.0	5.0	5.0	10.0	20.0	50.0	3.82	.613
	Faculty (n = 200)	10.0	10.0	10.0	10.0	10.0	50.0	4.24	.565
AI can grade students according to the scored marks	Deans (n = 25)	0.0	4.0	4.0	0.0	12.0	80.0	4.63	.515
	HODs (n = 100)	0.0	5.0	5.0	0.0	15.0	75.0	4.58	.617
	Faculty (n = 200)	0.0	10.0	0.0	2.0	10.0	88.0	4.62	.529
AI can detect students' weaknesses by analysing their scores	Deans (n = 25)	0.0	4.0	4.0	4.0	8.0	80.0	4.74	.735
	HODs (n = 100)	0.0	0.0	0.0	0.0	10.0	90.0	4.81	.837
	Faculty (n = 200)	0.0	4.0	4.0	8.0	4.0	80.0	4.70	.629
AI can provide students with feedback from their evaluations.	Deans (n = 25)	0.0	0.0	0.0	4.0	4.0	88.0	4.81	.535
	HODs (n = 100)	0.0	0.0	0.0	0.0	10.0	90.0	4.81	.817
	Faculty (n = 200)	0.0	0.0	4.0	0.0	4.0	92.0	4.84	.551
AI can detect plagiarism	Deans (n = 25)	0.0	4.0	4.0	0.0	8.0	84.0	4.66	.518
	HODs (n = 100)	0.0	5.0	5.0	0.0	10.0	80.0	4.56	.618
	Faculty (n = 200)	0.0	10.0	0.0	2.0	10.0	88.0	4.62	.529
Overall awareness	Deans (n = 25)	4.0	8.0	8.0	4.0	16.0	60.0	4.17	.648
	HODs (n = 100)	3.0	5.0	10.0	5.0	14.0	63.0	4.10	.721
	Faculty (n = 200)	4.0	4.0	12.0	6.0	8.0	66.0	4.12	.561

Table 2: Acceptance of AI to perform teaching tasks in Uganda's public universities

Teaching tasks AI can be accepted to perform	Respondents	% of respondents by their level of acceptance							
		0	1	2	3	4	5	Mean	Std.
Developing lesson plans	Deans (n = 25)	64.0	12.0	4.0	4.0	8.0	8.0	1.50	1.186
	HODs (n = 100)	60.0	10.0	10.0	10.0	10.0	10.0	1.02	1.183
	Faculty (n = 200)	62.0	10.0	10.0	10.0	4.0	4.0	1.44	1.165
Searching online for lecture content	Deans (n = 25)	0.0	0.0	4.0	16.0	0.0	80.0	4.86	1.055
	HODs (n = 100)	0.0	0.0	5.0	25.0	0.0	70.0	4.74	1.257
	Faculty (n = 200)	0.0	0.0	10.0	10.0	4.0	76.0	4.57	1.101
Searching online for relevant content for research	Deans (n = 25)	0.0	0.0	4.0	16.0	0.0	80.0	4.71	.515
	HODs (n = 100)	0.0	0.0	5.0	25.0	0.0	70.0	4.64	.617
	Faculty (n = 200)	0.0	0.0	10.0	10.0	4.0	76.0	4.55	.509

Teaching tasks AI can be accepted to perform	Respondents	% of respondents by their level of acceptance							
		0	1	2	3	4	5	Mean	Std.
Dictating lecture notes to students	Deans (n = 25)	0.0	12.0	10.0	0.0	74.0	4.0	4.06	1.105
	HODs (n = 100)	0.0	5.0	20.0	0.0	75.0	0.0	4.14	1.017
	Faculty (n = 200)	0.0	8.0	20.0	4.0	60.0	8.0	4.27	1.127
Facilitating tutorials	Deans (n = 25)	74.0	10.0	4.0	4.0	4.0	4.0	1.16	.126
	HODs (n = 100)	60.0	10.0	10.0	5.0	10.0	5.0	1.12	.313
	Faculty (n = 200)	62.0	10.0	10.0	10.0	4.0	4.0	1.14	.165
Setting coursework for students	Deans (n = 25)	80.0	4.0	4.0	4.0	0.0	8.0	1.74	.735
	HODs (n = 100)	90.0	0.0	0.0	0.0	0.0	10.0	1.81	.837
	Faculty (n = 200)	80.0	4.0	4.0	8.0	0.0	4.0	1.70	.629
Setting examinations	Deans (n = 25)	88.0	0.0	0.0	4.0	0.0	4.0	1.81	.535
	HODs (n = 100)	90.0	0.0	0.0	0.0	0.0	10.0	1.81	.817
	Faculty (n = 200)	92.0	0.0	4.0	0.0	0.0	4.0	1.84	.551
Assessing students through marking coursework	Deans (n = 25)	4.0	16.0	4.0	4.0	32.0	40.0	4.46	.736
	HODs (n = 100)	5.0	10.0	10.0	10.0	5.0	60.0	4.32	.833
	Faculty (n = 200)	0.0	10.0	10.0	10.0	0.0	70.0	4.24	.445
Evaluating students through marking examinations	Deans (n = 25)	4.0	16.0	4.0	4.0	36.0	36.0	3.56	.506
	HODs (n = 100)	5.0	10.0	5.0	10.0	50.0	20.0	3.82	.613
	Faculty (n = 200)	10.0	10.0	10.0	10.0	50.0	10.0	4.24	.565
Grading students according to the scored marks	Deans (n = 25)	4.0	0.0	4.0	12.0	0.0	80.0	4.63	.515
	HODs (n = 100)	5.0	0.0	5.0	15.0	0.0	75.0	4.58	.617
	Faculty (n = 200)	10.0	2.0	0.0	10.0	0.0	88.0	4.62	.529
Detecting students' interpersonal weaknesses that affect their learning	Deans (n = 25)	80.0	4.0	4.0	4.0	0.0	8.0	1.74	.735
	HODs (n = 100)	90.0	0.0	0.0	0.0	0.0	10.0	1.81	.837
	Faculty (n = 200)	80.0	4.0	4.0	8.0	0.0	4.0	1.70	.629
Providing students with feedback about their weaknesses	Deans (n = 25)	88.0	0.0	0.0	4.0	0.0	4.0	1.81	.535
	HODs (n = 100)	90.0	0.0	0.0	0.0	0.0	10.0	1.81	.817
	Faculty (n = 200)	92.0	0.0	4.0	0.0	0.0	4.0	1.84	.551
Detecting plagiarism	Deans (n = 25)	4.0	0.0	4.0	8.0	0.0	84.0	4.66	.518
	HODs (n = 100)	5.0	0.0	5.0	10.0	0.0	80.0	4.56	.618
	Faculty (n = 200)	10.0	2.0	0.0	10.0	0.0	88.0	4.62	.529
Discussing corrections with students	Deans (n = 25)	8.0	55.0	8.0	4.0	16.0	9.0	1.17	.648
	HODs (n = 100)	5.0	64.0	9.0	5.0	14.0	3.0	1.10	.721
	Faculty (n = 200)	4.0	66.0	12.0	6.0	8.0	4.0	1.12	.561

Teaching tasks AI can be accepted to perform	Respondents	% of respondents by their level of acceptance							
		0	1	2	3	4	5	Mean	Std.
Overall acceptance	Deans (n = 25)	32.0	12.0	4.0	12.0	4.0	36.0	3.06	1.561
	HODs (n = 100)	34.0	9.0	7.0	14.0	4.0	32.0	3.06	1.519
	Faculty (n = 200)	32.0	8.0	6.0	16.0	4.0	32.0	3.02	1.657

Table 3: Hindrances to AI adoption in Uganda's public universities

Factors	Respondents	% of respondents responses revealed a factor as a hindrance or not						
		SD	D	NS	A	SA	Mean	Std.
The university has a strategy for promoting AI as a tool for teaching	Deans (n = 25)	88.0	0.0	4.0	4.0	0.0	1.81	.435
	HODs (n = 100)	90.0	0.0	10.0	0.0	0.0	1.81	.417
	Faculty (n = 200)	92.0	4.0	4.0	0.0	0.0	1.84	.651
University's top management supports introduction of AI to support teaching	Deans (n = 25)	84.0	4.0	12.0	0.0	0.0	1.66	.718
	HODs (n = 100)	80.0	5.0	15.0	0.0	0.0	1.56	.318
	Faculty (n = 200)	88.0	0.0	22.0	0.0	0.0	1.62	.329
The university has ethical guidelines on the use of AI to perform teaching tasks	Deans (n = 25)	80.0	4.0	16.0	0.0	0.0	1.71	.565
	HODs (n = 100)	70.0	5.0	25.0	0.0	0.0	1.64	.667
	Faculty (n = 200)	76.0	10.0	10.0	4.0	0.0	1.55	.569
The university has policy regulations on how AI should be used to support teaching	Deans (n = 25)	74.0	10.0	16.0	0.0	0.0	1.06	.405
	HODs (n = 100)	75.0	20.0	5.0	0.0	0.0	1.14	.517
	Faculty (n = 200)	60.0	20.0	16.0	4.0	0.0	1.27	.227
Lecturers have the skills expected of them to use AI as a tool for teaching	Deans (n = 25)	72.0	4.0	20.0	0.0	4.0	1.16	.106
	HODs (n = 100)	70.0	10.0	15.0	0.0	5.0	1.12	.303
	Faculty (n = 200)	70.0	10.0	20.0	0.0	0.0	1.14	.125
Students have skills expected of them to use AI as a tool for supporting learning	Deans (n = 25)	84.0	8.0	4.0	4.0	0.0	1.24	.235
	HODs (n = 100)	90.0	10.0	0.0	0.0	0.0	1.21	.337
	Faculty (n = 200)	84.0	4.0	8.0	4.0	0.0	1.30	.429
The university has the funds required to install AI to support teaching	Deans (n = 25)	88.0	0.0	8.0	0.0	0.0	1.41	.335
	HODs (n = 100)	90.0	0.0	10.0	0.0	0.0	1.31	.317
	Faculty (n = 200)	92.0	4.0	4.0	0.0	0.0	1.04	.501
Lecturers do not fear that AI will replace rather than supplement their jobs when adopted as a teaching tool	Deans (n = 25)	76.0	4.0	20.0	0.0	0.0	1.46	.536
	HODs (n = 100)	65.0	10.0	20.0	5.0	0.0	1.32	.333
	Faculty (n = 200)	70.0	10.0	20.0	0.0	0.0	1.24	.745

Factors	Respondents	% of respondents responses revealed a factor as a hindrance or not						
		SD	D	NS	A	SA	Mean	Std.
Lecturers are ready to make use of AI to complement their teaching activities	Deans (n = 25)	80.0	4.0	12.0	0.0	4.0	1.23	.535
	HODs (n = 100)	75.0	5.0	15.0	0.0	5.0	1.28	.637
	Faculty (n = 200)	88.0	10.0	10.0	0.0	2.0	1.22	.559
Lecture content used by lecturers has a common database that AI needs to support teaching	Deans (n = 25)	84.0	12.0	4.0	0.0	0.0	1.44	.265
	HODs (n = 100)	90.0	10.0	0.0	0.0	0.0	1.31	.567
	Faculty (n = 200)	84.0	8.0	8.0	0.0	0.0	1.30	.379
AI can replicate a human touch when performing teaching tasks involving interacting with students	Deans (n = 25)	88.0	4.0	4.0	4.0	0.0	1.21	.215
	HODs (n = 100)	95.0	5.0	0.0	0.0	0.0	1.26	.317
	Faculty (n = 200)	84.0	4.0	8.0	4.0	0.0	1.33	.411
Overall assessment of a factor as a hindrance	Deans (n = 25)	78.0	8.0	10.0	2.0	2.0	1.43	.423
	HODs (n = 100)	74.0	12.0	10.0	2.0	2.0	1.41	.458
	Faculty (n = 200)	72.0	12.0	12.0	2.0	2.0	1.44	.458

The descriptive statistics corresponding to the overall acceptance indicate that deans (32%), HODs (34%) and faculty members (32%) who indicated '0' implied that they did not accept AI to perform the various teaching tasks in Table 2. The deans ($12\% + 4\% = 16\%$), HODs ($9\% + 7\% = 16\%$) and faculty members ($8\% + 6\% = 14\%$) who indicated '1' and '2' showed low and therefore bare acceptance. In addition, deans (12%), HODs (14%) and faculty members (16%) whose assessment was at '3' implied that their acceptance was moderate. Furthermore, deans ($4\% + 36\% = 40\%$), HODs ($4\% + 32\% = 36\%$) and faculty members ($4\% + 32\% = 36\%$) whose assessment was at '4' and '5' pointed to high acceptance of AI to perform the teaching tasks depicted in Table 2. These results suggest that respondents' acceptance of AI to perform teaching tasks varied in such a way some respondents lacked it while others had it at a low, moderate and high level.

The mean values corresponding to the overall acceptance (Mean = 3.06 for both deans and HODs and 3.02 for faculty members) were close to '3' when rounded off to the nearest whole number. On average, therefore, acceptance of AI to perform teaching tasks was moderate. The corresponding standard deviations (Std. = 1.561, 1.519 and 1.657) were greater than '1', suggesting high dispersion in the sample. This dispersion reveals that the assessment of acceptance of individual respondents digressed much from their average assessment as a whole sample. The moderate acceptance revealed by the results gives credence to the conclusion reached in the studies by Wu *et al.* (2022) and Rodway and Schepman (2023) that acceptance of AI was moderate among teachers. Being moderate implies that acceptance was not strong enough to guarantee adoption of AI to perform the teaching tasks summarised in Table 2.

Nevertheless, the fact that the standard deviations corresponding to the overall assessment were greater than '1' suggests that there were exceptions to the moderate view. These standard deviations indicate that there are respondents whose acceptance deviated much from the

average. These respondents are revealed by the frequency distribution corresponding to the overall assessment in Table 2. This distribution indicates that on the one hand, 34% of HODs and 32% of deans and faculty members did not accept that AI could perform all the depicted teaching tasks. On the other hand, 40% of the deans and 36% of the HODs and faculty members expressed high acceptance that AI can be used to perform these tasks. These results suggest that there were deans, HODs and faculty members who were strongly amenable to the adoption of AI to perform teaching tasks. A more critical scrutiny of the results in Table 2 suggests that high acceptance of AI corresponded to particular teaching tasks, which included searching online for lecture content and for relevant content for research and dictating lecture notes to student 70% to 80% of the respondents expressed high acceptance that AI could be used to perform each of these teaching tasks. In addition, 60% to 88% of the respondents strongly accepted that AI could be adopted to assess students through coursework marking, evaluate them through exam marking, grade them according to the scored marks, and detect plagiarism. These results support the observations made by scholars such as Mavrikis *et al.* (2019), Suvrat and Roshita (2019), Mousavinasab *et al.* (2021), and Crompton and Burke (2023) that AI can indeed perform each of these teaching tasks when it is adopted in higher education institutions.

Further critical analysis of the results in Table 2 reveals that respondents who did not accept AI were mostly those who were opposed to using it to perform the following teaching tasks: developing lesson plans, facilitating tutorials, setting coursework and examinations for students, detecting students' weaknesses by analysing their scores, providing students with feedback from their evaluation, and discussing corrections with students. A critical analysis of the frequency distribution corresponding to each of these teaching tasks reveals that 60% to 92% of the respondents did not accept that AI could perform them. This rejection of AI's execution of each of these teaching tasks suggests that they are the

tasks that can be left to the faculty members to perform as AI does the others for which it was accepted. Therefore, when AI is adopted, it can lessen the workload assigned to faculty members by performing some of the teaching tasks they are willing to cede to it.

The adoption of AI was further investigated by establishing whether there were any factors that could hinder it. Respondents were asked to use a 5-point Likert scale of responses running from Strongly Disagree (SD = 1) through Disagree (D = 2), Not Sure (NS = 3) and Agree (A = 4) to Strongly Agree (SA = 5) to indicate the extent to which they agreed or disagreed that a factor was a hindrance. With this scale, respondents who agreed and strongly agreed revealed that a given factor was not a hindrance. Those who disagreed and strongly disagreed indicated that the factor was a constraint. The respondents who were not sure showed that they could not tell whether a factor was a hindrance or not. The findings obtained from descriptive analysis of their responses are presented in Table 3.

Based on the interpretation the response scale provided above, the statistics corresponding to the overall assessment in *Table 3* indicate that the majority of the deans ($78\% + 8\% = 86\%$), HODs ($74\% + 12\% = 86\%$) and faculty members ($72\% + 12\% = 84\%$) strongly disagreed to all the factors as the corresponding mean values (1.43, 1.41 and 1.44) were all close to '1' when rounded off to the nearest whole number. Moreover, the corresponding standard deviations (Std. = .423, .458 and .458) were all less than '1'. Therefore, the results suggest that the majority of the respondents expressed a view that all the factors in Table 3 were hindrances to the adoption of AI as a tool for teaching in Uganda's public universities.

CONCLUSIONS AND RECOMMENDATIONS

The established high awareness of the teaching tasks that AI can perform indicates that the majority of the faculty deans and academic staff members of public universities in Uganda are well-informed about the role that AI can play in

facilitating their job as instructors. This awareness is, however, not consistent with acceptance of AI, which, itself, is moderate on average and hence, alluding to faculty reluctance to allow AI to perform the teaching tasks in Uganda's public universities. This reluctance is due to the fact that while most of the respondents strongly accept AI to perform some teaching tasks, they reject it with respect to performing other teaching tasks. As such, AI is acceptable as long as it is adopted to perform some, but not all teaching tasks.

Specifically, AI is acceptable to the majority of faculty deans, HODs and faculty members of Uganda's public universities if it is adopted to perform the following teaching tasks: searching online for lecture content and relevant content for research, delivering lecture notes through dictation, assessing and evaluating students through coursework and exam marking, grading students according to scored marks, detecting their weaknesses by analysing their scores and detecting plagiarism. In contrast, the majority of the deans, HODs and faculty members reject the adoption of AI to perform the following teaching tasks: developing lesson plans, facilitating tutorials, setting coursework and examinations for students, detecting students' interpersonal weaknesses, providing students with feedback about their weaknesses, and discussing corrections with students. These results indicate that AI can relieve lecturers in Uganda's public universities of the heavy teaching workload by performing the teaching tasks for which it is accepted. When AI is allowed to execute these tasks, it leaves faculty members with less workload that involves developing lesson plans, facilitating tutorials, setting coursework and examinations for students, detecting students' interpersonal weaknesses, providing students with feedback about their weaknesses, and discussing corrections with students. Therefore, the management of public universities in Uganda should introduce AI as a tool for reducing the heavy workload allocated to faculty members as a result of the intensifying massification of these institutions. Unfortunately, there are hindrances to the adoption of AI by these universities.

The hindrances include a lack of strategy for introducing AI as a tool for teaching; lack of ethical guidelines and policy regulations; lack of top management support; lack of skills expected of lecturers and students to use AI as a tool for teaching and to support learning, and lack of funds required to install AI. In addition, lecturers fear that AI will replace rather than supplement their jobs when adopted, are not ready to use AI to complement their teaching activities, the universities do not have common databases for lecture content, and AI cannot replicate the human touch when performing the teaching tasks involving interacting with students. These hindrances should be addressed if AI is to be adopted in Uganda's public universities. Addressing these hindrances requires the management of these universities to develop the strategy, ethical guidelines and policy regulations necessary to guide the adoption of AI as a teaching tool. These strategic, ethical and policy guidelines should be developed in such a way that they incorporate only the teaching tasks that lecturers can accept AI to perform in order to relieve them of the heavy workloads allocated to them as a result of massification. In addition, the top management of these universities should provide the necessary support towards the adoption of AI. This support should be provided by allocating enough funds to the installation of AI – which makes it necessary for the government of Uganda to increase funding and for the management to mobilise more internal funds for supporting AI installation. The top management should also support lecturers by supporting training that equips them with skills they need to use AI to supplement execution of their teaching job.

REFERENCES

- Akinwalere, S. N., & Ivanov, V. (2022). Artificial intelligence in higher education: Challenges and opportunities. *Border Crossing*, 12(1), 1-15. <https://doi.org/10.33182/bc.v12i1.2015>.
- Alajmi, Q., Al-Sharafi, M. A., & Abuali, A. (2020). Smart learning gateways for Omani HEIs towards educational technology: Benefits, challenges and solutions. *International Journal of Information Technology and Language Studies*, 4(1), 12-17.
- Al-Darayseh, A. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education: Artificial Intelligence*, 4, 100132. <http://doi.org/10.1016/j.caeai.2023.100132>
- AlKanaan, H. (2022). Awareness regarding the implication of artificial intelligence in science education among pre-service science teachers. *International Journal of Instruction*, 15(3), 895912. <https://doi.org/10.29333/iji.2022.15348a>
- Al-Tuwayrish, R. K. (2016). An evaluative study of machine translation in the EFL scenario of Saudi Arabia. *Advances in Language and Literary Studies*, 7(1), 5-10.
- Amie-Ogan, O.T., & Fekarurhobo, B.E. (2021). Perceived influence of work overload on academic staff job performance in universities in Rivers State. *International Journal of Innovative Social Sciences & Humanities Research*, 9(2), 56-67.
- Andrade C. (2020). Sample Size and its Importance in Research. *Indian Journal of Psychological Medicine*, 42(1), 102-103. https://doi.org/10.4103/IJPSYM.IJPSYM_504_19
- Atif, A., Jha, M., Richards, D., & Bilgin, A. A. (2021). Artificial intelligence (AI)-enabled remote learning and teaching using Pedagogical Conversational Agents and Learning Analytics. In: *Intelligent systems and learning data analytics in online education* (pp. 3-29). Academic Press
- Ayşe, T., & Nil, G. (2022). Automated feedback and teacher feedback: Writing achievement in learning English as a foreign language at a distance. *The Turkish Online Journal of Distance Education*, 23(2), 120-139. <https://doi.org/10.7575/aiac.all.v.7n.1p.5>
- Bartolomé, A., Castañeda, L., & Adell, J. (2018). Personalisation in educational technology: the

- absence of underlying pedagogies. *International Journal of Educational Technology in Higher Education*, 15(1), 14. <https://doi.org/10.1186/s41239-018-0095-0>
- Benvenuti, M., Cangelosi, A., Weinberger, A., Mazzoni, E., Benassi, M., Barbaresi, M., & Orsoni, M. (2023). Artificial intelligence and human behavioural development: A perspective on new skills and competences acquisition for the educational context. *Computers in Human Behaviour*, 148, 107903. <https://doi.org/10.1016/j.chb.2023.107903>.
- Budhwar, P., Malik, A. M. T., De Silva, T., & Thevisuthan, P. (2022). Artificial intelligence – challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management*, 33(6), 1065-1097. <https://doi.org/10.1080/09585192.2022.2035161>
- Burrow, R., Williams, R., & Thomas, D. (2020). Stressed, depressed and exhausted: Six years as a teacher in UK state education. *Work, Employment & Society*, 34(5), 949-958. <https://doi.org/10.1177/0950017020903040>
- Castañeda, L., & Selwyn, N. (2018). More than tools? Making sense of the ongoing digitizations of higher education. *International Journal of Educational Technology in Higher Education*, 15(22). <https://doi.org/10.1186/s41239-018-0109-y>
- Charlwood, A., & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence? *Human Resource Management Journal*, 32(4), 729-742. <https://doi.org/10.1111/1748-8583.12433>
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, 8, 75264– 75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- Chu, H., Tu, Y., & Yang, K. (2022). Roles and research trends of artificial intelligence in higher education: A systematic review of the top 50 most-cited articles. *Australasian Journal of Educational Technology*, 38(3), 22–42. <https://doi.org/10.14742/ajet.7526>
- Creagh, S., Thompson, G., Mockler, N., Stacey, M., & Hogan, A. (2023). Workload, work intensification and time poverty for teachers and school leaders: A systematic research synthesis. *Educational Review*, 1, 1-19. <https://doi.org/10.1080/00131911.2023.2196607>
- Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*, 20, 22. <https://doi.org/10.1186/s41239-023-00392-8>
- Dong, Y., Hou, J., Zhang, N., & Zhang, M. (2020). Research on how human intelligence, consciousness, and cognitive computing affect the development of artificial intelligence. *Hindawi Complexity*, 1680845, 1-9. <https://doi.org/10.1155/2020/1680845>
- Eton, M., & Chance, R. (2022). University e-learning methodologies and their financial implications: evidence from Uganda. *Asian Association of Open Universities Journal*, 17(3), 229- 241. <https://doi.org/10.1108/AAOUJ-05-2022-0069>
- Faqihi, A., & Miah, S.J. (2023). Artificial intelligence-driven talent management system: Exploring the risks and options for constructing a theoretical foundation. *Journal of Risk and Financial Management*, 16(1), 31-47. <https://doi.org/10.3390/jrfm16010031>
- Gaber, S.A., Shahat, H.A., Alkhateeb, I.A., Al Hasan, S.A., Alqatam, M.A., Almughyirah, S.M., & Kamel, M.K. (2023). Faculty members' awareness of artificial intelligence and its relationship to technology acceptance and digital competencies at King Faisal University. *International Journal of Learning, Teaching and Educational Research*, 22(7), 473-496. <https://doi.org/10.26803/ijlter.22.7.25>
- Gabriel, I. (2020, September 10). “Artificial intelligence, values, and alignment.” *Minds*

- and Machines*. <https://doi.org/10.1007/s11023-020-09539-2>
- Gallup (2023, September 13). "65 university statistics you must see in 2023: analysis of enrolment & funding." <https://financesonline.com/university-statistics/>
- García-Arroyo, J. A., & Segovia, A. O. (2019). Work overload and emotional exhaustion in university teachers: Moderating effects of coping styles. *Universitas Psychologica*, 18(2), 1- 12. <https://doi.org/10.11144/Javeriana.upsy18-2.woee>
- Ghalayini, M. (2023, September 15). "Unlocking the potential of AI in higher education." <https://www.universityworldnews.com/post.php?story=20230419095059196#:~:text=Use%20of%20AI%20in%20higher%20education&text=It%20provides%20personalised%20learning%20experiences,and%20support%20for%20each%20student.>
- Hammoudi-Halat, D., Soltani, A., Dalli, R., Alsarraj, L., & Malki, A. (2023). Understanding and fostering mental health and well-being among university faculty: A narrative review. *Journal of Clinical Medicine*, 12(13), 4425. <https://doi.org/10.3390/jcm12134425>
- Hand, C.L. (2023). *A case study of Makerere University in Uganda through the lens of U.S. land-grant higher education*. Doctoral Thesis, West Virginia Dissertations. <https://researchrepository.wvu.edu/etd/11923>
- Huang, M., & Rust, R.T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), pp.155-172, <https://doi.org/10.1177/1094670517752459>.
- Ifenthaler, D., & Yau, J. (2019). Higher Education Stakeholders' Views on Learning Analytics Policy Recommendations for Supporting Study Success. *International Journal of Artificial Intelligence*, 1(1), 28-42.
- Ihudiebube-Splendor, C. N., & Chikeme, P. C., (2020). A descriptive cross-sectional study: Practical and feasible design in investigating health care-seeking behaviours of undergraduates. In: *Sage Research Methods Cases: Medicine and Health*. SAGE Publications, <https://doi.org/10.4135/9781529742862>
- Johnson, O., Marus, E., Adyanga, A. F., & Ayiga, N. (2023). The experiences and challenges of doctoral education in public universities compared. *Journal of Social, Humanity, and Education*, 3(3), 237-252.
- Kamonges, W.A. (2021). Primary and secondary education in Uganda: challenges and prospects. *Interdisciplinary Journal of Education*, 4(1), 78-88.
- Kanyesige, B. (2022). *Influence of children's health on primary school academic performance in Africa: A case study of Fort Portal Municipality, Kabarole District, Uganda*. Makerere University: Faculty of Social Sciences.
- Kasozi, A. B. K. (2002). The role of the state in addressing challenges and opportunities posed by the rapid growth of universities in Uganda since 1988. *African Studies Review*, 45(2), 123– 139. <https://doi.org/10.2307/1514790>
- Khairunesa, I., & Palpanadan, S.T. (2020). Prevalence causes of stress and coping strategies among Malaysian university lecturers. *International Journal of Higher Education*, 9(5), 312-321. <https://doi.org/10.5430/ijhe.v9n5p312>
- Kibaliwandu, M.M., & Mwesigye, A.R. (2022). Uganda Higher Education Review. *Journal of the National Council for Higher Education*, 10(1), 1-20.
- Kiconco, E. (2023). *Effects of Covid 19 pandemic on higher education: a case of Makerere University and Kampala International University in Kampala District, Uganda*. Masters Dissertation, Kampala International University. <https://ir.kiu.ac.ug/bitstream/20.500.12306/14237/1/KICONCO%20EMILY.pdf>

- Konecki, M., Konecki, M., & Biškupic, I. (2023). 'Using Artificial Intelligence in Higher Education', In: Proceedings of the 15th International Conference on Computer Supported Education (CSEDU 2023) – Vol.2, pp.136-141.
- Labisso, W.L., Leka, Y., Leka, Y., & Haileselassie, W. (2020). A descriptive cross-sectional study on awareness and belief of people about cancer in southern Ethiopia: Special focus on breast and cervical cancers. *Risk Management Healthcare Policy*, 13, 2655- 2668 <https://doi.org/10.2147/RMHP.S267207>
- Lozano, A., & Blanco, F.C. (2023). Is the education system prepared for the irruption of artificial intelligence? A study on the perceptions of students of primary education degree from a dual perspective: current pupils and future teachers. *Educational Sciences*, 13, 733. <https://doi.org/10.3390/educsci13070733>
- Maas, J., Schoch, S., Scholz, U., Rackow, P., Schüler, J., Wegner, M., & Keller, R. (2021). Teachers' perceived time pressure, emotional exhaustion and the role of social support from the school principal. *Social Psychology of Education*, 24(2), 441-464. <https://doi.org/10.1007/s11218-020-09605-8>
- Marikyan, D., & Papagiannidis, S. (2023). Unified theory of acceptance and use of technology: A review', In: S. Papagiannidis (Ed), *TheoryHub Book*. <http://open.ncl.ac.uk.9781739604400>
- Mavrikis, M., Geraniou, E., Santos, S. G., & Poulouvassilis, A. (2019). Intelligent analysis and data visualization for teacher assistance tools: The case of exploratory learning. *British Journal of Educational Technology*, 50(6), 2920– 2942. <https://doi.org/10.1111/bj et.12876>
- Miller, J. (2019). Where does the time go? An academic workload case study at an Australian university. *Journal of Higher Education Policy and Management*, 41(6), 633-645
- Ministry of Public Service (2021). *Uganda public service standing orders 2021*. Kampala: Ministry of Public Service.
- Mosomi, M. (2022). "Implications of "institutional massification" for academic practices: A qualitative study on the perspectives and experiences of academics at a public university in Kenya conducted in light of social-practice theory." Doctoral Dissertation, University of Liverpool. https://livrepository.liverpool.ac.uk/3153982/1/201118451_April2022.pdf
- Mousavinasab, E., Zarifsanaiey, N., Kalhori, S. R. N., Rakhshan, M., Keikha, L., & Saeedi, M. G. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, 29(1), 142– 163. <https://doi.org/10.1080/10494820.2018.1558257>
- Mukhaye, D. (2022, September 14). "Kyambogo staff threaten demo over extra teaching load." <https://www.monitor.co.ug/uganda/news/national/kyambogo-staff-threaten-demo-over-extra-teaching-load-3708756>
- Muriisa, R.K., & Rwabyoma, A.S. (2019). Globalisation and knowledge production in higher education: the impact of internationalisation and liberalisation on university education in Rwanda and Uganda. *Africa Journal of Public Sector Development and Governance*, 2(1), 25-48.
- Murthi, M., & Bassett, R.M. (2022, September 10). "Higher Education: Understanding demand and redefining values." <https://blogs.worldbank.org/education/higher-education-understanding-demand-and-redefining-values#:~:text=Globally%2C%20in%202021%2C%20roughly%2020,higher%20education%20students%20by%202030>
- Mushabe, C., Abreh, M.K., & Mills, C.K. (2022). Reconceptualizing faculty workload as a measure of human resource motivation and performance in higher education. *Social*

- Sciences & Humanities Open*, 6(1), 100279. <https://doi.org/10.1016/j.ssaho.2022.100279>.
- Musika, W.R. (2019). *Universal primary education and the Uganda's economy*. Makerere University, Unpublished Masters Dissertation.
- Nakimuli, A., & Turyahebwa, A. (2016). Institutional efficiency in selected universities in Uganda. *Journal of Education and Practice*, 6(10), 90-97.
- National Council for Higher Education (NCHE) (2022). *State of higher education report, 2021/22*. Kampala: NCHE.
- Nja, C.O., Idiege, K.J., Uwe, U.E., Meremikwu, A.N., Ekon, E.E., Erim, C.M., Ukah, J.U., Eyo, E.O., Anari, M.I., & Cornelius-Ukpepi, B.U. (2023). Adoption of artificial intelligence in science teaching: From the vantage point of the African science teachers. *Smart Learn. Environ.* 10, 42 (2023). <https://doi.org/10.1186/s40561-023-00261-x>
- Noui, R. (2020). Higher education between massification and quality. *Higher Education Evaluation and Development*, 14(2), 93-103. <https://doi.org/10.1108/HEED-04-2020-0008>
- Otyola, R.W., Nalwadda, P., Bagamba, G.W., Bukenya, J., Kamaga, E., & Bantebya, S. (2022). Examining the successes of universal primary education and universal secondary education policies in Uganda. *American Journal of Education and Practice*, 6(3), 14-25.
- Pedró, F. (2020). Applications of artificial intelligence to higher education: possibilities, evidence, and challenges. *Open Journal of IUL University*, 1(1), 61-76.
- Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, 12(22), 1-13. <https://doi.org/10.1186/s41039-017-0062-8>
- Rasool, S.F., Samma, M., Wang, M., Zhao, Y., & Zhang, Y. (2019). How human resource management practices translate into sustainable organizational performance: The mediating role of product, process and knowledge innovation. *Psychology Research and Behaviour Management*, 12, 1009-1025
- Rodway, P., & Schepman, A. (2023). The impact of adopting AI educational technologies on projected course satisfaction in university students. *Computers and Education: Artificial Intelligence*, 5, 100150. <https://doi.org/10.1016/j.caeai.2023.100150>
- Ruff, C., Matheu, A., Ruiz, M., Juica, P., & Marcos, M.T.G. (2023). Cost-free education as a new variable of mixed financing policies in Chilean higher education and its impact on student trajectory and social mobility. *Heliyon*, 9(7), e17415. <https://doi.org/10.1016/j.heliyon.2023.e17415>.
- Rwothumio, J., Mbirithi, D., & Itolondo, W. (2021). Influence of training in determining academic staff performance in public universities in Uganda. *East African Journal of Education Studies*, 3(1), 39-51. <https://doi.org/10.37284/eajes.3.1.283>
- Sandmeier, A., Baeriswyl, S., Krause, A., & Muehlhausen, J. (2022). Work until you drop: Effects of work overload, prolonging working hours, and autonomy need satisfaction on exhaustion in teachers. *Teaching and Teacher Education*, 118, 103843. <https://doi.org/10.1016/j.tate.2022.103843>
- Shin, S., & Shin, H. (2020). A study on the application of artificial intelligence in elementary science education. *Journal of Korean Elementary Science Education*, 39(1), 117- 132. <https://doi.org/10.15267/KESES.2020.39.1.117>
- Siswantoa, S., Supriyanto, A.S., Ni'mah, U., Asnawi, N., & Wekke, I.S. (2019). Does a workload influence the performance of bank employees? *Management Science Letters*, 9, 639-650
- Suvrat, J., & Roshita, J. (2019). Role of artificial intelligence in higher education- an empirical investigation. *International Journal of*

- Research and Analytical Reviews*, 6(2), 144-150.
- Thambusamy, R.X., Singh, P., & Ramly, M.A. (2019). The inconvenient truth about digital transformation in higher education: What is massification of higher education? In: *Faculty roles and changing expectations in the new age* (pp.1-16). DOI: 10.4018/978-1-5225-7438-5.ch014
- Tuffaha, M., & Perello-Marin, M.R. (2022). Adoption factors of artificial intelligence in human resources management. *Future of Business Administration*, 1(1), 1-12. <https://doi.org/10.33422/fba.v1i1.140>
- Tumusiime, E.I. (2021). A comparative analysis of workload and career progression of faculty members in Uganda's private and public universities. *Kabale University Interdisciplinary Research Journal*, 1(1), 16-30.
- Türkoglu, M. E., & Cansoy, R. (2020). School principals' opinions on the meaning and sources of workload. *International Journal of Contemporary Educational Research*, 7(1), 177-191.
- Ugwuanyi, C.S., Okeke, C.I.O., & Ekwueme, U. H. (2021). Management of work stress in science education lecturers' population using rational emotive occupational health coaching: Implication for educational evaluators. *Journal of Community Psychology*, 49(7), 2517-2531. <https://doi.org/10.1002/jcop.22667>
- UNESCO (2022, September 10). "*Higher education global data report*." <https://cdn.eventsbase.com/www.whcc2022.org/uploads/users/699058/uploads/c4fb749e5ddb3daca6d92dc280de404ad4ff3935e798ec3bc823a0d5cd8ca83765b71059379ec37b4d42717a7689ec02b9a9.629a0f82b4e16.pdf>
- Van Droogenbroeck, F., Spruyt, B., & Vanroelen, C. (2014). Burnout among senior teachers: Investigating the role of workload and interpersonal relationships at work. *Teaching and Teacher Education*, 43, 99-109. <https://doi.org/10.1016/j.tate.2014.07.005>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>.
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157- 178. <https://doi.org/10.2307/41410412>.
- Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2021). Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. *The International Journal of Human Resource Management*, 2, 1- 30. <https://doi.org/10.1080/09585192.2020.1871398>.
- Waruru, M. (2023, September 15). "Wanted: thousands of lecturers for East African universities." <https://www.universityworldnews.com/post.php?story=20230509105401599>
- Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring factors of the willingness to accept AI-assisted learning environments: an empirical investigation based on the UTAUT model and perceived risk theory. *Frontiers in Psychology*, 13, 870777. <https://doi.org/10.3389/fpsyg.2022.870777>
- Xu, Y., & Wang, Y. (2023). Job stress and university faculty members' life satisfaction: The mediating role of emotional burnout. *Frontiers in Psychology*, 14, 1111434. <https://doi.org/10.3389/fpsyg.2023.1111434>
- Zydzianaite, V., Kontrimiene, S., Ponomarenko, T., & Kaminskiene, L. (2020). Challenges in teacher leadership: Workload, time allocation, and self-esteem. *European Journal of Contemporary Education*, 9(4), 948- 962. <https://doi.org/10.13187/ejced.2020.4.948.20>