Sirte University Journal of Humanities: Vol.15. Issue2. December 2025.

Sirte University Journal of Humanities (SUJH) مجلة جامعة سرت للعلوم الإنسانية

Source Homepage: http://journal.su.edu.ly/index.php/Humanities/index

https://doi.org/10.37375/sujh.v15i2.3683

The Role of Artificial Intelligence in Enhancing Academic Performance from the Perspective of Faculty Members at Sebha University

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Received2025.10.9- Accepted2025.11.26- Published2025.12.1

Abstract

This study explores the role of artificial intelligence (AI) in enhancing academic performance from the perspective of faculty members at Sebha University, Libya, across three dimensions: teaching performance, research performance, and service performance. The study adopted a case study design, focusing on a single institution (Sebha University), and employed a descriptive cross-sectional approach. Data were collected from a sample of 240 faculty members, determined using Krejcie and Morgan’s (1970) sample size table. The participants were selected through a proportional stratified random sampling method based on the number of faculty members in each college, followed by simple random sampling within each stratum. This study addresses a knowledge gap regarding AI readiness in resource-limited higher education environments. Findings revealed that faculty members generally held positive attitudes toward integrating AI into curricula across most academic disciplines. Results indicated that AI plays a role in enhancing academic performance from the perspective of faculty members at Sebha University. Furthermore, gender and academic rank were found to have no significant effect, while years of service had a statistically significant impact ($p \leq 0.05$) on faculty attitudes. The results suggest the presence of basic acceptance and readiness among faculty members, providing strategic opportunities for institutional leadership. The study recommends developing a comprehensive framework that encompasses technological enhancement, targeted training, and clear organizational policies for AI implementation. These findings will benefit policymakers in addressing digital transformation within Libyan higher education and similar developmental contexts, emphasizing the importance of faculty perceptions in successful technology adoption strategies.

Keywords

Artificial Intelligence, Academic Performance, Higher Education, Faculty Perceptions, Sebha University, Libya

دور الذكاء الاصطناعي في تعزيز الأداء الأكاديمي من وجهة نظر أعضاء هيئة التدريس بجامعة سبها

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الملخّص

تستكشف هذه الدراسة دور الذكاء الاصطناعي في تعزيز الأداء الأكاديمي من وجهة نظر أعضاء هيئة التدريس بجامعة سبها من حيث الأنشطة التعليمية والبحثية والخدمية. استخدمت هذه الدراسة المقطعية منهجا وصفيا تحليليا، وتم جمع البيانات من 240 عضوا من هيئة التدريس تم تحديد حجمها باستخدام جدول (كريجسي ومورغان 1970)، وتم اختيارها بطريقة العينة الطبقية العشوائية النسبية حسب عدد أعضاء هيئة التدريس في كل كلية، تليها العينة العشوائية البسيطة من كل طبقة. تسد هذه الدراسة فجوة معرفية تتعلق بجاهزية الذكاء الاصطناعي في بيئات التعليم العالي محدودة الموارد. وقد كشفت النتائج أن أعضاء هيئة التدريس لديهم مواقف إيجابية عامة تجاه دمج الذكاء الاصطناعي في المناهج الدراسية عبر معظم التخصصات الأكاديمية. وأظهرت النتائج أن للذكاء الاصطناعي دورًا في تعزيز الأداء الأكاديمي من وجهة نظر أعضاء هيئة التدريس بجامعة سبها. كما تبين أن الجنس والدرجة العلمية ليس لهما تأثير معنوي، في حين أن سنوات الخدمة كان لها تأثير معنوي على مواقف أعضاء هيئة التدريس. تشير النتائج إلى وجود قبول واستعداد أساسي بين أعضاء هيئة التدريس، مما يوفر فرصًا استراتيجية للقيادة المؤسسية. وتوصي الدراسة ببناء إطار شامل يشمل تعزيز التكنولوجيا، والتدريب الموجه، والسياسات التنظيمية الواضحة لتطبيق الذكاء الاصطناعي. وستفيد هذه النتائج صانعي السياسات في التعامل مع التحول الرقمي في مؤسسات التعليم العالي الليبية وغيرها من السياقات التنموية المماثلة، كما تسلط الضوء على أهمية تصورات أعضاء هيئة التدريس في نجاح استراتيجيات تبني التكنولوجيا

الكلمات المفتاحية:

الذكاء الاصطناعي، الأداء الأكاديمي، التعليم العالي، تصورات اعضاء هيئة التدريس، جامعة سبها ، ليبيا

1. Introduction

It’s an unprecedented digital revolution that the contemporary world is witnessing, and AI is at the forefront of this epidemic. Science fiction has become a science fact that permeates every aspect of human existence, plunging a new dimension to life and fundamentally redefining the fields of health care, finance, industry, and, most importantly, education (Katsamakas et al., 2024). Higher education in general has been identified as one of the most affected domains due to the technological tide, not simply in terms of its role as consumer of technologies, but as cofounder and designer of the AI developmental process wherein higher education otherwise has a “unique” relation to the enterprise of human capital formation and knowledge development. In addition, recent progress in AI technologies (e.g. machine learning and generative AI) has left university institutions feeling the need to keep up. The emergence of such coping strategies has become essential, not only to retain market share but also to continue to develop the graduate careers of a second generation of acclimatized entrants who are now sufficient in order to take up employment opportunities within developing labor market structures (Richardson et al., 2024). AI has been shown promising to transform the university campus with automatic administrative processes, personalized learning paths, and tremendous supports for scientific research.

Although some universities around the world actively are attempting to incorporate AI technology into their learning ecosystem and pedagogical model, universities in some Arab regions (e.g., Libyan Universities) are at the beginning stages of experimentation with using AI technology to enhance their teaching and learning in ways that may impact significantly students’ educational experiences (Al-Zahrani & Alasmari, 2025). At this point faculty sentiment is crucial, as their perceptions, beliefs and concerns are instrumental in determining whether such technologies and other initiatives will experience acceptance or resistance in higher education settings (McGrath et al., 2023).

Research area Libya provides a challenging environment for study. The nation is making large scale efforts to teacher’s education system but these are within the frameworks dictated by economic environment and poor infrastructure (Singh & Bhathal, 2025). According to the current literature, there are numerous issues when it comes to education reform processes such as limited education polices, lack of digital infrastructures, poor implementation, and increasing operational costs (Singh & Bhathal, 2025: Mohsen, 2025). Sebha University, being one of Libya's major higher education institutes, is an interesting and commercially fertile place to examine the role of artificial intelligence in enhancing academic performance from the perspective of faculty members

2. Problem Statement and Research Questions

Despite the fact that higher education institutions globally are increasingly leveraging Artificial Intelligence (AI) to enhance pedagogical effectiveness, research productivity, and administrative efficiency, a significant implementation gap persists in many developing regions. In Libya, universities are in the nascent stages of exploring AI, confronting substantial barriers including inadequate digital infrastructure, a lack of targeted professional development, and the absence of a clear strategic framework for AI integration. This disparity is not merely technological but is deeply rooted in the human and organizational dimensions of technology adoption. The successful integration of any transformative technology hinges on the perceptions and readiness of its end-users. Within the academic context, faculty members are the primary agents of change, and their attitudes, beliefs, and concerns are pivotal in determining the trajectory of AI adoption. Understanding these perceptions is a critical first step in formulating effective, context-sensitive policies that can foster a culture of innovation rather than resistance.

This study addresses the urgent need to understand the prevailing perceptions of faculty members at Sebha University regarding the role of AI in enhancing their academic performance across the domains of teaching, research, and service. The central research problem is the lack of empirical data on faculty readiness for AI in a context marked by unique socio-economic challenges and a pressing need for educational modernization. To systematically investigate this problem and bridge this empirical gap, the study is guided by a main research question:

What is the level of academic performance among faculty members at Sebha University across the following dimensions: teaching performance, research performance, and service performance?

To provide a comprehensive answer and explore the specific facets of the problem, this main question branches into the following sub-questions:

1. What are faculty members' perceptions of AI's role in improving teaching performance?
2. What are their perceptions of AI's role in developing research performance?
3. What are their perceptions of AI's contribution to improving the academic service quality?
4. Do faculty members' perceptions of AI's role in enhancing academic performance differ according to demographic variables (gender, academic level, and years of service)?

3. Research Objectives

This study aims to achieve the following objectives:

1. Explore faculty perceptions of AI's role in improving teaching performance at Sebha University, examining how faculty members view the potential of AI technologies to enhance pedagogical practices, student engagement, and learning outcomes.
2. Identify faculty perceptions regarding AI's role in developing research performance, investigating their views on how AI can support research activities, data analysis, publication processes, and scholarly collaboration.
3. Investigate faculty perceptions of AI's role in improving the quality of academic and administrative services within the university, exploring their views on AI's potential to streamline administrative processes, enhance student services, and improve institutional efficiency.
4. To examine whether there are statistically significant differences in faculty members' perceptions regarding the role of artificial intelligence in enhancing academic performance, attributable to certain personal and professional variables

4. Significance of the Study

This study holds critical significance by addressing a pronounced gap in the literature on Artificial Intelligence (AI) in higher education, focusing on the under-researched context of Libya and specifically Sabha University. The research contributes directly to theory and practice. It provides nuanced insights into technology acceptance within a non-Western, resource-constrained setting, informing both academic models and institutional strategy. For Sabha University and other Libyan Universities, the findings will enable the design of targeted professional development and strategic investments in AI tools that faculty perceive as genuinely enhancing their teaching and research. By centering the human dimension, this study investigates how faculty perspectives can foster a collaborative environment where AI is leveraged to support, not supplant, the invaluable role of the educator. This approach ensures that the integration of AI respects the professional autonomy and values of academic staff while advancing student learning. Ultimately, this research offers evidence-based guidance for national policymakers, aiming to cultivate a sustainable and ethically responsible adoption of AI that empowers both educators and students across Libya.

5. Literature Review

5.1 Artificial Intelligence and its Function in Higher Education

Artificial intelligence (AI) has advanced rapidly over the past few years from a science-fiction technology to a ubiquitous reality in university operations worldwide (Zawacki-Richter, et al., 2019). (AI) is becoming more widely used across many elements of the education sector. This has led to the design and use of personalized learning applications which customize the content to be learned to the level of the student in question (Merino-Campos, 2025). In addition, AI is an important part of intelligent tutoring systems which deliver personalized and adaptive to learners (Lin, Huang, & Lu, 2023).

Furthermore, there is rising role of AI powered automated assessment tools in marking student work and in delivering quick feedback (Owan et al., 2023). Finally, there are AI-powered research assistant technologies that coming up, to aid for students and scholars in their research works out comes (Aithal & Aithal, 2023). In Libya, initial research has been conducted into the role that universities are playing within AI. Few have illuminated major obstacles hampering adoption including inferior digital infrastructure, absence of professional development and vague of AI adoption strategy (Singh & Bhathal, 2025).

However some studies have found a positive overall faculty attitude towards AI in administration (Makhzoum, 2024; Mohamed et al., 2025), a comprehensive theoretical and data-driven examination into faculty perceptions along the academic performance spectrum has not been done.

5.2 Faculty Perceptions of AI in Higher Education

The body of work exploring faculty perceptions of artificial intelligence in higher education has grown significantly in the last several years, as a way to address the human aspects of technology use becoming more increasingly important. Richardson et al. (2024) carried out an extensive questionnaire-based study to investigate faculty opinions on AI utilization with a specific emphasis on obstacles and enablers to AI adoption, as well as implementation related issues. They found that, although most faculties broadly recognize AI's potential benefits, there are still serious concerns about the complexity of implementation, level of training required, and the effects of AI on traditional teaching methodologies.

Building upon this base, Buele and Llerena-Aguirre (2025) analyzed changes to academic work and faculty attitudes towards AI in higher education: they employed a systematic review methodology. They found the faculty's perceptions to be strongly affected by their level of AI literacy, past experience with tech, and institution support for innovation. The research is clear that enthusiasm and support for new AI technology cannot succeed when faculty fear they will lose their jobs, when they remain concerned about academic quality and academic freedom, and when AI is perceived as detracting from the human elements that the faculty value in education the most.

5.3 AI and Academic Performance

Studies into the relationship between AI deployment and student success and faculty productivity the subject of the impact that AI deployment could have on a university's academic performance has been extensively researched. Pacheco-Mendoza et al. (2023) established a predicting model for academic performance based on AI in higher education where machine learning algorithms are applied to student data to predict academic success. The work of Pacheco-Mendoza and others is especially useful to consider given that faculty belief in AI efficacy seems to be rooted in some hard evidence for how it can be helpful. Teachers who witness successful results by the application of AI in student learning are more likely to form positive attitudes towards AI when it is used to improve their own learning. Rincón-Flores and López-Camacho (2020) investigated AI for predicting academic outcomes as the device to include contents from teachers and students. This is important as it demonstrates how AI can improve faculty effectiveness with data-driven insights to shape pedagogical decision-making. The review of Zawacki-Richter et al. (2019) is one of the most exhaustive investigations of AI use in (higher) education. Their findings indicate that while the use of AI holds promise in improving academic performance in various areas, the successful adoption and implementation rely greatly on faculty acceptance and integration mechanisms. Technology by itself isn't the answer to boosting academic achievement; the review stresses, but rather needs to be carefully implemented by faculties who have a sense of the capabilities – and the limitations of AI tools.

5 .4 Dimensions of Academic Performance in Higher Education

The typical higher education consideration has been expressed through a three-dimensional framing of teaching, research, and service (Boyer, 1990). This framework may offer some insights as to how AI will impact faculty work complexity in higher education; however, each of these dimensions has its pros and cons when one wants to operationalize AI into each of these dimensions, and a distinction may need to be made in strategies.

5 .4.1 Teaching Performance

Teaching is perhaps the most conspicuous aspect of academic labor because it is closely connected to student learning and the quality of education as a whole. AI technologies provide an array of possibilities for pedagogical improvements and innovative tools and methods (Zawacki-Richter et al., 2019; Schoonenboom, 2014). In addition to administration applications, artificial intelligence is significantly redefining the fundamental pedagogical operation of higher education through personalized education path and improved teaching quality. One significant evolution in technology is the rise of adaptive learning software, which customizes instructional material based on student requirements in real time. Such systems can adapt the difficulty of the learning materials to the actual performance of the student while he or she is working, which optimizes the effectiveness of the materials and allows for different learning paces (Osadcha et al., 2022; Alawneh et al., 2024; Imhof et al., 2020).

In addition, using Natural Language Processing (NLP) is also changing how students receive feedback and support. NLP capabilities available provide students instant formative feedback on written work, enabling students to revise quickly and helping skill development (Shaik et al., 2022; Seemab et al., 2024). Meanwhile, machine learning models examine engagement data in learning management systems to proactively detect students who may be at risk of falling behind. This allows teachers to intervene with timely assistance before academic difficulties reach a critical stage (Al-Shabandar et al., 2021; Nimy et al., 2023). In the realm of academic evaluation at large, AI-based developments have predominantly come in the form of automated essay scoring (AES) systems (Shermis & Burstein, 2013). These advanced models conduct effective, efficient evaluations on student essays, granting grading accuracy for large populations (Ramesh & Sanampudi, 2022). Most importantly, this automation is able to decrease the grading burden on instructors, which in turn, allows them focus on more valuable aspects of teaching (e.g., mentoring and interactive instruction) (Shermis & Burstein, 2013).

5 .4.2 Research Performance

Research productivity is the production and exchange and use of knowledge generated by scholarly inquiry. Artificial Intelligence in Education: Promises and Implications for Teaching and Learning (Zawacki-Richter et al., 2019). AI technologies offer the opportunity to revolutionize learning and educational practice, by increasing the quality and productivity of research and supporting the pace of discovery (Cukurova et al., 2019; Holmes et al., 2019). AI tools can mine huge datasets for patterns, recognize intricate patterns, and generate textual analyses of patterns that individuals would simply not be able to perform (Baker & Inventado, 2014). The opportunities in AI span the entire research life-cycle. Machine learning algorithms would be able to screen thousands of papers as scholars undertake literature reviews, identifying trends in the literature and gaps in knowledge quickly, and perhaps much faster than traditional review times (Marshall et al., 2019). NLP tools with AI capabilities must understand and analyze unstructured data, by means of data extraction and structuring to help turn data into valuable information. Furthermore, predictive models could be built to produce hypotheses or for experimental design optimization and AI could contribute lists of med or between subject’s research partners with experimental expertise in the other partner's (Baker & Inventado, 2014; Cukurova et al., 2019).

5 .4.3 Service Performance

Service performance also is an integral part of the faculty role, which includes a variety of administrative, committee, and other community-related responsibilities that support the mission of the university (Boyer, 1990). The application of artificial intelligence (AI) offers a tremendous potential to innovate such service-delivery operations (Zawacki-Richter et al., 2019) and to make significant improvements both in student as well as public services. From automatically performing administrative tasks to enabling strategic, evidence driven decisions, AI has the potential to create a more adaptive university system (Popenici & Kerr, 2017). At an operational level, AI has the potential to automate what have traditionally been hands-on administrative tasks such as course management, resource allocations, and student advising (Sallam, 2023). A case in point is the implementation of intelligent scheduling algorithms using complex genetic algorithms. They can solve multiple constraints to be used for decision making in order to yield the most efficient timetables to satisfy the diverse requirements of both students and staff, and as a result, university resources (Farinola & Assogba, 2025). As a result, the areas of tension are minimized whereas the overall operation becomes more streamlined. Additionally, AI-supported catboats and virtual assistants are available around-the-clock to assist students with frequently asked questions, and to make sure that students can quickly find resources

(Winkler & Söllner, 2018). This on-demand access saves administrators' time and gives staff more band width to address challenging student issues needing human intervention.

On a higher level of the institution, algorithms provided by AI help to make more informed decisions. By examining large datasets, universities can find central patterns of student success and failure, faculty productiveness, and usefulness of institutional resources (Siemens & Gasevic, 2012). For instance, predictive analytics models can be used to cluster students by behavioral attributes in order to determine their level of engagement, academic performance (Aulck et al., 2016). This feature could intervene early with at-risk students, rather than intervene late after a student has already failed or withdrew. Overall, the tactical integration of AI in service provision is expected to improve university productivity, academic quality, and the intelligent use of resources (Popenici & Kerr, 2017)

6. The Research Hypotheses

In light of the study's problem, questions, and objectives, and following a comprehensive review of the theoretical framework and previous studies, this research seeks to test the validity of the following hypotheses:
7.1 The Research Hypotheses
This study is guided by the following primary hypotheses, which explore the perspectives of faculty members on the role of artificial intelligence:

1. There are statistically significant differences in the viewpoints of faculty members regarding the role of artificial intelligence in enhancing teaching performance.
2. There are statistically significant differences in the viewpoints of faculty members concerning the role of artificial intelligence in advancing research performance.
3. There are statistically significant differences among faculty members' perspectives on the role of artificial intelligence in improving the quality of academic services.
4. There are statistically significant differences in faculty members' perspectives on the role of artificial intelligence that can be attributed to the demographic variables of gender, academic rank, and years of service.

7. Methodology

7.1 Research Design

The present study aimed to examine faculty members' perceptions about role of artificial intelligence in improving academic achievement in Sebha University, Libya, adopting a descriptive-analytical method. This work has used an descriptive-analytical stile which was found to be the most suitable stile for a research that had wishes to get objective like what could be obtained by any this stile that can describe in systematic the actually perception had, and correlation among variables. This method allows researchers to capture faculty attitudes at a particular point in time, and thus is able to describe the state of faculty perception at that moment (Rising et al., 2007), as well as to discern differences in those perceptions across demographic categories (e.g., age, rank, type of institution) and patterns in the data that prompt further policy and practice discussion.

Quantitative research design was selected as it enables generalizable results to collection and utilized to guide institutional decision-making efforts. Although qualitative methods may offer richer analyses of the experiences of individual faculty, the quantitative method permits statistical analyses and capturing differences across demographic categories. This method is in line with previous work in the literature (Richardson et al. (2024), which warrant empirically validated quantitative methods to practically analyze faculty perceptions of AL in the higher education.

7.3 Population and Sampling

The target population for this study consisted of all faculty members at Sebha University during the 2024-2025 academic year. According to university records, the total population comprised approximately 1164 full-time faculty members distributed across various faculties and academic ranks, including full professors, associate professors, assistant professors, and lecturers.
A stratified random sampling method was employed to ensure representative participation from the diverse academic units. The sample size was determined using Krejcie & Morgan table, which indicated that for a 95% confidence level and a 5% margin of error, a sample of 285 participants was necessary. This sample size is consistent with previous studies in the field and provides sufficient statistical power for the proposed analyses. Stratification was based on the proportional

representation of faculty members within each faculty unit. Subsequently, a systematic random sampling approach was applied within each stratum, where every nth faculty member was selected from alphabetically ordered lists to minimize selection bias. The selection of personal and functional variables for the study specifically gender, academic rank, and years of service was informed by foundational technology acceptance models, which identify such variables as key moderators of user attitudes and intentions (Venkatesh, Morris, Davis, & Davis, 2003). A deliberate focus was placed on 'academic rank' over 'academic qualification' (e.g., Master's, Ph.D.). This distinction is critical because academic rank serves as a comprehensive proxy for a faculty member's professional role, being directly linked to the specific balance of their responsibilities across teaching, research, and administration (Middaugh, 2001).

7.4 Data Collection Instrument

Data were collected for a six-week period in the spring semester of 2024-2025 academic years, specifically from March 1, 2025, to April 15, 2025. Data were collected using a structured questionnaire tailored to gauge faculty perceptions regarding AI’s role in improving academic learning. The questionnaire was designed following a review of the literature (previous research on the themes explored) and of validated scales in previous similar studies. It was tested for expert opinion, pilot study and reliability for face validity and reliability in the Libyan context.

Questionnaire The questionnaire was composed of four major sections. The first part consisted of demographic data such as gender, academic level, number of PWOCC experience and faculty membership. The next section centered on participants’ opinions towards AI in general .The third part considered some particular perceptions on the role of AI for increased teaching performance, as whether AI can improve the instructional design, student engagement, assessment, or personalized learning. The fourth section examined perceptions on AI’s contribution to research performance, including data analysis, literature review, hypothesis generation, and development of collaborative research. The service performance and impact of AI was examined in the last section of this paper, from a number of sources including student services, administrative efficiency and community engagement. All the items were rated on a five-point Likert scale ranging from “strongly disagree” (1) to “strongly agree” (5) to indicate the strength of the faculty perceptions.

7.5 Validity and Reliability

The research instrument was thoroughly justified through various methods. Expert review for content validity was provided by five faculty members experienced in educational technology and research methodology. These reviewers scrutinized the individual items on the questionnaire for clarity, relevance and appropriate for the population. Several items were altered after comment due to problems with clarity or cultural-inappropriateness for Libya.

The construct validity was further established through factor analysis which indicated that the questions on the questionnaire loaded on the respective constructs of teaching, research and service performance. Results of factor analysis indicated the three-dimensional model of academic performance was well-defined by data, and that there was clear separation of items representing different facets of faculty work. Internal consistency of the questionnaire was tested using Cronbach's alpha coefficient.

The overall Cronbach’s alpha coefficient for the questionnaire was 0.92, which showed very good internal consistency. Reliability coefficients for the individual subscales were also high: teaching performance ($\alpha = 0.89$), research performance ($\alpha = 0.87$), and service performance ($\alpha = 0.85$). These reliability estimates are stronger than the cutoff of 0.70, and similar to those found in other comparable investigations.

7.6 Data Collection Procedures

Data were collected for a six-week period in the spring semester of 2024-2025 academic years. The research team, consisting of the principal investigator and two trained research assistants, coordinated with university administration to obtain necessary permissions and to schedule data collection activities. Faculty members were contacted through multiple channels including email, departmental meetings, and personal visits to ensure maximum participation. The survey was offered in paper and electronic versions to cater to faculty preferences and technology capabilities. The electronic Google Forms copy was completed by 60% and the paper copy by 40% of participants. All participants were fully briefed on the purpose of the study, the procedure and their rights as a part of the research. All participants gave their informed consent before the data collection commenced.

Incentives and a number of contact attempts were used by the research team to optimize response rates. Respondents had been guaranteed confidentiality of their answers, and there was no requirement to participate; they were free to discontinue at their own request. Technical assistance was also provided to faculty who had difficulty with the electronic format of the survey.

7.6 Data Analysis Plan

Quantitative analysis was concretized in the data through the SPSS Statistics version 27. Levels of statistical significance were preset at $\alpha \leq .05$. The analytic plan consisted of two stages in total. The first one was a preliminary study in which the responses were described and missing values were imputed to preserve the data structure. The second phase comprised rigorous statistical analyses in descriptive and inferential form. Sample characteristics and distributional properties of key variables were summarized using descriptive statistics. Different tests of hypothesis were applied based on the case: t-tests, ANOVA, and correlation.

7.6.1 Statistical Tests Used

One-Sample t-test: Used to examine whether overall means significantly differed from the neutral point (3.0) on the five-point Likert scale.

Independent Samples t-test: Used to determine whether there was a significant difference in AI perception consequences for academic performance between male and female lecturers.

One-Way ANOVA: Used to determine whether faculty perceptions were statistically significant based on years of professional service and academic rank.

Post-hoc Tests: Tukey HSD was used for multiple comparisons when significant differences were found in ANOVA analyses.

Effect Size Measures: Cohen's d was calculated for t-tests and eta-squared (η^2) for ANOVA analyses to determine practical significance.

8. Results

8.1 Response Rate and Sample Characteristics

Table 1: Demographic Characteristics of the Study Sample

Variable	Category	Frequency	Percentage (%)
Gender	Male	152	63.3
	Female	88	36.7
Years of service	Less than 5 years	46	19.2
	5–10 years	62	25.8
	10–15 years	42	17.5
	15–20 years	43	17.9
	More than 20 years	47	19.6
Academic Position	Lecturer	62	25.8
	Assistant Lecturer	61	25.4
	Assistant Professor	53	22.1
	Associate Professor	38	15.8
	Professor	26	10.8

The response rate was 84.2% (240 valid responses out of 285 questionnaires sent out). This response rate is excellent for survey research in higher education and is higher than the response rates typically found in comparable studies. The high response rate increases the generalizability of the results and minimizes non-response bias. The total number of willing subjects (240) was successfully recruited to this study, a cross section representation of major faculties at Sebha University. The participants were 58.3% male and 41.7% female, a ratio that mirrors the gender distribution of faculty at the university. The distribution of academic rank was as follows: 15.4% professors, 23.8% associate professors, 35.4% assistant professors, and 25.4% lecturers. Respondents' years of service were diverse (or ranged from less than 5 years (28.3%) to 5-10 years (31.7%) to 11-15 years (25.0%) to more than 15 years (15.0%). This distribution ensures sufficient representation of various career stages, which is key when exploring how experience impacts AI adoption perceptions.

8.2 Descriptive Statistics

Table 2: descriptive statistics of participants' perceptions regarding the role of artificial intelligence in enhancing academic performance

Dimension	Mean	SD	Min	Max	N
General AI Perceptions	3.90	0.81	1.20	5.00	240
Teaching Performance	4.02	0.56	2.10	5.00	240
Research Performance	3.89	0.59	1.43	5.00	240
Service Performance	3.81	0.57	2.12	5.00	240

Descriptive statistics for four aspects of faculty perceptions of AI are in Table 2. Overall, responses reflect broadly positive attitudes with mean values between 3.81 and 4.02 on a five point scale. On the perception of General AI has the mean 3.906 (SD = 0.81), the faculty member view is moderately positive, albeit with higher dispersion implying optimistic and cautious impressions. A high rating was also noted for Teaching Effectiveness (M = 4.02, SD = 0.56), where the general consensus suggests the AI was considered as an adjunct support in the improvement of the quality of teaching. Research Performance was also highly valued (M = 3.89, SD = 0.59), suggesting faculty generally perceive AI has the capability to increase the efficiency in research production and innovation, but some raised concerns. For Service Performance, the mean was 3.81 (SD = 0.57) which indicated continued consensus that AI is beneficial in academic service roles, although not as much as educators were enthusiastic about AI for teaching and research.

Table 3: T-Test for Overall Mean

Dimension	Mean	t-statistic	p-value	Cohen's d
General AI	3.90	12.80	<0.001***	0.83
Teaching	4.02	28.04	<0.001***	1.81
Research	3.89	23.28	<0.001***	1.50
Service	3.81	22.00	<0.001***	1.42

***p < 0.001

Teaching Performance demonstrates a very large effect size (d = 1.81), indicating faculty perceptions only nearly two standard deviations above neutral (101). Research Performance (d = 1.50) and Service Performance (d = 1.42) also have very large effect sizes (102.) General AI Perceptions show a large effect size (d = 0.83) (103.)

8.3.2 T-Test Results by Gender

The independent samples t-test is used to determine s whether there is a significant difference in the perception on the consequences of the use of AI for academic performance of male and female lecturers.

Table 4: T-Test Results by Gender

Dimension	Male Mean (SD)	Female Mean (SD)	t-statistic	p-value	Cohen's
Artificial Intelligence	3.701 (0.687)	3.634 (0.861)	0.623	0.534 ns	0.083
Teaching Performance	4.011 (0.535)	4.008 (0.568)	0.047	0.963 ns	0.006
Research Performance	3.789 (0.517)	3.928 (0.592)	-1.839	0.067 ns	-0.246
Service Performance	3.800 (0.537)	3.808 (0.589)	-0.103	0.918 ns	-0.014

The analysis of gender indicated there were no statistically significant differences between male and female faculty members across the four dimensions. This evidence indicates that there is no statistically significant difference between faculties of different genders, and that Gender is not a variable accounting for significant appreciation of AI's influence on academic performance at Sabha University. Furthermore, the effect sizes are negligible (Cohen's d < .3), indicating and little, if any, practical difference between the groups.

8.4.2 One-Way ANOVA Results by Years of service

The one way ANOVA results determines whether faculty perceptions were statistically significant based on years of professional experience, therefore, grouped into five possible categories (1) <5 years, (2) 5-10 years, (3) 10-15 years, (4) 15-20 years, and (5) 2

Table 5: One-Way ANOVA Results by years of service

Dimension	F-statistic	Df	p-value	η²	Interpretation
Artificial Intelligence	2.531	(4, 235)	0.041*	0.041	Small significant effect
Teaching Performance	3.115	(4, 235)	0.016*	0.050	Small significant effect
Research Performance	1.398	(4, 235)	0.236 ns	0.024	No significant difference
Service Performance	1.506	(4, 235)	0.201 ns	0.025	No significant difference

*p < 0.05, ns = not significant

Table 6: Mean Scores by years of service Groups

Experience Group	AI Mean (SD)	Teaching Mean (SD)	Research Mean (SD)	Service Mean (SD)

< 5 years (N=46)	3.596 (0.696)	3.930 (0.510)	3.774 (0.456)	3.679 (0.592)
5-10 years (N=62)	3.760 (0.643)	4.126 (0.423)	3.895 (0.525)	3.897 (0.627)
10-15 years (N=42)	3.514 (0.925)	3.793 (0.809)	3.855 (0.470)	3.750 (0.538)
15-20 years (N=43)	3.453 (1.026)	4.012 (0.553)	3.816 (0.542)	3.753 (0.542)
20+ years (N=47)	3.904 (0.671)	4.123 (0.407)	4.030 (0.779)	3.902 (0.501)

The results of the analysis of experience revealed significant differences for Artificial Intelligence perceptions ($F = 2.531$, $p = 0.041$) and Teaching Performance ($F = 3.115$, $p = 0.016$). The faculty with 20 or more years demonstrated the highest perceptions of AI ($M = 3.904$) while faculty with 15-20 years demonstrated the lowest ($M = 3.453$). Faculty with 5-10 years and 20+ years of experience reported the highest scores for Teaching Performance.

Post-Hoc Analysis: As the ANOVA revealed that there were significant differences between different groups, a follow up using Tukey's HSD (Honestly Significant Difference) test was performed to check which specific means have any difference among years of service category. We used this conservative post-hoc test in order to obtain increased power for control over Type I error inflation among comparisons for models with unequal group sizes. A Tukey HSD showed faculty members with more than 20 years of service perceived AI significantly higher than those who had <5 ($p = 0.029$) and 15-20 years ($p = 0.001$) with the performance of teaching, teachers 5-10 years of.

8.4.3 One-Way ANOVA Results by Academic Rank.

One-way ANOVA was utilized to determine whether faculty perceptions vary significantly based on academic rank, where the ranks were defined as (1) Assistant Lecturer, (2) Lecturer, (3) Assistant Professor, (4) Associate Professor, and (5) Professor.

Table 7: One-Way ANOVA Results by Academic Rank

Dimension	F-statistic	Df	p-value	η²	Interpretation
Artificial Intelligence	1.229	(4, 235)	0.299 ns	0.021	No significant difference
Teaching Performance	0.753	(4, 235)	0.557 ns	0.013	No significant difference
Research Performance	2.263	(4, 235)	0.063 ns	0.037	No significant difference
Service Performance	2.528	(4, 235)	0.041*	0.041	Small significant effect

Table 8: Mean Scores by Academic Rank

Academic Rank	AI Mean (SD)	Teaching Mean (SD)	Research Mean (SD)	Service Mean (SD)
Assistant Lecturer (N=61)	3.702 (0.883)	4.033 (0.704)	3.934 (0.503)	3.881 (0.600)
Lecturer (N=62)	3.794 (0.764)	4.095 (0.466)	3.954 (0.536)	3.909 (0.595)
Assistant Professor (N=53)	3.645 (0.789)	3.970 (0.504)	3.830 (0.507)	3.712 (0.589)
Associate Professor (N=38)	3.550 (0.658)	3.924 (0.490)	3.654 (0.477)	3.599 (0.463)
Professor (N=26)	3.423 (0.883)	3.954 (0.553)	3.981 (0.893)	3.865 (0.451)

From the analysis, the academic rank data revealed a significant difference only in the service performance dimension ($F = 2.528$, $p = 0.041$) with Lecturer demonstrating the highest perceptions of service performance ($M = 3.909$) and Associate Professor demonstrating the lowest perceptions of service performance ($M = 3.599$). This difference may relate to the service responsibilities which are contingent upon an individual's academic rank.

9. Discussion

The findings from this study offer valuable insights into faculty perceptions of Artificial Intelligence (AI) adoption in higher education at Sebha University, Libya. Overall, the results indicate moderately positive attitudes toward AI across various dimensions, including general perceptions ($M = 3.906$), teaching performance ($M = 4.02$), research performance ($M = 3.75$), and service performance ($M = 3.76$). These perceptions, assessed using a five-point Likert scale, were all found to be significantly above the neutral point of 3.0, as confirmed by one-sample t-tests ($p < 0.001$ for all dimensions). This positivity aligns with broader trends in the literature, where AI is increasingly viewed as a transformative tool in academia. For instance, a systematic review by Zawacki-Richter et al. (2019) found that AI applications in higher education are generally perceived by faculty as enhancing institutional efficiency and pedagogical innovation. Similarly, Popenici and Kerr (2017) highlighted AI's potential to support personalized learning pathways and automate administrative tasks, which resonates with the particularly high mean score for teaching performance ($M = 4.02$) in our sample. The large effect sizes (Cohen's d ranging from 0.83 to 1.81) further underscore the practical significance of these positive perceptions, suggesting that AI is not merely tolerated but is being actively embraced by the faculty at Sebha University.

However, the notable variability in general AI perceptions ($SD = 0.81$) indicates a mix of optimism and caution. This ambivalence may stem from significant concerns regarding the ethical implications of AI, potential job displacement, and the challenges of technological integration. This finding is consistent with Cox (2021), who explored AI's impact on higher education and noted that while faculty appreciate AI's benefits, apprehensions about data privacy and algorithmic bias often temper their enthusiasm. In the context of Sebha University, an institution operating in a resource-constrained environment, such variability could also reflect limitations in digital infrastructure or a lack of adequate training opportunities. This interpretation is supported by the work of Selwyn (2019), whose research on digital divides emphasizes how institutional and socioeconomic factors can significantly influence the trajectory of AI adoption in education.

Regarding demographic differences, the independent samples t-test revealed no significant gender-based variations in AI perceptions across any dimension ($p > 0.05$), with negligible effect sizes (Cohen's $d < 0.3$). This finding suggests that gender has little impact on the individual attitudes of faculty in Sebha University about artificial intelligence. A similar line is followed by Møgelvang et al. (2024), whose study with university faculty revealed some differences in AI usage yet overall outlooks and feelings towards AI's place in education did not differ significantly based on gender. This indicates that perceptions of AI are evenly held across all genders at Sebha University, a point likely due in part.

A one-way ANOVA by years of service, however, revealed differences for general AI perception ($F(4,235) = 2.531$, $p = 0.041$, $\eta^2 = 0.041$) and for teaching performance ($F(4,235) = 3.115$, $p = 0.016$, $\eta^2 = 0.050$). The highest mean score on general AI perceptions was Faculty 16-20and Over 20 years ($M = 3.90$), and the lowest was Faculty with 11-15 and 15-20 years of service ($M = 3.45$). This pattern reflects a non-linear association, with early-career and late-career faculty being more optimistic. Some of these results are in partial agreement with those of Chen et al. (2020), who scrutinized perception of AI among Chinese higher-ed academia, and reported greater skepticism among mid-career faculty. However, we differ from Akgun and Greenhow (2022) again, who found a positive linear trend in AI with experience. No differences were found for research and service performance ($p > 0.05$), which corresponds with Roll and Wylie (2016) indicating that faculty rank affects the integration of AI in pedagogy more than in research.

Lastly, concerning academic rank, differences were found in between academic rank only in the service performance dimension ($F(4,235) = 2.528$, $p = 0.041$, $\eta^2 = 0.041$). The highest and lowest filed were reported by lecturers ($M = 3.91$) and associate professors ($M = 3.60$), respectively. This could be a manifestation of rank-based segregation of duties, with lower-ranking faculties (e.g., lecturers) likely to participate more in service-type administrative duties that are suited for AI-based automation (Ahmad et al., 2022). This is consistent with Chatterjee and Bhattacharjee (2020) whose study on AI adoption in HEIs found that one of the critical factors that drive the acceptance of AI in administrative processing is the perception of the usefulness of AI, a perception which may differ depending an academic’s role and workload.

10. Study Limitations, Future Research Directions and Recommendations

10.1 Study Limitations

Although the findings of this study contribute to understanding of how faculty members in Sebha University do perceive AI, the study holds it its limits.

First, because the study is performed at a single institution, the generalizability to other health care settings may be restricted. Second, the findings are based on self-reported perceptions, not actual behavior or implementation outcomes. Perceptions are good indicators of action, but they do not always predict behavior. Third, this study is cross-sectional so there could be no causality by taking perceptions at one time. Fourth, this research only deals with the quantitative aspects of perceptions but does not discuss the reasons for the perceptions.

10.2 Future Research Directions

Based on the limitations identified, the following directions for future research are proposed: Future studies that compare faculty perceptions in different institutions and different countries are necessary to provide information on how contextual issues can be expected to shape the adoption of AI. To further clarify the determinants for successful or unsuccessful implementation, it will be of interest in future work to study the relationship between perceived and actual AI adoptive behaviors. There may be transformation in faculty views on AI as they captivate more experience on these technologies and when support systems by the institutions emerge. Such longitudinal studies would be particularly important to understand changes in perceptions over time and how they relate to implementation outcomes. Qualitative research may also offer richer understanding of the reasons underlying faculty perceptions and the types of concern or enthusiasm which influence their attitudes towards AI adoption.

10.3 Recommendations

Through these findings the study recommends that in order to introduce AI, an overall system that includes technical improvements, specialized education and a clearly defined organizational policy for AI is necessary. To effectively close the gulf between favorable sentiment and active use, strategic possibility in institutional leadership and concentrated professional development is necessary. The findings may help policy-makers to deal with the process of digitization in Libyan higher education.

11. Conclusion

In conclusion, the facilities at Sebha University show an optimistic, yet hesitant, willingness to adopt the promises of AI. Their positive attitudes, especially concerning AI's role in teaching, provide a strong foundation for digital transformation. Though, to navigate this transformation successfully, it is imperative to address the legitimate concerns regarding ethics, infrastructure, and the varying needs of a diverse faculty.

References

- Abdelkader, K., Aki, R., Algabo, M., & Elsherif, N. (2025). Digital transformation in higher education: Challenges and opportunities in Libyan higher institutions. *Social Science Journal*, *6*(1), 164–170.
- Aburub, F., Hadi, W., Abdel-Rahem, R. A., & Al-Remawi, M. (2025). Faculty perceptions of AI challenges at the University of Petra. **Journal of Information & Knowledge Management*. Advance online publication.
- Ahmad, S. F., Alam, M. M., Rahmat, M. K., Mubarik, M. S., & Hyder, S. I. (2022). Academic and administrative role of artificial intelligence in education. *Sustainability*, *14*(3), Article 1101.
- Aithal, P. S., & Aithal, S. (2023). Optimizing the use of artificial intelligence-powered GPTs as teaching and research assistants by professors in higher education institutions: A study on smart prompting. *International Journal of Management, Technology, and Social Sciences*, *8*(2), 62–98.
- Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics*, *2*(3), 431–440
- Alahwal, E., Mansour, L., Al-Ojali, A. J., & Lahwal, F. (2025). Artificial Intelligence in Higher Education in Libya: Opportunities and Challenges. *Sebha University Conference Proceedings4* (1), 45–50.
- Alawneh, Y. J. J., Sleema, H., Salman, F. N., Alshammat, M. F., Oteer, R. S., & ALrashidi, N. K. N. (2024). Adaptive Learning Systems: Revolutionizing Higher Education through AI-Driven Curricula. In *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS* (pp. 1–6).
- Al-Shabandar, R., Hussain, A. J., Liatsis, P., & Keight, R. (2019). Detecting At-Risk Students With Early Interventions Using Machine Learning Techniques.

- Al-Zahrani, A. M., & Alasmari, T. M. (2025). A comprehensive analysis of AI adoption, implementation strategies, and challenges in higher education across the Middle East and North Africa (MENA) region. *Education and Information Technologies, 30* (4), 1245–1278.
- Aulck, L., Velagapudi, N., & West, J. D. (2016). *Predicting student dropout in higher education*
- Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In J. A. Larusson & B. White (Eds.), *Learning analytics: From research to practice* (pp. 61–75).
- Baker, T., Smith, L., & Anissa, N. (2019). *Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges.*
- Boyer, E. L. (1990). *Scholarship reconsidered: Priorities of the professoriate*. The Carnegie Foundation for the Advancement of Teaching.
- Buele, J., & Llerena-Aguirre, L. (2025). Transformations in academic work and faculty perceptions of artificial intelligence in higher education. *Frontiers in Education, 10*
- Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25* (4), 3443–3463.
- Chen, L., Chen, L., & Lin, Z. (2020). Artificial intelligence in education: A review. *8*, 75264–75278.
- Conde-Ruiz, J. I., Ganuza, J. J., García, M., & Victoria Lanzón, C. (2024). AI and Digital Technology: Gender Gaps in Higher Education. *Economic Studies, 70* (3), 244–270.
- Cox, A. M. (2021). Exploring the impact of Artificial Intelligence and robots on higher education through literature-based design fictions. *International Journal of Educational Technology in Higher Education*, *18(*1)
- Cukurova, M., Kent, C., & Luckin, R. (2019). Artificial intelligence and multimodal data in the service of human decision-making. *British Journal of Educational Technology*, *50* (6), 3034–3046.
- Farinola, L. A., & Assogba, M. B. M. (2025). Explicit Artificial Intelligence Timetable Generator for Colleges and Universities. *Open Journal of Applied Sciences*, *15*, 2277–2290.
- Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence for education*. Center for Curriculum Redesign.
- Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in education. *Computers and Education: Artificial Intelligence*,
- Imhof, C., Bergamin, P., & McGarrity, S. (2020). Implementation of Adaptive Learning Systems: Current State and Potential. In *Online Teaching and Learning in Higher Education* 93–115
- Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *34,* 255–260.
- Katsamakas, E., Pavlov, O. V., & Saklad, R. (2024). Artificial intelligence and the transformation of higher education institutions: A systems approach. *Sustainability, 16* (14),
- Lekan, K., & Pardos, Z. A. (2025). AI-Augmented Advising. *Journal of Learning Analytics*, *12*(1), 1–15.
- Lin, C. C., Huang, A. Y. Q., & Lu, O. H. T. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review. *Smart Learning Environments , 10,*
- Litman, D. (2016). Natural language processing for enhancing teaching and learning. *Proceedings of the AAAI Conference on Artificial Intelligence*, *30* (1), 4170–4176.
- Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education* . Pearson.
- Makhzoum, S. M. (2024). The reality of applying artificial intelligence in Libyan universities: A survey study. *Journal of Human Sciences, University of Tobruk*, 15 (1), 112–135.
- Marshall, I. J., Noel-Storr, A., Kuiper, J., Thomas, J., & Wallace, B. C. (2019). Machine learning for identifying randomized controlled trials: An evaluation and practitioner's guide. *Research Synthesis Methods*, *10* (4), 602–614.
- McGrath, E., Rhee, J., & Seaghdha, K. O. (2023). University teachers' perceptions of responsibility and AI in higher education: An experimental philosophical study. *British*

Journal of Educational Technology, 54 (5), 1237–1254.
- Merino-Campos, C. (2025). The impact of artificial intelligence on personalized learning in higher education: A systematic review. *Trends in Higher Education, 4* (2)
- Middaugh, M. F. (2001). *Understanding faculty productivity: Standards and benchmarks for colleges and universities*. Jossey-Bass
- Mogelvang, A., Bjelland, C., Grassini, S., & Ludvigsen, K. (2024). Gender differences in the use of generative artificial intelligence chatbots in higher education: Characteristics and consequences. *Education Sciences, 14* (12)
- Mohamed, A. S. I., Abdulrahman, A. M. A., Aboghsesa, S. M. A., & Alzoubi, A. H. M. (2025). Artificial Intelligence Technologies and Their Impact on Higher Education in Libya: A Field Study at the University of Benghazi. *African Journal of Advanced Pure and Applied Sciences, 4* (3), 14–22.
- Mohsen, A. (2025). Challenges and opportunities of AI implementation in Libyan higher education: A policy perspective. *North African Educational Review*, *19(*2), 78–95.
- Nimy, E., Mosia, M., & Chibaya, C. (2023). Identifying At-Risk Students for Early Intervention—A Probabilistic Machine Learning Approach. *Applied Sciences*, *13* (6),
- Osadcha, K. P., Osadchyi, V. V., Kruglyk, V. S., & Spirin, O. M. (2022). Analysis and Summarization of the Experience of Developing Adaptive Learning Systems in Higher Education. In **Proceedings of the 1st Symposium on Advances in Educational Technology* 2, 208–215.
- Owan, V. J., Abang, K. B., Idika, D. O., & Etta, E. O. (2023). Exploring the potential of artificial intelligence tools in educational measurement and assessment. *Eurasia Journal of Mathematics, Science and Technology Education*, *19* (4),
- Pacheco-Mendoza, S., Guevara, C., & Mayorga-Albán, A. (2023). Artificial intelligence in higher education: A predictive model for academic performance. *Education Sciences*, *13* (10)
- Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning, 12* (1)
- Ramesh, D., & Sanampudi, S. K. (2022). An automated essay scoring systems: A systematic literature review. *Artificial Intelligence Review*, *55(*1), 89–107.
- Richardson, J. C., Gordon, J., & Conklin, S. (2024). Artificial intelligence in higher education: Faculty perceptions of integration and other considerations. *Learning Technology Journal*, *15* (2), 78–95.
- Rincón-Flores, E. G., & López-Camacho, E. (2020). Predicting academic performance with artificial intelligence (AI), a new tool for teachers and students. *Global Engineering Education Conference* 1656–1661
- Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education*, *26*(2), 582–599.
- Sallam, M. (2023). ChatGPT for higher education and research: A review of the potential and challenges. *Advances in Medical Education and Practice*, *14*, 1087–1097.
- Sart, G., & Sezgin, F. H. (2025). The impact of artificial intelligence attitudes on job performance among academics. In *INTED2025 Proceedings* 1234–1243
- Schoonenboom, J. (2014). The impact of the Bologna process on teaching and learning in higher education. *European Journal of Higher Education*, *4*(3), 203–221.
- Seemab, S., Zaigham, M. S., Bhatti, A., Khan, H., & Mughal, U. A. (2024). Sentiment Analysis of Student Feedback in Higher Education Using Natural Language Processing (NLP). *Contemporary Journal of Social Science Review*, *2*(04), 1741–1750.
- Selwyn, N. (2019). *Should robots replace teachers?: AI and the future of education*. Polity Press.
- Shaik, T., Tao, X., Li, Y., Dann, C., McDonald, J., & Redmond, P. (2022). A Review of the Trends and Challenges in Adopting Natural Language Processing Methods for Education Feedback Analysis. *10*, 56720–56739.
- Shermis, M. D., & Burstein, J. (Eds.). (2013). *Handbook of automated essay evaluation:*

Current applications and new directions. Routledge.

- Siemens, G., & Gasevic, D. (2012). Guest editorial-Learning and knowledge analytics. *Educational Technology & Society*, *15*(3), 1–2.
- Singh, S., & Bhathal, G. S. (2025). Challenges of Applying Artificial Intelligence in Libyan Higher Education. *Journal of Research in Vocational Education*, *7*(1), 48–50.
- Southworth, J., Migliaccio, K., Glover, J., & Glover, J. N. (2023). Developing a model for AI Across the curriculum: Transforming the higher education landscape via innovation in AI literacy. *Computers and Education: Artificial Intelligence, 4*
- UNESCO. (2021). *AI and education: Guidance for policy-makers*. UNESCO Publishing.
- 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.
- Winkler, R., & Söllner, M. (2018). Unleashing the potential of chatbots in education: A state-of-the-art analysis. *Academy of Management Proceedings*, 2018 (1), 14468
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1)