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Assessing The Purpose Of Implementing Artificial Intelligence-Based Robots In An Educational Institution For The Purpose Of Educating Learners

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ABSTRACT

Despite certain advancements, the incorporation of artificial intelligence into educational institutions is still inadequate. The demand for instructors will endure for a considerable period, yet the incorporation of AI-powered robots in schools has significantly diminished the importance of teachers. The aim of the current research was to assess the inclination of Jordanian institutions of higher learning to embrace artificial intelligence-based robots for educational objectives. Utilising the TAM, this research presents nine hypotheses to assess learners' inclination to embrace artificial intelligence-based robots in the field of education. The data of learners was gathered and examined employing PLS-SEM. The research's findings indicated that all hypotheses were confirmed. The findings suggest that learners are receptive to incorporating artificial intelligence-powered robots into their educational experience. Nevertheless, the results indicated that factors such as perceived ease of use, perceived utility, perceived risk, anxiety towards robots, self-efficacy in interacting with robots, and technology-related insecurity had no significant impact on the attitude towards artificial intelligence-based robots. The study's findings will offer valuable insights to university administrations on the importance of artificial intelligence-based robots in education. Furthermore, the results will assist developers of robots, policymakers, and university administrators in creating and executing artificial intelligence-driven robots that meet current educational requirements.

Keywords: *technology-related insecurity, perceived risk, Jordan, TAM, structural equation modeling.*

INTRODUCTION

The advent of a technological revolution in the early 20th century had a profound impact on contemporary civilization. The revolution has taken place in multiple sectors characterised by societal divisions, such as corporations, institutions, social and healthcare domains, as well as education (Atman et al., 2022; Mohammed et al., 2023). Essentially, the exponential advancement of technology has fundamentally transformed our methods of communication, medical treatment, and the acquisition of information (Chang et al., 2022). Information technologies have had a significant impact on methods of instruction and learning in universities; however, the changes may sometimes occur gradually (Hwang et al., 2022). Presently, the progress in technology within the field of education has not significantly improved the existing ways of

teaching and learning. Hence, any method of learning that integrates diverse technological capabilities should be connected to the enhancement of the instructional approach (Lin et al., 2022).
Teachers need to have heightened awareness of the current changes and demonstrate a willingness to incorporate novel tools to facilitate active and collaborative learning among student teachers (Wang et al., 2022). The institution of higher learning networks in Jordan has experienced significant growth over the past two decades. Hence, there is an immediate need for a profound transformation in the educational environment and administrative responsibilities in the delivery of higher learning in Jordan. Various aspects of higher education require updating. Contemporary educational settings and Artificial Intelligence-Based Robots (AI-BR) ideas encompass the utilisation of practical, intricate problem-oriented learning (Chandra et al., 2020). In order to ensure the relevance and enhance the influence of AI-BR in education, the field must adapt to these changes (Chang et al., 2020). The Artificial Intelligence (AI)-driven chatbot industry is experiencing significant growth because of the increasing demand for smartphones and the widespread usage of messaging applications in the era of AI-BR (Zhang et al., 2020; Yu & Nazir, 2021; Altay & Pal, 2022). In recent years, the financial, e-commerce, and food delivery sectors have all adopted chatbot technology.
The educational industry is poised to benefit significantly from the utilisation of this technology (Hooijdonk, 2021). The development of chatbots based on AI can provide significant benefits for education. It has the potential to improve effectiveness in education, productivity, and communication by minimising uncertainty in interactions (Skjuve et al., 2021). By utilising the AI-BR capabilities of this technology, a novel educational platform can effectively tackle urgent challenges in the field of education (Al-Zoubi et al., 2023). Al-Zoubi et al. (2023) examine the utilisation of AI-powered chatbots in education with the aim of enhancing the student learning experience. Alzoubi & Alzoubi (2020) demonstrate the utilisation of AI-BR in the field of education and its implementation in evaluating innovative design methods and tools that can enhance research, teaching, practical application, and policy-making in AI-BR to improve the well-being of humanity. AI-BR Li et al. (2021) delineated the obstacles encountered in the application of AI-BR within the education domain. In their research, Nawaz and Mohamed (2020) examined the use of AI-BR in Jordan's higher education system by employing the Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm.
The study demonstrated that the model has the potential to aid authorities in promoting the implementation of AI-BR in higher education. Chi (2022) performed a comprehensive analysis of existing literature regarding the advancements of AI-BR in the field of education. Chen et al. (2021) performed a comprehensive analysis of existing literature to investigate the use of educational robotics in the context of mathematics education. The technological aspect of educational robotics research is essential, as is its practicality. In terms of the technological component, the focus of their research has been on studying how users perceive the physical attributes of robots and their possible interactions with humans (Chen et al., 2020). Atman et al. (2022) examined the utilisation of robotics in the field of education. Chevalier et al. (2020) propose a framework for the application of AI-BR in education. In order to assess, construct, and execute educational AI-BR systems, researchers initially establish a framework known as eXplainablen, which encompasses six fundamental attributes of eXplainablen capability.
The key elements encompassed in this context are stakeholders, advantages, approaches for providing explanations, commonly employed categories of AI-BR models, human-centred designs of AI-BR interfaces, and the potential risks associated with delivering answers in the field of education. Conti et al. (2020) provide a concise overview and emphasise the significance of AI-BR in the process of instructing and assessing pupils. Our research indicates that AI-BR serves as the basis for intelligent tutor systems that utilise natural language processing. These systems utilise AI-BR to acquire abilities such as introspection, answering probing inquiries, reconciling contradictory assertions, generating innovative queries, and making decisions. Evripidou et al. (2020) developed and deployed AI-BR-powered educational tools for college athletics. Utilising human-computer interaction technology in AI-BR to develop an effective sports AI-BR teaching system is crucial for enhancing students' learning efficiency, broadening the utilisation of AI-BR technology in education and sports AI-BR, and improving students' learning efficiency. Moreover, the researchers discovered that neither reducing anxiety related to artistic intelligence nor increasing information about artistic intelligence had any impact on the readiness of students' creative intelligence.
In their research, Battistoni et al. (2023) investigated the elements that influenced the behavioural intention (BI) of 131 primary children to engage in creative intelligence learning. The study's findings indicate that the learning objective of artistic intelligence for the betterment of society is the most significant determinant of students' behavioural intention (BI). Boddu et al. (2022) posited that a chatbot is a technology in natural language processing employed for user interaction. On the other hand, robots that are based on AI-BR are tangible devices that can adjust to their environment and carry out particular assignments (Cheung et al.,

2023). There is a scarcity of research in the current body of literature that investigates the extent to which students are willing to embrace robotics that utilise AI-BR in the field of education. Gaining insight into the students' viewpoint on the introduction of robots based on AI-BR is crucial. Hence, this study sought to answer the subsequent research inquiries: This study uses AI-BR to assess the receptiveness of students towards AI-BR-powered robots at Jordanian higher education institutions. The present study employed a modified version of the technology acceptance model (TAM).

Previously, academics employed the theories of planned behaviour, the technology readiness index, and the unified theory of acceptance and use of technology (UTAUT). Nevertheless, studies suggest that the TAM provides a more thorough account of behavioural intention compared to UTAUT, the Technology Readiness Index, and the Theory of Planned Behaviour (Nawaz & Mohamed, 2020; Dondapati et al., 2022; Al-Zoubi et al., 2023; Battistoni et al., 2023). Hence, the present study will employ the modified TAM to forecast students' acceptance of AI-BR-powered robots in the field of education. The TAM model provides a thorough comprehension of students' acceptance of robots based on AI-BR. This is achieved by incorporating technology-related factors that are suitable for forecasting the acceptance of new and innovative technologies. The findings of the present study offer useful insights into the extent to which students are embracing AI-BR in the field of education. Moreover, the results of this study will enhance the advancement of AI-BR and aid university administrators in the implementation and utilisation of AI-BR in the higher education domain.

Technology Acceptance Model

Davis (1989) posited that the acceptability of technology by users is contingent upon their perception of its utility and simplicity. Perceived usefulness refers to an individual's belief in the technology's ability to improve their job performance. Perceived ease of use refers to an individual's view that the technology is not demanding in terms of the effort required for its use (Davis, 1989). Both constructs exert an impact on an individual's attitude towards accepting behaviour, as demonstrated by the studies conducted by Rita et al. (2022), Shih-Ting et al. (2022), and Suddin et al. (2023). Attitude refers to an individual's assessment of whether a behaviour is considered beneficial or not (Ajzen, 1989). Perceived ease of usage also impacts perceived utility. Subsequently, the mindset gives rise to the desire to carry out the action or drive, culminating in the execution of the tangible behaviour (Davenport et al., 2020; Daoud et al., 2021; Cheung et al., 2023).

H1: Perceived usefulness has a beneficial impact on attitudes towards AI-BR in higher education.

H2: Perceived ease of use has a beneficial impact on perceived usefulness.

H3: Perceived ease of use has a beneficial impact on attitudes towards AI-BR in higher education.

The theory of TAM has shown superior suitability over the UTAUT method for analysing the educational applications of AI-BR. This is due to its incorporation of perceived ease of use, perceived utility, and external factors. The use of the TAM has been restricted. Consequently, academics have advocated for its utilisation in various IT-based scenarios to gain a thorough understanding of technology uptake (Jalagat, 2016; Jayashree et al., 2021). The present study employed the TAM to investigate students' receptiveness towards artificial intelligence-powered robots in an educational setting. The theoretical model employed in this investigation is depicted in Figure 1.

Ancillary Constructs of the TAM

Individuals display emotions when engaging in a desired or undesired action. This pertains to the concept of attitude as defined by Fishbein and Ajzen in 1975. In their theory of the TAM, Davis et al. (1989) propose that the assessment of an individual's behavioural intention to use a technology is based on their attitude towards utilising it. Research indicates that attitude has a significant impact on users' behavioural intentions, as outlined in the Theory of Planned Behaviour (Ajzen, 1991). Attitude serves as a significant intermediary factor in interpreting behavioural intention, as demonstrated in various previous research studies (Aboelmaged 2010; Cox 2012). Several searches (Hung et al. 2009) provide evidence to support this analysis. Based on the many inputs and understanding the impact of attitude on the behavioural intention of users in implementing artificial intelligence in higher education, the following hypothesis is formulated: Behavioural intention refers to the evaluation of an individual's level of intention to engage in a particular behaviour within a specific situation (Fishbein and Ajzen, 1975). Behavioural intention is a reliable indicator of engaging in the specific activities that are intended (Deb & David, 2014). Behavioural intention serves as a mediating variable that successfully influences the performance of an action in support of the activity to which one's purpose is directed (Chang et al., 2022). Based on this crucial perspective, the following hypothesis is proposed:

H4: Attitude towards AI-BR in higher education has a beneficial impact on intention to use.
H5: Behavioural intention AI-BR in higher education has a beneficial impact on the adoption in Higher Education.

Perceived risk is commonly understood as the belief or conviction that an individual will experience a negative consequence when they pursue a particular goal involving AI-BR (Huang et al., 2021). AI-BR is a technology that operates through the internet. Perceived risk is the amalgamation of psychological uncertainty and ecological uncertainty. The internet's unfriendly nature and capricious functions contribute to behavioural insecurity, while its unpredictable nature is accountable for environmental insecurity (Pal et al., 2021). Research indicates that when perceived risk is diminished, it has a substantial influence on the user's mindset. A theoretical model pertaining to e-learning demonstrates that the perception of risk has a negative and considerable impact on the attitude of users. Hence, the perceived hazards of AI-BR usage in higher education are associated with the adverse emotions experienced by users (Sheshadri & Kalyan, 2020; Yu & Nazir, 2021).

H6: Perceived risk has a beneficial impact on the users' attitudes towards the adoption of AI-BR in higher education.

The inclusion of these structures will greatly enhance the overall comprehension of the implementation of innovative technology. Artificial intelligence-powered robots are cutting-edge technologies that can aid students in augmenting their education. Bandura's social cognitive theory is the source of self-efficacy (Graham, 2022). Self-efficacy is the term used to describe an individual's belief in their own competence to successfully complete a specific task (Ozturk et al., 2016). Salimon et al. (2018) found that the confidence of robots in their own abilities has a substantial impact on the attitude of artificial intelligence-based robots. The apprehension surrounding the utilisation of robots powered by artificial intelligence is predominantly shaped by humans' mindset concerning their readiness and capacity to adopt the technology (Wang et al., 2012). Anxiety refers to the degree of discomfort that an individual has when faced with the possibility of utilising technology (Lin et al., 2020). Researchers have recently found that the presence of robot anxiety has a bad impact on one's attitude.

H7: Robot anxiety has a beneficial impact on the users' attitudes towards the adoption of AI-BR in higher education.
H8: Robot self-efficacy has a beneficial impact on the users' attitudes towards the adoption of AI-BR in higher education.

Insecurity arises when people lack competence in understanding the benefits of a technology, leading to doubt and uncertainty. Insecurity is linked to both uncertainty and low utilisation (Altay & Pal, 2022). Students are concerned about the potential loss of their employment as a result of the implementation of robots. Studies indicate that robotics is increasingly being integrated into education, providing students with the advantages of executing repetitive tasks with exceptional accuracy, adaptability, and human-robot interaction. These gadgets provide diverse qualities that provide students with captivating activities and genuine experiences, thereby contributing to the creation of stimulating and attractive learning environments. Students harbouring a pessimistic disposition towards innovation tend to cultivate scepticism and alternative perspectives. Figure 1 depicts the visual depiction of the model. Researchers in the field of AI-BR within the realm of information and communication technology frequently use the TAM (Salimon et al., 2018; Huang & Rust, 2020; Alzoubi & Alzoubi, 2020; Chang et al., 2022).

H9: Insecurity has a beneficial impact on the users' attitudes towards the adoption of AI-BR in higher education.

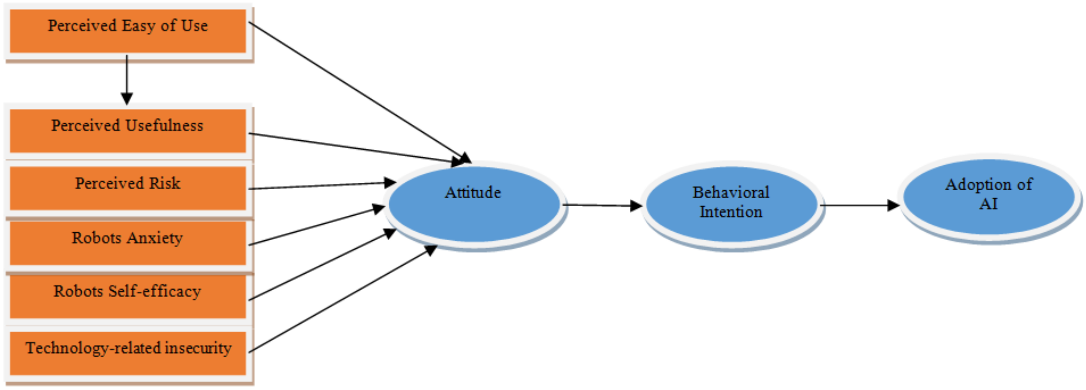

Fig. 1. Research Framework

RESEARCH METHODOLOGY

Research Instrument

This study utilises a modified TAM to evaluate the behavioural intention of university students towards AI-BR in the field of higher learning. The scale of measurement employed in the present research was derived from the existing literature (Table 1). The questionnaire was initially created in both English and Arabic and subsequently underwent slight adjustments to align with the specific parameters of the study. Education professionals assessed it to guarantee its suitability for the current study. Following that, a preliminary study was carried out involving 32 students to evaluate the suitability of the constructed items. All structures achieved a level of dependability above the threshold of 0.70, confirming the reliability of the data. The experts recommended making slight modifications to the phrasing. Subsequently, the questionnaire was administered to a cohort of 10 students who had previously completed the questionnaire in order to ascertain their comprehension of the intended concepts. Once the scale's face and content legitimacy were confirmed, it was officially distributed to university students.

Table 1. Construct measurement and sources.

Variables	No. items	References	Measure
Perceived Easy of Use	4	Rita, et al., (2022)	5-point Likert Scale
Perceived Usefulness	4	Rita, et al., (2022)	5-point Likert Scale
Perceived Risk	4	Al-Zoubi et al., (2023)	5-point Likert Scale
Robots Anxiety	4	Mohammed et al., (2023)	5-point Likert Scale
Robots Self-efficacy	3	Mohammed et al., (2023)	5-point Likert Scale
Technology-related insecurity	4	Rita, et al., (2022)	5-point Likert Scale
Attitude	5	Rita, et al., (2022)	5-point Likert Scale
Behavioral Intention	6	Rita, et al., (2022)	5-point Likert Scale
Adoption	4	Al-Zoubi et al., (2023)	5-point Likert Scale

Sample and Data Collection

The current study was conducted at institutions in the northern region of Jordan, specifically examining the integration of AI-BR in the field of learning. The academics administered the questionnaire to the learners within their respective study groups. The scholars have exclusively shared the online website URL with learners in the information technology and engineering disciplines due to their superior comprehension of AI-BR compared to learners from various departments. Bentler and Chou (1987) said that the sample size was determined using a specific procedure. The recommended number of replies per question for the construct is between five and 10. The researchers opted to gather a maximum of 10 replies per item, given that the total number of items was 38. A survey on AI-BR was administered to a total of 525 learners who were enrolled full-time. Among the total of 525 questionnaires distributed to the learners, only 302 were filled out, resulting in a response rate of 57.52%.

RESULTS

The researchers employed SPSS version 21 and partial least squares structural equation modelling (PLS-SEM) for data analysis in the present research. The software SPSS was utilised to evaluate common method bias (CMB) and identify any multivariate outliers. The measurement and structural models were evaluated using PLS-SEM (Bentler & Chou, 1987).

Common Method Bias

The CMB aids in evaluating the existence of bias in respondents' answers. In order to accomplish this, the researchers performed the Harman single-factor test utilising SPSS. The findings indicated that a solitary factor explained merely 29.982% of the variability, a value much lower than the 50% benchmark (Hair et al., 2011).

Measurement Model

The assessment of data reliability and validity was conducted using Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE) metrics. According to Hair et al. (2011), Table 2 displays the CA values with a threshold greater than 0.7 as well as the factor loadings of 0.70. According to

Hair et al. (2011), Table 2 shows composite reliability (CR) values that are greater than 0.70 and average variance extracted (AVE) values that are greater than 0.50. Discriminant validity pertains to the extent of distinction between variables within the suggested model. To evaluate discriminant validity, we utilised the HTMT ratio of correlations as proposed by Hair et al. (2011). The HTMT approach verified the discriminant validity, as all HTMT values were below the acceptable level of <0.85. The findings of the discriminant validity analysis are displayed in Table 3.

Table 2. Measurement Model

Factors	Loading	CA	CR	AVE
Perceived Easy of Use		0.912	0.931	0.734
	0.763			
	0.754			
	0.709			
	0.720			
Perceived Usefulness		0.908	0.885	0.782
	0.725			
	0.707			
	0.709			
	0.744			
Perceived Risk		0.822	0.833	0.914
	0.889			
	0.858			
	0.858			
	0.883			
Robots Anxiety		0.857	0.896	0.874
	0. 721			
	0.731			
	0.701			
	0.766			
Robots Self-efficacy		0.852	0.874	0.941
	0.847			
	0.815			
	0.889			
Technology-related insecurity		0.914	0.925	0.730
	0.713			
	0.788			
	0.741			
Attitude		0.902	0.944	0.757
	0.725			
	0.768			
	0.740			
	0.771			
Behavioral Intention		0.909	0.939	0.920
	0.715			
	0.724			
	0.737			
	0.767			
	0.765			
Adoption		0.890	0.893	0.895
	0.712			
	0.745			
	0.760			
	0.755			
	0.763			

Table 3. Discriminant validity

	BDA	CSA	PC	PEOU	PRA	EMA	MP
BDA	0.812						
CSA	0.833	0.707					
PC	0.815	0.771	0.727				
PEOU	0.765	0.710	0.723	0.711			
PRA	0.710	0.719	0.758	0.763	0.714		
EMA	0.836	0.763	0.737	0.784	0.715	0.780	
MP	0.701	0.713	0.753	0.721	0.792	0.782	0.709

Inner Model Predictive Power

Two ways were used to judge how good the inner model was: the coefficient of determination (R^2) and the model's predictive relevance, which was found by looking at the value of cross-validated redundancy (Q^2) (Hair et al., 2011). The R^2 value quantifies the percentage of the observed variance in endogenous components that exogenous constructions can explain. The findings demonstrate that the R2 values corresponding to the internal variables of perceived ease of use, perceived usefulness, perceived risk, robot anxiety, robot self-efficacy, and technology-related insecurity were 48.1%, 45.2%, 33.5%, 29.3%, 25.7%, and 35.4%, respectively. Afterwards, we assessed the cross-validated redundancy (Q^2). A positive (Q^2) score indicates the presence of predictive relevance in the model. The Q^2 values for the perceived ease of use, perceived usefulness, perceived danger, robot anxiety, robot self-efficacy, and technology-related insecurity are 19.2%, 23.2%, 18.4%, 44.3%, 42.6%, and 15.5%, respectively. These values indicate a moderate to high level of predictive significance for the inner model.

Structural Model

In order to assess the structural model, we followed the procedures specified in (Bentler & Chou, 1987). We began by analysing the path coefficients and determining the significance of the associations. A bootstrapping technique was conducted, involving 5000 iterations of resampling the data. The model requires nine hypotheses in the field of artificial intelligence. All of the presented hypotheses were accepted, as indicated in Table 4. H1: The perceived usefulness of something has a positive and significant influence on one's attitude towards it; Hypothesis 2 states that the perception of how easy a system is to use has a positive and significant effect on the perception of its utility. Hypothesis 3 states that the perception of ease of use also has a positive and significant effect on attitude. Hypothesis 4 states that attitude has a positive and significant effect on the intention to use the system. H5: The presence of a strong intention to engage in a particular behaviour has a favourable and noteworthy effect on the acceptance and implementation of artificial intelligence. The positive and strong impact of perceived risk on attitude is accepted in H6. H7: The presence of anxiety in robots has a beneficial and noteworthy effect on individuals' attitudes. H8: The level of confidence a robot has in its own abilities has a favourable and noteworthy influence on its attitude. H9: Insecurity has a beneficial and substantial influence on attitude.

Table 4. Hypothesis results.

Hypotheses	β	T	P	Decision
H1	0.334	4.258	0.000	Supported
H2	0.331	4.025	0.000	Supported
H3	0.285	6.274	0.000	Supported
H4	0.209	7.531	0.000	Supported
H5	0.274	3.546	0.000	Supported
H6	0.301	5.478	0.000	Supported
H7	0.298	5.169	0.000	Supported
H8	0.222	6.098	0.000	Supported
H9	0.277	7.548	0.000	Supported

DISCUSSION

The current study utilised the TAM and incorporated variables such as learners' perceived risk, robot anxiety, robot self-efficacy, and technology-related insecurity. The aim was to investigate students viewpoints on AI-BR tool-supported education, as well as their behaviour and the variables that influence them. In addition, the research model underwent testing, examining individual variations regarding the perceived risk of technology, anxiety towards robots, self-efficacy with robots, insecurity connected to technology, and other characteristics that influence learners' willingness to use technology. AI-BR has had a significant impact on the education sector (Atman et al., 2022; Al-Zoubi et al., 2023). AI-BR has been constantly beneficial for instructors and students in recent years. It includes robotic education and the creation of automated methods for grading answer sheets (Chen et al., 2021). AI-BR is increasingly being used in education to enhance learning experiences and optimise time-consuming learning tasks through the utilisation of AI-BR (Chang et al., 2022). The survey findings indicated that pupils showed a preference for incorporating AI-BR into schooling.

The study acknowledges the favourable and substantial impact of perceived usefulness and perceived ease of use on learners' behavioural intention to embrace robots that are based on artificial intelligence. The results align with the findings of Boddu et al. (2022), which demonstrated the favourable influence of PU and PEOU on BI to embrace AI-BR education. Moreover, the results align with Chocarro et al.'s [81] results, which assert that the perceived usefulness and perceived ease of use of robots contribute to their acceptance in educational settings. The favourable and substantial impact of perceived ease of use on perceived usefulness aligns with the findings of Boddu et al. (2022) and Wang et al. (2022). Behavioural intention strongly influences the acceptance and use of AI-BR in higher education. The researchers discovered that the perceived ease of use of AI-BR has a substantial impact on its effectiveness in the field of education. Moreover, the results suggest that perceived danger, anxiety towards robots, self-efficacy with robots, uncertainty connected to technology, and behavioural intention all play a significant influence in the acceptance and use of technology based on AI-BR.

The results align with other research that posited that feelings of uneasiness and perceived risk associated with technology had a substantial influence on individuals' attitudes towards AI-BR (Conti et al., 2020; Davenport et al., 2020; Huang et al., 2021). This demonstrates that classmates, friends, and family have a significant impact on the adoption of new technologies, specifically enriching the educational experience. The present research validated the favourable impact of robots' self-efficacy on their attitude towards technology based on AI-BR, aligning with the conclusions drawn by Mohammed et al. (2023). The correlation between robots' self-efficacy and attitude suggests that learners are inclined to utilise AI-BR in education due to their belief that incorporating these technologies will enhance their standing. The findings reveal that learners believed that they had the potential to operate and receive aid from AI-BR in education.

The results were in line with the conclusions reported by Nawaz & Mohamed (2020). Nevertheless, the findings suggest that the adverse influence of anxiety induced by AI-BR on attitude was negligible, implying that learners do not experience apprehension when it comes to utilising AI-BR in education. The results indicate that learners find AI-BR enjoyable and perceive it as lively and spontaneous. The concept is powerful and beneficial for the concerned authorities to implement the implementation of AI-BR that would increase the overall performances of higher educational establishments of Jordan. The results of earlier studies by Huang and Rust (2020) and Sheshadri and Kalyan (2020) are consistent with these findings.

CONCLUSIONS AND LIMITATIONS

The aim of this study was to investigate the willingness of Jordanian higher education learners to embrace the use of AI-BR for purposes of learning. The present research did a thorough literature analysis and found that the criteria of TAM are applicable in evaluating the acceptance of robots based on AI-BR among higher education learners in Jordan. The scholars intentionally gathered data from engineering and information technology learners enrolled in Jordanian universities and evaluated the efficacy of the TAM model within the educational setting. The study's findings indicate that the TAM model is extremely applicable in forecasting learners' adoption of instructional artificial intelligence-based robots. All nine submitted hypotheses were approved. These results will provide a clear direction for university administration and policymakers to actively promote the integration of AI-BR in learning environments. By doing this, not only will teaching efficacy be enhanced, but it will also significantly foster the growth of learners' analytical abilities. The scope of the research was limited to learners pursuing engineering and information technology (IT) disciplines in a higher education institution. The research at hand included certain constraints that require prompt fulfilment.

The study's constraint is its exclusive focus on the university level of education, necessitating an expansion to encompass schools in order to achieve more favourable results. The scope of this study was limited to the collection of data exclusively from graduate learners, with the potential for extrapolation to include postgraduate and school pupils. Conducted in a poor nation, the research has the potential to be expanded to developed nations. Nevertheless, in order to fully grasp its implementation, it is crucial to expand its range to encompass other departments and extend its influence to educational institutions. The research was carried out in an underdeveloped nation. Hence, it is vital for forthcoming studies to broaden their focus to encompass industrialised nations in order to gain a more comprehensive comprehension of the adoption of education-oriented robots based on artificial intelligence.

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