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# The adoption of ChatGPT marks the beginning of a new era in educational platforms

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**A B S T R A C T**

Technology has significantly transformed knowledge, education, and access to information by introducing online learning platforms, interactive games, and virtual reality simulations in traditional classrooms, creating a dynamic, engaging, and inclusive learning environment. The ChatGBT project (a pre-developed transformer for training) is a remarkable achievement in artificial intelligence technology. It allows students tailored and efficient learning experiences by providing individual feedback and explanations. ChatGPT e-learning platform has been extensively studied for its adoption and acceptance, but there is a significant gap in research on its acceptability and use, highlighting the need for further exploration. The goal of this work is to bridge this disparity by introducing a comprehensive model that includes three basic elements: performance expectation, expected effort, and social impact. A total of 241 graduate students were surveyed and their data were analyzed using structural equation modeling techniques. The results indicate that "expectation of performance and expected effort" have the greatest impact and importance in determining students' intentions to use learning platforms via ChatGPT, while social influence does not play an important role. This study enhances the current body of knowledge related to artificial intelligence and environmental sustainability, and provides important insights for professionals, policymakers, and producers of artificial intelligence products. These observations may provide guidance for creating and implementing artificial intelligence technologies to match consumers' needs and preferences more effectively, while also taking into account broader environmental conditions.



## 1. Introduction

Artificial intelligence has developed as a transformative tool, fundamentally changing lives on a global scale. A typical example of this transformation is the ChatGPT, also known as the pre-training mortuary transformer. This tool is of vital importance due to its ability to help students produce term papers, short stories, clarifications, and novels. The extensive reports and clarifications provided by this instrument sparked a wave of concern and concern at the American University. According to the school, this tool can generate paragraphs that meet acceptable quality standards, produce college-level research papers, and even provide answers to exam questions (Murad et al., 2023). The integration of natural language dispensation models into the field of education can greatly enhance the availability of information to teachers, students and academic staff. ChatGPT has recently gained significant recognition, which sets it apart from standard technologies like Google's platform.

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Furthermore, it provides a wide range of materials, including articles, books and websites. ChatGPT 's ability to understand the complexity of students' meanings and provide highly skilled responses enables students to use them for many reasons. (Murad et al., 2023). The function of ChatGPT has been thoroughly examined from several angles, including the fields of medicine, education, and engineering. Previous studies have shown that ChatGPT has a widespread impact on many user groups, such as students, doctors, patients, and others. However, it has limitations. Concern was expressed about ethical concerns and creativity. This research aims to study the factors that influence students' acceptance of e-learning using ChatGPT and to determine how these factors shape students' plans to use ChatGPT.

AI technologies, such as ChatGPT, have sparked interest in their potential to transform education by facilitating customized learning experiences. This research explores the acceptability and use of technologies like ChatGPT, a technology with potential in various applications but not fully understood in the educational setting, to enhance the existing literature on the topic, despite the recognition of their advantages. This research seeks opinions on the specific factors that influence students' propensity to use chat. The aim is to provide relevant information that can guide the development and integration of educational technologies in which the activities implemented will be used effectively in the future.

## 2. Theoretical Framework

The new model highlights the role of personal innovation in mediating the links between performance expectations, perceived effort, and social factors, which are directly linked to behavioral intentions. In addition, the success of both platforms is evaluated by exploring additional links, which confirms the benefits of using both platforms.

### *2.1 The Performance Expectancy (PE)*

Performance expectation refers to the extent to which a person feels that using the system will contribute to improving his performance at work and achieving its benefits. Users who view performance technology as having high expectations are more likely to continue using it and to endorse it to others. In contrast, consumers may stop using technology or may actively explore other solutions when it works according to their expectations (Abbad, 2021; Gunasinghe et al., 2020).

### *2.2 Effort Expectancy (EE)*

These expectations relate to the level of ease associated with using the system. This initiative plays a vital role in the ability of educational institutions to gain a competitive advantage through technology. Institutions can enhance their image and performance by providing students with technology that offers distinct features and advantages over other capabilities, thus attracting and retaining students. Simply put, hope for success is a critical factor for educational institutions seeking to successfully deploy a technology solution. Emphasizing the benefits students perceive from technology can provide educational institutions with a competitive edge, attracting and retaining students in the long term. (Abbad, 2021; Gunasinghe et al., 2020).

### *2.3 The Social Influence (SI)*

Social influence relates to the extent to which a person feels that important individuals believe he or she should use the new method. Social influence is the extent to which consumers are inclined to accept and use new technologies because of their unique and advanced characteristics that are not found in other technologies. User innovation is a critical factor for technology acceptability, as the extent to which consumers tend to actively seek out and explore new technologies is quantified (Abbad, 2021; Gunasinghe et al., 2020).

Based on the previous assumptions, the following other hypotheses are presented:

**H$_1$:** *The positive effect of ChatGPT on performance expectation significantly influences the intention to use educational platforms.*

**H$_2$:** *The positive effect of ChatGPT on the intention to use educational platforms is evident.*

**H$_3$:** *Social Influence plays a significant role in influencing individuals' behavior and intention to utilize educational platforms.*

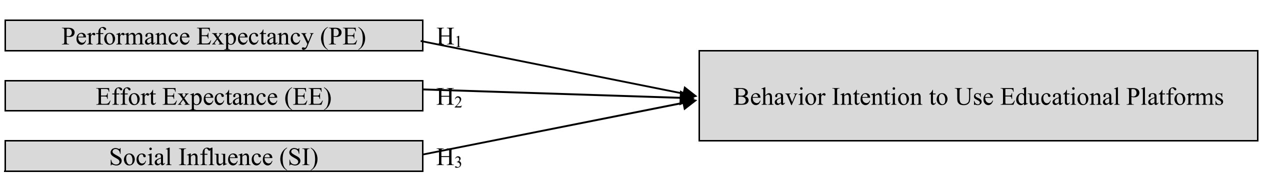


**Fig. 1.** The proposed method

## 3. Study Instrument

The current investigation utilized a questionnaire to validate the proposed assumption, selecting four reliable indicators and adding 14 new items. The aim was to enhance the effectiveness of research agents and provide evidence from various investigations. The study team made fundamental modifications to the survey questions, guided by previous research, to ensure the validity of the current framework.

**Table 1**
Measurement Items

| Constructs | Items | Instrument | Sources |
|---|---|---|---|
| Behavior, Intention Use Learning Platforms (**BIULP**) | **BIULP1** | ChatGPT provides an excellent opportunity to try. | (Davis, 1993) |
| | **BIULP2** | ChatGPT offers a valuable opportunity for experimentation. | Abbad, M. (2021) and Gunasinghe et al., (2020) |
| Performance Expectancy (PE) | PE1: | ChatGPT has proven to be a valuable tool for my learning process. | Venkatesh et al., 2011 |
| | PE2: | ChatGPT is a tool that allows me to complete my learning activities more efficiently. | Al-Shahrani, 2016 |
| | PE3: | The use of ChatGPT has significantly enhanced my learning productivity. | Abbad, M. (2021) and Gunasinghe et al., (2020) |
| | PE4: | The use of ChatGPT can significantly enhance the chances of obtaining better marks in the courses. | Abbad, M. (2021) and Gunasinghe et al., (2020) |
| Effort Expectancy (EE) | EE1 | My interaction with **ChatGPT** is clear and understandable | Abbad, M. (2021) and Gunasinghe et al., (2020) |
| | EE2 | I am skillful at using **ChatGPT** | Al-Shahrani (2016) |
| | EE3 | Learning to use **ChatGPT** is easy for me | Al-Qeisi et al. (2015) |
| | EE4 | I find it easy to get **ChatGPT** to do what I want it to do | Abbad, M. (2021) and Gunasinghe et al., (2020) |
| Social Influences (SI) | SI 1 | People who are significant to me suggest using ChatGPT. | Abbad, M. (2021) Gunasinghe et al., (2020) |
| | SI 2 | People who influence my behavior suggest using ChatGPT. | Venkatesh et al., (2011) |
| | SI3 | The pensioners in my college are highly proficient in using ChatGPT. | Al-Shahrani, (2016) |
| | SI4 | The college has generally endorsed the use of ChatGPT. | Abbad, M. (2021) and Gunasinghe et al., (2020) |

## 4. Findings and Discussion

Anderson and Gering's (1988) two-step methodology was used to analyze data and test study hypotheses. The first stage assessed measurement model accuracy and consistency, followed by scrutinizing the structural model to examine the study hypotheses.

**Table 2**
CFA Statistics of Model Fit

| Goodness Fit Indexes | Recommended Value | Result Model |
|---|---|---|
| CMIN /df | ≤ 3.11 | 1.369 |
| Goodness Fit Index (GFI) | ≥ 0.91* | 0.843 |
| Incremental Fit Index (IFI) | ≥ 0.89 | 0.951 |
| Adjusted Goodness Fit Index (AGFI) | ≥ 0.85 | 0.866 |
| Comparative fit index (CFI) | ≥ 0.88 | 0.975 |
| Root Mean Square Error Approximation(RMSEA) | ≤ 0.07 | 0.052 |

*GFI≥0.8 According Greenspoon and Saklofske (1998) and Forza and Filippini (1998)

**Table 3**
Reliability and Convergent Validity Coefficients

| Factor | Variables | Standardized Loadings (> 0.708) | Reliability ($R^2$) (> 0.50) | AVE (> 0.50) | Composite Reliability (CR) (> 0.70) | Cronbach's Alpha (> 0.70) |
|---|---|---|---|---|---|---|
| BIULP | BIULP1 | 0.711 | 0.533 | 0.535 | 0.766 | 0.792 |
| | BIULP2 | 0.743 | 0.556 | | | |
| SI | SI1 | 0.755 | 0.522 | 0.645 | 0.762 | 0.809 |
| | SI2 | 0.888 | 0.802 | | | |
| | SI3 | 0.843 | 0.777 | | | |
| EE | EE 1 | 0.780 | 0.600 | 0.655 | 0.835 | 0.842 |
| | EE2 | 0.851 | 0.744 | | | |
| | EE4 | 0.835 | 0.644 | | | |
| PE | PE1 | 0.766 | 0.555 | 0.645 | 0.800 | 0.833 |
| | PE2 | 0.845 | 0.711 | | | |
| | PE4 | 0.822 | 0.699 | | | |

*4.1 Measurement model*

Confirmatory factor analysis (CFA) revealed that consideration should be given to removing three items (PE3, EE3 and SI4) based on the proposed adaptation indices (>10) and standardized residual matrix (>3) (Hair et al., 2021). The resulting model resulted in indicators that showed a strong fit (refer to Table 3). The results show that the proposed perfect fits the experiential data well.

**Table 4**
Factor Correlations

| | BIULP | SI | EE | PF |
|---|---|---|---|---|
| **BIULP** | 1 | | | |
| **SI** | 0.166 | 1 | | |
| **EE** | 0.832 | 0.193 | 1 | |
| **PE** | 0.479 | 0.345 | 0.654 | 1 |

Factor correlations less than 0.85 in **bold**

The conceptual validity of the measurement model was assessed by estimating convergent and discriminant validity. Converter validity was assessed using factor loadings greater than 0.707, composite reliability greater than 0.7, and extracted average variance (AAV) greater than 0.5 (Hair et al., 2021). The results are shown in Table 3 and show satisfactory convergent validity and reliability (Cronbach's alpha > 0.7). Discriminant validity assesses the extent to which concepts are separated from each other and distinct from each other (Bagozzi et al., 1991). Table 4 shows that all constructs were clearly distinguishable, because the correlation coefficients between the components were below the recommended threshold of 0.86 (Kline, 2011).

*4.2 Structural model and hypotheses testing*

Subsequently, the structural model (Fig. 2) was tested. Hair et al.'s (2021) study utilized SEM to analyze the relationships between behavioral factors (PE, SI, EE) and learning platforms, specifically ChatGPT, using a comprehensive technique to examine proposed links among variables.

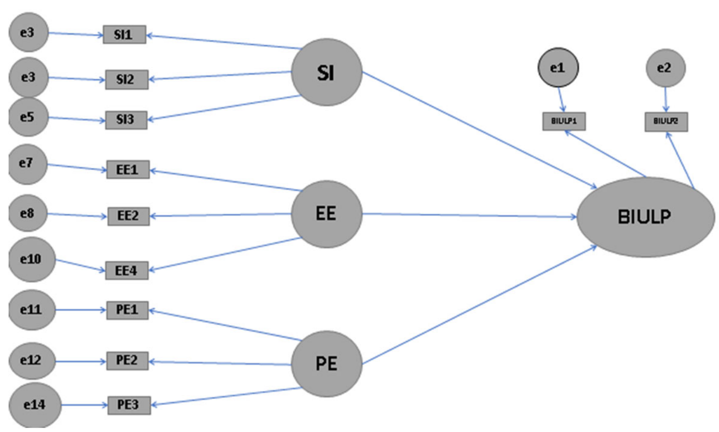


**Fig. 2.** The results of the structural model

Fig. 2 shows the final structural model resulting from the implementation of the refinement criteria outlined in the measurement model part, which includes a total of 13 components. Later, the entire model was scrutinized. Studying the structural model leads to several appropriate measures for the model, which are shown in Table 5. The results show that the fit with the data is considered sufficient. According to the results received by AMOS 22, the final model can be represented by a single equation using non-standardized regression coefficients:

**BIULP** = 0.533 PE + 0.342 EE + 0.145 SI

$R^2$ = 58.8 Error variance = 58.5

**Table 5**
Standardized Effects for the Model

| Factor | Determinant | Direct Effect | Indirect Effect | Total Effect |
|---|---|---|---|---|
| **BIULP** | PE | **0.356** | - | **0.106** |
| ($R^2$ = 58.8) | EE | **0.345** | - | **0.319** |
| | SI | **0.189** | - | **0.396** |

Effect sizes greater than 0.1 are in **bold**

The regression coefficient represents the path values in this structural equation. As an example, the error difference in the second equation is 0.401, which is calculated as 1 minus the coefficient of determination ($R^2$). The model accounts for approximately 58.8 percent of the behavioral change in intention to use learning platforms, as shown in Table 5. This value is very high, but it is below the 70 percent threshold recommended by Venkatish et al. (2011). The implications of the model are presented in Table 5, which shows the standardized direct, indirect, and total effects. Perceived expectancy and expected effort (EE) were significant factors influencing students' intention to use Moodle. EE had a total effect of 0.345, while social influence had a modest effect of 0.189. These factors, combined, resulted in a significant overall effect on students' actual behavior, as per Chuhen's guidelines.

**Table 6**
Results of Path Tests

| Relationship | Estimate | S.E. | C.R. | P | Comment |
|---|---|---|---|---|---|
| BIULP ← PE | .533 | .151 | 3.322 | *** | Sig. |
| BIULP ← EE | .342 | .107 | 2.911 | . *** | Sig. |
| BIULP ←SI | .145 | .091 | 1.469 | .129 | Not Sig. |

Table 6 displays the path values, critical ratio (C.R.) (also known as t-value = path values/standard error (S.E.), and significance level (p-value). Two of the three paths were considered significant based on the C.R. More than 1.96 and a B-value of less than 0.05. Table 7 provides a brief overview of the hypotheses that were confirmed and those that were not. Assumption 1, which relates to performance expectancy, and Assumption 2, which relates to effort expectancy, had a significant impact on behavioral intention to use ChatGPT. The effect of social influence (Hypothesis 3) on students' behavior intentionally using ChatGPT was not statistically significant.

**Table 7**
Summary of Hypotheses

| Hypothesis | Result |
|---|---|
| H1: The positive effect of ChatGPT on performance expectation significantly influences the intention to use educational platforms. | Supported |
| H2: The positive effect of ChatGPT on the intention to use educational platforms is evident. | Supported |
| H3: Social Influence plays a significant role in influencing individuals' behavior and intention to utilize educational platforms. | Not Supported |

## 5. Discussion and implications

The main objective of this study was to identify the characteristics that influence students' acceptance of ChatGPT, which signifies the beginning of a new era in educational programs. The results indicate that these components are able to account for the behavior of students who intend to use learning platforms, and all the links proposed in these factors were confirmed except for one link. It is noteworthy that the effect of social influence on intention to use ChatGPT was insignificant, consistent with previous research in the field of technology acceptance (Ajzen, 1985) as well as in the fields of e -government and e-learning (AlShehri et al., 2013; AlImarah et al., 2013). This result indicates that social influence does not serve as a strong predictor. This result indicates that social influence does not play a significant role in predicting the intention to use learning platforms, which ultimately affects actual use. The current group of individuals has been raised in a digital environment that reduces the need for guidance from teachers or peer influence. (Jambulingam, 2013; Abbad, 2021; Gunasinghe et al., 2020).

The level of performance expectancy was the strongest predictor of behavioral factors for using learning platforms. These findings were derived from a previous study conducted by Abbad, M. (2021) and Gunasinghe et al., (2020). Unsurprisingly, students focus primarily on improving their academic performance, and they see learning platforms as a technological tool that helps them achieve this goal. The study suggests that academics, experts, administrators, and e-learning system designers should prioritize enhancing the efficiency and effectiveness of the system to improve students' academic achievement. The level of expected effort was the second most important factor affecting individuals' intention to do a particular job. This finding is in line with studies conducted by Abbad (2021) and Gunasinghe et al. (2020), who used learning platforms for educational purposes in Arab countries. Specifically, Abbad (2021) and Gunasinghe et al. (2020) found that the factor that has the greatest influence on students' intentions to use university learning platforms in Jordan is effort expectancy. Abbad (2021) discovered that the expected level of effort is a reliable indicator of the likelihood of Saudi students wanting to adopt mobile learning. Accordingly, students who:

Users who find Moodle to be easy to use are more likely to have favorable intentions to use the system. Researchers have found similar results when using an alternative adoption model, such as the TAM model, in an IT setting (Davis, 1986, 1993; Abbad, M. 2021; Venkatesh & Davis, 2000; Gunasinghe et al., 2020; Abbad et al., 2009). Colleges should prioritize the e-learning system ease of use to boost student motivation and adoption, requiring minimal effort when building or changing it. Gaining a more complete understanding of the factors that affect students' intentions and use of learning approaches will help university decision makers choose the appropriate technology and motivate students to actively participate in the system. This can be achieved by creating and designing a technological situation that facilitates academic improvement. This is especially crucial during an emergency like the COVID-19 virus, which has forced educational institutions around the world to use learning platforms.

## 6. Conclusion

ChatGPT is a powerful tool in higher education that offers a dynamic and relevant learning experience. It can provide tailored comments, explanations, and assist students in drafting term papers, short stories, and understanding complex topics. The integration of ChatGPT enhances information availability and transforms traditional classrooms into interactive environments. The system can analyze students' intentions and provide skilled responses, enabling them to use it for various educational purposes. The potential of ChatGPT in e-learning is significant, as it enhances students' desire to use functional tools like ChatGPT in their educational endeavors. However, the research has several drawbacks, including data collected from a specific group of students in Jordan, which may not be generalizable to other populations or circumstances. Further research could focus on samples from alternative government institutions or diverse geographic regions to better understand the impact of ChatGPT on educational purposes.

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