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Future-ready learning: Investigating students' intentions to embrace OpenAI through extended UTAUT 2

Jaskiran Kaur[1], Razia Nagina[2], Suhad Farsi[3], Pretty Bhalla[4*]

[1]*Lovely Professional University, Phagwara, India.*
[2,4]*Mittal School of Business Lovely Professional University, India.*
[3]*College of Business Administration University of Business and Technology, India.*

Corresponding author: Pretty Bhalla (*Email: bhalla.pretty@gmail.com*)

Abstract

The research paper explores the diverse factors that influence students' behavioral intentions to adopt OpenAI technologies. Utilizing a comprehensive methodology, the study surveyed 509 participants from various academic levels through both paper and online questionnaires. Structural Equation Modeling was employed for data analysis. The key determinants analyzed include effort expectancy, performance expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, perceived risk, and trust. Gender was also considered a potential moderating factor. The findings underscore the pivotal roles of trust, perceived performance benefits, and facilitating conditions in promoting the adoption of OpenAI among students. The study found strong positive correlations between these factors and students' intentions to use OpenAI technologies. Despite examining gender as a moderating factor, it did not significantly impact the relationship between these determinants and behavioral intention, indicating that these factors influence students' intentions similarly across genders. These insights are crucial for educators and policymakers who aim to foster OpenAI adoption, as they highlight the importance of building trust, demonstrating performance benefits, and ensuring supportive conditions. By addressing these areas, efforts can be more effectively directed towards promoting future-ready learning environments that integrate OpenAI technologies.

Keywords: ChatGPT, Educational Institutions, Effort Expectancy, OpenAI, Performance Expectancy, UTAUT.

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1. Introduction

In the contemporary educational landscape, artificial intelligence (AI) is revolutionizing traditional teaching methods, with OpenAI leading the development of advanced AI technologies [1-3]. OpenAI's platforms, such as ChatGPT, Google Bard, and Microsoft's AI-powered Bing, are pivotal in creating personalized instruction, automated evaluation, and intelligent learning environments [4-7].

However, AI's rapid growth in education requires understanding its adoption dynamics, ethical implications, and pedagogical impacts [8, 9]. Acceptance of AI among students depends on factors like performance expectancy, effort expectancy, perceived ease of use, and social influence [10-13]. Ethical considerations, including equitable access, algorithmic fairness, and data privacy, are critical [14].

This study aims to analyze the adoption of OpenAI's technologies, such as ChatGPT and Google Bard, among students using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model. It seeks to understand the factors influencing students' attitudes towards AI-powered educational tools, providing insights for developers, educators, and policymakers [15]. By examining performance expectancy, effort expectancy, social influence, and facilitating conditions, this research aims to guide strategic interventions and policies to harness AI's potential while ensuring educational integrity and equity.

2. Literature Review

This study builds upon the UTAUT 2 model by Venkatesh et al. [16], aimed at comprehending technology adoption factors. UTAUT 2, an extension of UTAUT, delves into consumer technology acceptance [15], integrating insights from eight models. Unlike UTAUT's focus on organizational contexts [3, 17]. UTAUT 2 zooms into voluntary consumer behaviors [18, 19]. Research on student adoption of OpenAI's innovations uncovered various influencers: effort expectancy, performance expectancy, social influence, hedonic motivation, risk perception, trust, perceived risk, and price value [20]. This enhances comprehension of consumer technology uptake.

2.1. Effort Expectancy

Effort Expectancy (EE), defined as the perceived ease of using a technology, is a crucial predictor of user intention to adopt new technologies [21-23]. According to the UTAUT 2 model, factors such as prior experience, technical ability, technology complexity, and support availability influence effort expectancy. Studies have shown that greater perceived ease leads to higher adoption likelihood [24]. Recent studies on chatbot adoption highlight the significant role of effort expectancy [25]. For ChatGPT, a high level of perceived ease is likely to drive adoption and usage, emphasizing the need to understand and enhance effort expectancy [24, 26]. Thus, the hypothesis is:

$H_{1:}$ Effort expectancy positively influences the behavioral intention to use OpenAI.

2.2. Performance Expectancy

Performance Expectancy (PE) refers to the belief that using a system will help attain gains in job performance [22, 23]. It is a significant predictor of behavioral intention [27]. Research indicates that performance expectancy is a crucial factor in user acceptance and usage, shaped by perceived usefulness, compatibility, and impact on job performance [26, 28, 29]. For ChatGPT, it denotes users' beliefs about the technology's ability to enhance task performance [3]. Thus, the hypothesis is:

$H_{2:}$ Performance expectancy positively influences the behavioral intention to use OpenAI.

2.3. Social Influence

Social Influence (SI) includes the perceptions of friends, family, and experts, significantly affecting technology adoption. Positive social influence enhances perceptions of usefulness and ease of use while reducing perceived risks [22, 23, 26, 30]. Negative social influence can raise doubts about reliability and ethical concerns [31]. The rapid acceptance of ChatGPT highlights the role of social influence in its adoption [32, 33]. Thus, the hypothesis is:

$H_{3:}$ Social influence positively influences the behavioral intention to use OpenAI.

2.4. Facilitating Conditions

Facilitating Conditions (FC) within the UTAUT model highlight the importance of perceptions regarding the presence of organizational and technical support structures necessary for technology adoption [23, 34]. For ChatGPT, facilitating conditions include access to necessary technological resources and technical assistance [35]. Research underscores the role of facilitating conditions in the adoption of technologies like chatbots [26, 30, 36]. Thus, the hypothesis is:

$H_{4:}$ Facilitating conditions positively influence the behavioral intention to use OpenAI.

2.5. Hedonic Motivation

Hedonic Motivation (HM) refers to the intrinsic desire for enjoyment and pleasure derived from using a technology [22]. It significantly shapes students' intentions to adopt and use innovative technologies, influencing both initial acceptance and sustained engagement [37-39]. Thus, the hypothesis is:

$H_{5:}$ Hedonic motivation positively influences the behavioral intention to use OpenAI.

2.6. Price Value

Price Value (PV) involves the perceived benefits relative to the cost of a product or service [16]. In student adoption dynamics, price value significantly influences intentions to adopt and utilize innovative technologies [40]. Understanding students' perceptions of value relative to the price is crucial, especially for premium versions of OpenAI. Thus, the hypothesis is:

$H_{6:}$ Price value positively influences the behavioral intention to use OpenAI.

2.7. Habit

Habit (H), defined as the degree of repetitiveness of behavior, influences behavioral intentions for adopting OpenAI [11, 16, 41-43]. Thus, the hypothesis is:

$H_{7:}$ Habit positively influences the behavioral intention to use OpenAI.

2.8. Perceived Risk

Perceived Risk (PR) involves individuals' subjective assessment of potential negative consequences or uncertainties associated with adopting new technology [44]. High perceived risks can act as barriers to adoption, leading to hesitation or resistance [45]. Mitigating perceived risks is essential for promoting technology acceptance [46, 47]. Thus, the hypothesis is:

$H_{8:}$ Perceived risk negatively influences the behavioral intention to use OpenAI.

2.9. Trust

Trust (T) refers to the belief in the reliability, credibility, and integrity of a technology or its provider [48]. Trust significantly influences user acceptance and adoption [49, 50]. It mitigates concerns about privacy, security, and reliability [51]. Thus, the hypothesis is:

H9: Trust positively influences the behavioral intention to use OpenAI.

2.10. Behavioral Intention to Use

Behavioral Intention to Use represents individuals' planned actions regarding innovation adoption, influenced by factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions [22, 23]. Understanding these factors within the context of student adoption provides insights into technology acceptance dynamics in educational settings.

This review emphasizes the importance of understanding technology adoption factors, particularly in educational contexts. Leveraging the UTAUT 2 model, the study explores determinants like effort expectancy, performance expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value [52]. It integrates trust and perceived risk to provide a nuanced understanding of technology adoption. Additionally, it examines gender's moderating effect on technology adoption behaviors, offering insights to enhance technology acceptance within educational environments.

2.11. Research Gap

Despite extensive research on behavioral intention determinants, there is a dearth of comprehensive studies that simultaneously examine multiple factors such as effort expectancy, performance expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, perceived risk, and trust. This gap persists despite isolated studies exploring some factors independently. Moreover, research integrating these factors into a unified framework remains scarce. Understanding gender differences in technology adoption is crucial, yet most studies focus solely on main effects without exploring gender's moderating role in these relationships. Additionally, while past research has examined direct effects, understanding underlying mechanisms, such as how perceived risk or trust influences decision-making processes, remains limited. Investigating these mediating mechanisms can provide deeper insights into the cognitive and emotional processes involved in technology adoption. Addressing these gaps can enhance theoretical models and practical strategies for technology acceptance, catering to diverse user needs effectively.

3. Materials and Methods

3.1. Participants and Procedures

This study collected data from 580 youth studying in different courses ranging from undergraduate to doctoral degrees using the convenience sampling method. Prior to the distribution of the questionnaire, the purpose of this study was sufficiently explained to each individual. It was advised in advance to stop the survey immediately or replace it with an online survey, considering that the content and responses of the survey could be burdensome in that they reveal the individual’s perception and attitude toward the use of Open AI tools like ChatGPT, etc. Specifically, most of them individually responded through paper questionnaires, and 83 people responded via online surveys due to concerns about exposure to personal information and response content. Upon screening the responses for reliability, 67 copies were excluded, such that data from only 509 individuals were used for data analysis. According to the list-by-list deletion method suggested by DeSimone and Harms [53], questionnaires in which respondents omitted some responses or in which more than nine questions were consecutive were excluded from data collection. In particular, most of the excluded questionnaires had nine or more of the same responses in a row. The respondents consisted of 255 males (50.1%) and 254 females (49.9%).

3.2. Measures

The instrument for measurement was a questionnaire in which all questions, except for those about demographics, were measured using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Table 1.
Data statements.

Determinant	Code	Statement
Effort Expectancy	EE1	Open-AI is easy to use.
	EE2	The use and functions of Open-AI are clear and understandable.
	EE3	Using Open-AI saves time and energy
	EE4	It is easy to understand the operations of Open-AI
	EE5	The operations of Open-AI are controllable
Performance Expectancy	PE1	It is convenient to make the learning experience more engaging for students.
	PE2	Open-Ai helps in speedy and better student outcomes and understanding.
	PE3	The usage of Open-AI improves my efficiency in generating more innovative and creative study materials.
	PE4	Open-AI is better than traditional methods and can contribute to a more personalized and adaptive learning experience
	PE5	Usage of Open-AI increases productivity
Social Influence	SI1	People who are important to me would recommend using an Open-AI
	SI2	My family members and friends use Open-AI
	SI3	My family and friends influenced me to use an Open-AI
Facilitating Conditions	FC1	The support required to use an Open-AI is adequate/adequately provided
	FC2	I have knowledge and internet facility to use an Open-AI
	FC3	The software and hardware required to use an Open-AI is easily accessible
	FC4	The Open-AI services are compatible with other technologies that I use
	FC5	There is a dedicated support team or help desk available to assist users with any Open-AI-related queries or challenges
Hedonic Motivation	HM1	It is fun to use Open-AI
	HM2	Using an Open-AI seems to be enjoyable
	HM3	It is comfortable to use Open-AI
	HM4	It gives me pleasure in using Open-AI
Price Value	PV1	The features offered in the upgraded subscription plan are worth the additional cost.
	PV2	I believe that the benefits gained from upgrading justify the increased subscription cost.
	PV3	I am willing to commit to a subscription upgrade for the long term.
Habit	H1	I use Open-AI on a regular basis in my daily curriculum activities.
	H2	I consistently incorporate Open-AI into various aspects of my educational tasks.
	H3	Using Open-AI has become a regular part of my learning routine.
	H4	I rely on Open-AI to assist me in generating creative and engaging educational content.
Perceived Risk	PR1	I worry that Open-AI may not consistently deliver the desired level of performance in educational tasks.
	PR2	I am concerned about the security of the data and information shared while using Open-AI.
	PR3	I am concerned about becoming too dependent on Open-AI, which could pose challenges if the technology faces issues or limitations.
	PR4	I am concerned about potential ethical issues related to bias in Open-AI-generated content.
Trust	T1	I trust that Open-AI's algorithms are designed with a high level of accuracy and reliability.
	T2	I trust that Open-AI provides clear and transparent information about how its models operate and make decisions.
	T3	I am confident that Open-AI considers the ethical implications of its technology in various applications, including education.
	T4	I trust that Open-AI has implemented effective measures to ensure the security
Behavioural Intention	BI1	I intend to use Open-AI in the near future.
	BI2	Given the opportunity, I plan to use Open-AI regularly.
	BI3	I see myself adopting Open-AI as part of my routine.

4. Results and Discussion

Objective 1: To analyze the impact of effort expectancy, performance expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, perceived risk, and trust on behavioral intention.

A reliability analysis was conducted to assess scale accuracy, a crucial step toward achieving the stated objective.

Table 2.
Reliability Statistics.

Cronbach's Alpha	N of Items
0.974	40

The reliability analysis given in Table 2 yielded a Cronbach's alpha coefficient of 0.974, indicating high internal consistency among the scale items. With 40 items in the scale, this high coefficient suggests strong reliability and precision in measuring the intended construct [54]. These findings assure confidence in the scale's accuracy and suitability for further use in achieving the research or project objectives.

Table 3.
Descriptive Statistics.

	N	Minimum	Maximum	Mean	Std. Deviation
EE1	509	1	5	3.18	1.325
EE2	509	1	5	3.22	1.282
EE3	509	1	5	3.25	1.270
EE4	509	1	5	3.20	1.277
EE5	509	1	5	3.18	1.302
PE1	509	1	5	3.24	1.261
PE2	509	1	5	3.33	1.237
PE3	509	1	5	3.23	1.283
PE4	509	1	5	3.20	1.293
PE5	509	1	5	3.23	1.239
SI1	509	1	5	3.23	1.267
SI2	509	1	5	3.20	1.234
SI3	509	1	5	3.21	1.287
FC1	509	1	5	3.23	1.297
FC2	509	1	5	3.26	1.274
FC3	509	1	5	3.24	1.234
FC4	509	1	5	3.26	1.249
FC5	509	1	5	3.24	1.275
HM1	509	1	5	3.22	1.234
HM2	509	1	5	3.16	1.283
HM3	509	1	5	3.23	1.269
HM4	509	1	5	2.94	1.337
PV1	509	1	5	3.03	1.306
PV2	509	1	5	3.01	1.307
PV3	509	1	5	3.06	1.270
H1	509	1	5	3.06	1.247
H2	509	1	5	3.04	1.295
H3	509	1	5	3.10	1.274
H4	509	1	5	3.06	1.327
PR1	509	1	5	3.08	1.301
PR2	509	1	5	3.05	1.333
PR3	509	1	5	2.99	1.297
PR4	509	1	5	3.03	1.295
T1	509	1	5	3.00	1.327
T2	509	1	5	3.03	1.353
T3	509	1	5	3.06	1.343
T4	509	1	5	2.97	1.308
BI1	509	1	5	2.96	1.331
BI2	509	1	5	2.99	1.323
BI3	509	1	5	2.91	1.329
Valid N (listwise)	509				

The descriptive statistics in Table 3 reveal the distribution of variables related to effort expectancy (EE), performance expectancy (PE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), habit (H), perceived risk (PR), trust (T), and behavioral intention (BI). The means for each variable range from approximately 3 to 3.33, suggesting moderate to slightly above-moderate levels across the constructs [55]. Standard deviations range from about 1.23 to 1.34, indicating variability within each construct [56]. These statistics provide insight into the central tendency and dispersion of the data, laying a foundation for further analysis of their relationships and impact on behavioral intention [57].

Table 4.
Correlations.

		EE	PE	SI	FC	HM	PV	H	PR	T	BI
EE	Pearson Correlation	1	0.877**	0.855**	0.884**	0.842**	0.537**	0.565**	0.539**	0.604**	0.543**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	509	509	509	509	509	509	509	509	509	509
PE	Pearson Correlation	0.877**	1	0.841**	0.881**	0.851**	0.559**	0.571**	0.562**	0.636**	0.519**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	509	509	509	509	509	509	509	509	509	509
SI	Pearson Correlation	0.855**	0.841**	1	0.847**	0.794**	0.504**	0.518**	0.496**	0.558**	0.474**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	509	509	509	509	509	509	509	509	509	509
FC	Pearson Correlation	0.884**	0.881**	0.847**	1	0.846**	0.547**	0.555**	0.545**	0.609**	0.531**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000
	N	509	509	509	509	509	509	509	509	509	509
HM	Pearson Correlation	0.842**	0.851**	0.794**	0.846**	1	0.656**	0.689**	0.679**	0.715**	0.571**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000
	N	509	509	509	509	509	509	509	509	509	509
PV	Pearson Correlation	0.537**	0.559**	0.504**	0.547**	0.656**	1	0.837**	0.860**	0.818**	0.561**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000
	N	509	509	509	509	509	509	509	509	509	509
H	Pearson Correlation	0.565**	0.571**	0.518**	0.555**	0.689**	0.837**	1	0.867**	0.828**	0.546**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
	N	509	509	509	509	509	509	509	509	509	509
PR	Pearson Correlation	0.539**	0.562**	0.496**	0.545**	0.679**	0.860**	0.867**	1	0.839**	0.544**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000
	N	509	509	509	509	509	509	509	509	509	509
T	Pearson Correlation	0.604**	0.636**	0.558**	0.609**	0.715**	0.818**	0.828**	0.839**	1	0.680**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000
	N	509	509	509	509	509	509	509	509	509	509
BI	Pearson Correlation	0.543**	0.519**	0.474**	0.531**	0.571**	0.561**	0.546**	0.544**	0.680**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	N	509	509	509	509	509	509	509	509	509	509

Note: **. Correlation is significant at the 0.01 level (2-tailed).

The correlation table (Table 4) indicates strong positive associations between factors and behavioral intention (BI) towards OpenAI usage. Effort expectancy (EE), performance expectancy (PE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), habit (H), perceived risk (PR), and trust (T) all demonstrate significant correlations with BI, ranging from 0.519 to 0.680, all significant at the 0.01 level. This suggests that as these factors increase, so does the likelihood of users intending to engage with OpenAI [3]. These findings underscore the multifaceted nature of user intention formation, influenced by various factors such as ease of use, social norms, perceived benefits, and trustworthiness [58]. Understanding these correlations can guide strategies to enhance user adoption and acceptance of OpenAI technology [59].

Table 5.
Model Summary[b].

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.707[a]	0.499	0.490	0.81192

Note: a. Predictors: (Constant), T, SI, PV, HM, H, FC, PR, PE, EE
b. Dependent Variable: BI

The model summary given in Table 5 indicates that the predictors collectively account for a substantial portion of the variance in behavioral intention (BI) towards OpenAI, with an R-squared value of 0.499. This means that approximately 49.9% of the variability in BI can be explained by the combination of predictors included in the model. The adjusted R-squared, which accounts for the number of predictors in the model, is 0.490. The standard error of the estimate, measuring the average difference between the observed and predicted BI values, is 0.81192. The model includes predictors such as trust (T), social influence (SI), price value (PV), hedonic motivation (HM), habit (H), facilitating conditions (FC), perceived risk (PR), performance expectancy (PE), and effort expectancy (EE) [60]. These results suggest that these factors collectively contribute to understanding and predicting behavioral intention towards using OpenAI [61].

Table 6.
ANOVA[a].

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	328.206	9	36.467	55.319	0.000[b]
	Residual	328.947	499	0.659		
	Total	657.153	508			

Note: a. Dependent Variable: BI
b. Predictors: (Constant), T, SI, PV, HM, H, FC, PR, PE, EE

Table 6 demonstrates significant results, indicating that the predictors collectively contribute to explaining the variance in behavioral intention (BI) towards OpenAI. The regression model accounts for a substantial portion of the variance, as evidenced by the large F-value of 55.319 ($p < 0.001$). This suggests that the relationship between the predictors and BI is statistically significant. The sum of squares for the regression model is 328.206, with 9 degrees of freedom, resulting in a mean square value of 36.467. In contrast, the residual sum of squares is 328.947, with 499 degrees of freedom. The overall model provides a strong fit to the data, underscoring the importance of the included predictors in explaining variability in BI towards OpenAI usage [62].

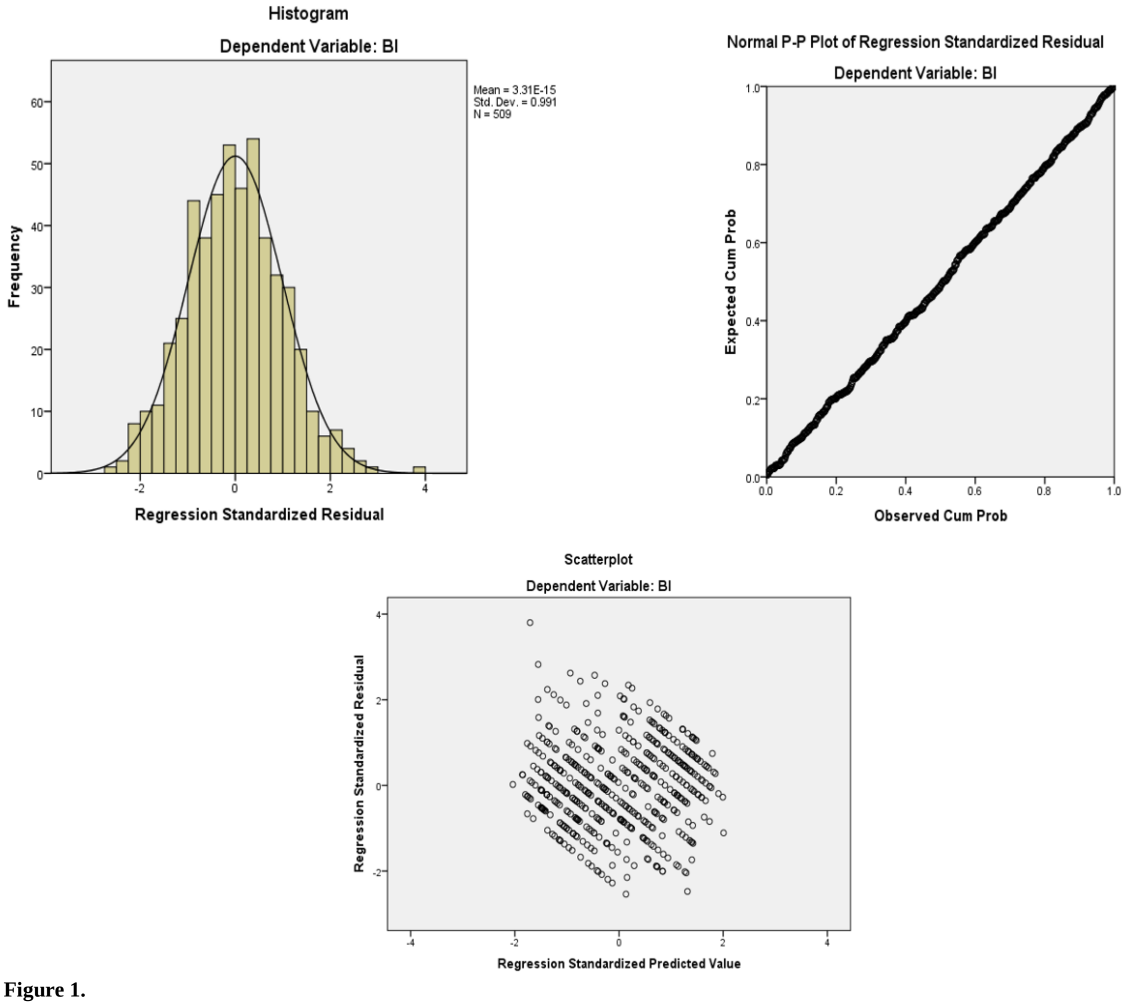
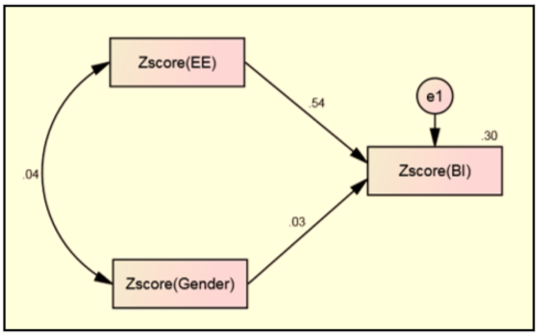


Figure 1.
Charts of the Study.

The histogram displaying a bell-shaped curve in Figure 1 suggests that the distribution of data points is approximately normal, indicating that the data is symmetrically distributed around the mean [63]. The normal P-P plot of regression standardized residuals showing a straight line suggests that the residuals are normally distributed, further validating the assumption of normality in the data [64]. Lastly, the scatterplot with scattered dots illustrates the relationship between two variables [65]. Overall, these visualizations aid in assessing the assumptions and relationships within the data, crucial for accurate statistical analysis and interpretation [66].

4.1. SEM Model

After performing regression analysis on SPSS, regression analysis using AMOS software was run. The results are shown as in Figure 2.



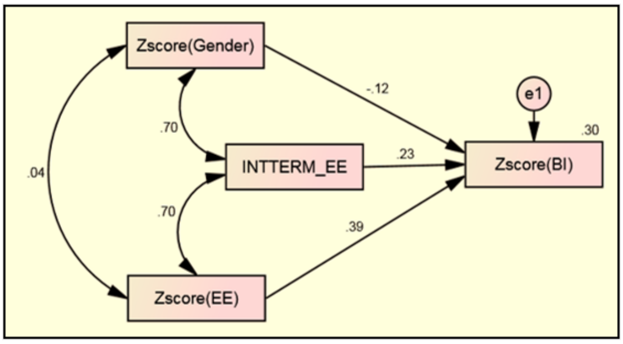


Figure 2.
SEM Model of the Study.

Table 7.
Regression Weights: (Group number 1 - Default model)

			Estimate	**S.E.**	**C.R.**	**P**	**Label**
HM4	<---	HM.	1.000				
HM3	<---	HM.	1.214	0.085	14.243	***	
HM2	<---	HM.	1.246	0.087	14.385	***	
HM1	<---	HM.	1.140	0.082	13.906	***	
T4	<---	T.	1.000				
T3	<---	T.	1.266	0.084	14.997	***	
T2	<---	T.	1.265	0.085	14.911	***	
T1	<---	T.	1.275	0.084	15.221	***	
PE5	<---	PE.	1.000				
PE4	<---	PE.	1.083	0.057	19.121	***	
PE3	<---	PE.	1.080	0.056	19.242	***	
PE2	<---	PE.	1.014	0.054	18.638	***	
PE1	<---	PE.	1.103	0.055	20.151	***	
H4	<---	H.	1.000				
H3	<---	H.	.920	0.047	19.735	***	
H2	<---	H.	.943	0.047	19.956	***	
H1	<---	H.	.918	0.045	20.238	***	
PR4	<---	PR.	1.000				
PR3	<---	PR.	1.014	0.050	20.193	***	
PR2	<---	PR.	1.059	0.051	20.634	***	
PR1	<---	PR.	1.010	0.050	20.007	***	
EE1	<---	EE.	1.000				
EE2	<---	EE.	0.942	0.046	20.397	***	
EE3	<---	EE.	0.949	0.045	20.875	***	
EE4	<---	EE.	0.933	0.046	20.230	***	
EE5	<---	EE.	.954	0.047	20.320	***	
SI1	<---	SI.	1.000				
SI2	<---	SI.	1.013	0.053	19.219	***	
SI3	<---	SI.	1.020	0.055	18.423	***	
PV3	<---	PV.	1.000				
PV2	<---	PV.	1.013	0.050	20.378	***	
PV1	<---	PV.	1.039	0.049	21.105	***	
FC5	<---	FC.	1.000				
FC4	<---	FC.	0.952	0.049	19.581	***	
FC3	<---	FC.	0.969	0.048	20.359	***	
FC2	<---	FC.	0.975	0.050	19.681	***	
FC1	<---	FC.	0.990	0.050	19.615	***	
BI1	<---	BI.	1.000				
BI2	<---	BI.	0.983	0.055	17.783	***	

			Estimate	S.E.	C.R.	P	Label
BI3	<---	BI.	0 .909	0.055	16.387	***	

Table 7 from the SEM analysis using AMOS reveals the strength and direction of relationships between latent and observed variables. For hedonic motivation (HM), all observed variables (HM1, HM2, HM3, HM4) have strong positive regression weights, with HM4 being the strongest indicator (weight = 1.000). Trust (T) indicators (T1, T2, T3, T4) also show strong positive weights, with T1 being the highest (weight = 1.275). Other constructs like performance expectancy (PE), habit (H), perceived risk (PR), effort expectancy (EE), social influence (SI), price value (PV), and facilitating conditions (FC) also exhibit significant positive weights. These results highlight the significant impact of these factors on behavioral intention towards using OpenAI Emon et al. [61], and provide insights for strategies to promote OpenAI adoption [67].

Objective 2: To analyze the moderating role of gender on the relationship between Effort Expectancy and Behavioral Intention.

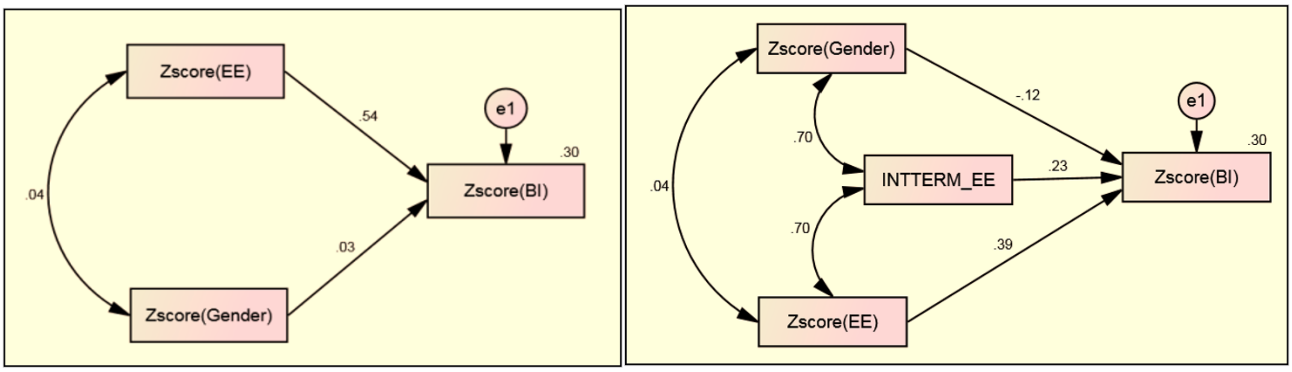


Figure 3.
Direct and Indirect Model with Gender as Moderator on the relationship between Effort Expectancy and Behavioral Intention.

Table 8.
Regression Weights: (Group number 1 - Default model).

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	-0.122	0.117	-1.044	0.297	
ZBI	<---	INTTERM_EE	0.095	0.069	1.383	0.167	
ZBI	<---	ZEE	0.388	0.117	3.313	***	

Table 8 and Figure 3 suggest that gender moderates the relationship between effort expectancy (EE) and behavioral intention (BI). The interaction term (INTTERM_EE) between gender and EE is not significant (p = 0.297), indicating a weak moderating effect. However, the direct effect of EE on BI (ZEE) is significant (p < 0.001), suggesting that EE positively influences BI. Overall, while gender appears to have a limited moderating role, effort expectancy significantly contributes to behavioral intention regardless of gender. These findings imply that efforts to enhance effort expectancy (EE) may positively impact behavioral intention (BI), irrespective of gender differences in this context [68].

Objective 3: To analyze the moderating role of gender on the relationship between social influence and behavioral intention.

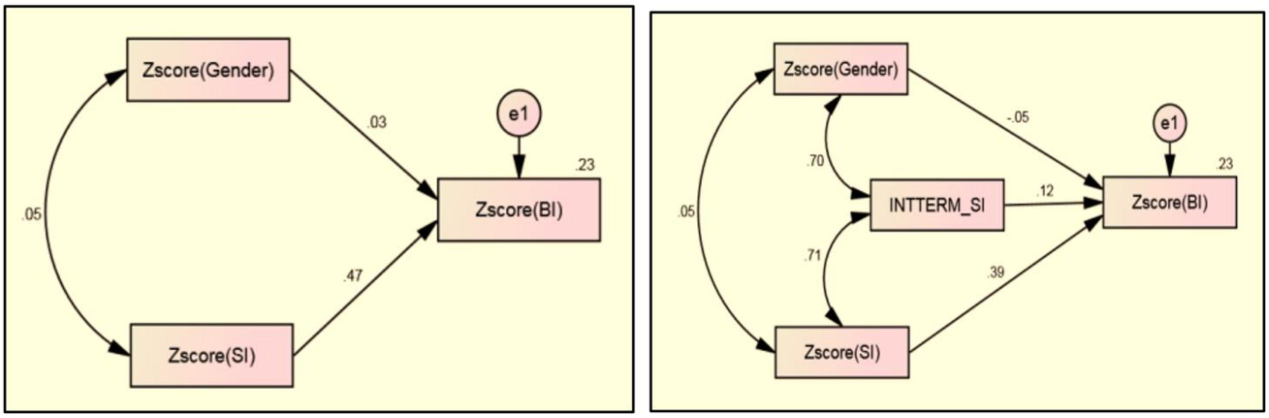


Figure 4.
Direct and Indirect Model with Gender as Moderator on the relationship between Social Influence and Behavioral Intention.

Table 9.
Regression Weights: (Group number 1 - Default model).

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	-0.050	0.123	-0.407	0.684	
ZBI	<---	INTTERM_SI	0.050	0.072	0.683	0.494	
ZBI	<---	ZSI	0.391	0.125	3.139	0.002	

The regression weights given in Table 9 indicate that gender does not significantly moderate the relationship between social influence (SI) and behavioral intention (BI). The interaction term (INTTERM_SI) between gender and SI is not significant ($p = 0.494$) as shown in Figure 4, suggesting no substantial moderating effect. However, the direct effect of SI on BI (ZSI) is significant ($p = 0.002$), indicating that SI positively influences BI regardless of gender. Despite gender not exerting a moderating influence, social influence remains a significant predictor of behavioral intention. These results imply that enhancing social influence can positively impact BI, irrespective of gender differences in this context [69].

Objective 4: To analyze the moderating role of gender on the relationship between Price Value and Behavioral Intention.

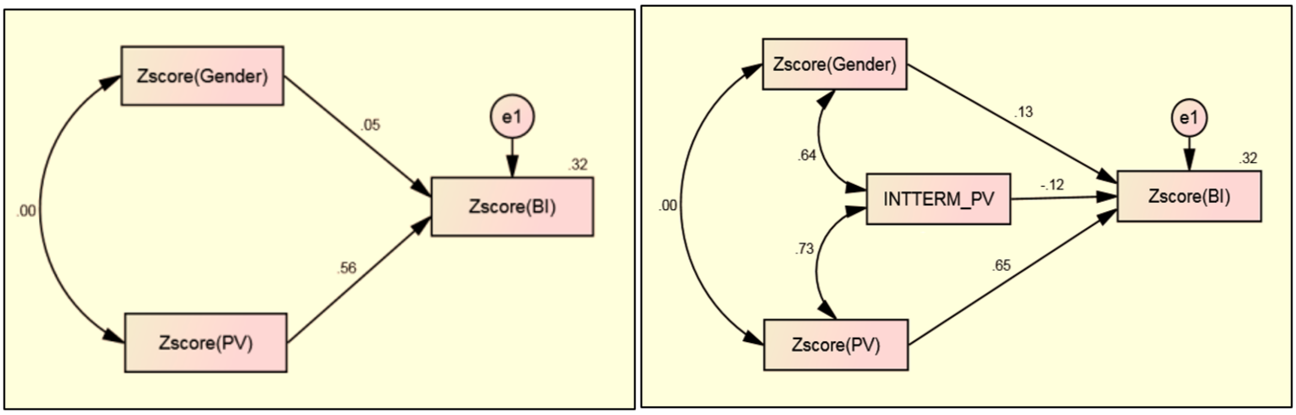


Figure 5.
Direct and Indirect Model with Gender as Moderator on the relationship between Price Value and Behavioral Intention

Table 10.
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	0.127	0.105	1.208	0.227	
ZBI	<---	INTTERM_PV	-0.051	0.065	-0.790	0.430	
ZBI	<---	ZPV	0.650	0.118	5.521	***	

Table 10 indicates that gender does not significantly moderate the relationship between price value (PV) and behavioral intention (BI). The interaction term (INTTERM_PV) between gender and PV is not significant ($p = 0.430$), suggesting no substantial moderating effect. However, the direct effect of PV on BI (ZPV) is significant ($p < 0.001$), indicating that PV positively influences BI regardless of gender. Despite gender not exerting a moderating influence, price value remains a significant predictor of behavioral intention. These results imply that enhancing perceived value for the price can positively impact BI, irrespective of gender differences in this context [70].

Objective 5: To analyze the moderating role of gender in the relationship between facilitating conditions and behavioral intention.

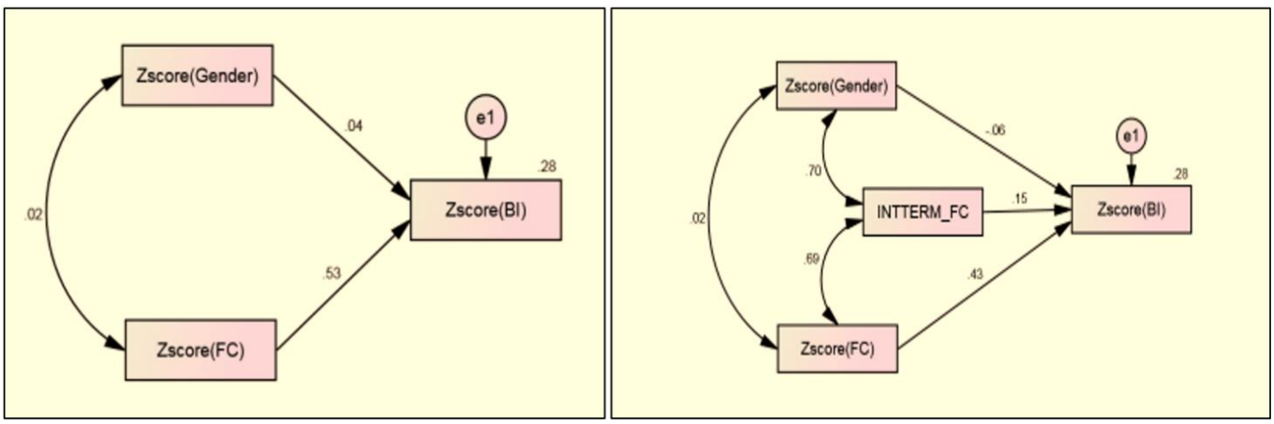


Figure 6.
Direct and Indirect Model with Gender as Moderator on the relationship between Facilitating Conditions and Behavioral Intention.

Table 11.
Regression Weights: (Group number 1 - Default model).

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	-0.060	0.122	-0.488	0.625	
ZBI	<---	INTTERM_FC	0.063	0.072	0.876	0.381	
ZBI	<---	ZFC	0.431	0.119	3.620	***	

Table 11 results suggest that gender does not significantly moderate the relationship between facilitating conditions (FC) and behavioral intention (BI). The interaction term (INTTERM_FC) between gender and FC is not significant ($p = 0.381$), indicating no substantial moderating effect. However, the direct effect of FC on BI (ZFC) is significant ($p < 0.001$), suggesting that FC positively influences BI regardless of gender. Despite gender not exerting a moderating influence, facilitating conditions remain a significant predictor of behavioral intention. These findings imply that improving facilitating conditions can positively impact BI, irrespective of gender differences in this context [71].

Objective 6: To analyze the moderating role of gender on the relationship between perceived risk and behavioral intention.

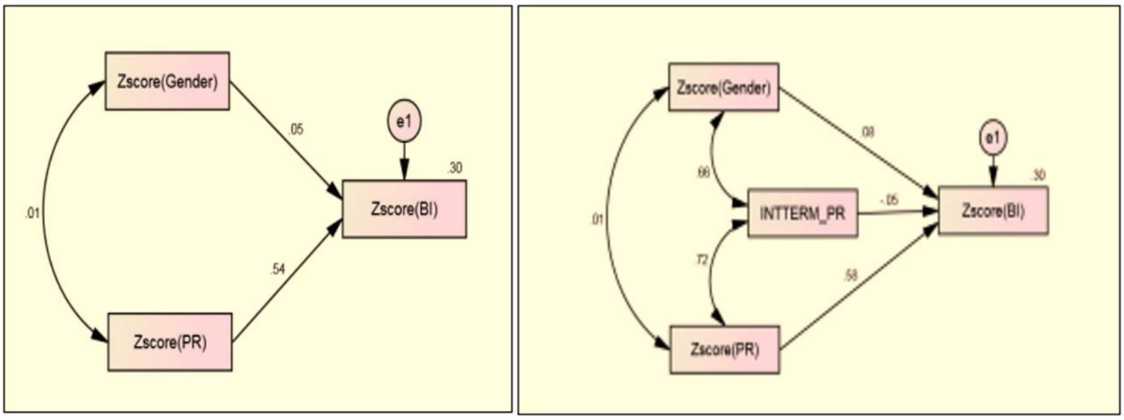


Figure 7.
Direct and Indirect Model with Gender as Moderator on the relationship between Perceived Risk and Behavioral Intention.

Table 12.
Regression Weights: (Group number 1 - Default model).

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	0.082	0.108	0.759	0.448	
ZBI	<---	INTTERM_PR	-0.023	0.067	-0.351	0.725	
ZBI	<---	ZPR	0.582	0.116	5.006	***	

Table 12 results indicate that gender does not significantly moderate the relationship between perceived risk (PR) and behavioral intention (BI). The interaction term (INTTERM_PR) between gender and PR is not significant ($p = 0.725$), suggesting no substantial moderating effect. However, the direct effect of PR on BI (ZPR) is significant ($p < 0.001$), indicating that PR positively influences BI regardless of gender. Despite gender not exerting a moderating influence, perceived risk remains a significant predictor of behavioral intention. These results imply that mitigating perceived risks can positively impact BI, irrespective of gender differences in this context [72].

Objective 7: To analyze the moderating role of gender on the relationship between habit and behavioral intention.

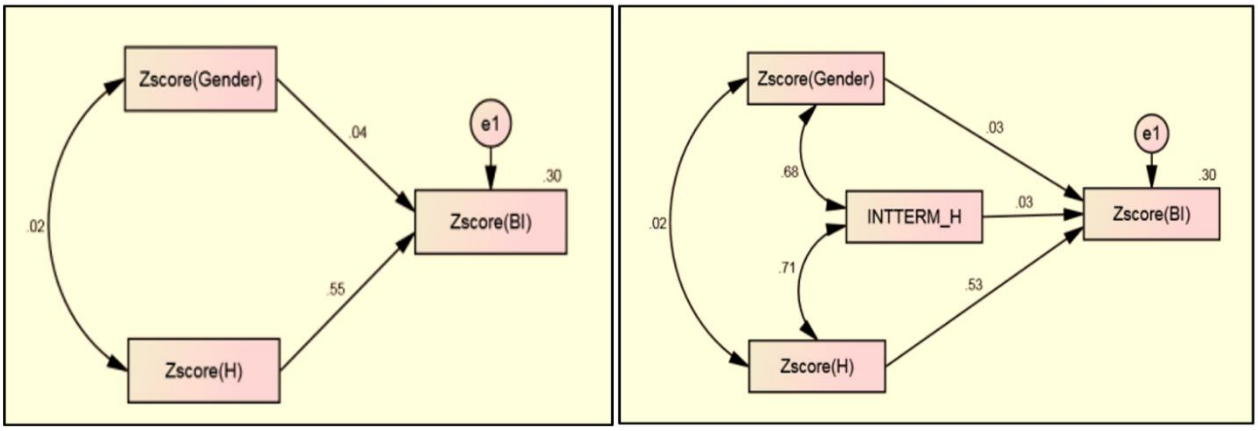


Figure 8.
Direct and Indirect Model with Gender as Moderator on the relationship between Habit and Behavioral Intention.

Table 13.
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	0.027	0.111	0.239	0.811	
ZBI	<---	INTTERM_H	0.011	0.069	0.161	0.872	
ZBI	<---	ZH	0.528	0.116	4.540	***	

Table 13 suggests that gender does not significantly moderate the relationship between habit (H) and behavioral intention (BI). The interaction term (INTTERM_H) between gender and H is not significant (p = 0.872), indicating no substantial moderating effect. However, the direct effect of H on BI (ZH) is significant (p < 0.001), suggesting that habit positively influences BI regardless of gender. Despite gender not exerting a moderating influence, habit remains a significant predictor of behavioral intention. These findings imply that reinforcing habitual behavior can positively impact BI, irrespective of gender differences in this context [73].

Objective 8: To analyze the moderating role of gender on the relationship between Performance Expectancy and Behavioral Intention.

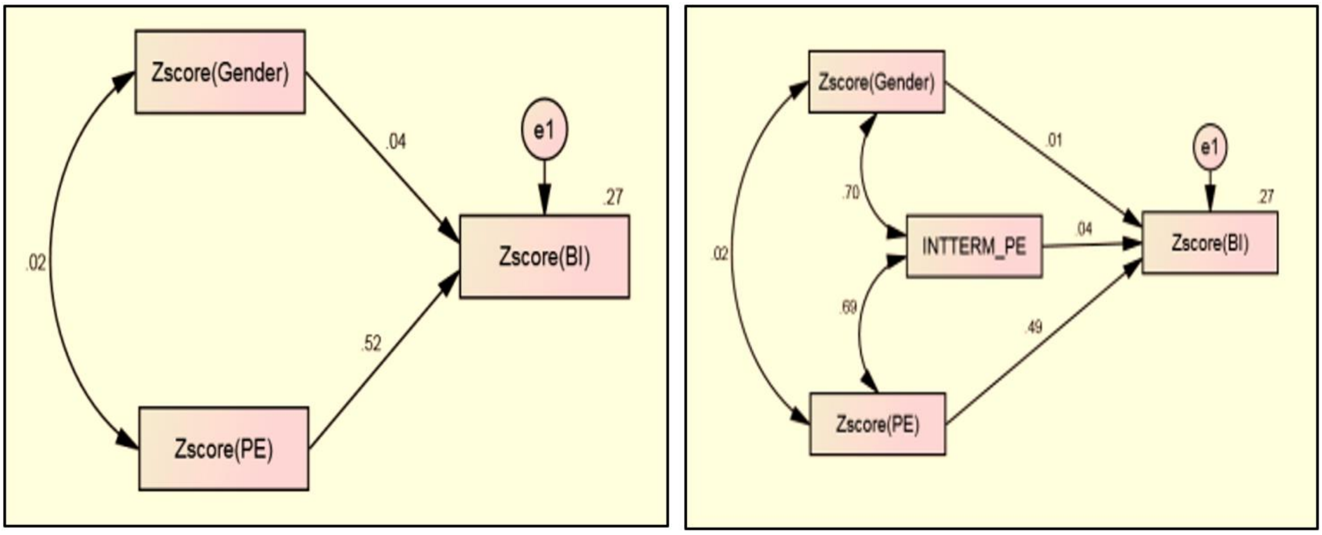


Figure 9.
Direct and Indirect Model with Gender as Moderator on the relationship between Performance Expectancy and Behavioral Intention

Table 14.
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	0.014	0.123	0.112	0.911	
ZBI	<---	INTTERM_PE	0.016	0.072	0.221	0.825	
ZBI	<---	ZPE	0.493	0.120	4.099	***	

Table 14 indicates that gender does not significantly moderate the relationship between performance expectancy (PE) and behavioral intention (BI). The interaction term (INTTERM_PE) between gender and PE is not significant (p = 0.825), suggesting no substantial moderating effect. However, the direct effect of PE on BI (ZPE) is significant (p < 0.001), indicating that PE positively influences BI regardless of gender. Despite gender not exerting a moderating influence, performance expectancy remains a significant predictor of behavioral intention. These results imply that enhancing perceived performance outcomes can positively impact BI, irrespective of gender differences in this context [74].

Objective 9: To analyze the moderating role of gender on the relationship between trust and behavioral intention.

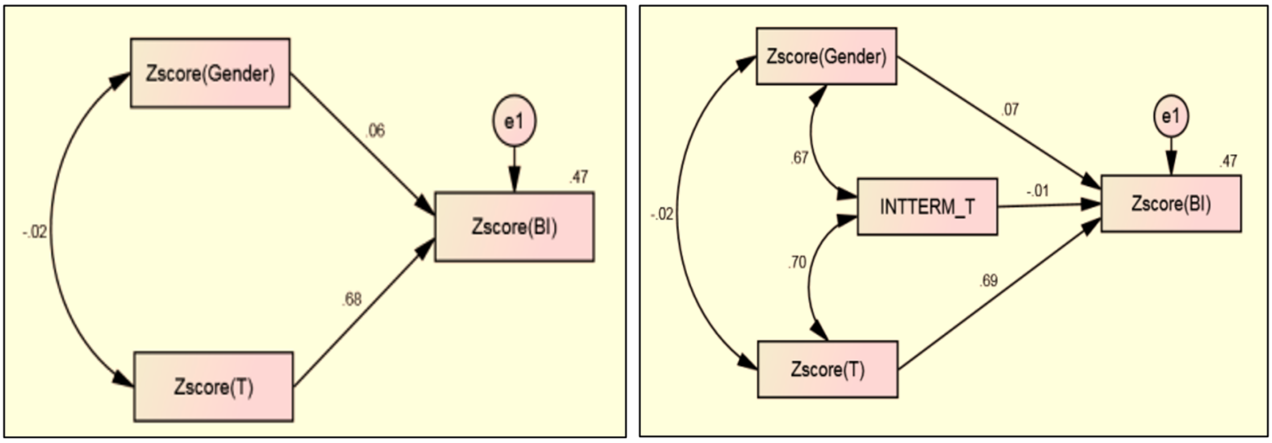


Figure 10.
Direct and Indirect Model with Gender as Moderator on the relationship between Trust and Behavioral Intention

Table 15.
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	0.069	0.097	0.714	0.476	
ZBI	<---	INTTERM_T	-0.004	0.060	-0.066	0.947	
ZBI	<---	ZT	0.687	0.100	6.839	***	

Table 15 suggests that gender does not significantly moderate the relationship between trust (T) and behavioral intention (BI). The interaction term (INTTERM_T) between gender and T is not significant ($p = 0.947$), indicating no substantial moderating effect. However, the direct effect of T on BI (ZT) is significant ($p < 0.001$), suggesting that trust positively influences BI regardless of gender. Despite gender not exerting a moderating influence, trust remains a significant predictor of behavioral intention. These findings imply that fostering trust in a context can positively impact BI, irrespective of gender differences in this relationship [75].

Objective 10: To analyze the moderating role of gender in the relationship between hedonic motivation and behavioral intention.

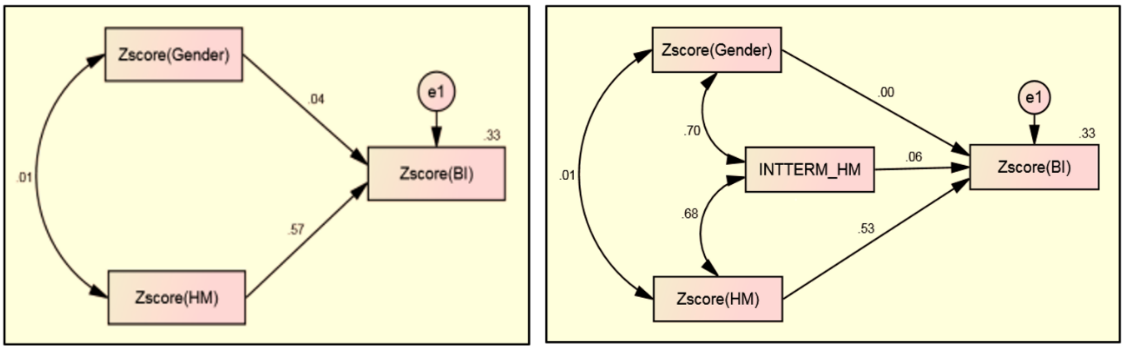


Figure 11.
Direct and Indirect Model with Gender as Moderator on the relationship between Hedonic Motivation and Behavioral Intention.

Table 16.
Regression Weights: (Group number 1 - Default model).

			Estimate	S.E.	C.R.	P	Label
ZBI	<---	ZGender	0.000	0.118	0.002	0.998	
ZBI	<---	INTTERM_HM	0.028	0.072	0.388	0.698	
ZBI	<---	ZHM	0.528	0.115	4.572	***	

Table 16 indicates that gender does not significantly moderate the relationship between hedonic motivation (HM) and behavioral intention (BI). The interaction term (INTTERM_HM) between gender and HM is not significant ($p = 0.698$), suggesting no substantial moderating effect. However, the direct effect of HM on BI (ZHM) is significant ($p < 0.001$), indicating that hedonic motivation positively influences BI regardless of gender. Despite gender not exerting a moderating influence, hedonic motivation remains a significant predictor of behavioral intention. These results imply that stimulating hedonic motives can positively impact BI, irrespective of gender differences in this relationship [72].

5. Conclusion

The research paper investigates the factors influencing students' behavioral intentions to adopt OpenAI technology, focusing on determinants such as effort expectancy, performance expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, perceived risk, and trust, while also examining gender as a potential moderating factor.

5.1. Reliability and Descriptive Analysis

High internal consistency among scale items was found, ensuring accurate measurements. Descriptive statistics indicated moderate to slightly above-moderate levels across constructs, setting the stage for further analysis.

5.2. Correlation Analysis

Strong positive correlations between the factors and behavioral intention were observed, highlighting their significant impact on students' intentions to engage with OpenAI. All examined factors exhibited significant correlations with behavioral intention.

5.3. Regression Analysis

The regression model explained a substantial portion of the variance in behavioral intention towards OpenAI, with trust, social influence, price value, hedonic motivation, habit, facilitating conditions, perceived risk, performance expectancy, and effort expectancy significantly contributing to this variance. These findings suggest that these factors collectively help predict behavioral intentions towards OpenAI.

5.4. Moderating Role of Gender

Gender did not significantly moderate the relationships between determinants and behavioral intention. The examined factors consistently influenced behavioral intention positively, irrespective of gender.

The study highlights the complex nature of user intention formation towards adopting OpenAI technology. Trust, perceived performance benefits, and facilitating conditions are critical determinants in promoting OpenAI adoption. The findings suggest that efforts to build trust, ensure performance benefits, and enhance facilitating conditions are vital for fostering user acceptance and intention to use OpenAI. These insights are valuable for educators and policymakers aiming to promote OpenAI adoption among students and support future-ready learning practices.

6. Implications

In the contemporary educational landscape, artificial intelligence (AI) is revolutionizing traditional teaching methods, with OpenAI leading the development of advanced AI technologies [1-3]. OpenAI's platforms, such as ChatGPT, Google Bard, and Microsoft's AI-powered Bing, are pivotal in creating personalized instruction, automated evaluation, and intelligent learning environments [5-7].

The adoption of AI-powered educational tools is surging. UNESCO reports that AI skills in India exceed the global average, highlighting AI literacy's growing role in education [4, 76]. ChatGPT's rapid adoption, reaching over 100 million users in months, exemplifies the widespread appeal of AI in education [77]. AI's ability to meet individual learning needs, enhance engagement, and optimize academic outcomes underscores its educational value [75, 78]. AI also promises to democratize access to quality education, reduce biases, and enhance learning through adaptive, inclusive methods [76].

However, AI's rapid growth in education requires understanding its adoption dynamics, ethical implications, and pedagogical impacts [8, 9]. Acceptance of AI among students depends on factors like performance expectancy, effort expectancy, perceived ease of use, and social influence [10-13]. Ethical considerations, including equitable access, algorithmic fairness, and data privacy, are critical[14].

This study aims to analyze the adoption of OpenAI's technologies, such as ChatGPT and Google Bard, among students using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model. It seeks to understand the factors influencing students' attitudes towards AI-powered educational tools, providing insights for developers, educators, and policymakers [15]. By examining performance expectancy, effort expectancy, social influence, and facilitating conditions, this research aims to guide strategic interventions and policies to harness AI's potential while ensuring educational integrity and equity.

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