

Revolutionizing Online Shopping via AI Chatbots: Investigating User Satisfaction, Choice Dynamics, and Web Insights

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ABSTRACT

The advent of artificial intelligence-driven chatbots has brought about a paradigm shift in online shopping. This study employs Structural Equation Modeling (SEM) to comprehensively investigate the transformative potential of AI chatbots in e-commerce. We delve into three critical dimensions: user satisfaction, choice dynamics, and web insights, with SEM serving as a robust analytical framework to understand the complex interplay of variables. Our findings reveal intricate relationships between AI chatbot interactions and user satisfaction, shedding light on the factors that significantly impact users' overall contentment. Moreover, we explore how AI chatbots influence the decision-making processes of online shoppers, uncovering the nuances of choice dynamics in the digital retail landscape. Furthermore, SEM allows us to extract valuable web insights from the data generated by chatbot interactions, offering actionable information for businesses to optimize their online shopping platforms. By integrating SEM analysis into our research, this study provides a holistic understanding of how AI chatbots are reshaping online shopping, offering insights that can guide businesses in enhancing customer experiences and driving success in the digital marketplace.

Keywords: AI Chatbots, Web Insights, Choice Dynamics, Structural Equation Modelling (SEM).

Introduction

In the quickly changing digital world of today, internet shopping is now a daily need. However, as the e-commerce industry continues to expand, so do the expectations of consumers (Gupta et al., 2023). Enter AI chatbots, the innovative technology that is revolutionizing the way we shop online. These intelligent virtual assistants are not just reshaping the customer experience; they are fundamentally transforming the entire e-commerce ecosystem (Mirzakhanyan, 2005). With their ability to provide personalized recommendations, answer queries in real-time, and streamline the buying process, AI chatbots are ushering in a new era of convenience, efficiency, and engagement in online shopping. In this era of AI-driven retail, consumers are empowered like never before, and businesses have the opportunity to forge deeper connections with their customers, ultimately redefining the future of online shopping. (Learning et al., 2022)

With a new era of innovation, the advancement in artificial intelligence (AI), and revolution across a wide range of industries, including the educational sector. Traditional approaches to learning and teaching have the potential to be revolutionised by new tools and applications made possible by advances in AI technology (Gentsch & Gentsch, 2019). There is a vast range of possible applications for AI in education, including the enhancement of Productivity, learning results, individualised teaching, immediate feedback, and student engagement are all things that may be improved. A few examples of

these innovations are Personalised learning platforms, automated grading systems, and intelligent tutoring systems apps now being used in education that make use about synthetic intelligence. (Chen et al., 2020). The potential offered by these programmes is rather substantial. Improving students' academic achievement while also enabling educators to provide more individualised instruction to each student direction or instruction. Intelligent teaching systems, for instance, may do this by providing individuals with individualised feedback and help (Huang & Sciuchetti, 2023). Adapt the teachings to the requirements of the pupils. It is possible for educators to concentrate on more vital tasks, such as lesson preparation and student assistance via the use of automated grading methods, which might result in significant time savings for them. (Aldeman et al., 2021).

Investigating User Satisfaction

Investigating user satisfaction is a critical endeavour for businesses and organizations across various industries. It involves a systematic analysis of customer experiences and perceptions to gauge the overall contentment and loyalty of their user base (Gkikas & Theodoridis, 2022). Through methods such as surveys, feedback forms, and data analytics, companies can gain valuable insights into what aspects of their products, services, or platforms are meeting user expectations and where improvements are needed. Understanding user satisfaction not only helps in keeping hold to current clients while also drawing in new ones. It serves as a compass for decision-making, enabling businesses to adapt and refine their offerings to better align with user preferences and needs. By continuously investigating user satisfaction, companies can build stronger relationships with their clientele, enhance their reputation, and stay competitive in an ever-evolving marketplace. (Rehman & Ansari, 2023)

- **Choice Dynamics**

"Choice dynamics" typically refers to the complex set of factors and processes that influence how individuals make decisions and choices in various contexts. It encompasses an array of psychological, social, economic, and environmental elements that interact to shape our preferences and behaviors. These dynamics can vary widely depending on the specific decision being made, whether it's related to consumer choices, career decisions, or even personal life choices. (Stöcker et al., 2021)

Understanding choice dynamics is crucial in fields such as marketing, economics, and psychology, as it allows researchers and professionals to predict and influence decision-making processes. It involves examining factors like cognitive biases, social influences, risk perception, information availability, and the role of emotions in choices. Researchers often use various models and theories to study choice dynamics, aiming to develop a deeper comprehension of how and why individuals make the choices they do. (Nagar, 2016)

In essence, choice dynamics encapsulates the intricate interplay of factors that guide human decision-making, providing valuable insights for businesses, policymakers, and individuals seeking to make informed choices in a complex world. (Nagar, 2016)

- **Web Insights**

"Web insights" typically refer to valuable information and data derived from the analysis of web-related activities, behaviors, and trends. This term encompasses a wide range of information that can be gathered from the internet and websites, and it is often used for various purposes, including business intelligence, marketing, user experience optimization, and more. (Aldeman et al., 2021)

Web insights can include data on website traffic, user demographics, user engagement, conversion rates, click-through rates, search engine rankings, and social media interactions. Businesses and website owners use web insights to make informed decisions about website design, content strategy, digital marketing campaigns, and overall online presence. By analyzing web insights, organizations can better understand their audience, identify opportunities for improvement, and track the performance of their online initiatives. (Adiguzel et al., 2023)

Moreover, web insights can also help in identifying emerging trends in online behavior, which can be valuable for adapting to changing user preferences and technological advancements. In essence, web insights are essential to the efficient administration and improvement of online platforms and digital strategies, contributing to a more data-driven and responsive approach to the online world (Adiguzel et al., 2023).

▪ Artificial intelligence.

At present, artificial intelligence (AI) is implemented at the point where it is almost unavoidable in everyday life. An extensive variety of instances show the ways in which artificial intelligence has impacted several facets of human existence. Some of these examples include using the Internet to get information, reading and watching news, being detected by monitoring systems, the state of the financial markets, people getting welfare benefits, and the way in which drivers and pedestrians navigate (Yi & La, 2004). In 1955, James Comey first used the term "artificial intelligence," which describes the process of training a computer to act in ways that, if shown by a person, would be considered intelligent. It defines artificial intelligence as the practice of creating computer software that are capable of doing activities that normally need human intellect. Despite the fact that these early ideas of AI date back many decades, they provide a reasonable beginning. Firstly, let's define it: is artificial intelligence (AI) really intelligent? If not, how does it differ? In point of fact, artificial intelligence is not intelligent in and of itself; rather, it has the capability to carry out activities with a degree of success that are commonly thought to need intelligence. (Roeein, 2019)

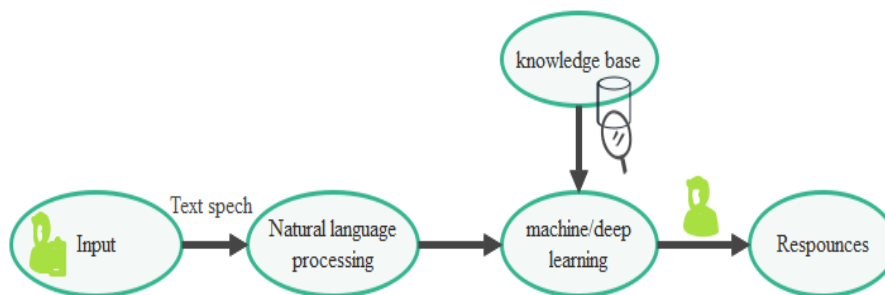


Figure 1: How a Chatbot Functions

Many authors discussed regarding Revolutionizing Online Shopping via AI Chatbots using different methods and approaches some of them are given below,

This paper provides a thorough analysis of AI technologies, including their possible uses in education and associated challenges. We discuss chatbots and related algorithms that, given natural language input, may simulate human conversations and generate writing that seems human. Beyond the benefits of state-of-the-art chatbots such as ChatGPT, their usage in education presents significant practical and ethical issues. In addition to encouraging responsible and ethical usage, The authors want to provide useful information on how AI may be effectively integrated into the classroom for the mutual benefit of teachers and students (Stöcker et al., 2021). This study attempts to provide a thorough and systematic assessment of significant works on Artificial intelligence in education (AIEd), considering AIEd's expanding importance and the lack of a complete overview on the subject. The top journals, organisations, countries/regions, most-used terminology, theories, and technologies, as well as their annual distribution used, we examined 45 papers. Additionally, we assessed definitions of AIEd from both wide and limited viewpoints and elucidated the connections between AIEd, Learning Analytics, Computer-Based Education, and Educational Data Mining (Peng et al., 2019). As a result, we look into possible appropriate actions to prevent or minimise returns throughout the pre-, during, and post-purchase stages. We examine the most important factors influencing returns of fashion assortments as well as recent technology advancements in return management. The actions we look at address all three buying stages and provide a comprehensive understanding of the problem (Huang & Sciuchetti, 2023). This study's objective is to look at how adjusted expectations function in the CS–RPI relationship. In a family-restaurant context, the suggested model was evaluated using structural equation analysis. The results show that the influence of CS on RPI may be mitigated by altered expectations. The findings also imply that the fundamental processes governing the CS–RPI link vary across customers with low and high levels of loyalty. More specifically, nonloyals are more affected by the transitory route than loyals are. This route illustrates the indirect path from CS to RPI through modified expectancies (Samala et al., 2022). In order to investigate the impacts of product attributes, reviewer criticality, product kind, consuming environment, and evaluation duration in assessing latent customer contentment, We suggest

using a multi-facet item response theory (MFIRT) method. Studies of TripAdvisor hotel reviews and Beer Advocate beer ratings indicate that different reviewer segments emphasise different traits when evaluating different items over time, and that product attributes vary in terms of their threshold and discriminating qualities (Näykki & You, 2021). The analysis's findings revealed that several of the most significant factors influencing a customer's choice to leave include "problems with data speed," "poor relationship building," "problems with service area coverage," and "billing issues." The churn consequence influencers model also provides an overview of the characteristics that lead to general unhappiness and, ultimately, churn behaviour. The study discovered how the netnography technique is used in a field of research where quantitative dominance is the norm. It is notable for its findings drawn from a wealth of qualitative data (Son & Oh, 2018).

Aim of the Study

"Revolutionising Online Shopping via AI Chatbots" seeks to investigate how e-commerce may be revolutionised by artificial intelligence-driven chatbots. This study seeks to investigate how AI chatbots can enhance the online shopping experience for both consumers and businesses. Specifically, It seeks to evaluate how AI chatbots affect customer happiness, look into the dynamics of user choices influenced by these chatbots, and uncover valuable insights from the web data generated by their interactions. By achieving these objectives, the study aims to provide a comprehensive understanding of how AI chatbots can revolutionize online shopping, ultimately helping businesses adapt and optimize their strategies to meet the evolving needs and expectations of online shoppers.

Objectives

- To examine whether a positive relationship exists between the level of user satisfaction and the quality of interactions with an AI chat bot.
- To investigate the influence of choice dynamics on the duration of user engagement with an AI chat bot.
- To assess **whether the utilization of AI chat bot data enhances the quality and depth of web insights compared to traditional methods.**

Hypothesis

- H1:** There is a significant positive relationship between the level of user satisfaction and the quality of interactions with an AI chat bot.
- H2:** Choice dynamics significantly influence the duration of user engagement with an AI chat bot
- H3:** The utilization of AI chat bot data significantly enhances the quality and depth of web insights.

Research Questions

- How do AI chatbots influence user satisfaction in the context of online shopping, and what are the key factors that contribute to user satisfaction or dissatisfaction with chatbot interactions?
- What are the choice dynamics involved when consumers engage with AI chatbots during their online shopping journeys, and how do these chatbots impact the decision-making process, including product selection, purchase intent, and brand loyalty?
- To what extent do AI chatbots contribute to personalized and tailored online shopping experiences, and how can businesses effectively utilize chatbots to enhance customer engagement and customization?
- What web insights can be derived from the data generated by AI chatbot interactions, and how can businesses leverage these insights to improve their product offerings, marketing strategies, and overall online shopping platforms?
- What are the challenges and ethical considerations associated with the implementation of AI chatbots in online **shopping, and how can businesses address these concerns to ensure a positive and trustworthy user experience?**

Methodology

This study's primary goal is to investigate the Revolutionizing Online Shopping via AI Chatbots: Investigating User Satisfaction, Choice Dynamics, and Web Insights. In this study, quantitative methods are utilized to obtain the data regarding current information Revolutionizing Online Shopping via AI Chatbots. To examine the significant relationship between bounce rate and abandonment rate in the

context of AI-powered interactions, indicating predictive patterns, Utilising the Structural Equation Modelling, or SEM, AMOS.

Research Design

The study's research design is comprised of a number of techniques and approaches that have been established to rationally combine many research components to be able to adequately address the research question that has been investigated so far. This chapter's objective is to provide readers an overview of the study's methodology. How analysis of data, information collecting, and research are conducted is determined by the study design.

Sampling Technique

For this study, 400 responses were collected from respondents with full questionnaire saved for future research. A self-designed structured questionnaire was prepared should use the random sample approach to collect the data in this investigation.

Random Sampling

Random sampling, a method for selecting samples from a population, guarantees that each potential participant has an equal chance of getting picked. Choosing a sample from a random pool may often result in an accurate depiction the whole populace. Sampling at random constitutes one of the easiest ways to get information from a whole population. When it comes to random sampling, the general rule follows: if a sample is chosen only once.

$$P = 1 - \left(\frac{N-1}{N}\right)\left(\frac{N-2}{N}\right).....\left(\frac{N-n}{N-(n-1)}\right)$$

P denotes probability in this instance, n denotes sample size, and N denotes population.

Now, $P = n/N$ will be the outcome if $1-(N-n/n)$ is cancelled. Additionally, it is important to allow for multiple sample selections: $P = 1-(1-(1/N))^n$.

Data Collection

One of the most important parts of any research project is information collection. Information is often gathered using one of two methods: primary or secondary data collecting. A questionnaire will be used to gather primary data and secondary data, that may be obtained in websites, including journals, articles, publications, research papers, and yearly reports.

Tools for Data Collection

The information is gathered from the surveys by questionnaire form via email, or through online survey platforms like Google Forms or Survey form.

Interview Schedule

The collection of field data (primary data collection) will be conducted using the Interview Schedule tool. This is the pre-draft question that will be asked during the structured interview process.

Inclusion Criterion & Exclusion Criterion

- Males and females, who have knowledge Revolutionizing Online Shopping via AI Chatbots with age limit (18- above 45) irrespective of their personal details were willing to participate in the research.
- Males and females, who don't have any knowledge on Revolutionizing Online Shopping via AI Chatbots as **well as who declined to take part in the research and those who were not available at the place during the period of data collection.**

In this analysis we are taking dependent, independent and moderating variables this variable are mentioned below It will be measured through a set of Likert scale questions exploring the primary examine digital innovation in strategic management and its impact on organization growth. In this we taking five Likert scale i.e., 1 to 5

- 1- Strongly disagree
- 2- Disagree
- 3- Neutral
- 4- Agree
- 5- Strongly agree

• Data Analysis Techniques

In order to analyse the data, The use of SEM (structural equation modelling) will hypothesized relationships between strategic management, organization growth and digital innovation in strategic management. It will be possible to examine the direct as well as indirect effects using the SEM.

Structural Equation Modelling

A structure-based model that provides a theory on the interplay of several variables serves as the foundation for the multivariate, hypothesis-driven method known as structural equation modelling (SEM). Blood oxygen level-dependent (BOLD) phases of $y_1 \dots y_n$ different brain locations in the context of these factors are quantified using functional magnetic resonance imaging (fMRI), and the proposed causal connections are predicated on relationships among The areas that are tenable physically. The Because it shows how, the "route coefficient," which is comparable with the partial regression coefficient, The variability of y_i is dependent upon the variance of if all other influences on y_j are maintained constant. y_j , indicates the strength of each connection. The letters. $y_i \rightarrow y_j$

The equation provides a summary of the conventional SEM statistical model. $y = Ay + u$

where y is a $n \times S$ matrix of n area-specific time series with s scans each and u is a $n \times S$ matrix of components with the simulation system is driven by zero mean Gaussian errors. (the "innovations"; see equation). A may be thought of as a matrix of with route coefficients of size $n \times n$ (with zeroes for missing connections). It is possible to estimate parameters by reducing the distinction between the covariance matrices of the model and the observed model. Σ . By translating equation, Σ may be calculated for any given combination of parameters.

$$y = (I - A)^{-1}u$$

$$\Sigma = yy^T$$

$$= (I - A)^{-1}uu^T(I - A)^{-1T}$$

Don't forget to behave in a way that corresponds to the identity matrix. The first line of the equation offers a generative model for how the system's connectional structure leads to system function: The interregional connection matrix function is used to produce the observed time series y using the Gaussian innovations u . $(I - A)^{-1}$

Model Fit Assessment

Model fit indices such as chi-square (χ^2), To evaluate Don't forget to behave in a way that corresponds to the identity matrix. The Root Mean Square Error Approximation (RMSEA), the Tucker-Lewis Index (TLI), the Comparative Fit Index (CFI), and the Standardised Root Mean Square Residual (SRMR).

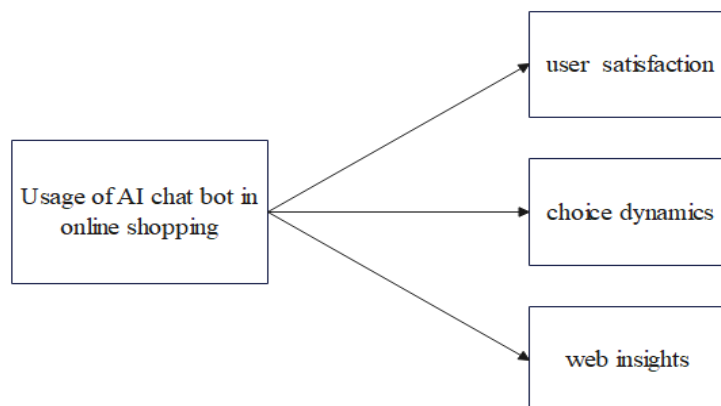


Figure 2: Conceptual Frame Work

Results

• Demographic Variables

Table 1: Demographic Variables Frequency Analysis

	Frequency	Percentage	Mean	Total sample
Age				
18 – 24 years	44	17.4	2.2609	253
25 – 34 years	126	49.8		
35 – 44 years	56	22.1		
45 Above years	27	10.7		
Total	253	100		
Gender				
Male	145	57.3	1.4269	253
Female	108	42.7		
Total	275	100		
Educational Qualification				
High School Diploma or Less	40	15.8	2.9605	253
Some college or associate's degree	70	27.7		
Bachelor's Degree	40	15.8		
Master's Degree	66	26.1		
Doctorate or professional degree	37	14.6		
Total	275	100		
Income				
Less than 25,000 per year	80	31.6	2.3794	253
25,000 - 49,999 per year	64	25.3		
50,000 - 74,999 per year	42	16.6		
Above 75000 per year	67	26.5		
Total	253	100		
Location				
Rural	145	57.3	1.3992	253
Urban	108	42.7		
Total	253	100		

The above table exhibits the descriptive statistics related to demographic variables. It is clear that among the total participants 57.3 per cent were male and 42.7 per cent were female. The data indicates that 17.4% of respondents were in the 18–24 age group, 49.8% were in the 25–34 age group, 22.1 percent were in the 35–44 age group, and 10.7 percent were in the 45 years and above age group coming to Educational Qualification 15.8 percent are High School Diploma or Less, 27.7 percent are Some college or associate's degree 26.1 percent have a master's degree, and 15.8 percent have a bachelor's degree 14.6 percent are Doctorate or professional degree. Coming to the Location 57.3 percent are from Rural ,42.7 percent participants are from urban.

The second measure of dependability is Cronbach's alpha. Cronbach's alpha values for the constructions are shown in Table 4. Most of the time, Cronbach's alpha coefficients need to be at least 0.7. The Cronbach's alpha value for "User satisfaction" is 0.724, for "Choice dynamics" is 0.753, for "AI Chat bot" is 0.748, and for "Web Insights" is 0.796. The measurement of this research is reliable since, All four constructions have Cronbach's alpha values greater than 0.7.

To meet In order for a concept to meet the criteria for discriminative validity, its AVE square root must be higher compared to the correlations between it along with the other constructs of the model. As seen in Table 4, the square root of the The AVEs of choice dynamics and user satisfaction are 0.713 and 0.741, respectively. Table 4 of this research indicates that all structures' square roots All of the AVEs exceed the correlations of every construct in Table 2. Consequently, the measurement's discriminative validity in this study is deemed good. Second, an idea is said to have convergent validity if its average variance surpasses 0.5. The AVEs of the four constructions are 0.741, 0.713, 0.763, and 0.831, which are all larger than 0.5, as shown in table 4. It suggests that this research has convergent validity. As a

result, the study's measurement is appropriate in terms of convergent and discriminative validity. The findings of many dependability and validity tests, this research has sufficient reliability and validity.

Correlation

Table 2: Means, Standard Deviation, and Correlations of the Constructs

Constructs	Mean	Standard deviation	User Satisfaction	Choice Dynamics	AI Chat bot	Web Insights
User satisfaction	3.6552	.55163	1			
Choice dynamics	3.4700	.40859	.156*	1		
AI Chat bot	3.5682	.36108	.219**	.420**	1	
Web Insights	3.5000	.43244	.211**	.670**	.807**	1
*. Correlation is significant at the 0.05 level (2-tailed).						
**. Correlation is significant at the 0.01 level (2-tailed).						

Table 3: Factor Analysis

Constructs	Number of Items	Number of factors
User satisfaction	9	1
Choice dynamics	8	1
AI chatbot	12	1
WebInsights	12	1

Table 3 depicts the four components' factor analysis. In this study, every construct may be categorised into just one component. To create questionnaire questions, the research resorted to prior studies. This research used two pretests for questionnaire adjustments before distributing the questionnaire to the respondents. As a result, the content validity of this study's measurement is acceptable. Two measures are used to validate the structures' dependability. To begin, one way to assess dependability is to look at how each construct's loadings component elements. Table 3 displays the loads of all four structures. These loadings are noteworthy in terms of the calibre of the sample's measuring model.

• Test of the Proposed Model

The model was examined using a SEM technique. For this, AMOS Ver. 17 was used. Processing the data for the instrument yielded the observable variables that were used for predicting the latent variables for SEM. The SEM analysis's findings demonstrate how well the model matches The information. We employed the seven fit indices (chi-square/degrees of freedom, GFI, AGFI, NNFI, the CFI, RMSR, & RMSEA) that are often used in the literature to assess the model fit. Based on the findings of structural model analysis, Table 4 presents the widely used model fit metrics.

Table 4: Item loadings and the construct's Cronbach's alpha and AVEs

Factors and items	Cronbach alpha values	Post CFA factor loadings	AVE	Square root of AVE	CR
User Satisfaction	.835		.741	.861	.907
US1		.743			
US2		.753			
US3		.844			
US4		.607			
US5		.788			
US6		.731			
US7		.691			
US8		.768			
Choice dynamics	.759		.713	.844	.903
CD1		.766			
CD2		.686			
CD3		.662			
CD4		.633			
CD5		.754			
CD6		.811			

CD7		.734			
CD8		.677			
CD9		.695			
AI Chabot	.755		.763	.873	.907
AICB1		.668			
AICB2		.705			
AICB3		.722			
AICB4		.855			
AICB5		.812			
AICB6		.755			
AICB7		.823			
Web Insights	.877		.731	.854	.913
WI1		.868			
WI2		.835			
WI3		.790			
WI4		.724			
WI5		.703			
WI6		.637			
WI7		.612			
WI8		.745			
WI9		.665			

Table 5: Summary statistics of model fit.

Variable	Value
Chi-square value(χ^2)	606.739
Degrees of freedom (df)	266
CMIN/DF	2.281
P value	0.068
GFI	0.901
RFI	0.906
NFI	0.923
IFI	0.955
CFI	0.955
RMR	0.047
RMSEA	0.055

The quality of fit was acceptable representation of the sample data ($\chi^2 = 606.739$), NFI (Normed Fit Index) = 0.923; IFI (Incremental fit index) = 0.955, GFI (Goodness of Fit) = 0.901, RFI (Relative Fit Index) = 0.906 and CFI (Comparative Fit Index) = 0.955 which is much larger than the 0.90. Similarly, RMR (Root Mean Square Residuals) = 0.047 and RMSEA (Root mean square error of approximation) = 0.055 values are lower the 0.080 critical value. Results indicated a good fit for the model presented including RMSEA of 0.055, RMR of 0.047, GFI of 0.901, and CFI of .955.

Table 6: SEM Results of the Proposed Model

Relationships	Proposed Effect	Test Results
H1: User satisfaction→AI chat bot	+	supported
H2: Choice dynamics-→ AI chat bot	+	supported
H3: Web insights→ AI chat bot	+	supported

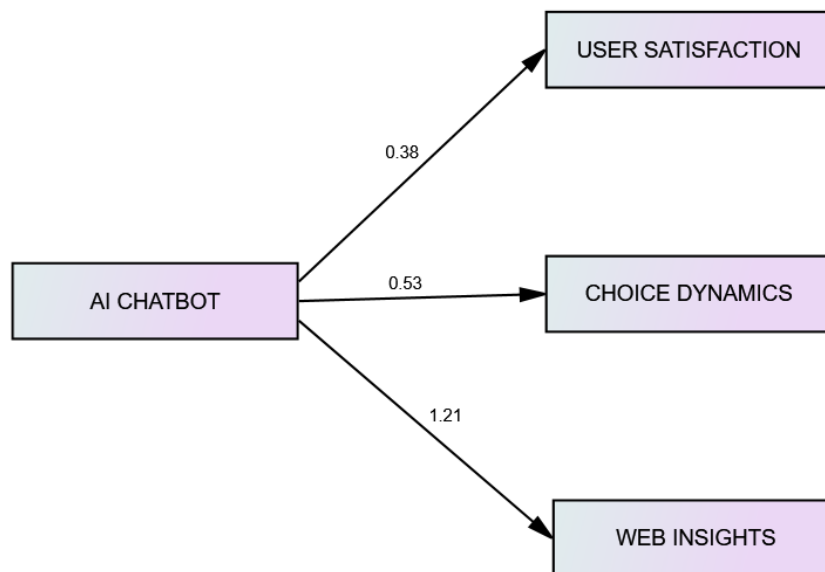


Figure 3: Test of Research Model

Figure 2 depicts the graphical presentation of the results alongside the standardised coefficients of paths. The important correlations between the variables are shown in Figure 1 of the investigation. Each of the three anticipated paths is important. Since the regression coefficient shows a substantial direct link between user happiness and AI chatbot, the first hypothesis is accepted of 0.38, t value of -2.48, and a significance level of p .05. Therefore, it is acknowledged that User There is a strong positive link between contentment and AI chatbot. In addition, In this case, this regression coefficient was 0.53, t = 4.51, & p .05. Additionally, the straight route from Choice dynamics towards AI chatbot is substantial, supporting the second hypothesis. This implies that increased Choice dynamics result in an improved Ai chatbot. H3 hypothesises that web insights have a strong positive correlation with Ai chatbot. The correlation between web insights and Ai chatbot has a p -value less than 05, of and a t -value of -2.61 and a regression coefficient of 1.21, indicating that it is significant. The positive symbol denotes a substantial and The two variables have a positive correlation, which indicates that as web insights rise, so does Ai chatbot. Therefore, the hypothesis that an increase in AI chatbots will benefit web insights is supported.

Discussion

The purpose of the research was to look at the connection between user satisfaction & the quality of interactions with an AI chatbot, exploring the potential influence of choice dynamics on the duration of user engagement with the AI chatbot, and assessing whether the utilization of AI chatbot data contributes to improved quality and depth of web insights compared to traditional methods. The analysis's findings showed a strong positive correlation between customer happiness and the quality of AI chatbot interactions, underscoring the importance of enhancing these interactions to foster user contentment. Additionally, the study identified choice dynamics as a significant factor influencing the duration of user engagement with the AI chatbot, shedding light on the factors affecting user engagement and retention. Lastly, the utilization of AI chatbot data was found to enhance the quality and depth of web insights, highlighting the potential of AI-driven data analysis to provide valuable and comprehensive insights compared to traditional methods. These findings collectively emphasize the significance of improving AI chatbot interactions and leveraging AI-generated data for enhanced user satisfaction and more effective web analytics.

References

1. Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology*, 15(3). <https://doi.org/10.30935/cedtech/13152>

2. Aldeman, N. L. S., de Sá Urtiga Aita, K. M., Machado, V. P., da Mata Sousa, L. C. D., Coelho, A. G. B., da Silva, A. S., da Silva Mendes, A. P., de Oliveira Neres, F. J., & do Monte, S. J. H. (2021). Smartpathk: a platform for teaching glomerulopathies using machine learning. *BMC Medical Education*, 21(1), 248. <https://doi.org/10.1186/s12909-021-02680-1>
3. Chen, X., Xie, H., Zou, D., & Hwang, G. J. (2020). Application and theory gaps during the rise of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence*, 1(August), 100002. <https://doi.org/10.1016/j.caeai.2020.100002>
4. Gentsch, P., & Gentsch, P. (2019). Conversational AI: how (chat) bots will reshape the digital experience. *AI in Marketing, Sales and Service: How Marketers without a Data Science Degree Can Use AI, Big Data and Bots*, 81–125.
5. Gkikas, D. C., & Theodoridis, P. K. (2022). AI in Consumer Behavior. *Advances in Artificial Intelligence-Based Technologies: Selected Papers in Honour of Professor Nikolaos G. Bourbakis—Vol. 1*, 147–176.
6. Gupta, S., Singhvi, S., & Granata, G. (2023). Assessing the Impact of Artificial Intelligence in e-Commerce Portal: A Comparative Study of Amazon and Flipkart. In *Industry 4.0 and the Digital Transformation of International Business* (pp. 173–187). Springer.
7. Huang, J., & Sciuchetti, M. J. (2023). ChatGPT Unveiled: Unleashing AI Magic in Online Shopping and ChatGPT Unveiled: Unleashing AI Magic in Online Shopping and Digital Marketing. 12(2).
8. Learning, M., Interest, C., Learning, M., Interest, C., Forests, R., Learning, M., Learning, M., Features, D., Behavior, N., Analysis, D., Learning, M., Applications, L. W., Classification, Z. I., Coupled, U., Embedding, D., Learning, M., Applications, W., Learning, M., Applications, W., ... Learning, M. (2022). Erratum regarding missing Declaration of Competing Interest statements in previously published articles. *Machine Learning with Applications*, 10(November), 100438. <https://doi.org/10.1016/j.mlwa.2022.100438>
9. Mirzakhanyan, A. (2005). Economic and social development. *The Armenians: Past and Present in the Making of National Identity*, 196–210. <https://doi.org/10.4324/9780203004937>
10. Nagar, K. (2016). Drivers of E-store Patronage Intentions: Choice Overload, Internet Shopping Anxiety, and Impulse Purchase Tendency. *Journal of Internet Commerce*, 15(2), 97–124. <https://doi.org/10.1080/15332861.2016.1148971>
11. Näykki, A., & You, S. (2021). This is a self-archived version of an original article . This version may differ from the original in pagination and typographic details . Copyright : Rights : Rights url : Please cite the original version : identify the socio-emotional and socio-cognitiv. *Learning, Culture and Social Interaction*, 30(JUNE), 100536. <https://doi.org/10.1016/j.lcsi.2021.100536>
12. Peng, L., Cui, G., Chung, Y., & Li, C. (2019). A multi-facet item response theory approach to improve customer satisfaction using online product ratings. *Journal of the Academy of Marketing Science*, 47, 960–976.
13. Rehman, S. F. U., & Ansari, M. F. (2023). Predicting Customer Satisfaction of Online Shoppers Using AI – A Theoretic Framework. *Ijarccce*, 12(1). <https://doi.org/10.17148/ijarccce.2023.12112>
14. Rooein, D. (2019). Data-driven EDU chatbots. *The Web Conference 2019 - Companion of the World Wide Web Conference, WWW 2019*, 46–49. <https://doi.org/10.1145/3308560.3314191>
15. Samala, N., Katkam, B. S., Bellamkonda, R. S., & Rodriguez, R. V. (2022). Impact of AI and robotics in the tourism sector: a critical insight. *Journal of Tourism Futures*, 8(1), 73–87. <https://doi.org/10.1108/JTF-07-2019-0065>
16. Son, Y., & Oh, W. (2018). “Alexa, buy me a movie!”: How AI speakers reshape digital content consumption and preference. *International Conference on Information Systems 2018, ICIS 2018*, 1–17.
17. Stöcker, B., Baier, D., & Brand, B. M. (2021). New insights in online fashion retail returns from a customers' perspective and their dynamics. *Journal of Business Economics*, 91(8), 1149–1187.
18. Yi, Y., & La, S. (2004). What influences the relationship between customer satisfaction and repurchase intention? Investigating the effects of adjusted expectations and customer loyalty. *Psychology & Marketing*, 21(5), 351–373.

