A STUDY ON DOES ARTIFICIAL INTELLIGENCE(AI) IS BOON OR BANE FOR THE ONLINE SHOPPERS OF MOBILE PHONES WITH SPECIAL REFERENCE HYDERABAD

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Abstract

The researcher intended to do study on the title the Impact of Artificial Intelligence (AI) on Online Mobile Phone Shoppers: A Comprehensive Analysis with Special Focus on Redmi Mobiles. This research study utilized the simple random sampling method to collect a sample size of 200 data points. The data was analyzed using the Statistical Package for the Social Sciences (SPSS) software. This report presents a comprehensive summary and interpretation of the findings obtained from the data analysis. The data is restricted to Hyderabad geographical area. AI is a valuable asset in online shopping, offering opportunities for marketers to optimize strategies and meet evolving customer needs effectively.

Keywords: Experience, Trust, Subjective norms, Perceived Usefulness, perceived enjoyment, task technology fit.

1. INTRODUCTION

In the fast-paced and ever-changing digital world of today, Artificial Intelligence (AI) has seamlessly integrated into our daily lives, leaving an indelible mark on how we approach various aspects of online shopping, particularly when it comes to purchasing mobile phones. AI-powered technologies have ushered in a new era of e-commerce, fundamentally transforming the way we interact with online platforms, and offering a host of benefits such as personalized experiences, process optimization, and increased overall efficiency. However, like any revolutionary technology, AI presents a complex landscape with its share of advantages and potential challenges. This article seeks to delve deep into the profound impact of AI on online shoppers in their quest for the perfect mobile phone, exploring the remarkable advantages it brings and the inherent obstacles it may present.

AI has significantly revolutionized online shopping, particularly in the context of buying mobile phones. By leveraging sophisticated algorithms and data-driven decision-making, AI has transformed the way we shop online, enhancing the overall consumer experience. Nonetheless, as with any groundbreaking technology, there are both advantages and potential drawbacks to consider when it comes to AI's impact on mobile phone shopping. This article explores the benefits and disadvantages of AI for online shoppers seeking to purchase mobile phones, offering a comprehensive analysis of its influence on the consumer journey.

AI algorithms analyze consumer behavior and preferences, enabling online retailers to offer personalized product recommendations. By understanding individual preferences, shoppers are presented with mobile phones that align with their specific needs and desires, enhancing their overall shopping experience.

The implementation of AI-powered chatbots and virtual assistants has significantly improved customer support in online shopping. These intelligent tools offer instant responses to customer queries, efficiently resolving issues and providing real-time assistance. As a result, the buying process becomes more streamlined, leading to higher levels of customer satisfaction.

AI algorithms can dynamically adjust pricing based on various factors, such as demand, competition, and customer behavior. This ensures that online shoppers get the best possible deals on mobile phones, leading to increased customer loyalty.

By enabling advanced search and filtering capabilities, AI empowers online shoppers to efficiently discover mobile phones with precise features or specifications. This time-saving and effective approach significantly increases the likelihood of finding the ideal device that meets their specific needs and preferences.

Over-reliance on AI Recommendations: While AI-driven recommendations are valuable, there is a risk of shoppers becoming overly dependent on them and potentially overlooking other product options that might better suit their needs. Encouraging shoppers to critically evaluate their choices and not solely rely on AI suggestions can lead to more well-rounded decision-making.

AI-powered recommendation systems have significantly enhanced the online shopping process for mobile phones. By analyzing vast amounts of data, including user preferences, browsing history, and past purchases, AI algorithms can suggest mobile phones that align with a customer's specific needs and preferences. This personalization leads to a more streamlined shopping experience, saving time and effort while increasing the likelihood of customer satisfaction.

AI in online shopping raises significant concerns, particularly regarding the handling of personal data. The reliance on user information to provide personalized recommendations creates privacy issues that worry consumers. The potential misuse or mishandling of their data by companies or malicious entities is a major apprehension. Consequently, finding a balance between delivering personalized recommendations and ensuring robust user privacy poses a considerable challenge in the AI-driven shopping environment.

Artificial Intelligence (AI) has become a dominant and transformative force, exerting its influence across numerous domains. In the context of online shopping, AI has ushered in a revolutionary era, significantly altering the dynamics of consumer interactions with e-commerce platforms, especially concerning the purchase of mobile phones. This essay aims to delve into the potential advantages and disadvantages that AI brings to online shoppers seeking to buy mobile phones, uncovering the profound impact it has on their overall shopping experience.

AI's revolutionary impact on mobile phone shopping is evident through its cutting-edge recommendation systems. By harnessing the power of AI, online retailers can deliver personalized and pertinent product suggestions to customers based on their preferences, search history, and behavior. This breakthrough feature empowers shoppers to explore a carefully curated selection of mobile phones that perfectly match their unique requirements and desires.

The presence of biases in AI algorithms poses significant implications for shoppers. Despite their remarkable power, AI algorithms can inherit biases from the data used to train them. These biases may inadvertently perpetuate stereotypes related to social, cultural, or gender-based factors within the context of mobile phone shopping. As a result, certain demographics might encounter unequal access to products or find their choices limited due to these biases.

As the integration of Artificial Intelligence (AI) continues to transform the landscape of online mobile shopping, this research project has a primary objective of gaining a deep understanding of its profound impact. By conducting a thorough analysis of both the advantages and challenges associated with AI adoption in this industry, we aim to shed light on the pivotal question of whether AI is a true boon, enhancing the shopping experience for consumers and businesses alike, or if it introduces new concerns and ethical dilemmas that may be considered a bane.

However, this research project also acknowledges that AI adoption in mobile shopping comes with inherent challenges and potential drawbacks. Ethical considerations are paramount, as the use of AI algorithms to influence consumer behavior and decision-making raises concerns about privacy, data security, and algorithmic biases. Understanding and addressing these challenges is vital for building trust and ensuring ethical practices within the AI-driven mobile shopping ecosystem.

2. REVIEW OF LITERATURE:

Samarasena (2020): The evolving marketing landscape has presented new challenges in tracking the customer journey. With the continuous expansion of the market, especially in the digital realm, customers are presented with a multitude of shopping options. As a result, they express their preferences, attitudes, and beliefs through various channels and platforms, emphasizing the increasing importance of delivering exceptional customer experiences in the digital space. Addressing this demand, artificial intelligence (AI) emerges as a valuable solution for enhancing the digital experience and providing personalized content. By leveraging AI, marketers can tap into the vast reservoir of customer-curated data, extracting valuable insights to inform and optimize their strategies.

Keiningham (2020): AI engineering holds transformative potential, revolutionizing the way businesses deliver services and products to their customers. The field of digital marketing automation has reached new heights of dynamism, enabled by advanced AI technologies. By analysing buyer behaviour, AI-driven insights lead to highly accurate predictive results.

Yussaivi (2021): When artificial intelligence is combined with human-generated data, companies can establish trust in their digital platforms and elevate customer experiences to a new level of personalization and satisfaction. This deep integration of AI in digital marketing opens up exciting opportunities for businesses to excel in a rapidly evolving and competitive landscape.

Barmada (2020): Despite this significant adoption of AI in web shops, there remains a paucity of research concerning the process of how consumers embrace and utilize these AI-powered platforms. To address this gap, this study adopts the Technology Acceptance Model (TAM) as a theoretical framework, aiming to investigate and understand the factors influencing consumers' acceptance and usage of AI-infused web shops. By exploring consumer behaviour in this context, valuable insights can be gained to inform businesses on optimizing their AI implementations and better meet the needs of their customers in the rapidly evolving digital marketplace.

Davenport (2018): Following the redefined theoretical model, a nested model was created and examined, building upon the TAM framework. This nested model, also rooted in TAM, aimed to explore and validate consumer acceptance of Artificial Intelligence in online shopping. The TAM proved to be a well-suited and widely utilized basis for investigating this aspect of consumer behaviour.

Dumitriu (2018): The significant role of trust in influencing consumer attitudes towards the adoption and utilization of Artificial Intelligence in the context of online shopping. Trust emerged as a critical factor that shaped consumers' perceptions and acceptance of AI-powered solutions in their online shopping experiences. This valuable insight sheds light on the importance of building trust in AI implementations to effectively engage and satisfy online shoppers.

Aranyossy (2016): The extensively adopted Technology Acceptance Model (TAM) proved to be well-suited as a theoretical framework for studying consumer acceptance of Artificial Intelligence in the realm of online shopping. Notably, trust emerged as a significant determinant influencing consumer attitudes towards AI.

Asling (2017): In the context of attitudes and behavioral intentions, the study revealed that perceived usefulness held greater importance than perceived ease of use. In other words, consumers' perceptions of how AI technology can benefit them in their online shopping experiences had a more substantial impact on their attitudes and likelihood of engaging with AI-powered platforms than the ease of using such technology.

Abubakar (2019): The integration of big data-powered artificial intelligence and the process of external knowledge creation play a crucial role in shaping B2B marketing rational decision-making. The study highlights the significant impact of customer knowledge creation, user knowledge creation, and external knowledge creation on this decision-making process.

Alvesson (2018): That B2B marketing rational decision-making itself has a substantial effect on firm performance. In essence, the effective utilization of big data-driven AI, along with the active creation and integration of external knowledge, influences decision-making in B2B marketing, which, in turn, contributes significantly to a firm's overall performance.

Balducci (2021): This study emphasizes the significance of big data-powered artificial intelligence in three key paths: customer knowledge creation, user knowledge creation, and external knowledge creation. Each of these paths has been found to hold considerable importance in the context of B2B marketing rational decision-making.

Gunasekaran (2019): The integration of big data-powered AI significantly impacts customer knowledge creation. Secondly, the utilization of big data-driven AI also plays a crucial role in fostering user knowledge creation. Lastly, big data-powered AI has a noteworthy influence on external knowledge creation.

Dwivedi (2019): The research findings highlight the substantial effects of customer knowledge creation, user knowledge creation, and external knowledge creation on B2B marketing rational decision-making processes. Moreover, it was observed that the path of B2B marketing rational decision-making significantly affects a firm's overall performance. Taken together, these insights underscore the critical role of big data-driven AI in shaping decision-making in B2B marketing and its ultimate impact on firm performance.

Chatterjee (2020): The integration of artificial intelligence with customer relationship management (CRM) systems has brought about a revolutionary change in how organizations analyse vast amounts of customer data. To effectively navigate the opportunities and challenges arising from this transformation, organizations are actively developing competencies and refining processes to enhance their agility, aligning them with the artificial intelligence customer service system (AICS) and broader digitalization landscape. In this research, the focus is on identifying the factors that influence the adoption of an AI-integrated CRM system (AICS) within agile organizations as an integral part of their digitalization strategy.

Nelson (2020): The study's conclusive outcomes hold significant practical implications for organizations, providing valuable insights into the factors that influence the adoption of AICS and its perceived value. Furthermore, the research identifies specific areas that warrant further investigation, offering clear and focused directions for future research endeavours in this field. This valuable knowledge can aid organizations in making informed decisions and developing effective strategies to leverage AICS technology effectively for their benefit.

OBJECTIVES:

1. To study the demographic profile of the respondents.

2. To explore the impact of experience, trust, & subjective norms of perceived usefulness.
3. To test the impact of all exogenous variables (Innovativeness, perceived ease of use, perceived usefulness, perceived enjoyment, & task technology fit) on attitude of the respondents.
4. To test the role of attitude in between the perceived usefulness & behavioral intention.
5. To measure the impact of attitude on behavioral intentions.

Hypothesis:

In this section, the researcher has developed hypotheses based on the stated objectives. This approach allows the researcher to make informed predictions about the relationships between the variables or constructs being studied. Formulating hypotheses enables logical assumptions to be made about the connections among the variables or constructs under investigation.

For this specific study, the hypotheses have been formulated to align with the predetermined objectives.

- H02: There is no significance impact of experience, trust, & subjective norms of perceived usefulness.
- H03: There is no significance impact of all exogenous variables (Innovativeness, perceived ease of use, perceived usefulness, perceived enjoyment, & task technology fit) on attitude of the respondents.
- H04: There is no significance role of attitude in between perceived usefulness & behavioral intention.
- H05: There is no significance impact of attitude on behavioral intentions.

RESEARCH METHODOLOGY:

This section delves into fundamental concepts that serve as the bedrock for the research methodology, which is indispensable for advancing the study. It furnishes readers with valuable understanding of the tools and techniques utilized by the researcher to gather and analyze data, enabling the derivation of precise conclusions from the study.

SOURCES OF DATA COLLECTION:

To achieve the study's goals, both primary and secondary data sources were used. For primary data, a carefully designed questionnaire was created with help from existing literature. The questionnaire was detailed in the previous section and aligned with the study's objectives.

In addition, secondary data from various sources like books, research articles, websites, and news articles was collected to better understand the theoretical concepts related to the study's topics. This information from secondary sources was used to support the evidence found in the study.

SAMPLE SIZE & SAMPLE TECHNIQUES:

The study utilized convenience sampling to distribute questionnaires randomly among a targeted group of individuals in specific and specialized areas. The questionnaires were handed out to carefully chosen respondents.

The researcher distributed 250 questionnaires to individuals who are online shoppers for data collection. Out of the 250 questionnaires, 20% of the responses were deemed invalid and were excluded from further analysis. As a result, the researcher obtained 200 valid responses, which accounts for a response rate of 80%. The final sample size for the study was determined to be 200 valid responses from the study area.

PILOT STUDY & RELIABILITY TEST:

The researcher conducted a pilot survey with 50 respondents from different companies, using 38 valid responses for the reliability test. Cronbach's Alpha was applied to each construct (excluding Section 1 for demographics), and items with Cronbach coefficients below 0.5 were removed to improve reliability. Refining the questionnaire based on the pilot survey ensured suitability for the study and enhanced the data collection's dependability and trustworthiness.

To determine the reliability threshold values for Cronbach's alpha coefficient, the researcher relied on previous studies. A coefficient above 0.7 indicates high reliability, while values ranging from 0.55 to 0.7 suggest acceptable reliability (Cuieford, 1965). **The test results are presented in the following table.**

TABLE 1: Reliability of the structured questionnaire

S.No	Major Sections		No. of Items	Construct wise Alpha coefficient	Second Order Alpha Coefficient
1	Characteristics of perceived usefulness		**15**	----	**0.958**
	1.1	Perceived usefulness	04	0.971	
	1.2	Experience	04	0.963	
	1.3	Trust	04	0.963	
	1.4	Subjective norms	03	0.936	
2	Perceived ease of use		**04**	**0.948**	----
3	Behavioral intention		**03**	**0.988**	----
4	Characteristics of Attitude		**13**	----	**0.928**
	4.1	Attitude	03	**0.928**	----
	4.2	Innovation	03	**0.909**	----
	4.3	Perceived enjoyment	03	**0.925**	----
	4.4	Task Technology Fit	04	**0.951**	----
Overall			35	**0.955**	

DATA ANALYSIS & INTERPRETATION

TABLE 2: Classification of the respondents based Demographic factors					
		Frequency	Percent	Valid Percent	Cumulative Percent
Age	Below 20 years	14	7.0	7.0	7.0
	20 - 30 years	79	39.5	39.5	46.5
	30 - 40 years	72	36.0	36.0	82.5
	40 - 50 years	24	12.0	12.0	94.5
	Above 50 years	11	5.5	5.5	100.0
	Total	200	100.0	100.0	
Gender	Male	122	61.0	61.0	61.0
	Female	78	39.0	39.0	100.0
	Total	200	100.0	100.0	
Marital Status	Married	158	79.0	79.0	79.0
	Un-Married	42	21.0	21.0	100.0
	Total	200	100.0	100.0	
Monthly income	10000-30000	7	3.5	3.5	3.5
	30001-50000	79	39.5	39.5	43.0
	50001-70000	48	24.0	24.0	67.0
	70001-90000	56	28.0	28.0	95.0
	Above 90000	10	5.0	5.0	100.0
	Total	200	100.0	100.0	
Educational Qualification	School Level	6	3.0	3.0	3.0
	Diploma	61	30.5	30.5	33.5
	Under Graduate	67	33.5	33.5	67.0
	Post Graduate	66	33.0	33.0	100.0
	Total	200	100.0	100.0	
Occupation	Agriculture	1	.5	.5	.5
	Business	69	34.5	34.5	35.0
	Employed in Private	56	28.0	28.0	63.0
	Employed in Government	65	32.5	32.5	95.5
	Professional	9	4.5	4.5	100.0
	Total	200	100.0	100.0	

Objective2: To explore the impact of experience, trust & subjective norms of perceived usefulness

TABLE 3: Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.718[a]	.515	.508	2.61822
a. Predictors: (Constant), subjective norms, trust, experience				

The model summary indicates that subjective norms, trust, and experience together explain about 71.8% of the changes in the outcome variable. These factors play a significant role, accounting for approximately 51.5% of the differences in the outcome. The model fits the data reasonably well, as the average difference between our predictions and the actual data points is around 2.6. Lower values are better, indicating better predictions. Overall, subjective norms, trust, and experience are important for understanding the outcome, but there might be other factors not considered in the model that also influence the outcome.

TABLE 4: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1429.404	3	476.468	69.506	.000b
	Residual	1343.591	196	6.855		
	Total	2772.995	199			
a. Dependent Variable: perceived_usefelness						
b. Predictors: (Constant), subjective norms, trust, experience						

The ANOVA table reveals the results of a regression model studying how "perceived usefulness" is related to subjective norms, trust, and experience, along with the constant. The model explains a large part of the data's variation (total sum of squares explained = 1429.404), and the significant F-statistic ($F = 69.506$, $p < 0.001$) confirms the model's relevance. Subjective norms, trust, and experience have a notable impact on perceived usefulness. However, there might be other factors not included in the model that also influence perceived usefulness, as shown by the remaining variability (residuals).

TABLE 5: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.055	.457		4.502	.000
	experience	.077	.059	.088	1.295	.197
	trust	.350	.068	.347	5.158	.000
	subjective norms	.501	.085	.389	5.925	.000
a. Dependent Variable: perceived_usefelness						

The regression coefficients show how experience, trust, and subjective norms are related to "perceived usefulness." Experience doesn't seem to have a big impact on perceived usefulness (p-value > 0.05). However, trust (coefficient = 0.350) and subjective norms (coefficient = 0.501) have a significant positive influence on perceived usefulness. When trust and subjective norms increase, perceived usefulness also tends to increase. Hence the null hypothesis is rejected.

11.3. Objective3: To test the impact of all exogeneous variables (Innovation, perceived usefulness, perceived ease of use, perceived enjoyment & task technology fit) on attitude of the respondents

TABLE 6: Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.956[a]	.913	.911	.84334
a. Predictors: (Constant), task_technology_fit, perceived_ease_use, innovation, perceived_usefelness, perceived_enjoyment				

The regression model has a strong fit with the data, showing a high correlation (R = 0.956) and explaining a substantial variance in the dependent variable "attitude" (R Square = 0.913). The predictors are robust in explaining the outcome variable, as indicated by the Adjusted R Square (0.911) being close to R Square. The model's predictions are accurate, with a low standard error of the estimate (0.84334). Overall, it is highly reliable and suitable for predicting attitudes using the given predictors.

TABLE 7: ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1453.203	5	290.641	408.651	.000[b]
	Residual	137.977	194	.711		
	Total	1591.180	199			
a. Dependent Variable: attitude						
b. Predictors: (Constant), task_technology_fit, perceived_ease_use, innovation, perceived_usefelness, perceived enjoyment						

The ANOVA results indicate that the regression model, with predictors (task-technology fit, perceived ease of use, innovation, perceived usefulness, perceived enjoyment), has a significant effect on the dependent variable "attitude" ($p < 0.001$).

TABLE 8: Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.155	.166		-.930	.353
	innovation	-.009	.032	-.009	-.299	.765
	perceived_ease_use	.005	.031	.007	.153	.878
	perceived_usefelness	.691	.023	.912	30.220	.000
	Perceived enjoyment	-.025	.067	-.024	-.366	.715
	task_technology_fit	.070	.037	.092	1.874	.062
a. Dependent Variable: attitude						

The regression model found that perceived usefulness (Beta = 0.912, $p < 0.001$) and task-technology fit (Beta = 0.092, $p = 0.062$) had significant positive effects on attitude. However, other predictors (innovation, perceived ease of use, perceived enjoyment) had no significant effects ($p > 0.05$). The intercept was also not significant ($p = 0.353$). In summary, perceived usefulness and task-technology fit were the main significant predictors of attitude, while the other predictors had no significant effects. Hence the null hypothesis is rejected.

11.4. Objective4: To test the role of attitude in between the perceived usefulness & behavioral intention.

11.4.1 To measure the impact of perceived usefulness on behavioral intention.

TABLE 9: Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.760[a]	.578	.575	1.86014
a. Predictors: (Constant), perceived_usefelness				

Interpretation: The regression model indicates a moderately strong positive correlation (R = 0.760) between perceived usefulness and the outcome variable. It explains 57.8% of the outcome's variability (R Square = 0.578), which remains similar after adjusting for predictors (Adjusted R Square = 0.575). The standard error of the estimate is 1.86014, showing predictions are about 1.86 units away from actual values on average. The model fits well, with perceived usefulness as a significant predictor.

TABLE 10: ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	936.770	1	936.770	270.733	.000[b]
	Residual	685.105	198	3.460		
	Total	1621.875	199			
a. Dependent Variable: behavioural intention						
b. Predictors: (Constant), perceived_usefelness						

ANOVA results show that the regression model is significant ($p < 0.001$). Perceived usefulness is a significant predictor of behavioral intention. The model explains a large portion of the variance in behavioral intention (R Square = 57.8%).

TABLE 11: Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.078	.312		3.461	.001
	perceived_usefelness	.581	.035	.760	16.454	.000
a. Dependent Variable: behavioural intention						

In this regression model, perceived usefulness has a significant positive effect on behavioral intention (Beta = 0.760, $p < 0.001$). For every one-unit increase in perceived usefulness, there is a corresponding increase of 0.760 units in behavioral intention. The constant term (intercept) is also significant (p = 0.001), representing the expected value of behavioral intention when perceived usefulness is zero.

11.4.2: To measure the impact of perceived useful ness and attitude on behavioral intention.

TABLE 12: Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.762[a]	.580	.576	1.85963
a. Predictors: (Constant), perceived_usefelness, attitude				

Interpretation: The regression model with perceived usefulness and attitude, along with the constant, strongly explains the dependent variable (R Square = 0.580, R = 0.762). The model fits the data well (Adjusted R Square = 0.576) with an average deviation of 1.85963 between predictions and actual data (Std. Error of the Estimate). Perceived usefulness and attitude are crucial predictors, but other factors not considered could also influence the dependent variable.

TABLE 13: ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	940.606	2	470.303	135.996	.000[b]
	Residual	681.269	197	3.458		
	Total	1621.875	199			
a. Dependent Variable: behavioural intention						
b. Predictors: (Constant), perceived_usefelness, attitude						

Interpretation: The ANOVA table shows a significant regression model that explains how "behavioral intention" relates to predictors perceived usefulness and attitude, along with the constant. The model effectively explains the variability in "behavioral intention" (F-statistic = 135.996, $p < 0.001$) using perceived usefulness and attitude as predictors (total sum of squares explained = 940.606). However, other factors not considered in the model could also influence the outcome.

TABLE 14: Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.089	.312		3.495	.001
	attitude	.164	.155	.162	1.053	.294
	perceived_usefelness	.463	.118	.605	3.935	.000
a. Dependent Variable: behavioural intention						

Interpretation: The regression model examines how attitude and perceived usefulness influe"behavioral intention." Perceived usefulness significantly impacts "behavioral intention" (coefficient = 0.463, $p < 0.001$), indicating that higher perceived usefulness leads to increased "behavioral intention." However, attitude (coefficient = 0.164, p = 0.294) does not have a significant effect on "behavioral intention." In summary, perceived usefulness is a crucial predictor for "behavioral intention," while attitude's influence is not significant in this model.

11.5. Objective5: To measure the impact of attitude on behavioral intentions.

TABLE 15: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.740[a]	.547	.545	1.92645
a. Predictors: (Constant), attitude				

The model examines the relationship between the dependent variable and the single predictor, attitude, along with the constant term. It shows a strong positive correlation (R = 0.740), with attitude explaining 54.7% of the variance (R Square = 0.547). The adjusted R Square (0.545) provides a reliable fit estimate. The standard error of the estimate is 1.92645. In conclusion, the regression model with attitude as the predictor has a strong relationship with the dependent variable, explaining a significant portion of its variance.

TABLE 16: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	887.054	1	887.054	239.020	.000[b]
	Residual	734.821	198	3.711		
	Total	1621.875	199			
a. Dependent Variable: behavioural intention						
b. Predictors: (Constant), attitude						

The ANOVA table shows that the regression model with attitude as the predictor significantly explains the variation in "behavioral intention" (F-statistic = 239.020, $p < 0.001$). Attitude plays a crucial role in predicting "behavioral intention."

TABLE 17: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.462	.308		4.752	.000
	attitude	.747	.048	.740	15.460	.000
a. Dependent Variable: behavioural intention						

The regression model shows that "behavioral intention" is strongly and positively influenced by attitude (coefficient = 0.747, $p < 0.001$). Higher attitude scores lead to increased "behavioral intention." The constant term (coefficient = 1.462) represents the predicted "behavioral intention" when attitude is zero. In conclusion, attitude is a crucial predictor for "behavioral intention," significantly influencing the outcome. Hence the null hypothesis is rejected.

FINDINGS:

1. The largest segment corresponds to the age group between 20 and 30 years old, comprising 39.5% of the total. Following closely, the second largest segment represents individuals between 30 and 40 years old, accounting for 36% of the group. The age group between 40 and 50years old forms the third largest segment, making up 12% of the total. The smallest segment is attributed to individuals above 50 years old, constituting 5.5% of the group. Lastly, the age group below 20 years old is shown as a separate segment, representing 7% of the total.
2. The bar chart depicts the gender distribution of 200 individuals, with two bars representing males (61%) and females (39%). The significantly longer bar for males on the vertical axis indicates their majority in the group, while the shorter bar for females signifies their smaller proportion. This visual representation makes it effortless to compare the number of males and females in the sample, highlighting the gender distribution among the 200 individuals.
3. The bar chart illustrates the marital status distribution of 200 individuals, with the largest segment representing married individuals (79%) and the second segment representing unmarried individuals (21%). This clear visual representation highlights that a significant majority (79%) are married, while the remaining 21% are unmarried, making it easy to grasp the distribution of marital status within the sample.
4. The bar chart shows the distribution of educational levels among the individuals in four categories. Post-graduate degree holders form the largest group at 33%, followed by undergraduates at 33.5%. Diploma holders represent a significant portion with 30.5%, while individuals who finished school account for the smallest proportion at 3%. The chart effectively highlights the educational background distribution within the sample, enabling easy comparison of the percentages in each category.
5. The cumulative percentage bar chart depicts the distribution of monthly income among individuals. The horizontal bar axis represents the cumulative percentage, while the vertical axis represents monthly income levels. The chart shows the income ranges from 0 to 10,000 per month, with 3.5% of individuals falling into the 10,000 to 30,000 range. The percentages rise as we move along the chart, with 43% earning up to 50,000, 67% up to 70,000, and 95% up to 90,000 per month. The rightmost part of the chart represents the income range above 90,000 per month, comprising 5% of individuals. This visual representation allows for easy comparison of the cumulative percentage of individuals earning up to specific income levels, effectively illustrating the monthly income distribution within the group.
6. The bar chart presents the distribution of occupations among the individuals in four sectors. The smallest sector comprises individuals working in agriculture, accounting for 0.5% of the total. The second sector represents those involved in business, making up 35% of the group. The third sector corresponds to individuals employed in the private or government sectors, constituting 63% of the total. The largest sector represents individuals in professional occupations, comprising 4.5% of the group. This visual representation enables easy comparison of the percentage of individuals in each

occupation category, providing a clear understanding of the diverse occupational backgrounds within the sample.

7. The model summary indicates that subjective norms, trust, and experience together explain approximately 71.8% of the changes in the outcome variable. These factors account for about 51.5% of the differences in the outcome, highlighting their importance. The model shows a reasonably good fit with an average difference of around 2.6 between predictions and actual data points, suggesting favorable predictions. However, it's essential to consider other unaccounted factors that may also influence the outcome. While subjective norms, trust, and experience are significant explanatory variables, exploring additional factors can provide a more comprehensive understanding of the outcome.
8. The ANOVA table shows the results of a regression model studying the relationship between "perceived usefulness" and subjective norms, trust, experience, and the constant. The model explains a large portion of the data's variation (total sum of squares explained = 1429.404), and the significant F-statistic ($F = 69.506$, $p < 0.001$) confirms the model's relevance, indicating that subjective norms, trust, and experience have a notable impact on perceived usefulness. However, the presence of residual variability suggests the influence of other unaccounted factors on perceived usefulness. In summary, the regression model is significant, explaining much of the data's variation, but considering other unexplored factors is essential for a comprehensive understanding of perceived usefulness.
9. The regression analysis reveals that "perceived usefulness" is influenced significantly by trust and subjective norms, with coefficients of 0.350 and 0.501, respectively. As trust and subjective norms increase, perceived usefulness tends to increase as well. However, experience does not have a statistically significant impact on perceived usefulness (p-value > 0.05), suggesting its limited role in influencing the outcome. In conclusion, this analysis emphasizes the crucial positive roles of trust and subjective norms in shaping perceived usefulness, providing valuable insights to enhance user experiences across various contexts.
10. The model, incorporating task technology fit, perceived ease of use, innovation, perceived usefulness, and perceived enjoyment as predictors, exhibits strong explanatory power, explaining approximately 91.3% of the dependent variable's variation. These predictors show significant positive correlations ($R = 0.956$) with the outcome, confirming their influential role. The model's goodness-of-fit is high, with an Adjusted R Square of 0.911, indicating a close fit to the data. Additionally, the low standard error of the estimate (0.84334) demonstrates the model's accurate predictions. Overall, this combination of predictors is highly reliable in understanding and predicting the outcome, providing valuable insights for decision-making and optimization in the studied context.

Conclusion:

In conclusion, AI plays a crucial role in shaping the online shopping experience for mobile phones, as evident from the regression models and ANOVA tables. AI-driven technologies, such as personalized recommendations and chatbots, enhance user experiences and positively influence customer attitudes. Sentiment analysis tools help monitor feedback and adapt marketing strategies to meet customer preferences. While AI improves convenience and efficiency, addressing potential concerns and unexplored factors is essential for a balanced and customer-centric approach. Overall, AI is a valuable asset in online shopping, offering opportunities for marketers to optimize strategies and meet evolving customer needs effectively.

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