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Predictive Analysis of Determinants impacting Buying Intentions of Groceries using Mobile-Commerce

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ABSTRACT

The Mobile-Commerce industry experienced a momentous shift resulting in to proliferation of data and predictive analytics. Predictive analysis plays a crucial role in forecasting changes and understanding consumer preferences, which in turn aids in analyzing consumers' purchasing power. Predictive analysis is a process of assessing historical data, statistical models, and machine learning techniques to predict the future trends. Predictive analytics processes large datasets, consumer sentiment data, and demographic information to support future demand forecasting and strategic decision-making. The objective of the research is to develop a comprehensive statistical regression model to analyze the obtained data in order to foresee consumer preferences, behavioral buying pattern, enabling businesses to tailor improved customer satisfaction, strengthening competitive positioning

Keywords: Predictive Analysis, Mobile-Commerce, Consumer Intention, Statistical Regression Model

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INTRODUCTION:

Mobile Commerce is a huge shift for online retail shopping particularly in groceries segment. The first consumer preference is shopping directly through mobile application. (Khrais & Shidwan, 2020) Mobile Commerce is personalised, tech-driven, consumer friendly applications integrated with highly optimised helps in making faster and accurate decisions. Referencing the statistics (as of 2024), over 65% of all Electronic Commerce sales comes from mobile-devices. According to the report by (India Online Grocery Market Size, Share & Trends Analysis Report, 2024) Indian Online Grocery Market Outlook, the Indian online grocery market size reach $11.4 billion in 2024 and the researchers expects the market to reach $96.3 billion by 2033, exhibiting CAGR of 25.385 during 2025-2033. The scalability factors including smartphone penetration, change and evolving lifestyle, and initiatives in promoting digitalisation. According to the (India Online Grocery Market 2024-2034: Trends & Growth Insights, 2024) India Online Grocery Market 2024-2034: Trends & Growth Insights report, market players are no longer limiting their focus to Tier 1 cities. They are now actively expanding their presence and strengthening logistics and supply chain networks to tap into untapped opportunities in Tier 2 and Tier 3 cities.

An era of Artificial Intelligence, empowering richer (Liao & Chen, 2021) Mobile Commerce experiences—from personalized interactions and smart recommendations to seamless AI-driven search mechanisms that enhance engagement and drive higher conversions. Voice based search gaining the traction, offering hands-free experience for the consumer. (Alkudah & Almomani, 2024)The increased and informed development and adoption of technologies have significantly improved that in turn has led to the development of an influenced Mobile Commerce processes. Artificial Intelligence hasn't just improved online shopping-it has transformed the way businesses think, operate, and connect in an increasingly fast-paced world. (Raji, et al., 2024) A thorough understanding and recognition of consumer buying intention in today's competitive landscape is critical for businesses and marketing divisions, allowing them to maintain a competitive edge, optimize customer satisfaction, and maximize profitability. Business verticals increasingly rely on data, trends, patterns, and insights to enable informed decision-making, minimize uncertainties, enhance operational efficiency, and maintain a competitive edge. This is possible using Predictive Analytics.

(Kumar & Garg, 2018) Predictive Analytics is a branch of data analytics that focuses on forecasting future events and behaviours based on historical data. (Parmar, Sharma, & Agarwal, 2022) It is a multidisciplinary field that combines elements of statistics and probability, machine learning and artificial intelligence (ML&AI), data mining, and big data. Common techniques employed in predictive analytics include regression analysis, time series forecasting, neural networks, and other advanced modelling methods. (Agu, Chiekezie, Abhulimen, & Obiki-Osafiele, 2024) Predictive Analytics helps break down complex datasets to extract meaningful insights. The research investigates the factors influencing consumer buying intention and employs statistical regression model to conduct predictive analysis.

While prior studies have examined factors such as ease of use, perceived usefulness, trust, and risk in shaping consumer buying behaviour, at certain instance they often overlook variations across demographics, purchasing habits, and purchasing power. Addressing these gaps offers the potential to generate actionable insights for business decision-makers, drive targeted digital engagement, and inform technology adoption strategies that deepen understanding of Mobile-Commerce behaviour.

REVIEW OF LITERATURE

The shift towards the Mobile Commerce is observed due to a several reasons and not limited to psychological, social, economic, and technological influences. Mobile Commerce provides a seamless user experience which influences buying intention of the consumer. (Ghai & Tripathi, 2019) Buying Intention can be determined by several other key factors including convenience, ease of purchase, past experiences, affordability, and quality. These variables play an important role in shaping the decision.

(Nodirovna & Sharif o'g'li, 2024) Personalized experience of Mobile Commerce also helps in making the key decision, and it is not only simplifying the experience but also accelerate the process of online purchase. (Kler, Prasad, Prasad, Goswami, & Mitra, 2022) Brand image plays a critical role in building the customer attraction which aids in predicting their expectations and subsequently influences buying intentions. The product availability of offered by different marketers helps in making a meaningful evaluation, and makes more informed decision.

(Guliyeva, 2022) Consumer buying intention are also influenced factors such as brand positioning, association, performance measures, pricing attributes, and brand loyalty. (Hamad & Schmitz, 2019) Demographic characteristics significantly influenced the buying intentions and hence shopping orientation affects the preferences. (Eriksson & Stenius, 2022) Health concern also considered as a significant factor influencing consumer buying. Increased in health awareness has strengthened the consumer preference. (N Ramya & Ali, 2016) Facilitators play an important role in understanding the diverse needs and expectations of consumers across various demographic segments. By enhancing the functionality and usability of mobile applications, they contribute to a seamless user experience that simplifies the purchasing process. (Davis, 1989) Perceived ease of use and perceived usefulness are considered primary determinants of consumer acceptance of widely adopted technologies. These constructs significantly influence users' attitudes toward technology adoption and play a crucial role in shaping behavioral intentions.

(Zuelseptia, Rahmiati, & Engriani, 2018) It usefulness works on the idea of consumer belief, attitude, and intentions to adapt the technology. These perceptions influence tech adaptation and contribute in enhancing consumer buying intentions.

(Renny, Guritno, & Siringoringo, 2013) (Cho & Sagynov, 2015) (Gunawan, Mukti Ali , & Nugroho, 2019) Perceived Usefulness significantly helps in shaping the attitude towards online buying and therefore strengthen buying intentions. It exhibited a statistically significant influence on customer purchase intention, indicating its critical role in shaping consumers' behavioral outcomes in the online purchasing context. It also demonstrated a comparatively stronger effect on consumers than the other factors examined in the study.

(Renny, Guritno, & Siringoringo, 2013) (Nayak, Bhatt, & Nagvadia, 2021) (Uzun & Poturak, 2014) Perceived Trust is one of the key factors that significantly influences buying intention of the consumer in the context of online shopping. A higher level of trust reduces perceived risk and uncertainty, thereby strengthening consumers' willingness to engage in online transactions and increasing their purchase intentions. Trust positively influences buyers' attitudes toward the usability of Mobile-Commerce but hesitation regarding online transactions often stems from concerns about transaction security.

(Kutty, Vasudevan, & Aslan, 2024) Price and product quality are also significant determinants of consumer behavior; however, they rank slightly below convenience and trust in terms of their relative influence.

(Annisa, Siahaan, & Lumbanraja, 2024) Trust, considered as a moderating variable, significantly strengthens the relationship between Perceived Usefulness and online shopping behavior. (Iriani & Andjarwati, 2020) (Ou , Chen, Tseng, & Lin, 2022) Uncertainties may arise due to product- or technology-related factors, potentially impacting the buying cycle negatively. In the context of mobile commerce, privacy and financial risks are considered the most significant concerns for consumers. Both the direct and indirect effects of Perceived Risk indicate its significant influence on buyers'. (Rajan, Sammansu, & S.Suresh, 2021) Consumer Satisfaction is recognized as a key indicator of overall success and the effectiveness as a strategic tool.

DATA AND METHODOLOGY

The study aims to employ a Statistical Regression Model to examine predictive relationships among key determinants of consumer buying intention. The analytical framework incorporates demographic variables including age, gender, education, and family size—through dummy coding—alongside core perceptual constructs, including Perceived Ease of Use (PEU), Perceived Usefulness (PU), Perceived Trust (PT), and Perceived Risk (PR). These variables are analyzed in relation to Buying Intention (BI), enabling a comprehensive assessment of the factors influencing consumer decision.

Considering Buying Intention as the dependent variable and other as the independent variables:

$$BI = \alpha + \beta1*PEU + \beta2*PU + \beta3*PT + \beta4*PR + \beta5*AD1 + \beta6*AD2 + \beta7*AD3 + \beta8*GD1 + \beta9*FD1 + \beta10*FD2 + \beta11*ED1$$

Where, BI = Buying Intentions, PEU = Perceived Ease of Use, PU = Perceived Usefulness, PT = Trust, PR = Perceived Risk.

Dummy Variables:

AD1 = 1 If Age group between 25 – 34 years;

= 0 Otherwise

AD2 = 1 If Age group between 35 – 44 years;

= 0 Otherwise

AD3 = 1 If Age group 45 & above;

= 0 Otherwise

GD1 = 1 If Gender is Male;

= 0 Otherwise

FD1 = 1 If Family size 2 – 3 people;

= 0 Otherwise

FD2 = 1 If Family size 4 – 5 people;

= 0 Otherwise

ED1 = 1 If Education is PG;

= 0 Otherwise

A structured questionnaire was designed to collect the data on demographic and non-demographic variables. The data on PEU, PU, PT, PR, and BI are collected using a 5-point Likert Scale (1 – Strongly disagree; 5 – Strongly agree). The sample of 123 respondents was selected using a random sampling procedure. The stepwise regression analysis was employed using an open-source software Gretl, wherein the non-significant variables were eliminated step-by-step based on higher p-values of the coefficients. Both the models were tested for goodness of fit based on R-square value and F statistics. Also, the multicollinearity between the independent variables were tested using Variance Inflation Factor and Conditional Index. The variables includes: Perceived Ease of Use (PEU), Perceived Usefulness (PU), Perceived Trust (PT), Perceived Risk (PR), and Buying Intentions (BI)

RESULTS AND DISCUSSION

The sample composition based on various demographic attributes (age, gender, family size and education) and corresponding scores on perceived ease of use, perceived usefulness, perceived risk, perceived trust, and buying intentions are presented below in TABLE II based on mean and standard deviation:

Table II Sample Composition and Summary Statistics showing Mean and Standard Deviation

	Sample	*PEU*	*PU*	*PR*	*PT*	*BI*
Age						
18-24	14	3.5446 (0.4483)	3.3928 (0.8513)	3.5408 (0.5408)	3.2500 (0.6193)	3.4047 (0.9444)
25-34	71	3.6144 (0.4420)	3.5187 (0.5028)	3.3702 (0.6294)	3.5000 (0.5534)	3.5915 (0.5045)
35-44	33	4.0037 (0.5408)	3.8131 (0.5617)	3.1818 (0.8027)	3.6161 (0.7459)	3.8989 (0.7794)
> 45	5	4.0000 (0.3852)	3.8000 (0.2173)	3.6285 (0.4694)	3.7333 (0.4013)	3.7333 (0.3651)
Gender						
Male	83	3.6957 (0.5410)	3.5722 (0.6193)	3.3648 (0.6960)	3.4578 (0.6537)	3.6184 (0.7064)
Female	40	3.7906 (0.4007)	3.6416 (0.4692)	3.3178 (0.6226)	3.6250 (0.5226)	3.7416 (0.5363)
Family Size						
1 Person	5	3.2750 (0.5548)	3.3000 (0.4472)	2.8857 (0.6259)	4.5000 (0.4564)	3.9333 (0.1490)
2-3 Persons	44	3.7727 (0.4298)	3.6287 (0.5980)	3.4090 (0.6961)	3.4015 (0.5502)	3.7045 (0.6151)
4-5 Persons	74	3.7297 (0.5262)	3.5945 (0.5674)	3.3455 (0.6544)	3.5112 (0.6102)	3.6126 (0.6979)
Education						
≤ Graduate	72	3.7065 (0.4991)	3.5902 (0.6197)	3.3888 (0.6904)	3.4884 (0.6472)	3.6157 (0.6296)

	Sample	***PEU***	***PU***	***PR***	***PT***	***BI***
PG	51	3.7549 (0.5049)	3.6013 (0.5078)	3.2941 (0.6448)	3.5457 (0.5764)	3.7189 (0.6940)
Total	123	3.7266 (0.5000)	3.5948 (0.5738)	3.3495 (0.6708)	3.5121 (0.6170)	3.6585 (0.6562)
Source: Computed by authors based on primary data.						

From TABLE II, it can be seen that for the total 123 respondents, the mean scores of independent variables perceived ease of use is the highest (3.7266), followed by perceived usefulness (3.5948), perceived trust (3.5121), perceived risk (3.3495) and buying intention (3.6585), The mean score of perceived ease of use also appears to be highest in all the other subcategories of demographic attributes as well. Thus, perceived ease of use may be considered as the one of the most significant factors impacting online mobile-commerce of grocery shopping.

Table III Stepwise Regression Output (Dependent Variable: BI)

Particulars	***Coefficient***	***Std. Error***	***t-ratio***	***p-value***	***VIF***	***CI***
const	−0.0089	0.3391	−0.026	0.9789	--	1.000
PEU	0.3376	0.1140	2.960	0.0037 ***	1.870	15.115
PT	0.4255	0.0773	5.502	<0.0001 ***	1.309	17.757
PU	0.2544	0.1039	2.448	0.0158 **	2.044	25.401

Goodness of Fit Indices			
R-squared	0.5192	Adjusted R-squared	0.5070
F (3, 119)	42.8353	P-value(F)	7.59e-19

Notes:

Variance Inflation Factors (VIFs): Values > 10.0 may indicate a collinearity problem

Conditional Index (CI): Values > 30.0 may indicate a collinearity problem

* Significant at 10% ls; ** Significant at 5% ls; *** Significant at 1% ls.

Source: Authors Computation based on Primary Data Using Open-Source Software Gretl

The TABLE III given above, shows the results of stepwise regression model. It is seen that the demographic attributes age, gender, family size and education are significantly determining the buying intentions (BI). Perceived Risk is not significant and hence eliminated. It can be seen that the coefficients in the model are significant and are with correct sign. The variables perceived ease of use (PEU) and perceived trust (PT) are significant at 1% level and perceived usefulness (PU) is significant at 5% level. The value of R2 is 0.5192 indicating moderately high value and F statistics is significant at 1% level of significance. Thus, the model also fulfils the criteria of goodness of fit. Also, the variables are tested for possible multicollinearity using variance inflation factor (VIF) and conditional index (CI). It is found that there is no problem of multicollinearity existing between the variables as the values are less than the threshold values. Thus, it can be interpreted that only three variables PEU, PT and PU are significantly impacting the buying intentions (BI).

CONCLUSION

The results of the stepwise regression analysis demonstrate the model's adequacy as a predictive framework for consumer buying intention. The specification comprises of the determinants (Wafiyyah & Kusumadewi, 2021) (Doshi, 2018)Perceived Ease of Use, (Wafiyyah & Kusumadewi, 2021) Perceived Trust, and (Wafiyyah & Kusumadewi, 2021) (Doshi, 2018) (Smith, 2008)Perceived Usefulness are responsibly robust. The underlying model explains 51.92% variance in buying intention, indicates strength with the behavioural research. The F-statistics confirms the joint significance of the predictors, which in-turn validates the model is good fit. VIF and CI confirms that there is no significant problem of multicollinearity, this helps in ensuring stability and reliability of coefficient estimates. The elimination of non-significant variables - Perceived Risk, improves model parsimony and reduces estimation bias. Together with the results establishes above, this statistical stepwise regression model validates the predictive instrument. Therefore, the model explains statistical reliable foundation for forecasting, offering implication for data-driven strategic and inclusive decision making for consumer buying intention.

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