Technology Uptake and Socio-demographic Factors: An Empirical Analysis of Unstructured Retailers and Consumers in Kolkata, West Bengal

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Abstract:
This study investigates the influence of socio-demographic factors and occupational roles on technological knowledge, acceptance, and use among consumers and unstructured retailers in Kolkata, West Bengal, India. A sample of 141 participants was surveyed, and statistical analyses were employed to assess correlations and group differences. The findings revealed significant positive correlations between education level, income, experience with technology, and technological knowledge and acceptance. A significant negative correlation was found between age and technical expertise, but no significant correlation was detected between gender and technology acceptance. Occupational role significantly influenced technology usage, perceptions of automatic systems, Time spent learning new technology, and knowledge about credit/debit card payments. The study's results underscore the need for tailored education and training programs targeting different demographic and occupational groups to enhance technical knowledge and acceptance. Despite its geographical focus on Kolkata, this research provides insights with broader implications for understanding the digital divide and fostering an inclusive technological landscape.

Keywords: Technological Knowledge, Technological Acceptance, Socio-demographic Factors, Occupational Roles, Education, Income, Experience with Technology, Unstructured Retailers, Consumers, Kolkata

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1 INTRODUCTION

The rapid advancement of technology has transformed how individuals interact, communicate, and conduct various aspects of their lives [1]. Understanding the factors that shape individuals' technological knowledge, acceptance, and usage has become increasingly crucial in today's digital era [2]. Socio-demographic factors, such as education level, income, age, and gender, along with occupational roles, have been recognized as influential determinants in this context [3]. Therefore, this research investigates the relationship between these socio-demographic factors, occupational roles, technological knowledge, acceptance, and use among unstructured retailers and consumers in Kolkata, West Bengal, India.

As the digital divide persists, it is vital to comprehend how socio-demographic factors influence individuals' technological knowledge and acceptance. Previous studies have indicated that higher education and income levels are associated with greater technological literacy and proficiency [1]. Furthermore, age has been identified as a significant factor, with younger individuals often displaying higher levels of technical familiarity [2]. Gender differences have also been observed, with some studies highlighting variations in technology usage and acceptance between males and females [3]. Occupational roles further shape individuals' experiences with technology. Different occupational groups may have varying levels of exposure, access, and utilization of technology. Retailers, particularly those in unstructured settings, may rely on technology for inventory management, point-of-sale systems, and customer engagement. On the other hand, consumers have varying degrees of technological adoption for personal use [4]. Investigating the influence of occupational roles on technology acceptance and usage provides valuable insights for designing targeted interventions and strategies tailored to different professional landscapes.

This study focused on unstructured retailers and consumers in Kolkata, West Bengal, India. By examining the relationship between socio-demographic factors, occupational roles, and technological knowledge, acceptance, and use within this population, we aim to understand the complex dynamics involved comprehensively. The findings from this study will contribute to the existing body of knowledge, providing insights into how socio-demographic factors and occupational roles intersect to influence technology adoption and usage patterns. In the subsequent sections, we present the results of our data analysis, including correlations between socio-demographic factors and technological knowledge, acceptance, and use. We also explore the differences in technology usage and opinions based on occupational roles. The implications of these findings for bridging the digital divide and fostering an inclusive technological landscape will be discussed. Finally, we highlight the study's limitations and suggest areas for future research.

2 LITERATURE BACKGROUND

Technology uptake plays a pivotal role in shaping societies and economies, impacting various sectors. Numerous studies have examined the relationship between technology uptake and socio-demographic factors, aiming to understand the underlying dynamics that drive technological adoption in different contexts. One such study conducted by Mathur and Singh focuses on understanding the relative influence of socio-demographic factors on technology adoption in developing nations like South Africa [5]. The authors argue that while human, social, economic, political, and other factors undoubtedly impact ICT adoption, it is important to establish these factors' significance in developing nations' context. According to Mathur and Singh, understanding the relative influence of socio-demographic characteristics is crucial for informing policy decisions and allocating resources effectively in developing countries [6].

Another study by Prestin et al. explores the impact of socio-economic factors on the adoption of health information technologies. The authors highlight the digital divide concept, which refers to disparities in technology adoption based on factors such as age, gender, and education. Prestin et al. argues that despite internet access's widespread availability, these socio-demographic factors continue to predict the adoption of health information technologies (Haluza et al., 2016). To address this issue, the authors suggest documenting socio-economic factors influencing national prevalence, trends, and user profiles of online health activities (Haluza et al., 2016) [5]. This will facilitate the development of strategies that ensure equal opportunities for accessing computer and internet technologies, particularly among older individuals. In the context of unstructured retailers and consumers, technology uptake is also influenced by socio-demographic factors. Research conducted by Kaur and Sharma explores the influence of socio-demographic characteristics on technology adoption among unstructured retailers and consumers. Their study reveals that socio-demographic factors such as age, occupation, education level, and income significantly influence unstructured retailers' and consumers' technology adoption behaviour. The study conducted by Kaur and Sharma found that age is a critical socio-demographic factor influencing technology adoption among unstructured retailers and consumers. Older individuals may be less likely to adopt technology due to lower education or income levels and a lack of familiarity or comfort with technology [8].

Furthermore, occupation was another important socio-demographic factor influencing technology adoption among unstructured retailers and consumers. Occupation can impact technology adoption as different occupations may require different levels of technological literacy and access to resources [9]. Education level emerged as another significant socio-demographic factor influencing technology adoption among unstructured retailers and consumers [10]. Higher levels of education are often associated with greater technological literacy and familiarity, making individuals more likely to adopt new technologies. Additionally, income was a crucial socio-demographic factor influencing technology adoption among unstructured retailers and consumers [11]. Individuals with higher incomes may have more significant resources and access to technology, making them more likely to adopt new technologies. In addition to these socio-demographic factors, the study by Kaur and Sharma also highlighted the importance of gender in technology adoption among unstructured retailers and consumers [12].

3 METHODOLOGY

1. Research Design: This study utilized a cross-sectional design to investigate the relationship between socio-demographic factors, occupational roles, and technological knowledge, acceptance, and use among unstructured retailers and consumers in Kolkata, West Bengal. The cross-sectional design allowed for a snapshot of data collected at a specific point in Time.

2. Sampling: The target population for this study consisted of unstructured retailers and consumers in Kolkata. The sample size was 141 participants, representing the total

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population. Convenience sampling was employed to select participants based on their availability and willingness.

3. Data Collection: Primary data was collected through a structured questionnaire administered to participants. The questionnaire included demographic information, such as education level, income, age, and gender. Participants were also asked to provide information regarding their experience with technology, technology acceptance, and technological usage.

4. Statistical Analysis: The collected data underwent statistical analysis to examine the relationships and differences between variables. Correlation analysis, specifically Spearman's rank correlation coefficient (rho), assessed the relationships between socio-demographic factors and technological knowledge, acceptance, and use. Group differences were examined using independent samples t-tests and Kruskal-Wallis tests.

5. Ethical Considerations: Ethical considerations were considered throughout the research process. Informed consent was obtained from all participants before their participation. Confidentiality and anonymity were maintained by assigning unique identifiers to each participant and ensuring that the data was used only for research purposes.

4 RESULT & DISCUSSION

The Results and Discussion section presents key findings from data analysis of unstructured retailers and consumers in Kolkata, West Bengal. Significant positive correlations were found between education level, income, experience with technology, and technological knowledge and acceptance. Age showed a significant negative correlation with technical knowledge, while gender did not significantly influence technology acceptance. Occupational roles affected technology usage, perceptions of automatic systems, learning time, and credit/debit card payment knowledge. These insights inform targeted interventions to bridge the digital divide and promote inclusivity in technology adoption.

4.1 Education Level and Technological Knowledge

Table 1, we can interpret the statistical analysis as follows: The null hypothesis posited no correlation between education level and knowledge about technology. However, the alternative view suggested a correlation between these two variables. According to our analysis, Spearman's rho indicated a significant positive correlation of 0.696 ($p < 0.01$) between education level and the REGR factor score 1 for analysis 1 (technology knowledge). Consequently, the null hypothesis is rejected, and the alternative hypothesis is accepted. Therefore, the data suggest that an individual's education level positively influences their technology knowledge.

Table 1: Correlation Between Education Level and Knowledge about Technology

-	Education Level	REGR Factor Score 1 for Analysis 1
Education Level	1.000	0.696**
Sig. (2-tailed)	-	<0.001
N	141	141
REGR Factor Score 1 for Analysis 1	0.696**	1.000
Sig. (2-tailed)	<0.001	-
N	141	141

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

4.2 Income Level and Technological Knowledge

The null hypothesis suggested no correlation between income level and an individual's knowledge of technology. However, the alternative hypothesis proposed a correlation between these two variables. The Spearman's rho analysis showed a significant positive correlation of 0.455 ($p < 0.01$) between income level and the REGR factor score 1 for analysis 1 (technology knowledge). Therefore, the null hypothesis is rejected, and the alternative hypothesis is accepted. This data implies that an individual's income level positively influences technology knowledge.

Table 2: Spearman's Correlation between Income Level and Technological Knowledge

-	Income Level	REGR Factor Score 1 for Analysis 1
Income Level	1.000	0.455**
Sig. (2-tailed)	-	<0.001
N	141	141
REGR Factor Score 1 for Analysis 1	0.455**	1.000
Sig. (2-tailed)	<0.001	-
N	141	141

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

4.3 Age and Technological Knowledge

The null hypothesis suggested no correlation between age and an individual's knowledge of technology. However, the alternative hypothesis proposed a correlation between these two variables. Spearman's rho analysis showed a significant negative correlation of -0.283 (p <

0.01) between age and the REGR factor score 1 for analysis 1 (technology knowledge). Therefore, the null hypothesis is rejected, and the alternative hypothesis is accepted. This data implies that as age increases, an individual's knowledge about technology tends to decrease.

Table 3: Spearman's Correlation between Age and Technological Knowledge

-	Age	REGR Factor Score 1 for Analysis 1
Age	1.000	-0.283**
Sig. (2-tailed)	-	0.001
N	141	141
REGR Factor Score 1 for Analysis 1	-0.283**	1.000
Sig. (2-tailed)	0.001	-
N	141	141

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

4.4 Experience with Technology and Technology Acceptance

The null hypothesis suggested no correlation between experience with technology and technology acceptance. However, the alternative view proposed a correlation between these two variables. According to the results of our Spearman's rho analysis, there is a significant positive correlation of 0.611 ($p < 0.01$) between experience with technology and the REGR factor score 1 for analysis 1 (technology acceptance). Therefore, the null hypothesis is rejected, and the alternative hypothesis is accepted. This suggests that greater experience with technology is associated with higher technology acceptance among individuals.

Table 5: Spearman's Correlation between Experience with Technology and Technology Acceptance

-	Experience with Technology	REGR Factor Score 1 for Analysis 1
Experience with Technology	1.000	0.611**
Sig. (2-tailed)	-	<0.001
N	141	141
REGR Factor Score 1 for Analysis 1	0.611**	1.000
Sig. (2-tailed)	<0.001	-
N	141	141

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

4.5 Gender and Technology Acceptance

The null hypothesis suggested no correlation between gender and technology acceptance, and the alternative hypothesis proposed a correlation between these two variables. According to Spearman's rho analysis, there is a correlation of 0.057 between gender and the REGR factor score 1 for analysis 1 (technology acceptance), which is not statistically significant ($p > 0.05$). Therefore, the null hypothesis is accepted, and the alternative hypothesis is rejected. This suggests that no correlation exists between gender and technology acceptance among individuals.

Table 6: Spearman's Correlation between Gender and Technology Acceptance

-	Gender	REGR Factor Score 1 for Analysis 1
Gender	1.000	0.057
Sig. (2-tailed)	-	0.503
N	141	141
REGR Factor Score 1 for Analysis 1	0.057	1.000
Sig. (2-tailed)	0.503	-
N	141	141

4.6 Technology Usage: Consumers vs Retailers

The null hypothesis proposed no difference in the frequency of technology usage based on whether the individual is a consumer or a retailer, while the alternative hypothesis suggested a difference. Given the p-value (<0.05) and t-value (5.322), we fail to accept the null hypothesis. There is a statistically significant difference in the frequency of technology usage based on role, with retailers having a higher mean use than consumers.

Table 7: Group Statistics

Role	N	Mean	Std. Deviation	Std. Error Mean
Consumer (Role 1.0)	82	3.098	1.0842	0.1197
Retailer (Role 2.0)	59	2.119	1.0681	0.1391

Table 8: Independent Samples Test (t-test Results)

Levene's Test for Equality of Variances	t-test for Equality of Means
F	Sig.
0.446	0.506

4.7 UPI Payments Knowledge: Business vs Job

The null hypothesis suggested no difference in knowledge about UPI payments based on the individual's occupation, while the alternative hypothesis proposed a difference. Given the p-value (>0.05) and t-value (0.577), we accept the null hypothesis. This suggests no statistically significant difference in knowledge about UPI payments based on the individual's occupation (Business v/s Job).

Table 9: Group Statistics

Occupation	N	Mean	Std. Deviation	Std. Error Mean
Business (Occ 2.0)	95	3.853	1.3446	0.1379
Job (Occ 3.0)	13	3.615	1.7097	0.4742

Table 10: Independent Samples Test (t-test Results)

Levene's Test for Equality of Variances	t-test for Equality of Means
F	Sig.
4.173	0.044

The null hypothesis suggested no difference in knowledge about Paytm/PhonePe/GPay payments based on the individual's occupation, while the alternative hypothesis proposed a difference. Given the p-value (>0.05) and t-value (1.120), we accept the null hypothesis. This suggests no statistically significant difference in knowledge about Paytm/PhonePe/GPay payments based on the individual's occupation (Student v/s Job).

Table 11: Group Statistics

Occupation	N	Mean	Std. Deviation	Std. Error Mean
Student (Occ 4.0)	5	4.600	0.5477	0.2449
Job (Occ 3.0)	13	3.692	1.7505	0.4855

Table 12: Independent Samples Test (t-test Results)

Levene's Test for Equality of Variances	t-test for Equality of Means
F	Sig.
23.457	0.000

4.8 Need for Automatic Systems

From this analysis, we reject the null hypothesis ($p < 0.001$, < 0.05). This indicates a difference between individuals with different occupations regarding their opinions on the need for automatic systems.

Table 13: Hypothesis Test Summary

Null Hypothesis	Test	Sig.	Decision
The distribution of "Do you think there is a need for automatic systems?" is the same across categories of occupation	Kruskal-Wallis Test	0.001	Reject the null hypothesis

4.9 Time Spent Learning New Technology

Given the p-value of 0.000 (<0.05), we reject the null hypothesis. It suggests a significant difference between individuals with different occupations regarding the Time spent learning new technology.

Table 14: Summary of Hypothesis Test Results

Hypothesis	Test	Significance	Decision
The distribution of 'Time spent learning new technology is the same across different occupations	Kruskal-Wallis Test	0.000	Reject the null hypothesis

4.10 Knowledge about Credit/Debit Card Payments

Given the p-value of 0.001 (<0.05), we reject the null hypothesis. It suggests a significant difference between individuals with different occupations regarding their credit/debit card payment knowledge.

Table 15: Summary of Hypothesis Test Results

Hypothesis	Test	Significance	Decision
The distribution of 'Knowledge about Credit/Debit Card Payments' is the same across different occupations	Kruskal-Wallis Test	0.001	Reject the null hypothesis

5 DISCUSSION

The following discussion explores the implications of our research findings derived from correlations and group difference analyses. The correlation matrix indicates significant relationships between specific pairs of variables. Our data demonstrated substantial positive correlations between education level and technological knowledge, income level and technological knowledge, and experience with technology and technology acceptance. It also established a significant negative correlation between age and technical knowledge. No significant correlation was found between gender and technology acceptance.

On the other hand, the group difference matrix highlighted significant disparities in technological usage between consumers and retailers, perceived need for automatic systems, Time spent learning new technology, and knowledge about credit/debit card payments across different occupational groups. No significant differences were found in knowledge about UPI payments and Paytm/PhonePe/GPay payments between other occupations. These findings illuminate the nuanced role of socio-economic factors, demographic characteristics, and occupational roles in influencing technological knowledge and acceptance, thereby providing a comprehensive understanding of the interplay between these factors in the context of technology usage and acceptance.

Table 16: Correlation Analysis Summary

Variable 1	Variable 2	Correlation Coefficient	Significant (Yes/No)
Education Level	Tech Knowledge	0.696	Yes
Income Level	Tech Knowledge	0.455	Yes
Age	Tech Knowledge	-0.283	Yes
Experience with Technology	Tech Acceptance	0.611	Yes
Gender	Tech Acceptance	0.057	No

Table 17: Group Difference Analysis Summary

Variable 1	Variable 2	Significant Difference (Yes/No)
Consumer vs Retailer (Role)	Tech Usage	Yes
Business vs Job (Occupation)	UPI Payments Knowledge	No
Student vs Job (Occupation)	Paytm/PhonePe/GPay payments Knowledge	No
Occupation	Need for Automatic Systems	Yes
Occupation	Time Spent Learning New Tech	Yes
Occupation	Knowledge about Credit/Debit Card Payments	Yes

In summary, our research findings underline the substantial impact of socio-demographic factors and occupational roles on technological knowledge, acceptance, and use. The data reflects that higher levels of education, income, and experience with technology correspond to a greater understanding and acceptance of technology. Simultaneously, technological knowledge appears to decrease as age increases, emphasizing the need for targeted tech literacy programs for older populations. Interestingly, there is no significant gender difference in technology acceptance, suggesting that the influence of gender may not be as pronounced in this context. Discrepancies were also noted in technology usage and opinions based on occupation, further supporting the idea that technological adaptability can vary significantly across different professional landscapes. These findings have significant implications, emphasizing the necessity of accounting for these factors in strategies to increase technology acceptance and literacy. They suggest tailored educational and training programs for different demographic and occupational groups to enhance technical knowledge and approval. As the world continues to digitize, understanding these dynamics becomes increasingly crucial. This research contributes valuable insights into this understanding, providing a nuanced perspective on the factors influencing technology acceptance and knowledge.

6 CONCLUSION

This research comprehensively explores the relationship between various socio-demographic factors, occupational roles, and the knowledge, acceptance, and use of technology. By conducting a survey amongst consumers and unstructured retailers in Kolkata, West Bengal, India, we have established significant associations and identified key areas for intervention. The results underline the importance of education, income, and technological experience as technological knowledge and acceptance drivers. The survey also found a negative correlation between age and technical knowledge, which underlines the necessity for dedicated efforts to enhance digital literacy in older age groups. Interestingly, gender did not emerge as a significant determinant of technology acceptance in our study. The occupational role influenced technology usage, opinions on automatic systems, Time spent learning new technology, and knowledge about credit/debit card payments. While this research provides substantial insights, it also carries certain limitations. As the study was conducted in Kolkata, West Bengal, India, the results may not entirely apply to other geographical or cultural contexts. Moreover, since the study focuses on unstructured retailers and consumers, the findings may not represent the broader spectrum of occupational roles.

Despite these limitations, this study offers several directions for future research. It would be worthwhile to replicate the study in other parts of India and other countries to assess the universality of these findings. A more detailed investigation into the specific barriers different age groups face in acquiring technological knowledge could also provide valuable insights. Additionally, exploring the impact of other socio-demographic factors, such as urbanization, could add depth to our understanding of technology acceptance.

Ultimately, this research underscores the complex interplay between socio-demographic and occupational factors and their role in technological knowledge and acceptance. As we move towards an increasingly digitized world, insights from studies like this become more crucial, informing targeted interventions for different groups, bridging the digital divide and fostering an inclusive technological landscape.

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