Consumer Technology Acceptance in the Digital Age: Investigating the Influence of Age and Education

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Abstract
Understanding the factors influencing its acceptance is crucial as technology permeates various facets of life. This study investigates the role of education level and age in technology acceptance. Utilizing a dataset of 108 individuals, Factor Analysis was conducted on a set of variables related to "Knowledge about Technology" using Principal Component Analysis (PCA). This procedure yielded one significant component, then used in two separate correlation analyses with education level and age. The results indicated a positive correlation between technology acceptance and education level, while age was negatively correlated with technology acceptance. These findings underscore the importance of considering individual characteristics when promoting technology acceptance. The implications of these results for technology design, educational programs, and policy-making are discussed. Further research is encouraged to consider other demographic and individual factors that may impact technology acceptance.

Keywords: *Technology Acceptance, Factor Analysis, Principal Component Analysis, Education Level, Age, Correlation Analysis.*

1. INTRODUCTION

As we continue to embark on the digital age, the pervasiveness of technology in our daily lives is increasingly evident. Whether it's communication, education, healthcare, or entertainment, technology is vital in enhancing efficiency, accessibility, and overall quality of experiences [1]. However, the success and effectiveness of technological solutions depend heavily on end-user acceptance. Therefore, understanding what influences technology acceptance has become a significant interest for researchers and industry practitioners. Technology acceptance refers to the willingness of individuals to embrace and use new technology for the tasks it is designed to support [2]. Several factors can influence this acceptance, including perceived usefulness, ease of use, and subjective norms. However, in addition to these technology-specific factors, individual characteristics such as education level and age can also play a substantial role. Recognizing and understanding these factors can help us create more user-friendly technologies and implement effective strategies to increase their acceptance [3].

Research has shown that individuals with higher education levels tend to have greater technology acceptance. This is likely because education equips individuals with the cognitive abilities and skills necessary to understand and use technology effectively. Age, on the other hand, has been found to correlate negatively with technology acceptance. Older individuals often face physical and cognitive challenges that can make technology use more difficult. Furthermore, their lower exposure to technology than younger generations can impede acceptance. However, most existing research on this topic has focused on specific types of technology (e.g., healthcare technology, educational technology), and generalizations across different technologies are therefore limited. Moreover, most studies have examined education level and age separately, overlooking the potential interplay between these factors. This study explores the impact of education level and age on technology acceptance to address these gaps, considering a broad technology acceptance scale. The results of this study will contribute to the existing body of knowledge in the field and could inform the development of strategies and interventions to enhance technology acceptance among different demographic groups. This paper proceeds as follows. The next section presents the research methodology, including a description of the dataset and an overview of the statistical analyses conducted. The results section then presents the findings of the factor and correlation analyses. This is followed by a discussion of the results and their implications, and finally, a conclusion summarizing the essential findings and their potential impact on technology acceptance.

2. LITERATURE REVIEW

The adoption and integration of digital technology in the retail industry have interested scholars and practitioners alike. However, the literature on advanced, innovative technologies in unstructured retail settings and customer-related behaviour is still somewhat limited [4]. Previous research has focused chiefly on structured retail environments, such as supermarkets and department stores, where the adoption of digital technology is more prevalent. Foroudi, Gupta, Sivarajah, & Broderick highlight that previous work failed to address the influence of intelligent technology usage, combined with the customer's behavioural intention, on the dynamics and experience of customers in unstructured retail settings [5] [4]. Moreover, technology deployment within the retail sector has been found to reduce the requirements of person-to-person interaction. As technology proliferates across the retail industry, consumer behaviour has been found to show growing adoption of technology replacing traditional in-person retail shopping behaviours. In addition, the growing penetration of digital technologies has produced significant changes in shopping habits designed to create a new scenario for shopper marketing [6]. Furthermore, adopting technology in unstructured retail settings is not without challenges. Some researchers have identified obstacles such as the cost of implementing technology in smaller retail environments, the lack of knowledge or technical skills required to operate new technologies, and the resistance to change among retailers accustomed to traditional business practices. Despite these challenges, technology adoption in unstructured retail settings has potential benefits that cannot be ignored. Research has shown that integrating digital technology can enhance customer experiences, promote greater engagement with products and services and increase sales revenue. However, there is a need for further research to deal with the challenges emerging from the adoption of such intelligent technologies in unstructured retail settings [7]. Moreover, many firms acknowledge the potential of new technologies for enhancing customer experiences and revamping traditional retail practices, but they remain uncertain about the benefits such adoption offers [8]. Therefore, technology adoption decision-making processes by retailers should also incorporate the anticipated response from their customers to fully realize the advantages of these innovations. In the highly competitive retail landscape, small retailers must keep up with digital trends to remain relevant and compete with larger competitors [9]. However, evidence suggests that small retail stores may be disconnected from the development and adoption of digital technologies by their customers and supply chain partners. Hence, it is critical to remain competitive in the retail sector to understand the factors that may influence small retailers' adoption and continued usage of digital technologies and the challenges they face in integrating them into their operations [10]. Additionally, research has demonstrated that successful retail technology adoption can help fuel omnichannel customer experiences, intelligent offerings, and lean operations. Therefore, retail managers should anchor their technology deployment plans on the firm's purpose and pursue a strategy that supports their competitive positioning by leveraging digital technologies. In conclusion, while there are challenges associated with technology adoption in unstructured retail settings, research highlights the potential benefits that cannot be overlooked.

3. METHODS

This paper's methodology section will delineate the process of investigating the factors influencing technology acceptance. It begins with a dataset description, including details about the sample size and variables considered. This is followed by an overview of the statistical analyses conducted, specifically Factor Analysis using Principal Component Analysis (PCA) and Correlation Analysis employing Spearman's rho. These methods were chosen based on our data's nature and research objectives. The procedures for each analysis will be discussed in detail, along with the corresponding results and interpretations. By transparently detailing our research methodology, we aim to contribute to rigorous, replicable, and responsible science.

3.1. Data Set Description

The data set used in this study comprised responses from 108 individuals. The variables used for the analysis were primarily dependent variables related to technology acceptance, encapsulated in a "Knowledge about Technology" scale. Demographic variables, namely education level and age, were used as independent variables for correlation analysis.

3.2. Factor Analysis

Factor analysis was applied to the dependent variables to simplify the data structure and reveal underlying 'super-variables' or factors. This data reduction method helps to condense the information held in numerous variables into fewer dimensions, making interpretation more manageable. In this study, we used Principal Component Analysis (PCA), a commonly applied technique in factor analysis. Mathematically, PCA seeks to transform the original variables into a new set of uncorrelated variables, or 'principal components'. These components are linear combinations of the original variables, such that:

Component = a1*Variable1 + a2*Variable2 + ... + an*Variablen

Where 'a' are the component loadings, or weights, and 'Variable' represents the original variables.

Our analysis employed the Kaiser criterion, which suggests retaining only components with eigenvalues greater than 1, as they explain more variance than a single original variable. The results of the factor analysis showed that one factor, the result, explains a substantial amount of variance in the data (89.073%). This high percentage suggests that this single factor captures most of the information in the original set of dependent variables. Therefore, it can be used to represent technology acceptance in subsequent analyses.

3.3. Correlation Analysis

Two correlation analyses were performed using Spearman's rho, a non-parametric correlation measure. This test was chosen because it does not require the assumption of normality and can capture linear and non-linear relationships.

The mathematical equation for Spearman's rho is:

$\rho = 1 - [(6 \Sigma d^2)/(n(n^2 - 1))]$

Where 'd' is the difference in ranks of each pair of observations, and 'n' is the total number of observations.

The first analysis aimed to determine the correlation between technology acceptance (as represented by Component 1) and education level. The null hypothesis stated no correlation, while the alternative view proposed that a correlation existed. The second analysis investigated the correlation between technology acceptance and the age of the respondents. Similar to the first analysis, the null hypothesis was that there was no correlation, and the alternative hypothesis suggested a correlation. In both cases, the results provided evidence against the null hypothesis, showing statistically significant correlations. These findings indicate that education level and age influence technology acceptance.

4. RESULTS & DISCUSSION

The data analysis began with a factor analysis of the dependent variables using a "Knowledge about Technology" scale. This scale was used to summarize and condense the data into a more compact form, often called dimension reduction. The commonly used Principal Component Analysis (PCA) was adopted as the extraction method.

Table 1: Factor Analysis - Total Variance Explained

Component	Initial Eigenvalues	Extraction Sums of Squared Loadings
	Total	% of Variance
1	12.470	89.073
2	.823	5.875
3	.664	4.741
4	.043	.310

Component	Initial Eigenvalues	Extraction Sums of Squared Loadings
5-14	Varies	Varies

Extraction Method: Principal Component Analysis.

Table 2: Correlation Analysis - Technology Acceptance and Education Level

	Education	REGR factor score 1 for analysis 1
Spearman's rho		
Education	Correlation Coefficient: 1.000	.274**
	Sig. (2-tailed):.	.004
	N: 108	108
REGR factor score 1 for analysis 1	Correlation Coefficient: .274**	1.000
	Sig. (2-tailed): .004	.
	N: 108	108

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

Table 3: Correlation Analysis - Technology Acceptance and Age

	REGR factor score 1 for analysis 1	Age
Spearman's rho		
REGR factor score 1 for analysis 1	Correlation Coefficient: 1.000	-.725**
	Sig. (2-tailed):.	.000
	N: 108	108
Age	Correlation Coefficient: -.725**	1.000
	Sig. (2-tailed): .000	.
	N: 108	108

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

The below table succinctly presents the objectives, hypotheses, and results of the correlation analyses carried out in this research.

Objective	**Hypothesis**	**Result**
To check whether technology acceptance is correlated with education level	Null: There is no correlation between technology acceptance and education level Alternative: There is some correlation between technology acceptance and education level	A significant positive correlation (Spearman's 0.274) at $p < 0.01$ level.
To check whether technology acceptance is correlated with the age of consumers	Null: There is no correlation between technology acceptance and the age of consumers. Alternative: There is some correlation between technology acceptance and the age of consumers	Significant negative correlation (Spearman's -0.725) at $p < 0.01$ level.

The first analysis investigated the correlation between technology acceptance and education level. The finding of a statistically significant positive correlation indicates that as the level of education increases, so does the acceptance of technology. This finding corroborates with existing literature, suggesting that higher levels of education equip individuals with the cognitive abilities and skills necessary to understand and use technology effectively (Venkatesh et al., 2003). As such, education initiatives might play a crucial role in enhancing technology acceptance.

The second analysis probed the relationship between technology acceptance and the age of the consumers. The observed significant negative correlation implies that as individuals age, their technology acceptance diminishes. This trend is consistent with existing research, which suggests that cognitive flexibility and prior exposure to technology, which may decrease with age, are influential factors in technology acceptance (Chen & Chan, 2014). However, it is crucial to remember that correlation does not equate to causation, and other factors not considered in this study might be influencing these relationships. More comprehensive and in-depth research is required to investigate these correlations further and elucidate the underlying causal mechanisms. The findings of this study, though based on relatively small sample size, provide valuable insights for future research and inform policy-making aiming to enhance technology acceptance among various demographic groups.

5. RECOMMENDATIONS

Based on the findings from this study, several recommendations emerge. Firstly, the positive correlation between education level and technology acceptance implies that promoting educational programs could augment individuals' understanding and acceptance of technology. These programs could range from technology skill-building workshops to integrating technology-focused curricula in educational institutions. Secondly, the study highlights a negative correlation between age and technology acceptance, which calls for targeted initiatives to encourage technology use among older individuals. Strategies could include the development of user-friendly technological designs and providing technology training programs specifically designed for older adults, along with personalized assistance. Thirdly, in technology design, developers need to create products that cater to diverse user groups, considering variations in education levels and age. Emphasis should be placed on user-friendly interfaces, comprehensive user guides, and complete customer support services to foster greater technology acceptance across all demographics. Lastly, this study underscores the need for further research in this domain. Future studies should explore additional factors that might influence technology acceptance, such as socio-economic status, technological self-efficacy, or previous experience with technology, which were not addressed in this study. Moreover, delving into the causal relationships between these variables could shed more light on the dynamics of technology acceptance. This deeper understanding could be achieved through longitudinal studies or controlled experiments, offering significant potential for research in this area.

6. CONCLUSION

This study has made significant strides in understanding the factors influencing technology acceptance: education level and age. Our research revealed a strong positive correlation between technology acceptance and education level, demonstrating that as individuals' education increases, so does their acceptance of technology. Contrarily, age was inversely correlated with technology acceptance, indicating a tendency for older individuals to be less accepting of technology. These findings underscore the importance of considering individual factors when addressing technology acceptance. They also highlight the critical need to design strategies and interventions sensitive to these factors. In light of the digital revolution and the increasingly integral role of technology in every aspect of our lives, understanding and enhancing technology acceptance is not just beneficial – it's essential. Educational programs to boost technical skills and understanding can raise technology acceptance levels. Simultaneously, special attention must be given to older adults, potentially through developing user-friendly interfaces, dedicated support, and training programs to foster their comfort and proficiency with technology. While this study has contributed valuable insights, there is much more to explore. Future research should consider the possible impact of other factors on technology acceptance, such as geographic location, income level, and cultural background. Analysing these factors will paint a complete picture of technology acceptance and enhance our ability to encourage it effectively. In conclusion, this study has taken an essential step towards understanding technology acceptance better. The insights gained have both practical and theoretical implications, and it is hoped that they will spur further research and action in this significant study area.

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