EXPLORING HOW DEMOGRAPHIC FACTORS INFLUENCE CONSUMER ATTITUDES AND TECHNOLOGY USAGE

Lydiah Kiburu[a*], Nathaniel Boso[b] and Nancy Njiraini[c]

[a]*Strathmore Business School, Strathmore University, Ole Sangale Rd, Madaraka Estate, P. O Box 59857-00200, Nairobi, Kenya*
[b]*School of Business, Kwame Nkrumah University of Science and Technology, School of Business, Kwame Nkrumah University of Science and Technology, Ghana*
[c]*Strathmore Business School, Strathmore University, Ole Sangale Rd, Madaraka Estate, P. O Box 59857-00200, Nairobi, Kenya*

Abstract

As technology continue to define lifestyle and interactions, firms are increasingly seeking empirical evidence on how consumers' attitudes towards technology influence technology usage. There is inadequate research from the emerging markets on the extent to which demographic factors influence the relationship between consumer attitudes and technology usage. This study therefore addressed this gap by using data from mobile banking users in Kenya to test the moderating role of education levels, age, levels of income and gender. Kenya was preferred study context because of the high penetration and levels of mobile technology usage.

Results show that only education levels had statistically significant influence. Theoretical and consumer management implications as well as avenues for additional research are discussed. The study discusses the implications of the study from a theoretical, empirical, policy and industry practice perspective. Future research directions are also recommended.

Keywords: demographic factors, consumer attitudes, technology usage, mobile banking, Kenya

1. INTRODUCTION

Rapid technological advancement is changing people's lives in various ways, coupled with the need for firms to ensure a successful return on technology investment. The changes occurring in technology usage have triggered growing scholarly and managerial interest in how consumer demographic characteristics may contribute to consumer technology usage (Billanes & Enevoldsen, 2021).

As more technological advancements continue to impact lives in various ways,

earlier-held empirical evidence on the role of demographic characteristics is showing a tendency to evolve and change. Research trends show that earlier empirical evidence that males were more quick to adoption technology compared to their female counterparts in the last two decades has started to change significantly reducing the gap to a negligible level (Harrison & Rainer Jr, 1992; Straub et al., 1997; Bigné et al., 2007; Thakur, 2018).

In addition, while literature is increasing on the role of demographic factors in influencing consumer technology usage, not much attention has been placed on the context of emerging markets, especially those in sub-Saharan Africa. For instance, in a review of 54 studies on the factors influencing consumer technology usage between 2011 and 2020, only one study was from Africa (Billanes & Enevoldsen, 2021). The current study aims at establishing how demographic factors moderate consumers' attitude on technology and consumers' technology usage from a sub-Saharan African market context – Kenya.

This study, therefore, contributes to the existing technology adoption and usage literature by examining the extent to which demographic characteristics condition the relationship between consumer attitude and technology usage using mobile banking in an emerging market context. Findings from the study provide insights into further empirical studies, policy formulation on technology research and development, marketing strategies and consumer education. The study further provides guidelines on how firms can develop technology products and marketing plans to drive usage.

The rest of the paper is organised as follows: the next section focuses on the theoretical foundations of the study followed by an empirical literature review and hypotheses development. The research method and findings are subsequently presented, followed by a discussion of the findings. The paper ends with a conclusion, implications of the study findings, limitations of the study and a recommendation of future research opportunities revealed by the study.

2. THEORETICAL BACKGROUND

2.1. Using the technology acceptance model to explain consumer technology usage

TAM was advanced by Davis (1989) who posited that a person's acceptance and usage of technology is influenced by their attitude towards that technology. TAM's popularity in explaining technology acceptance and usage has been attributed to its parsimony. TAM uses two constructs to measure consumers' technology usage: perceived ease of use (PEOU) and perceived usefulness (PU). According to Davis (1993), perceived usefulness (PU) is defined as the extent to which an individual believes that using a system will enhance performance. Perceived ease of use (PEOU) is defined as the extent to which an individual believes that using a system will be relatively free of effort. As an information systems' specific theory, TAM provides an adequate explanation of usage across a wide spectrum of users and a variety of technologies across cultures and geographies (Rafique et al., 2020). Secondly, it has a strong theoretical base with widely-researched and validated psychometric measures which are generalisable. Thirdly, the theory has strong empirical evidence for its overall prediction

power (Yousafzai et al., 2007). TAM replication studies have served to validate the generalisability of the theory across persons, settings, cultures, times and geographical locations, which is a requirement for robust theories (Kamal et al., 2020; Rahimi et al., 2018).

A key critique of TAM is the view that performing a given behaviour is predicted by behaviour intention. Scholars have argued that various steps exist between the time intention is formed in the mind of a consumer and the time that the consumer initiates action (Bagozzi, 2007). In this study, we measure a direct relationship between PU and PEOU to actual behaviour without going through behaviour intention. This study is therefore premised on the success of TAM's predictive power and progresses from this assumption to examine the moderating role of demographic factors on the relationship between consumer attitude to technology and consumer technology usage.

2.2. Consumer attitudes and consumer technology usage

In a study to validate TAM's measurement scale, Davis (1989) conducted a two-part research study and found that PU was more statistically significant in influencing usage compared to PEOU. The findings were corroborated by Adams et al. (1992) in a replication two-part study in the USA that examined the relationship between ease of use, usefulness and system usage. The two studies evaluated the psychometric properties of PU and PEOU scales while examining the relationship between PU, PEOU and system usage. The results demonstrated the reliability and validity of the measurement scale. The studies in the

two organisations focused on users in a controlled environment where usage of technology was mandatory, while this study focuses on consumer technology usage among consumers in a voluntary setting.

TAM extension studies have focused on different variables while other studies integrated TAM with other theories, thereby introducing multiple variables and reporting mixed outcomes. Other studies measured behavioural intention as the outcome variable, which is different from actual usage and which has been criticised as not necessarily translating into actual consumer usage; Joo et al. (2016) analysed relationships between factors that predicted the usage of a mobile-based learning system among university students and concluded that perceived ease of use predicted perceived usefulness, perceived usefulness and satisfaction predicted continuance intention, while continuance intention predicted actual usage. Ashraf et al. (2014) extended TAM by incorporating trust and perceived behavioural control to examine its impact among university students in Pakistan and Canada. The findings revealed complex relationships between PEOU, PU and consumers' intention to adopt technology in each country. Kulviwat et al. (2007) argued that consumer attitude as explained by TAM lacked sufficient explanatory power to explain consumer attitude towards technology usage in voluntary contexts.

The above findings indicate that individual characteristics have a role to play in moderating TAM's predictive power on consumer attitudes towards technology and its usage. This study contributes to the empirical knowledge by examining the role of demographic factors (gender, education levels, income levels and age) in moderating

the relationship between consumers' attitudes and consumers' technology usage in a voluntary setting within an emerging market environment.

2.3. Hypotheses

2.3.1. Education

The level of education is considered to positively influence consumers' attitudes towards technology usage (Davis & Davis, 1990; Chong, 2013; Park et al., 2007) Similarly, Lohse et al. (2000) argued that consumers with higher education levels tended to have higher income and were more likely to own more technology devices such as computers and mobile phones and access the internet and Leblanc (1990) opined that users of bank automatic teller machines (ATMs) were more highly educated. However, recent empirical studies have contradicted the above findings (Thakur, 2018; Venkatesh & Morris, 2000). In view of the foregoing findings, we hypothesize as follows:

H1 (a): As education levels increase among technology users, the relationship between perceived ease of use of technology and technology usage strengthens.

H1 (b): As education levels increase among technology users, the relation between perceived usefulness of technology and technology usage strengthens.

2.3.2. Gender

There has been no consensus on the role of gender in influencing consumers' attitudes towards technology and technology usage. Although Venkatesh et al. (2003) argued

that, although there was no adequate research on gender differences in decision-making regarding technology usage, existing studies revealed that the role of gender was crucial. Croson and Gneezy (2009) and Huyer (2016) opined that women were more risk-averse than men. Similarly Klugman et al. (2014) argued that, in developing countries, the rate of mobile phone access was 21% lower among women compared to men.

Recent studies have started to show a reverse in this trend; a study on adoption of mobile commerce adoption found that gender influence was not statistically significant (Faqih & Jaradat, 2015). Similarly, Bigné et al. (2007), demonstrated that in Spain, where mobile technology penetration was at 86%, there was no difference in attitude between men and women, while in China there existed a positive moderating effect of gender, indicating a cultural influence.

We therefore hypothesise as follows:

H2 (a): Perceived ease of use influences technology usage more strongly among male consumers than female consumers.

H2 (b): Perceived usefulness influences technology usage more strongly among male consumers than female consumers.

2.3.3. Income levels

Empirical studies have reported that individual characteristics such as income have a significant impact on technology usage while others argue that these factors are not significant. Homburg & Giering, (2001) opined that income had a strong impact on choice and decisions because people with higher income levels were likely

to achieve a higher level of education, therefore they were likely to engage more in information processing and evaluation prior to decision making. In a literature review on consumer innovativeness, Kaushik and Rahman (2014) reported that income had a significant impact on new product adoption compared to education, marital status and family size. Lockett and Littler (1997) analysed consumers' attitudes towards direct banking and concluded that adopters of new technology generally earned higher incomes.

In contrast, Porter and Donthu (2006) argued that lower income levels correlated with perceived usefulness of new technologies. Venkatesh and Moris (2000) argued that income and education were non-significant predictors of intention to adopt technology. In a study of the key drivers of mobile commerce adoption among Spanish mobile users, age was the only demographic factor that was found to be significant while other factors including income levels were insignificant. We, therefore, hypothesise as follows:

H3(a): The higher the income levels, the stronger the relationship between perceived ease of use of technology and consumer technology usage.

H3(b): The higher the income levels, the stronger the relationship between perceived usefulness of technology and consumer technology usage.

2.3.4. Age

The relationship between age and technology usage has drawn mixed findings. According to Niehaves and Plattfaut (2014), there exists an age-related digital divide that prevents elderly people from using technology, even though technology is seen as a means of enhancing their quality of life by increasing the period of their lives when they remain independent. Chung et al. (2010), argued that there existed a negative relationship between technology usage and age. This view was supported by scholars who hold the view that information processing and retrieval from memory and attention span decline with age (Al Ajam, 2013; Katona et al., 2011). Contrastingly, Chong et al. (2012) argued that older consumers were more likely to adopt m-commerce compared to younger consumers in Malaysia (Chong et al., 2012). In view of the foregoing, we hypothesize that:

H4(a): There exists a strong relationship between perceived ease of use of technology and technology when consumers are older than when they are younger.

H4(b): There exists a strong relationship between perceived usefulness of technology and technology usage when consumers are older than when they are younger.

3. METHODOLOGY

We conducted a household-based survey targeting mobile banking users in Kenya. The target population was individuals aged 18 years and above who had linked their bank accounts to their mobile phones in order to access banking services using their mobile handsets as a channel. The National Sample Survey and Evaluation Programme (NASSEP V) from the Kenya National Bureau of Statistics (KNBS) was used as the sampling frame.

A total of 30 clusters spread across the entire area of study were selected using equal

probability sampling methods since the Enumeration Areas (EAs) were standardised to a measure of size of approximately 50-149 households during the listing of the NASSET V framework. The selection was carried out independently within each stratum. A fixed take of 38 households was selected independently from each cluster using systematic random sampling from the household roster of the clusters. Primary data was collected in May and June 2021. A questionnaire was administered to the selected households by trained researchers using Computer Aided Personal Interviews (CAPI).

Screening questions were used to ascertain the members of the household who were above 18 years and were subscribed to mobile banking. A seven-point Likert-type scale questionnaire (ranging from 7- strongly agree to 1- strongly disagree) was used for the study. A total of 1739 residents were screened, 1475 were above 18 years of age and only 452 respondents, constituting 29% of the sampled population, had subscribed to mobile banking services.

3.1. Research quality

To ensure the quality of data, validity and reliability tests were carried out during the pilot study. The first step involved testing the questionnaire with experts in research methods, data analysis and marketing before conducting the pilot study among respondents. Response and analysis of the findings from the pilot study were used to make improvements to the final survey questionnaire. The pilot also revealed that, due to the Covid-19 pandemic, there were many vacant homes in the urban areas, which informed the need to increase the population in order to achieve an adequate study sample.

A Cronbach's alpha of 0.7 was used as the cut-off threshold to measure internal consistency. Reliability tests were carried out during the pilot phase and during the main study. Factor analysis was used to test for construct validity of the variables that could not be observed. The factors were subjected to Kaiser-Meyer-Olkin (KMO), Bartlett's sphericity tests and an Eigenvalue cut-off of 1.0. Specifically, Explorative Factor Analysis was undertaken using Principal Component Analysis (PCA).

3.2. Data analysis

Categorical data were collected in the form of nominal data and Likert-scale type data (ordinal data). Descriptive statistics were used to reduce, summarise and present analysed data on the respondents' demographics using frequency tables, tables and bar charts. Mean and standard deviations were used as measures of central tendencies and dispersion respectively. Inferential statistics were used to analyse the relationship between the moderating variables, and the dependent and independent variables. Regression analyses were used to determine the effect of the moderating variables on the joint effect of the independent variables on the dependent variable. A parametric method (Pearson's) correlation coefficient was used to measure the strength of the relationship between two variables.

4. RESULTS AND INTERPRETATION

4.1. Respondent characteristics

The demographic characteristics results show that, in terms of gender, 50.4% of the

sample were males and the rest (49.6%) were females. The majority of the respondents were between 21 and 40 years old, constituting 72.8% of the sample. 46.6% had secondary school education whilst 42.4% held up to first degree/college. Finally, data on income level showed that the majority of the respondents (65.2%) earned up to Ksh 50,000.

4.2. Validity and reliability measures

To evaluate the validity and reliability of the measures, a covariance-based confirmatory factor analysis with a maximum likelihood estimator was used in LISREL 8.5. The model has a good fit for the data given: $\chi^2 = 198.08$; df = 101; $\chi^2/df = 1.96$; p = 0.00; RMSEA = 0.05; GFI = .94; CFI = .97; SRMR = .03; NNFI = .97 (Hair Jr et al., 2014). The results showed that all the factor loadings were greater than 0.60 and they were statistically significant. Further, the composite reliability, average variance extracted and Cronbach's alpha values for each of the set of measures were greater than the recommended thresholds of 0.60, 0.50 and 0.70, respectively. This result indicated that unidimensionality, convergent validity and reliability were achieved in the set of measures (Hair Jr et al., 2014) Moreover, the average variance extracted values were greater than the squared correlations between the constructs. Thus, discriminant validity is demonstrated.

5. HYPOTHESES TESTING

The study tested the relationship between the variables using hierarchical linear regression analysis in SPSS. The results are displayed in Table 1. Model 1 captures only the control variables, while Model 2 includes the main effect variables (consumer attitudes towards technology, education level, income, age and gender). Models 3 – 6 include the interaction terms as well as the full model. Model 1 significantly explains an 8% variance in consumer technology usage, given F = 1.84, p < 0.05. Models 2 – 3 significantly explain 19% variance each in consumer technology usage, given $\Delta F = 9.34$ and 4.33, p < 0.01 respectively. Models 4 – 6 do not have a significant variation in consumer technology usage.

5.1. Educational levels

Hypothesis 1 (a) and (b) proposed that the relationship between consumers' attitudes towards technology as measured by PEOU and PU is strengthened as the educational level increases. In Model 3, the coefficient estimate for the interaction term is positive and statistically significant.

The influence of PEOU ($\beta = .44$, t = 2.08, p < 0.1) and PU ($\beta = .44$, t = 2.05, p < 0.1) offered support for hypothesis 1. Thus, the relationship between consumer attitudes towards technology and consumer technology usage is strengthened when consumer educational level increases.

5.2. Gender

Hypothesis 2 (a) and (b) proposed that the relationship between consumers' attitudes measured by PEOU (2(a) and PU (2(b)) was stronger among male consumers than among female consumers. In model 6, the coefficient estimate for the interaction term is positive but not statistically significant for both the influence of PEOU ($\beta = .19$, t = .93) and PU (data cannot be seen). There is therefore not enough evidence to support

Table 1. Hierarchical linear regression results

Antecedents	Outcome Variable: Consumer Technology Usage					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	β(t)	β(t)	β(t)	β(t)	β(t)	β(t)
Controls						
EMPLOY	-.13 (-1.51)	-.17 (-2.09) *	-.18 (-2.18)*	-.18 (-2.18)*	-.18 (-2.20)*	-.19 (-2.24)*
INTLEXP	.09 (.69)	.07 (.56)	.09 (.67)	.09 (.67)	.09 (.69)	.09 (.66)
MOBEXP	-.12 (-1.21)	-.07 (-.70)	-.07 (-.76)	-.07 (-.76)	-.07 (-.72)	-.07 (-.70)
MOBITYP	.02 (.09)	.03 (.19)	.04 (.26)	.04 (.26)	.05 (.29)	.05 (.32)
SMART	.12 (.30)	.18 (.47)	.13 (.34)	.13 (.34)	.12 (.33)	.13 (.34)
NMDEVI	-.00 (-.06)	-.01 (-.08)	.01 (.20)	.01 (.20)	.01 (.16)	.01 (.14)
BMAPPS	-.00 (-.17)	-.02 (-.81)	-.01 (-.62)	-.01 (-.62)	-.01 (-.61)	-.01 (-.64)
INTUSAGE	-.00 (-.00)	.10 (.31)	.09 (.27)	.09 (.27)	.09 (.27)	.09 (.27)
BEXP	.12 (1.34)	.15 (1.71) +	.13 (1.54)	.13 (1.53)	.13 (1.44)	.13 (1.42)
KCB	.07 (.50)	.04 (.31)	.06 (.47)	.06 (.46)	.06 (.46)	.07 (.48)
EQUITY	-.28 (-2.00)*	-.20 (-1.54)	-.20 (-1.49)	-.20 (-1.48)	-.19 (-1.47)	-.19 (-1.45)
COOP	-.19 (-1.35)	-.16 (-1.16)	-.14 (-1.05)	-.14 (-1.05)	-.14 (-1.01)	-.14 (-1.02)
DTB	.50 (1.12)	.49 (1.15)	.44 (1.04)	.44 (1.04)	.44 (1.03)	.46 (1.06)
SCB	.46 (1.40)	.30 (.94)	.28 (.88)	.28 (.88)	.30 (.93)	.28 (.88)
ABSA	.56 (2.06)*	.49 (1.89) +	.47 (1.82) +	.47 (1.81) +	.47 (1.80) +	.48 (1.83) +
ABC	1.74 (1.51)	1.63 (1.48)	1.61 (1.47)	1.61 (1.47)	1.62 (1.47)	1.61 (1.47)
MOBSER	.13 (1.65)	.08 (1.09)	.07 (.94)	.07 (.94)	.07 (.94)	.08 (1.02)
MOBSUP	.51 (.63)	.57 (.74)	.57 (.74)	.57 (.74)	.57 (.74)	.62 (.81)
HOUSIZ	-.09 (-1.57)	-.10 (-1.75)	-.10 (-1.92) +	-.10 (-1.91) +	-.10 (-1.89) +	-.11 (-1.94) +
Main Effect						
CATT		.67 (6.45)**	.49 (3.69)**	.49 (3.46)**	.58 (2.29)*	.50 (1.82) +
EDU		.03 (.25)	.01 (.06)	.01 (.06)	.01 (.10)	.03 (.19)
INC		.06 (.43)	.05 (.33)	.05 (.33)	.04 (.30)	.03 (.23)
AGE		-.10 (-.78)	-.10 (-.82)	-.10 (-.81)	-.09 (-.72)	-.09 (-.71)
GEN		.17 (1.51)	.18 (1.64)	.18 (1.63)	.18 (1.61)	.18 (1.58)
Interaction						
CATT*EDU			.44 (2.08)*	.44 (2.05)*	.40 (1.71) +	.38 (1.60)
CATT*INC				.00 (.01)	.02 (.08)	.02 (.09)
CATT*AGE					-.11 (-.44)	-.12 (-.48)
CATT*GEN						.19 (.93)
Model Fit						
R	.29	.43	.44	.44	.44	.44
R²	.08	.19	.19	.19	.19	.20
ΔR²	.08	.10	.01	.00	.00	.00
F	1.84	3.56	3.62	3.47	3.34	3.25
ΔF	1.84*	9.34**	4.33*	.00	.19	.87

Notes: EMPLOY: Employment status; INTLEXP: International experience outside Kenya; MOBEXP: Experience using a mobile device; MOBITYP: Type of Mobile phone; SMART: Smartphone; NMDEVI: Number of mobile Devices; BMAPPS: Number of mobile apps usage; INTUSAGE: Internet usage; BEXP: Banking Experience; KCB: Bank type – KCB; EQUITY: Bank type - Equity Bank; COOP: Bank type - Coop Bank; DTB: Bank type – DTB; SCB: Bank type - Standard chartered; ABSA: Bank type - Barclays/ ABSA; ABC: Bank type – ABC; MOBSER: Experience using mobile service; MOBSUP: Mobile Service Subscription; HOUSIZ: Household Size; CATT: Customer Attitudes toward Technology; EDU: Education level (Up to secondary school = 0, Above secondary school = 1); INC: Income (Up to Ksh 50,000 = 0, Above Ksh 50,000 = 1; Age (Up to 30 years = 0, Above 30 years = 1); GEN: Gender (Male = 1, Female = 0).
** p < 0.01; p < 0.05; p < 0. 10

hypothesis 2.

5.3. Income levels

Hypothesis 3 (a) and (b) proposed that the relationship between consumers' attitudes towards technology and consumer technology usage measured by perceived usefulness 3(a) and perceived ease of use 3(b) was strengthened as the consumer

income level increased. In model 4, the coefficient estimate for the interaction term was positive but not statistically significant for 3(a) (β = .00, t = .01) and 3(b) (β = .02, t = .08). There is therefore not enough evidence to support hypothesis 3.

5.4. Age

Hypothesis 4 (a) and (b) proposed that the relationship between consumer attitudes towards technology and consumer technology usage measured by PEOU (4(a)) and PU (4(b)) was strengthened as consumer age increased. In model 5, the coefficient estimate for the interaction term is positive but not statistically significant for PEOU (β = -.11, t = -.44) and PU (β = -.12, t = -.48). There is therefore not enough evidence to support hypothesis 4.

6. DISCUSSION, CONCLUSION AND IMPLICATIONS

This study sought to establish the moderating role of demographic factors on consumer attitude to technology and consumer technology usage. The study context was an empirical study of mobile banking usage in Kenya. Demographic factors that were examined comprised education levels, income levels, age and gender. With the exception of education levels, which were found to have significant influence, income, age and gender did not demonstrate any significant moderating influence. The findings are indicative of a shifting trend in the factors that moderate consumers' attitudes to technology and consumer technology usage.

Firstly, as technological advancement continue to define and drive society's lifestyle, consumers have responded with increased adoption and usage behaviour. Restrictions related to the Covid-19 pandemic accelerated consumer technology usage.

Secondly, the perceived usefulness of the various technological innovations in people's lives, the ease of use and the convenience at different stages of individuals' lives have started to reduce the role of demographics in moderating consumer attitude to technology and consumer technology usage.

Thirdly, other factors such as affirmative action in giving females an equal opportunity to education including science and technology skills appear to level the gender gap in consumer technology usage, especially in emerging markets.

Fourthly, the level of convenience in technology-driven services such as mobile-based services, coupled with increased usefulness and friendliness of the applications, and affordability and penetration of mobile phone usage, appears to be reducing the age and income divide in consumer technology usage.

Education appears to play a moderating role in the relationship between consumer attitudes towards technology and consumer technology usage. It has been argued that people with higher education levels are able to explore technology much faster than the less educated ones, and this may influence the speed of adoption as less educated consumers rely on support to understand and use technology. In emerging markets such as the one that formed the context for this study, consumer technology usage appears to be receiving faster acceptance as a means of closing the development gap that exists, compared to more developed countries where consumers have various choices and options.

The findings have theoretical, managerial and policy implications. The declining moderating influence of demographic factors on consumers' attitudes to technology and consumer technology usage needs further research to understand the antecedents causing the change in comparison to earlier-held empirical evidence. This could bring forth new theoretical foundations to explain the changing factors influencing individual consumer behaviour. On the managerial implications, the findings provide insights that could help marketing managers in developing effective segmentation and targeting in their marketing strategies. Technology product development teams can benefit from the findings by ensuring that technology products are designed and packaged to suit the various demographic varieties.

7. LIMITATIONS AND FUTURE RESEARCH

The study used one technology type in one country to examine the study question. Future studies could use several technologies across several countries to deepen the empirical evidence. The study also used a cross-sectional research design that studies consumers' behaviour at a point in time. Future studies could explore a longitudinal study to assess consumers' attitudes at the adoption stage and post-adoption stage to explore the impact of time on consumer technology usage behaviour. This study used the TAM model, which has withstood the test of time as the most robust theory in explaining consumer acceptance and usage of technology, to carry out the study and used a quantitative data analysis method. As technology advances and influences

consumer behaviour, future studies could explore grounded theory to establish any new factors that could be impacting consumer attitude.

Finally, new regulations such as data protection laws have impacted how information is shared in a world where information is becoming increasingly available through technology. How is this paradigm shift impacting consumers' technology usage? Future studies could explore this dimension in relation to consumers' attitudes towards technology and consumer technology usage. The mixed findings on the role of demographic factors in predicting consumer technology usage raise the need to establish antecedent factors that influence demographic factors in predicting consumers' attitudes towards technology and consumer technology usage.

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ИСТРАЖИВАЊЕ УТИЦАЈА ДЕМОГРАФСКИХ ФАКТОРА НА СТАВ ПОТРОШАЧА И КОРИШЋЕЊЕ ТЕХНОЛОГИЈЕ

Lydiah Kiburu, Nathaniel Boso, Nancy Njiraini

Извод

Како технологија наставља да дефинише начин живота и интеракције, компаније све више траже емпиријске доказе о томе како ставови потрошача према технологији утичу на коришћење технологије. Постоје неадекватна истраживања на тржиштима у развоју о томе у којој мери демографски фактори утичу на однос између ставова потрошача и употребе технологије. Стога, ова студија је разрешила овај јаз користећи податке корисника мобилног банкарства у Кенији, како би се тестирала модерирајућа улога нивоа образовања, старости, нивои прихода и пола. Кенија је одабрана за ово истраживање због високе пенетрације и нивоа употребе мобилне технологије.

Резултати показују да је само ниво образовања имао статистички значајан утицај. Разматране су теоријске импликације и импликације на управљање потрошачима, као и правци за даља истраживања. Студија разматра импликације истраживања са теоријске, емпиријске, политичке и индустријске перспективе. Такође се препоручују будући правци истраживања.

Кључне речи: демографски фактори, ставови потрошача, употреба технологије, мобилно банкарство, Кенија

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