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Moderating Role of User Expertise on the Relationship between Smart Technology Usage and Performance: Empirical Evidence from Non-Governmental Organizations in Nairobi City County, Kenya

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Abstract: ***Although non-governmental organizations are instrumental to development of unindustrialized countries, they have received reprimands for diminished performance. In Kenya, the ratio of gross domestic product to these organizations is approximately 1% compared to the national growth of about 5% over the last decade. The constricted performance was attributed to lack of innovation and reduced technology uptake. The increase in stakeholders' needs over-time have eclipsed these organizations' performance. Therefore, this study examined the moderating effect of user expertise on the relationship between smart technology usage and performance. The study was anchored on the Information Success Model. Stratified and random sampling technique was used to sample 266 respondents, from a population of 801 organizations. A semi-structured questionnaire was used for primary data gathering. Empirical data was analyzed through descriptive and inferential statistics. The study established that user expertise moderates the relationship between smart technology usage and organizational performance. The study findings provide knowledge on smart technology deployment and the effect on organizational performance. Consequently, top managers should leverage of this technology for superior organizational performance. Strategies focusing on nurturing skills development among employees in technology use should be developed, in order to enhance their productivity and net benefits for the organizations.***

Keywords: Expertise, Performance, Smart Technology, Stakeholder, Usage

1. Introduction

There are approximately ten million non-governmental organizations (NGOs) worldwide and the numbers are increasing [56]. NGOs have become increasingly influential in world economies characterized by over 20 percent of total overseas development aid channeled through these organizations [58]. In sub-Sahara Africa, the number of NGOs have increased exponentially. In South Africa, there are over 270,000 registered NGOs [52]; while in Kenya, there are over 12,000 registered non-governmental organizations [34]. NGOs are crucial in political and socio-economic development of countries where they operate. According to [57] report, approximately 90% of projects financed by this organization are awarded to NGOs. According to [36] report, this figure is an increase from a low of 21% in 1990s. In Kenya, NGOs spent over 900 million dollars in projects implementation in the year 2022 only [35].

Despite the pivotal role played by NGOs in socio-economic and political development of countries where they operate, they have faced a backlash for inability to change lives of poor neighborhoods and for poor performance. According to [16], NGOs have difficulty demonstrating their performance due to heightened controlling role of stakeholders and turbulence in the operating industry environment. In sub-Saharan Africa, NGOs have posted diminished performance results [16]. A report by [19] indicate that NGOs in the East Africa region have posted contracted performance, contrary to expectations of stakeholders. In Kenya, cumulatively 2468 or 20% of NGOs have so far been deregistered for non-compliance and poor performance compared to 130 (0.01%) reinstated during the same period [35].

Financial indicators infrequently measure performance of NGOs because they are not commercial organizations. Instead, their worth is ascertained by the effectiveness of services rendered and how successful they are able to achieve their mission. This is despite finances being critical in their operations [3]. Performance refers to the capability related to the accomplishment of organizational goals and stakeholders' expectations along with market survival. Superior performing NGOs benefit the communities where they operate, offer direct and indirect employment opportunities, entrench confidence among donors, partners

and other stakeholders, besides promoting socio-economic development [28]. Therefore, NGO performance determination remains a subject of concern to researchers since 1990s when multi-national organizations channeled bilateral aid and mega projects through these organizations [40]. Scholars argue that NGOs should account for all the donor funds received by undertaking live-transforming projects in communities where they operate. In so doing, they would attract more donors and partners and boost their performance. Kenya has an established and vibrant NGO sector and a regulatory framework in place within the East Africa region [57].

There are varied reasons why NGOs measure performance, key among them financial transparency and capacity building [54]. According to [33], mimetic isomorphism is the main reason NGOs assess their performance. This is an arrangement where NGOs follow the management and professional model used by other organizations in the same field because they are larger and better equipped. Among the scholars, there has being little consensus on the appropriate indicators to choose or a mix of them adequate to assess performance. According to [38] categorized NGOs performance measures into financial and non-financial indicators. Financial indicators encompass fundraising efficiency - ability of NGO to access to funding and financial transparency - preparing reports and submitting them to the concerned stakeholders. Non-financial indicators include projects non-financial efficiency, outcomes performance (effectiveness), impact performance, partnerships and quality of services provided by an NGO. This study adopts fundraising efficiency, financial transparency, outcomes performance and partnerships as suggested by [29].

According to [43] user expertise is a combination of inherent abilities, capabilities and other complex skills, experiences and knowledge. Likewise, [42] viewed user expertise as a part of competence that refers to highly specialized skills and knowledge of a person about a technology use. In a study [5] categorized user expertise into five levels: novice, advanced beginner, competent, proficient, and expert. In a study [37] postulate that experts have a substantial knowledge base that affect what they notice, and how they organize, represent and interpret information compared to novices. Based on the level of expertise, technology users synthesize and solve problems differently. Expert users are able to utilize more features of a technology, solve more technology-based problems using their domain-specific knowledge and leap more benefits from technology than novices [39]. Expertise, being the degree to which a user perceives their mastery of knowledge, or skill an individual possesses about a given technology, is reliable when predicting performance for the individual and organization at large [18].

This study operationalizes smart technology as a device that integrates telecommunication with computing into one gadget, such as a smartphone. These gadgets are ubiquitous, offer Internet access, data storage, financial transaction and email capability, among others in the workplace to achieve job-related objectives and targets. Smart technology devices represent a critical part of contemporary society, because they facilitate communication, are Internet-enabled and provide e-mail and social media access [31]. The study by [51] suggested two classifications of smart technology usage: process and social usages. Process usage involves utilizing non-social features of smart technology such as for news consumption, entertainment or relaxation, among others while social usage encompass utilizing social features of this devices such as for social networking, messaging, calling, and conferencing, among others [14]. Although, scholars investigating addictive and habitual smart technology behavior have used these two classifications, they are also applicable in the workplace and often contribute to superior performance. They have also being widely used in studies investigating problematic smart technology usage and adoption of smart technologies, especially among students [12], [15].

The last decade has seen the emergence of a cashless era and digitalization of financial services marked by the birth of mobile money (m-money) as an alternative to cash payment that is part of contemporary lifestyle [2]. Mobile Money (m-money) is a platform that allow customers to gain access to financial services using smart technology devices. M-money usage as a new business model has attracted great interest from academics and practitioners from numerous perceptions. M-money has become the leading payment platform for the digital economies of many developing countries [55]. Sub-Sahara Africa hosts 12 of the world's economies with more adults having a smart technology money account than bank accounts [56]. In Kenya, smart technology financial usage has flourished more any other country in Africa. By the end of 2023, smart technology financial transactions stood at over 6 billion dollars [26]. Smart technology financial usages are categorized into payments, bank transfers, sending money and settling bills by [4]. The usage of these technologies in banks, Small and Medium Enterprises (SMEs) and other organizations is documented in literature [24], [25]. However, studies on their usage in NGOs and contribution to performance are still scanty.

Twenty-first century has seen the world transition into mobile cloud computing (MCC), where cloud-users access numerous services through the Internet via smart technology devices [46]. Mobile Cloud Computing is a combination of mobile computing; cloud computing, and smart technology devices to make available computational resources to users. Mobile cloud computing allows smart technological devices to access mobile applications (Apps) remotely. Globally, MCC usage is growing and in 2024, its market share reported a total value of over 60 million dollars [31]. In Africa, cloud-computing usage has grown exponentially in the last three years and currently stands at 1.2 billion dollars [34]. In Kenya, the cloud computing market is valued at over 900 million dollars and is projected to continue expanding [8]. MCC is categorized based on areas of application into: data management, communication and social media, navigation and maps, virtual assistants and artificial intelligence, among others [47].

2. Literature Review

Literature review presented in this section grouped into theoretical grounding and empirical reviewed literature.

2.1 Theoretical Literature

This study is anchored on updated information success model (ISM) presented by [9]. The model is a comprehensive framework for measuring the performance of information systems. This model consists of a taxonomy of six interrelated dimensions of information systems success: system quality, information quality, service quality, intention to use/use, user satisfaction, and net benefits [10]. Further, [10] posit that system utilization is the most appropriate variable for estimating the achievement of information system (IS). Additionally, intention to use is a significant element of system success because it is untenable to put to use a technology one is uninterested in [20]. The usage intention of a technology indicates the extent of usage of the system by its users in order realize individual and organization level accomplishments, also known as net benefits [21].

In a study [21] confirmed that end-users of a technology were keen on details of system quality; compatibility and system quality that could lead to satisfaction. Additionally, [48] reported a positive relationship between system quality and both behavioral usage intentions and user satisfaction in a learning system. As users work with complex technologies, in-built tools provide them with a range of features such as flexibility and functionality that help them to perform tasks more efficiently. In so doing, this help them accomplish newer tasks that are even more sophisticated [18]. Based on ISM theory, the use of smart technology will lead to acquisition of user expertise, which is attributable to net benefits for the individual and the organization.

2.2 Empirical Literature

The study by [1] concluded that expertise and personal innovativeness moderate user's acceptance of smart meter technologies. The study collected data from 318 smart meters consumers who had expertise in their use. Data was analyzed using partial least squares structural equation modelling. Likewise, [23] determined that user expertise positively moderates crowdsourcing - practice of firms outsourcing employees from the public - on new product design quality. The study population was 1.3 million members of a socialized new product design community. Empirical data was analyzed using multiple regression. The study established that insufficiently skilled designers and scarce resources forced SMEs to tap into external knowledge resources that were inherent in ordinary crowds for product design innovation. Additionally, User skills in science, technology, engineering and mathematics (STEM) and management skills have been associated with improved organizational performance by [50].

Smart technology usage was determined by [53] to enhance bank service efficiency in Nigeria due to their portability, ease of usage, speed of transaction and security. The study sampled 218 respondents. Data analysis was through multiple regression. However, the study was conducted in profit-making enterprises while the current study focused on non-governmental organizations. Moreover, a study by [49] established that web traction and social media usage promote better communication with the public, facilitate fundraising and attract more partners for non-profit organizations thereby enhancing performance. However, the study relied on web access and chatting thereby ignoring other smart technology usages.

The study by [45] sought to determine the application of big data management and organizational performance in small and medium enterprises (SMEs) working in Pakistan. Empirical data was collected from 210 respondents. The study findings revealed that data analytics and data management influenced organizational performance. Additionally, knowledge management practices partially mediated the relationship of the variables of the study. However, the study failed to identify the role of smart technology devices in data management as suggested by [44].

Scholarly work by [22] investigated the effect of personal communication habits on workplace communication expectations of generation Z. The study sampled 207 respondents comprising alumni of Arizona University in USA. Empirical data was analyzed using Qualtrics survey tool. The study established that the young generation used smart technology for communication. Moreover, it was determined that this generation often export their technological expectations to the workplace. The study established that texting was the most preferred method of communication while calling was the least utilized. E-mail was the most utilized form of communication in the workplace while video conferencing was the least utilized. Consequently, generation Z faced a delicate balancing act between work and private life. However, this study surveyed alumni of one university only making generalizability of the findings difficult.

These studies confirm that there exists an empirical gap in the field of smart technology usage and organizational performance. This study therefore aims at advancing the existing literature by studying the relationship between smart technology usage, user expertise and performance of non-governmental organizations in Nairobi City County, Kenya. Based on the literature reviewed the study proposed the following hypothesis:

H_0: User expertise has no significant moderating effect on the relationship between smart technology usage and performance of NGOs in Nairobi City County, Kenya.

3. Research Methodology

This study adopted explanatory research design as recommended by [42]. This design was necessary for explaining the characteristics of the study variables as well as explaining the cause-effect relationships, investigating patterns and trends in existing data, previously not investigated. Moreover, the study did not anticipate any disturbance on the variables. The study collected primary data through a structured questionnaire. The target population was 801 NGOs operating in Nairobi City County, Kenya. Slovins formula generated a sample size of 266 NGOs. Out of 193 questionnaires received, 170 met the threshold for data analysis while, 23 were rejected for being incomplete. Primary data was collected for the independent,

dependent and moderating variables. The instrument collected both quantitative and qualitative data using close-ended and open-ended questions, respectively. Open-ended responses were analyzed using content analysis while quantitative data relied on SPSS statistical software.

3.1 Empirical Model for the Moderation Relationship

To test for the moderating effect of user expertise on the relationship between smart technology usage and performance, the model depicted by figure 3.1 was used.

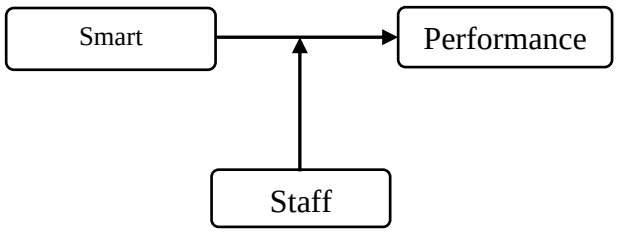

Figure 3.1: Moderation Model

Performance was regressed on smart technology usage (STU) and the corresponding R square value **(R^2)** noted at $p < 0.05$ level of significance as shown in model 3.1.

$$\mathbf{P = \beta_0 + \beta_1 * STU + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.1}$$

Staff expertise (UX) was then introduced and the new R square value (R2) noted at $p < 0.05$ level of significance for the interactive term of the independent variable and moderating variable as shown in model 3.2.

$$\mathbf{P = \beta_0+\beta_1*STU+\beta_2*UX+\beta_3*STU*UX + \varepsilon \ldots\ldots\ldots\ldots 3.2}$$

Where;
P = Composite index for Performance
β_0 = Constant
β_1 - β_3 = Beta coefficients
STU = Composite index for Smart Technology Usage
UX = Composite index for User Expertise
STU * UX = Interaction (INT) of Smart Technology Usage and User Expertise

As recommended by [7], the regression coefficient for the interaction term, β_3 provided an estimate of the moderation effect of user expertise on the relationship between smart technology usage and performance. If β_3 is statistically different from zero, there is evidence that user expertise significantly moderates the relationship between smart technology usage and performance. The significance of moderation is determined by identifying the level of significance of beta coefficient for the interaction term. If ($p < 0.05$) then H_0 will be rejected and if ($p > 0.05$) H_0 will not be rejected.

4. Results and Discussion

In this study, user expertise was the moderating variable and was measured using number of years worked in the organization as reflected by the primary data collected.

The findings presented in table 4.1 indicate that user expertise had a mean of approximately 3.1 (close to the true mean), which translates to agree to a moderate extent on a Likert scale of 1 to 5. The responses had a high standard deviation of 0.8971 indicating that the mean responses had a high variability.

Table 4.1: User Expertise Summary

	N	Min	Max	Mean	Std. Deviation
User Expertise	170	1	5	3.0765	0.8971
Valid N (listwise)	170				

The study findings revealed that 22% of respondents were novice and advanced beginners while 78% had adequate skills in the use of smart technology devices. The bulk of respondents were in the competent category at 46% while only 3% of respondents were experts in smart technology usage as shown in figure 4.1. These findings agree with those of [27] who examined the development of expertise in an applied discipline. The study determined that that expertise in applied disciplines occurs through years of engaging in the high-value, non-routine work.

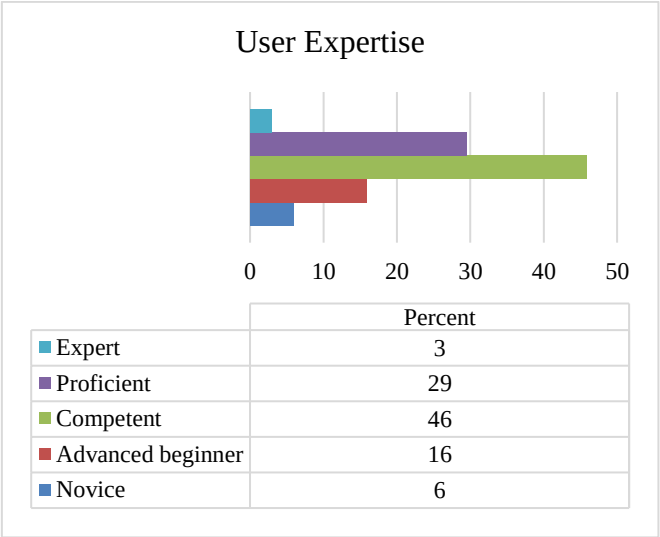

Figure 4.1: User Expertise Levels

4.2.2. Smart Technology Usage

The findings shown in table 4.2 indicate that the accumulated mean for the elements of the indicators of smart technology was 3.1995 and standard deviation of 0.6349. The comparison of each of the indicators is as shown in figure 4.2. The highest variation within the attributes was observed in financial usage while the least variance was seen in social usage. The results are consistent with those of [29] who observed that social smart technology usage was a crucial driver in organizational performance to office workers.

Table 4.2: Smart Technology Usage Summary

Smart Technology Usage	N	Min	Max	Mean	Std. Deviation
Social Usage	170	2	5	3.3364	0.4646
Process Usage	170	2	5	3.1746	0.5931
Financial Usage	170	1	5	3.0709	0.8088
MCC Usage	170	2	5	3.2162	0.6731
Overall Aggregate				**3.1995**	**0.6349**

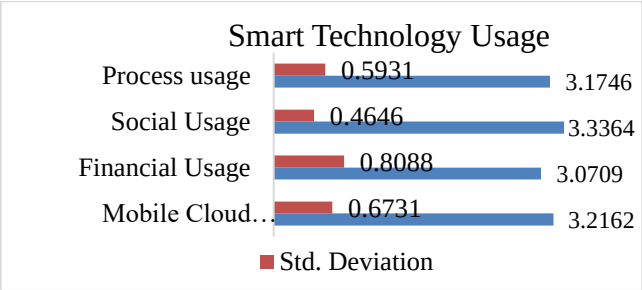

Figure 4.2: Smart Technology Usage Summary

4.2.3 Performance

The collective sample mean and standard deviation for the indicators of NGO performance were 3.1490 and 0.8067 respectively as shown in table 4.3. Low standard deviation indicated that the mean responses had a low variability. Subsequently, the mean of the responses was close to the true mean. Programs outcome (effectiveness) had the highest variability while partnerships had the least variant.

Table 4.3: Descriptive Analysis of Dependent Variable

Indicator	N	Min	Max	Mean	Std. Deviation
Programs Outcome	170	1	5	3.0459	0.8947
Partnerships		2	5	3.4471	0.6568
Financial Transparency		1	5	3.0544	0.8233
Fundraising Efficiency		1	5	3.0485	0.8519
Overall Aggregate				**3.1490**	**0.8067**

4.2 Test of Hypothesis

This section presents the findings of hypotheses testing. Primary data obtained from the field was cleaned and then formatted using Microsoft Excel before subjecting it to inferential statistics.

4.2.1 Mediation Effect of Competitive Advantage on the Relationship between Smart Technology Usage and Performance

The study adopted a moderation regression model as suggested by [15]. The test involved computation of composite variable for independent variables – Smart Technology Usage (STU), interaction variable (INT) computed using product of STU and User Expertise (UX) (moderating variable). Then regression model was fitted with the product of STU and UX, STU, UX as predictor variables of performance. The results are shown in table 4.4.

Table 4.4: Summary for Moderated Regression Model

Model	R	R Square	MSE	F	p
1	0.9120[a]	0.4160	0.2618	43.768	0.000
a: Predictors: (Constant), STU*INT, STU, INT					

The findings in table 4.4 show R-Square value of 0.4160, which implies that smart technology usage explains 41.6% of the variation in the performance. However, the study relied on significance level to test whether user expertise moderated the relationship between smart technology usage and performance.

Table 4.5: Coefficients for Moderated Regression Analysis

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.254	0.207		10.877	0.000
	STU	0.220	0.092	0.294	2.396	0.018
	INT	0.019	0.012	0.195	1.585	0.015
Dependent Variable: Performance						

The moderation effect results of the interaction term (INT) are shown in table 4.5. The moderating variable, user expertise, has a p-value of 0.015. This resulted in regression equation model 4.1.

Staff Expertise = 2.254 + 0.220 STU + ……Model 4.1

Since $p < 0.05$, the moderator variable, user expertise, had significant effect on the relationship between smart technology usage and performance.

Table 4.6: Regression Coefficients for Moderated Regression Analysis

Model	Coefficient	Se	t	p
constant	3.1553	0.0314	100.5522	0.000
STU	0.2484	0.0726	3.4197	0.008
UX	0.0796	0.0437	1.8192	0.007
Int_1	0.0192	0.0439	0.4363	0.017

Source: Researcher (2024)

The moderated regression analysis model findings are shown in table 4.6. The findings revealed that all p-values for smart technology usage (STU), user expertise (UX), and Intercept (Int_1) were significant (p-value ≤ 0.05).

Table 4.7: Conditional Effects of the Focal Predictor at Values of the Moderator

User Expertise (UX)	Effect	Se	t	p
-0.8971	0.2656	0.0721	3.6827	0.0003 <0.05
0.0000	0.2484	0.0726	3.4197	0.0008 <0.05
0.8971	0.2312	0.0920	2.5141	0.0129 <0.05

Finally, table 4.7 revealed that the conditional effects of the moderating variable, User Expertise (UX) at values of the moderator were significant (p-value ≤ 0.05) at levels -.0.8971, 0.0000, and 0.8971 (SD, Mean, +SD). Therefore, the study rejected the null hypothesis H0: User expertise does not moderate the relationship between smart technology usage and performance of NGOs in Nairobi City County, Kenya. Consequently, it was concluded that user expertise significantly moderated the relationship of smart technology usage with performance. The findings of this study concur with those of [6] who determined the moderating role of user expertise in the relationship between controlling use, job performance and organizational performance.

5. Conclusions and Policy Recommendation

Based on the findings aforementioned, this study concluded that user expertise moderates the relationship between smart technology usage and performance for non-governmental organizations. Further, the study established that smart technology usage assessed by process; social, financial and mobile cloud computing usages, positively influences performance of NGOs. The study established that user skills or expertise obtained using a focal technology, like smart technology, measured by the extent to which the user has engaged a given technology (years worked); and, the degree to which a user perceives their mastery of knowledge of a given technology moderates the relationship between the technology and organizational performance. The level of expertise determines the extent of usage of smart technology devices and hence, the net benefits realized by the organization. NGOs with a higher number of employees who are either competent, proficient or expert in smart technology usage are likely to perform better than NGOs with a sizable number of novice users, or advanced beginners.

Drawing from the findings, the study recommends to management of the non-governmental organizations to invest and leverage on smart technology usage to realize superior performance. Additionally, these organizations should put in place strategies that encourage employee retention in order for them to acquire the requisite expertise in the usage of smart technology devices and realize superior performance. Use of smart technology devices is not only innovative for NGOs but also beneficial. These devices are deployed by NGOs for community development activities, fundraising, creating partnerships, stakeholder engagement and even financial reporting. The study further recommends that managers of NGOs consider delivering superior value to the communities where they operate though implementation of smart technology usage. In conclusion, the study recommends that scholars in the field of management information systems identify gaps in the study or test the robustness of the study findings in a different industry.

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