Influence of Identifying Adaptive Challenges Behavior on the Digital Transformation of Insurance Firms in Kenya

John ODINDO[1], George K'AOL[1], and Kefah NJENGA[1]

1. Chandaria School of Business, United States International University - Africa

Corresponding Author: johnogilla@gmail.com

Submitted 15th June 2023, Accepted 15th June 2023 and Published 19th August 2023

ABSTRACT

The purpose of this study was to examine the influence of identifying adaptive challenges behavior on the digital transformation of insurance firms in Kenya. The study employed an adaptive leadership theoretical framework and a postpositivist philosophical stance. The study utilized a descriptive correlational research design, and stratified random sampling technique for data collection data using a self-administered questionnaire that employed a 5-point Likert scale. The target population consisted of 392 supervisors representing 56 insurance firms, listed by the IRA website in 2021. A sample population of 198 was selected using a stratified random sampling technique. Factor analysis was conducted to test for reliability and validity of the research instrument. Descriptive and inferential statistics were applied to analyze the data and test the hypothesis. The ordinal logistic regression results revealed that identifying adaptive challenges behavior explained 59.7% of the variance in digital transformation, $R^2 = .597$. The parameter estimates indicated that this behavior predicted digital transformation, $\beta 2 = -4.787$, $p \leq .05$. Thus, the null hypothesis that this behavior has no significant influence on digital transformation was rejected. Hence, the study concluded that identifying adaptive challenges behavior has significant influence on the digital transformation of insurance firms in Kenya. The research recommended that identifying adaptive challenges behavior is emphasized in driving digital transformation in the insurance industry. Since the scope of this study was limited to insurance firms in Kenya, further research should consider the broader financial services industry and other countries to establish if research would yield comparable results.

Keywords: *Adaptive challenges, adaptive leadership, digital transformation, experimentation, identifying adaptive challenges, team collaboration, work complexity*

I. INTRODUCTION

Digital transformation involves the adoption of new technologies and processes to improve a company's operations in response to changing business environments by increasing the value proposition, value capture, and customer interface (Dehnert, 2020). Many leaders and scholars have considered the digital transformation environment to be unprecedentedly complex (Roux, 2020). This complexity is attributed to the multifaceted and multidimensional dynamic phenomenon of digital transformation. Chanias et al. (2019) have argued that the challenges faced by leaders in the context of digital transformation stem from the constant flux inherent in this evolving landscape. They posit that conventional leadership styles that focus on strategic planning and execution methodologies are ill-suited to cope with this dynamic environment. Moreover, other researchers, such as Ramalingam et al. (2020), explicitly advocate for a departure from the traditional hierarchical, autocratic, and top-down leadership style. Instead, they propose the adoption of a more flexible leadership styles that foster collaboration and experimentation, thereby enabling organizations to effectively address the intricacies of contemporary work complexities.

Globally, amongst the financial services industry leaders, digital transformation has been recognized as one key challenge facing their organizations (Cappiello, 2020). Indeed, some scholars opined that the leaders of traditional financial services organizations and channels would likely face significant profitability challenges as more agile FinTechs transform the industry with disruptive digital services combined with superior value propositions (Anagnostopoulos et al., 2018). According to Cappiello (2020), the insurance sector, in particular, is undergoing complex digital transformation challenges driven by advancements in technology and shifting customer expectations. Mobile money, predictive analytics, blockchain, digital assets, and cloud services are among the disruptive technologies adopted by FinTechs (Goncalves et al., 2020). Adaptive leadership, as posited by Heifetz (1994) in his seminal work "Leadership without Easy Answers," constitutes a distinct approach to leadership that emphasizes the mobilization of organizations to navigate complex and uncertain situations. Departing from traditional authoritarian leadership theories, this framework highlights the importance of addressing adaptive challenges and engaging the entire organization in finding innovative solutions (Northouse, 2019). The concept of adaptive leadership gained significance in the context of digital transformation as scholars recognized its potential to guide organizations through rapid changes and foster adaptability (Larjovuori et al., 2018).

In Africa, a study by Preko (2022) postulated that adaptive leadership behaviors enable rapid response to change by providing leaders and followers with opportunities for experimentation and collaboration in response to complex adaptive challenges. Still in the region, a South African study focused further on several adaptive leadership behaviors in the financial services industry (April & Dalwai, 2019). The scholars extended the research on the leadership competencies required for digital transformation. The qualitative study interviewed 15 banking executives, including CEOs, CIOs, and other top executives. The study revealed that one adaptive leadership behavior, experimentation within a holding environment, is a critical leadership competency, ranking higher than business skills, influencing skills, and cognitive skills. In Kenya, several researchers have emphasized the significance of adaptive leadership in the face of the challenges posed by digital transformation (Kiula et al.,2019). It is argued that digital transformation engenders both technical and adaptive challenges, with the latter being more intricate and necessitating a distinctive leadership approach (Nyakomitta, 2021). Nevertheless, scholars specializing in adaptive leadership advocate for additional empirical studies, as there exists a dearth of research investigating this contemporary leadership style (Wamburu et al., 2022). A comprehensive understanding of the behaviors and characteristics associated with adaptive leadership can significantly assist organizations in effectively addressing adaptive challenges, such as digital transformation, and achieving positive outcomes.

Research has shown that only one-third of the 1,300 digital transformation leaders across more than 750 global organizations perceived themselves as possessing the necessary leadership capabilities to effectively navigate the challenges of digital transformation (Bonnet & Westermann, 2021). These highlighted gaps emphasize the importance of developing leaders with contemporary skills and behaviors to overcome the challenges posed by the rapidly changing digital landscape (Raei, 2018). Development of adaptive leadership styles and behaviors have gained considerable attention for their hypothesized suitability for navigating and adapting to the complexity of digital transformation (Han et al., 2020). According to Northouse (2019), adaptive leadership involves identifying and effectively addressing complex challenges, embracing change, and promoting innovation within an organization. One specific behavior of adaptive leadership is the identification of adaptive challenge, which encompasses work complexity, team collaboration, and experimentation practices by leadership (Wong, 2019; Zhang et al., 2021). While the importance of adaptive leadership behaviors in facilitating digital transformation is widely espoused by some scholars, others note the scant empirical research on this contemporary leadership style (Wamburu et al., 2022). This study aims to fill this research gap by examining the relationship between identifying adaptive challenges behavior and digital transformation in the insurance industry. The insurance industry is currently undergoing a significant shift towards digital transformation as firms recognize the need to adapt to changing business dynamics and leverage technological advancements (Cote, 2022). Some of the highlighted contemporary industry challenges include customer expectations, evolving regulatory requirements, and disruptive competition from insurtechs (Sibanda et al., 2020). To address these challenges, its leaders are embracing digital technologies and innovative business models to enhance operational efficiency, improve customer experience, and foster growth (Owuor, 2018; Kang'e et al., 2020). Still, the results are varied. The decline in insurance market penetration from 2.71% in the previous year to 2.43% in 2018 and a significant decrease in year-over-year revenue growth from 6.5% in 2017 to 3% in 2018 highlighted the significance of the above challenges (IRA, 2020). The objective of this study was to investigate the extent to which identifying adaptive challenges behavior influences the digital transformation of insurance firms in Kenya.

This study was anchored on the adaptive leadership theory by Heifetz and Laurie (1997) with the independent variable being the identifying adaptive challenges behavior. These adaptive challenges refer to complex organizational problems that require adaptation to existing beliefs, values, and behaviors to effectively address them (Northouse, 2019). Therefore, adaptive challenges behavior arises from the need to navigate work complexity, foster team collaboration, and promote experimentation (Yukl et al., 2019). However, unlike technical challenges that have known solutions, adaptive challenges demand organizations experiment, collaborate, and learn from stakeholders to develop innovative approaches (Pak et al., 2020). The dependent variable is digital transformation, which was conceptualized by Dehnert's (2020) operational model for the digital transformation of financial service firms. This study measured the model's three pillars: the value creation pillar by returns on assets, the value proposition pillar by digital innovation, and the customer interaction pillar by customer experience capabilities measures. The resultant framework for the study is given in Figure 1.

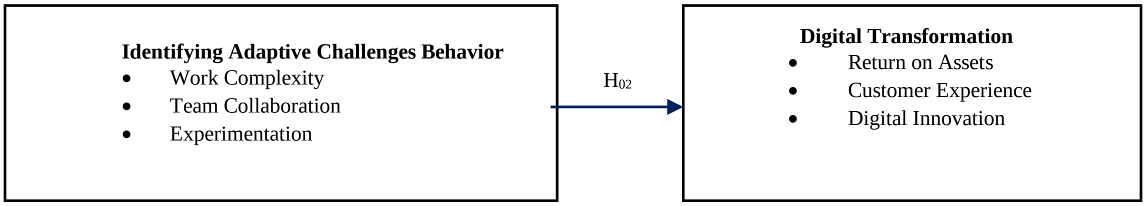

Figure 1 Conceptual Framework

Previous empirical studies have explored the relationship between identifying adaptive challenges constructs of work complexity, team collaboration, and experimentation in various contexts. Identifying adaptive challenges can be defined as the adaptive leader's behavior of addressing tough challenges characterized by work complexity using experimentation and team collaboration (Heifetz & Laurie, 1997; Northouse, 2019). According to Zhang et al. (2021), adaptive leaders that promote teams that practice experimentation and collaboration are able to be effective in the face of change that causes work complexity. Therefore, identifying adaptive challenges behavior of a leader encompasses navigating external dynamic challenges by orchestrating organizational evolution (Cote, 2022). In a recent European study conducted by Bornay-Barrachina and Herrero (2017), the focus was on the relationship between work complexity, dyadic co-worker relationships, and team performance. The research specifically targeted research and development teams in technology and science companies. To gather data, a questionnaire was employed as a research tool. The study followed a longitudinal design, collecting data at two different time points. A total of 410 questionnaires were completed by team members within 81 teams. The study's findings supported the hypothesis that as work complexity increases, there is a greater need for a strong dyadic work relationship, while the need for such relationships may decrease as work complexity decreases.

In a study conducted in Slovenia by Manfreda and Štemberger (2018), the focus was on the collaboration between business leaders and IT managers. The findings indicated a positive correlation between collaboration when considering the perceived value and business orientation of the IT department. However, it was observed that an IT department solely focused on technology could hinder collaborative efforts. The study findings which emphasized the importance of establishing strong collaboration between business and IT departments for successful digital transformation, were supported by other later studies (Garzoni et al., 2020). Additionally, Singh and Hess (2017) conducted research that emphasized the role of leadership in enhancing collaboration. They suggested that companies undergoing digital transformation appoint Chief Digital Officers to facilitate this process, previously under IT managers. A study in Pakistan investigated the influence of entrepreneurial behavior on firm performance within SMEs (Hayat et al., 2019). The study interviewed owners and top management within a sample size of 350. The study returned a response rate of 88%. The correlation between experimentation support via entrepreneurial leadership and firm performance was realized, $\beta = 0.47$, $T = 2.792$, with a p-value below 0.05, indicating a positive medium influence. Furthermore, one of the measures applied to firm performance was the return on assets, implying a positive relationship between experimentation and returns on assets.

II. METHODOLOGY

This study aimed to analyze the influence of identifying adaptive challenges behavior on digital transformation. To investigate the relationship between the independent variable (identifying adaptive challenges behavior) and the dependent variable (digital transformation), a descriptive correlational research design was adopted. This is because the findings of a descriptive correlational study provide valuable insights into the associations between variables, contributing to a comprehensive understanding of the observed phenomena (Babbie, 2020). The target population for this study comprised 392 supervisors selected from the 56 insurance firms listed by the Insurance Regulatory Authority of Kenya (IRA) as of October 2021. The study identified the units of analysis as the 56 principal officers of the IRA insurance firms, while the unit of observation was established as the 392 supervisors. Thus, the population of interest encompassed seven supervisor roles within each of the 56 listed IRA insurance firms, including finance, information technology, actuarial and risk, sales and marketing, strategy and operations, compliance and legal, and human resources. The population of interest was segregated into three distinct segments (See Appendix I), namely long-term insurance, general insurance, and composite insurance firms, in accordance with the classification provided by the IRA (2021). The sample size of 198 supervisors was determined using stratified random sampling. This probability technique was used to ensure that each element of the target population, within each stratum, had an equal and known chance of being selected with a controlled margin of error (Creswell, J. W., & Creswell, 2018). The research applied Yamane's (1974) formula, shown below, to determine the sample size. This formula is widely used to determine sample size when the population (N) and acceptable margin of error (e) is provided by;

$$n = \frac{N}{\left(1 + N(e^2)\right)}$$

Where:

n= sample size;
N = population size (for this study, population = 392 as defined earlier in Section 3.4); and
e = Margin of error; with 95% confidence level (or margin of error, e = 0.05, i.e., 5%)
n = 392 / (1 +392 (0.05^2)) = 392/1.98 = 198 (After rounding to whole number per stratum)

Therefore, the sample size was 198 respondents. Table 1 shows how the stratified sampling technique calculated the sample size.

Table 1:

Sample Size

Stratum	Supervisor Population	Sample Proportion n/N	Sample Size per Stratum (Rounded)
General Insurance	245	63%	124
Long Term Insurance	126	32%	64
Composite Insurance	21	5%	10
Total	392	100%	198

A structured questionnaire was utilized as the primary data collection instrument. Prior to data collection, a pilot study was undertaken on the questionnaire to check for appropriateness, and factor analysis was conducted to reduce variables and identify latent constructs. Thirty (30) supervisors were randomly selected from the 198 in the sample size and included in the pilot study. The results of the pilot study were used to update the research questions to make them clearer and unambiguous for the respondents. Reliability tests revealed that all constructs had Cronbach's alpha scores above 0.7 and were therefore retained for further analysis in the main study. Validity tests also revealed high KMO greater 0.833, and Bartlett's test of sphericity was significant ($p<.05$) for all the research question. As the criterion-based, construct, and discriminant validity were all satisfied, the research instrument was deemed suitable for addressing the research questions at hand. Since the data was collected via a Likert scale, ordinal procedures and tests were employed in the analysis. Both descriptive and inferential statistics were utilized for data analysis. To test the hypothesis regarding the relationship between the independent variables and the dependent variable, an ordinal logistic regression model was applied.

III. RESULTS

Spearman's Correlation Analysis

Spearman's correlation analyzed the relationship between identifying adaptive challenges behavior and digital transformation. The results presented in Table 2 revealed a significant positive relationship between these variables, $r(127) = 0.530$, $p < 0.05$. This indicates a moderately positive association between identifying adaptive challenges behavior and digital transformation.

Table 2:

Spearman's Correlation Analysis

Variables		Identify Adaptive Challenges Behavior	Digital Transformation
Identify Adaptive Challenges	Correlation Coefficient	1	.530
	Sig. (2-tailed)		<.001
	N	127	127
Digital Transformation	Correlation Coefficient	.530	1
	Sig. (2-tailed)	<.001	
	N	127	127

Chi-Square Test

Furthermore, a chi-square test examined the association between identifying adaptive challenges behavior and digital transformation. The results displayed in Table 3 indicated a statistically significant association between the two variables, $\chi^2(12, N = 127) = 156.042$, $p \leq .05$.

Table 3:

Chi-square Test

Chi-Square Tests	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	156.042	12	<.001
Likelihood Ratio	128.172	12	<.001
Linear-by-Linear Association	35.409	1	<.001
N of Valid Cases	127		

Chi-square is significant at $p \leq .05$ (2-tailed)

One-Way ANOVA

Additionally, a one-way ANOVA was carried out to examine differences in the means of identifying adaptive challenges behavior concerning various demographic variables. The results presented in Table 4 of the appendices revealed significant differences in means for the demographic variable of years of experience in digital transformation, $F(2, 126) = 3.964$, $p \leq .05$. See table 4 in the appendices.

Ordinal Logistic Regression Assumptions

1. *Dependent Variable (Digital Transformation) Assumption*

The ordinality assumption requires that the level of measurement for the dependent variable to be on an ordinal scale. For this study, digital transformation was measured using three constructs; returns on assets, digital transformation and customer experience, whose indicators were on a five-level Likert scale. This is an ordinal level of measurement, and thus, the assumption was not violated.

2. *Test for Multi-Collinearity Assumption*

The multicollinearity test was conducted using the Spearman's correlation coefficient, with a threshold of $r < 0.8$ to indicate low correlation between the independent variables. The results, presented in Table 5 of the appendices, show that the values for the independent variables identifying adaptive challenges were below the threshold, thus the test for multicollinearity was not violated.

3. *Test for Proportional Odds Assumption*

The assumption was tested using the log likelihood ratio Chi-Square test, with a significant value ($p \geq .05$) indicating that the proportional odds assumption holds. The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

The test result presented in Table 6 demonstrates the proportional odds assumption was violated in this analysis, $\chi 2$ (8) = 46.485, $p < .05$. These results imply that the relationship between identifying adaptive challenges behavior and digital transformation is not the same for each pair of outcome groups. Therefore, it is essential to exercise caution while interpreting the results of subsequent ordinal regression analyses, as the reliability of the results may be compromised for certain outcome levels.

Table 6:

Test of Parallel Lines

Model	-2Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	46.485			
General	.000	46.485	8	<.001

Hypothesis Testing

Ordinal logistic regression model was used to assess the extent to which identifying adaptive challenges predicted digital transformation. Hypothesis testing for parameter estimates in ordinal logistic regression can be performed using either the likelihood ratio test or the Wald test (Agresti & Tarantola, 2018). In this study, the significance of rejecting or failing to reject the null hypothesis was determined based on the Wald test p-value for the parameter estimates (β). In addition, the Nagelkerke Pseudo R-Square value was used to represent the goodness-of-fit of the ordinal logistic regression model. The hypothesis and the parameter estimate test are given below:

H_{02}: Identifying adaptive challenges behavior has no significant influence on the digital transformation of insurance firms in Kenya.

Test: $\text{Logit}\,[P\,(Y \leq j)] = \alpha j - \sum\{\beta_2 X_2\} + \mathcal{E}$
Reject H_{02} if $p \leq 0.05$, fail to reject H_{02} if $p \geq 0.05$.

1. *Model Fitting Information*

The model fitting information test, which uses the Chi-square statistic, was used to assess whether there was a significant improvement in the fit of the final model with identify adaptive challenges behavior predictor variable compared to the intercept-only statistical model with no predictor variables. The results, presented in Table 7, show that the final model had a significant improvement in fit compared to the base model, implying a better prediction and fit of data thus revealing that the model adequately captures the underlying structure of the data, χ^2 (4) = 98.582, $p \leq .05$.

Table 7:

Model Fitting Information

Variables in the Equation	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	145.067			
Final	46.485	98.582	4	<.001

Link function: Logit

2. *Goodness-of-Fit Test*

To evaluate the adequacy of the fitted model for predicting the influence of identifying adaptive challenges behavior on digital transformation, a goodness-of-fit test was administered. The results of the test were presented in Table 8 and showed significant results, which supported the null hypothesis that the model does not provide an adequate fit to the actual data, χ^2 (8) = 41.758, $p < .05$. This indicates that the model was unable to sufficiently explain the variation in the dependent variable, digital transformation. Therefore, there may be other predictors that were not accounted for in the model, and the results should be interpreted with caution.

Table 8:

Goodness of Fit Test

	Chi-Square	Df	Sig.
Pearson	41.758	8	<.001
Deviance	29.590	8	<.001

Link Function: Logit.

3. *Pseudo-R-square*

A pseudo-R-square statistic was evaluated to assess the goodness-of-fit of a regression model and determine the influence of identifying adaptive challenges behavior on the digital transformation. The Pseudo R-coefficient results presented in Table 9 (see appendix), indicate that identifying adaptive challenges behavior explained 59.7% of the variance in digital transformation, Nagelkerke R^2 = 0.597. This indicated that this behavior significantly influenced the digital transformation of insurance firms in Kenya.

Table 9:

Pseudo-R-Square

Link function	Logit
Cox and Snell	.540
Nagelkerke	.597
McFadden	.332

Link Function: Logit.

4. *Parameter Estimates*

The parameter estimates from an ordinal logistic regression model were obtained in this study to understand the log-odds ratio for a one-unit change in the digital transformation variable while keeping all the identifying adaptive challenges behavior predictor variable constant. The model for the influence of identifying adaptive challenges, X_2, on digital transformation, Y_{DT}, is presented below:

$$\text{Logit}\,[P\,(Y_{DT} \leq j)] = \alpha j - \beta_2 X_2$$

The findings of the ordinal regression parameter estimates are presented in Table 9 of the appendices. The results reveal a statistically significant relationship between identifying adaptive challenges behavior (X_2) and digital transformation (YDT) in the study, with X2 = 5 serving as the reference point. Specifically, for every unit increase in the independent variable, the predicted decrease in the logs odd of falling into a lower level of digital transformation was found to be significant, with a decrease of 4.787 in the logs odd scale at $X_2=4$, $\beta_2 = -4.787$, $p<0.05$. These results imply that identifying adaptive challenges behavior has a significant influence on digital transformation.

IV. DISCUSSION

The current study examined the impact of identifying adaptive challenges behavior, encompassing work complexity, team collaboration, and leadership experimentation practices, on the digital transformation of insurance firms in Kenya. Correlational analysis demonstrated a significant positive relationship between identifying adaptive challenges behavior and digital transformation in these firms ($r = 0.530$, $p < .05$), aligning with prior research emphasizing the positive influence of work complexity, team collaboration, and experimentation on organizational outcomes. Notably, work complexity (Zhang et al., 2021), team collaboration (Costumato, 2021), and experimentation (Wong, 2020) have previously been found to have a positive impact on organizational outcomes. However, some studies reported weak associations for these factors (Audenaert et al., 2017; Bornay-Barrachina & Herrero, 2017). Moreover, the present study revealed significant differences in identifying adaptive challenges behavior across different levels of leadership experience in digital transformation, suggesting demographic factors may influence work complexity, team collaboration, and experimentation. Ordinal logistic regression analysis further indicated that identifying adaptive challenges behavior significantly predicted digital transformation ($R2=0.597$, $\beta = -4,787$, $p<0.05$), consistent with a European study linking work complexity to individual innovation outcomes (Audenaert et al., 2017). Collaboration between leaders and IT managers (Manfreda & Stemberger, 2018) and experimentation support via entrepreneurial leadership (Jang et al., 2019) were also found to positively impact organizational outcomes. These results highlight the significance of identifying adaptive challenges behavior, specifically work complexity, team collaboration, and experimentation, in driving digital transformation within insurance firms in Kenya. Leaders should foster a creative work environment, implement policies supporting cross-organizational collaboration, and remove barriers to experimentation to facilitate digital transformation.

Conclusion

Ordinal logistic regression results established that identifying adaptive challenges behavior explained 59.7% of the variance in digital transformation, Nagelkerke Pseudo $R^2 = .597$. In addition, the parameter estimates indicated that this identifying adaptive challenges behavior predicted digital transformation, $\beta2 = -4.787$, $p \leq .05$. Thus, the study concluded that identifying adaptive challenges behavior significantly influences the digital transformation of insurance companies in Kenya.

Recommendations

Using ordinal regression analysis, the study established that identifying adaptive challenges positively and significantly predicted digital transformation. This implies that insurance firm leaders who focus on identifying adaptive challenges will increase organizational value creation, value proportion, and customer retention measures of digital transformation. Insurance firms should therefore clearly define their adaptive challenges in terms of work complexity, team collaboration, and experimentation focused on digital transformation. While the study confirmed the important role identifying adaptive challenges plays in digital transformation, the violation of the proportional odds assumption suggests that further broader research may target large sample populations and other financial services industry demographics to build on the study's results. Additionally, further research is warranted to explore these dynamics in more depth within different levels of management and across the broader financial services industry, providing valuable insights for both researchers and practitioners seeking to drive digital transformation efforts.

V. REFERENCES

Agresti, A., & Tarantola, C. (2018). Simple ways to interpret effects in modeling ordinal categorical data. *Statistica Neerlandica, 72(3), 210-223. https://doi.org/10.1111/stan.12130*

Anagnostopoulos, I. (2018). Fintech and regtech: Impact on regulators and banks. *Journal of Economics and Business, 100, 7-25. https://doi.org/10.1016/j.jeconbus.2018.07.003*

April, K., & Dalwai, A. (2019). Leadership Styles Required to Lead Digital Transformation. *Effective Executive*, 22(2), 14–45. https://www.proquest.com/openview/ce3d2a6e398785c360a6466013cf4088/1?pq-origsite=gscholar&cbl=2029988

Audenaert, M., Vanderstraeten, A., & Buyens, D. (2017). When innovation requirements empower individual innovation: The role of job complexity. *Personnel Review, 46(3), 608–623*. https://doi.org/10.1108/PR-10-2014-0219

Bonnet, D., & Westerman, G. (2021). The new elements of digital transformation. *MIT Sloan Management Review*, *62*(2), 82-89. https://sloanreview.mit.edu/article/the-new-elements-of-digital-transformation/

Bornay-Barrachina, M., & Herrero, I. (2017). Team creative environment as a mediator between CWX and R&D team performance and moderating boundary conditions. *Journal of Business and Psychology*, *33*, 311-323. https://doi.org/10.1007/s10869-017-9495-8

Cappiello, A. (2020). The Technological Disruption of Insurance Industry: A Review. *International Journal of Business and Social Science*, 11(1), 1–11. https://doi.org/10.30845/ijbss.v11n1p1

Cote, R. (2022). Adaptive Leadership Approach With COVID 19 Adaptive Challenges. *Journal of Leadership*, Accountability & Ethics, 19(1). https://doi.org/10.33423/jlae.v19i1.4992

Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications. https://us.sagepub.com/en-us/nam/research-design/book270550

Costumato, L. (2021). Collaboration among public organizations: a systematic literature review on determinants of interinstitutional performance. International Journal of Public Sector Management, 34(3), 247-273. https://doi.org/10.1108/IJPSM-03-2020-0069

Dehnert, M. (2020). Sustaining the current or pursuing the new: incumbent digital transformation strategies in the financial service industry. *Business Research*, *13*(3), 1071-1113. https://doi.org/10.1007/s40685-020-00136-8

Garzoni, A., De Turi, I., Secundo, G., & Del Vecchio, P. (2020). Fostering digital transformation of SMEs: a four levels approach. *Management Decision*, *58*(8), 1543–1562. https://www.emerald.com/insight/0025-1747.htm

Goncalves, D., Bergquist, M., Bunk, R., & Alänge, S. (2020). Cultural aspects of organizational agility affecting digital innovation. *Journal of Entrepreneurship, Management and Innovation, 16(4), 13-46. https://doi.org/10.7341/20201641*

Han, S. J., Kim, M., Beyerlein, M., & DeRosa, D. (2020). Leadership role effectiveness as a mediator of team performance in new product development virtual teams. *Journal of Leadership Studies*, *13*(4), 20-36. https://doi.org/10.1002/jls.21677

Hayat, A., Latif, A., Humayon, A. A., Ahmed, M., & Azeem, M. (2019). The mediating role of entrepreneurial leadership in the relationship between entrepreneurial orientation and firm performance of ICTs SMEs. *Journal of Multidisciplinary Approaches in Science*, *5*(1), 16-23. https://scholar.google.com/citations?view_op=view_citation&hl=en&user=8IN6cKQAAAAJ&citation_for_view=8IN6cKQAAAAJ:J_g5lzvAfSwC

Heifetz, R. A. (1994). Leadership without easy answers (Vol. 465). Harvard University Press. https://ebookcentral.proquest.com/lib/uskenya-ebooks/detail.action?docID=3300701.

Heifetz, R. A., & Laurie, D. L. (1997). *The work of leadership*. Harvard Business Review, 75, 124-134. https://hbr.org/2001/12/the-work-of-leadership

Insurance Regulatory Authority. (2020, November 25). IRA. Retrieved from https://www.ira.go.ke/

Jang, Y., Ahn, Y., Park, M., Lee, H. S., & Kwon, N. (2019). Business models and performance of international construction companies. *Sustainability, 11(9), 2575*. https://doi.org/10.3390/su11092575

Kang'e, M., Senaji, E. D. T. A., & Orero, R. (2020). Distribution Models And Performance Of Private Health Insurance Sector In Kenya. *European Journal Of Business And Strategic Management*, *5*(1), 55-69. https://www.iprjb.org/journals/index.php/EJBSM/article/view/1074

Kiula, M., Waiganjo, E., & Kihoro, J. (2019). The Role of Leadership in Building the Foundations for Data Analytics, Visualization and Business Intelligence. *2019 IST-Africa Week Conference, IST-Africa 2019*, 1–8. https://doi.org/10.23919/ISTAFRICA.2019.8764827

Manfreda, A., & Indihar Štemberger, M. (2018). Establishing a partnership between top and IT managers: A necessity in an era of digital transformation. *Information Technology & People*, *32*(4), 948–972. https://doi.org/10.1108/ITP-01-2017-0001

Northouse, P. G. (2019). *Leadership: Theory and Practice* (8th ed.). Thousand Oaks, CA: Sage.

Nyakomitta, K. O. (2021). *Influence of Transformation Leadership on the Performance of Commercial Banks in Kenya* [Doctoral dissertation, JKUAT-COHRED]. http://ir.jkuat.ac.ke/bitstream/handle/123456789/5504/LIBRARY%20FINAL.pdf?sequence=1&isAllowed=y

Larjovuori, R. L., Bordi, L., & Heikkilä-Tammi, K. (2018, October). Leadership in the digital business transformation. In Proceedings of the 22nd International Academic Mindtrek Conference (pp. 212-221). https://doi.org/10.1145/3275116.3275122

Owuor, E. (2018). Impact of disruptive technology on the performance of insurance firms in Kenya. *Journal of Strategic Management*, *3*(1), 72-82. https://doi.org/10.47672/jsm.367

Pak, K., Polikoff, M. S., Desimone, L. M., & Saldívar García, E. (2020). The Adaptive Challenges of Curriculum Implementation: Insights for Educational Leaders Driving Standards-Based Reform. *AERA Open*, *6*(2). https://doi.org/10.1177/2332858420932828

Preko, A. K. (2022). Leadership and Human capital management in new public management. New Public Management in Africa: Contemporary Issues, 105-131. https://doi.org/10.1007/978-3-030-77181-2_5#DOI

Raei, M. (2018). Development and Validation of the Adaptive Leadership With Authority Scale. *Journal of Chemical Information and Modeling*, *53*(9), 1689–1699. https://aura.antioch.edu/etds/446

Ramalingam, B., Nabarro, D., Oqubuy, A., Carnall, D., & Wild, L. (2020). Principles to guide adaptive leadership. *Harvard Business Review*. https://hbr.org/2020/05/principles-to-guide-adaptive-leadership.

Roux, M. (2020). Leadership 4.0. In *Maturing leadership: How adult development impacts leadership* (pp. 7-35). Emerald Publishing Limited. https://doi.org/10.1108/978-1-78973-401-020201015

Sibanda, W., Ndiweni, E., Boulkeroua, M., Echchabi, A., & Ndlovu, T. (2020). Digital technology disruption on bank business models. *International Journal of Business Performance Management*, *21*(1-2), 184-213. http://dx.doi.org/10.1504/IJBPM.2020.106121

Singh, A., & Hess, T. (2017). How chief digital officers promote the digital transformation of their companies. *MIS Quarterly Executive*, *16*(1). https://aisel.aisnet.org/misqe/vol16/iss1/5

Wamburu, A., Nyambegera, S. M., & Kibet, E. (2022). Influence of gaining perspective dimension of adaptive leadership on organizational performance of insurance companies in Kenya. *DBA Africa Management Review*, *12*(3), 1-23. http://uonjournals.uonbi.ac.ke/ojs/index.php/DBAAMR/article/view/1117

Wong, S. I., & Berntzen, M. N. (2019). Transformational leadership and leader–member exchange in distributed teams: The roles of electronic dependence and team task interdependence. *Computers in Human Behavior*, *92*, 381-392. https://doi.org/10.1016/j.chb.2018.11.032

Yukl, G., Mahsud, R., Prussia, G., & Hassan, S. (2019). Effectiveness of broad and specific leadership behaviors. *Personnel Review*, *48*(3), 774–783. https://doi.org/10.1108/PR-03-2018-0100

Zhang, Y., Fong, P. S. W., & Yamoah Agyemang, D. (2021). What Should Be Focused on When Digital Transformation Hits Industries? Literature Review of Business Management Adaptability. *Sustainability*, 13(23), 13447. https://doi.org/10.3390/su132313447

APPENDICES

Appendix I: Target Population from 56 IRA Listed Firms

Target Population

NUMBER	INSURANCE COMPANIES	CATEGORY	Supervisors
	Long Term Insurance Total		126
1	APA Life Assurance Company Limited	Long Term	7
2	ABSA Life Assurance Kenya Limited	Long Term	7
3	Britam Life Assurance Company (K) Limited	Long Term	7
4	Capex Life Assurance Company Limited	Long Term	7
5	CIC Life Assurance Limited	Long Term	7
6	Geminia Life Insurance Company Limited	Long Term	7
7	ICEA LION Life Assurance Company Limited	Long Term	7
8	Jubilee Life Insurance Limited	Long Term	7
9	Kenya Orient Life Assurance Limited	Long Term	7
10	Kuscco Mutual Assurance Limited	Long Term	7
11	Liberty Life Assurance Kenya Limited	Long Term	7
12	Madison Life Assurance Kenya Limited	Long Term	7
13	Metropolitan Cannon Life Assurance Limited	Long Term	7
14	Old Mutual Life Assurance Limited	Long Term	7
15	Pioneer Assurance Company Limited	Long Term	7
16	Prudential Life Assurance Kenya Limited	Long Term	7
17	Sanlam Life Insurance Limited	Long Term	7
21	UAP Life Assurance Company Limited	Long Term	7
	Composite Insurance Total		21
18	Kenindia Assurance Company Limited	Composite	7
19	The Kenyan Alliance Insurance Company Limited	Composite	7
20	The Monarch Insurance Company Limited	Composite	7
	General Insurance Total		245
22	AAR Insurance Company Limited	General	7
23	Africa Merchant Assurance Company Limited	General	7
24	AIG Kenya Insurance Company Limited	General	7
25	Allianz Insurance Company of Kenya Limited	General	7
26	APA Insurance Limited	General	7
27	Britam General Insurance Company (K) Limited	General	7
28	CIC General Insurance Limited	General	7
29	Corporate Insurance Company Limited	General	7
30	Directline Assurance Company Limited	General	7
31	Fidelity Shield Insurance Company Limited	General	7
32	First Assurance Company Limited	General	7
33	GA Insurance Limited	General	7
34	GA Life Assurance Limited	General	7
35	Geminia Insurance Company Limited	General	7
36	ICEA LION General Insurance Company Limited	General	7
37	Intra Africa Assurance Company Limited	General	7
38	Invesco Assurance Company Limited	General	7
39	Jubilee Allianz General Insurance (K) Limited	General	7
40	Jubilee Health Insurance Limited	General	7
41	Kenya Orient Insurance Limited	General	7
42	Madison General Insurance Kenya Limited	General	7
43	Mayfair Insurance Company Limited	General	7
44	Metropolitan Cannon General Insurance Company Limited	General	7
45	MUA Insurance (Kenya) Limited	General	7
46	Occidental Insurance Company Limited	General	7

47	Pacis Insurance Company Limited	General	7
48	Pioneer General Insurance Limited	General	7
49	Resolution Insurance Company Limited	General	7
50	Sanlam General Insurance Company Limited	General	7
51	Takaful Insurance of Africa Limited	General	7
52	Tausi Assurance Company Limited	General	7
53	The Heritage Insurance Company Limited	General	7
54	Trident Insurance Company Limited	General	7
55	UAP Insurance Company Limited	General	7
56	Xplico Insurance Company Limited	General	7
	Total		392

Source: IRA Website (2021) https://www.ira.go.ke/images/LICENCED-INSURANCE-COMPANIES-2021.pdf

Appendix: Tables

Table 4:

One-way ANOVA

Variable		Sum of Squares	df	Mean Square	F	Sig.
Leadership Role of Respondent	Between Groups	3.98	6	0.663	0.943	0.467
	Within Groups	84.445	120	0.704		
	Total	88.425	126			
Gender of respondents	Between Groups	0.324	1	0.324	0.459	0.499
	Within Groups	88.102	125	0.705		
	Total	88.425	126			
Age-group	Between Groups	4.006	2	2.003	2.942	0.056
	Within Groups	84.42	124	0.681		
	Total	88.425	126			
Highest academic qualification	Between Groups	1.211	2	0.606	0.861	0.425
	Within Groups	87.214	124	0.703		
	Total	88.425	126			
Years of Experience	Between Groups	5.314	2	2.657	3.964	0.021
	Within Groups	83.111	124	0.67		
	Total	88.425	126			

Table 5:

Multicollinearity Test Result

Model		Collinearity Tolerance	Statistics VIF
Experimentation	Spearman's Correlation Coefficient	.360	2.775
	Sig. (2 -tailed)		
	N		
Team Collaboration	Spearman's Correlation Coefficient	.360	2.775
	Sig. (2 -tailed)		
	N		

**Dependent Variable: Work Complexity*

Table 9:

Parameter Estimates

	Estimate	Std Error	Wald	df	Sig	95% Confidence Interval

							Lower Limit	Upper Limit
Threshold	$Y_{DT}=2$	-6.543	.908	51.918	1	<.001	-8.323	-4.763
	$Y_{DT}=3$	-3.031	.490	38.338	1	<.001	-3.991	-2.072
	$Y_{DT}=4$	.801	.307	6.812	1	.009	0.199	1.402
Location	$X_2=1$	-4.787	1.648	8.434	1	.004	-8.018	-1.556
	$X_2=2$	-7.156	1.026	48.641	1	<.001	-9.167	-5.145
	$X_2=3$	-1.395	.491	8.080	1	.004	-2.357	-.433
	$X_2=4$	-4.787	.879	29.664	1	<.001	-6.510	-3.064
	$X_2=5$	0^a	.	.	0	.	.	.

Link function: Logit This parameter is set to zero because it is redundant.