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Logistic Regression Analysis of Effect of Perceived External Determinants on Memebership Churn in Professional Organizations in Kenya: A Case Study of the Kenya Institute of Management

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Abstract: Membership churn brings about significant challenges to professional organizations, thus threatening their financial stability and long-term sustainability. This study investigates the perceived external determinants influence on membership churn at the Kenya Institute of Management using logistic regression. Specifically, the study evaluated the effect of economic conditions, availability of similar services and industry and professional changes on membership churn. A cross-sectional research design was employed and with data collected from 384 KIM members through structured online surveys based on quota stratified sampling. The logistic regression model identified industry changes as the most significant predictor of churn (OR = 1.51, $p < 0.001$) followed by economic conditions (OR = 1.28, $p = 0.012$). Availability of similar services was found not to be statistically significant ($p = 0.071$). Model evaluation by Hosmer-Lemeshow test ($p = 0.8403$) confirmed a good model fit supported by Nagelkerke's R^2 showing that 72.2% of churn variance was explained by the perceived predictors. The findings suggest that professional organizations should strategically adapt to industry and professional shifts and economic fluctuations to reduce member churn. Implementation of flexible payment plans and differentiation of services help mitigate churn risks. This study enhances the understanding of membership dynamics in professional bodies and offering strategic insights to enhance member retention in similar organizations.

Key words: Membership churn, Similar Services, Industry changes, Economic conditions, Logistic regression

I. Introduction

Membership churn is an enormous concern for membership-based institutions globally. Membership churn or attrition is the rate at which members of member-based organizations discontinue their membership for a specified period usually annually. Membership-based organizations such as professional associations, subscription-based services, and trade unions rely on a stable and engaged member base for their financial sustainability and strategic growth. However, persistent membership churn poses as a great challenge, where individuals discontinue their affiliation thus leading to decline in revenues, reduced organizational influence and weakened community engagement. KIM will propose and implement targeted strategies that would promote member satisfaction, member retention and long-term viability and sustainability in general from the study (Ahn, Han, & Lee, 2006). Traditional research on churn has focused extensively on internal factors like member satisfaction, service quality and member engagement levels. However, external determinants of economic conditions, competition from similar services, and industry and professional changes play a significant role in a member's decision to renew or fail to renew their status at the end of the current period. Unlike internal factors, external influences are beyond organization's direct control thus making them harder to predict and manage.

Logistic regression is a statistical tool in modeling the probability of a binary result or two mutually exclusive outcomes dependent on one or more predictor factors. The influence of these perceived external predictors on the likelihood that members terminate their subscriptions at the end of their current term is the goal of this study thus the need for evaluation based on the ranks of their impact member on churn.

The Kenya Institute of Management is a distinguished professional body in Kenya was established in 1954 to provide personalized training, consultancy, membership services, Diploma and Certificate courses, and professional certification courses to the general Kenyan population. KIM is renowned for its passion to professional development and management training to Kenya firms and their employees. Despite KIM's proactive approach the institution encounters immense challenges. Economic fluctuations, competition from professional bodies offering similar services and evolving member expectations are contributors to member retention rates' fluctuation at KIM. This institutional context enables KIM's pivotal role to enhance professional excellence and leadership in Kenya.

Statement of problem

Membership-based institutions like the Kenya Institute of Management, face persistent challenges in managing high churn rates by threatening their financial stability, member engagement and long-term sustainability (Ahn, Han, & Lee, 2006). Despite offering training, consulting and certification services, professional organizations continue to experience churn, suggesting that current retention measures are insufficient. Existing research highlights determinants such as satisfaction, engagement and

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economic conditions as key predictors of churn (Park & Ahn, 2022; Routh, Roy, & Meyer, 2020), yet data-driven insights specific to Kenyan organizations remain limited. Furthermore, most studies rely on linear regression which is considered inappropriate for modeling a binary churn outcome (Hosmer, Lemeshow, & Sturdivant, 2013). This study applies logistic regression to identify and quantify the perceived external determinants influencing churn at KIM thus providing actionable insights for targeted retention strategies.

Purpose of the study

The purpose of the study was to analyze and rank determinants associated with member churn at the Kenya Institute of Management using logistic regression.

Specific objectives

i. To explore perceived external factors and their influence on membership churn.

ii. To fit an appropriate logistic regression model and rank predictors' effects on membership churn.

Hypothesis

H0: There is no significant relationship between perceived external factors and membership churn at KIM, $\beta_1 = \beta_2 = \beta_3 = \cdots = \beta_k$.

H1: There is a significant relationship between external factors and membership churn at KIM, $\boldsymbol{\beta_1 \neq \beta_2 \neq \beta_3 \neq \cdots \neq \beta_k \neq 0}$.

Scope of the study

This study aimed to identify the significant determinants associated with member churn at the Kenya Institute of Management. The study investigated the predictor variables of the perceived external determinants' effect on member churn across KIM's membership base with 8989 members spread across diverse Kenyan regions in 13 branches. The study's geographic scope was confined to KIM's membership department located at KIM headquarters South C, along Popo Road in Nairobi county. The study employed stratified quota sampling techniques based on membership categories from 384 members. The study's data was collected using online surveys and descriptive and inferential data analysis. The study was conducted etween June to November 2024.

Limitation

The study was based on self-reported data from surveys which may have caused biases due to respondents' recall and desire to reveal true information. Furthermore, the external factors of economic fluctuations and industry changes could have emerged unpredictably thus may have influenced the study's significance over time, but the study assumed no variation. Acknowledgement of these limitations was critical in interpretation of results and recommendation on future research on membership dynamics and organizational management.

II. Literature Review

Theoretical review

Logistic regression is a statistical technique used to make predictions of probability of a binary outcome influenced by one or more predictor variables. Logistic regression is used when the dependent variable is of binary nature like success or failure, yes or no, and churn or no churn. The model transforms the linear regression model's output to fit in a range of 0 to 1 using a logistic function to allow for the moderate estimation of probabilities rather than the continuous values.

Odds

In categorical data analysis the odds indicate the ratio of likelihood of binary outcomes occurring to its likelihood of not occurring. Equation (1) represents a ratio of the likelihood of success to the likelihood of failure/ not occurring.

$$Odds = \frac{P(Y=1|x)}{1-P(Y=1|x)} = \frac{P(Success)}{1-P(Success)} \qquad \textit{Equation 1}$$

Odds ratio

The odds ratio indicates the proportion of the odds of event occurrence in a group to those of its occurrence in another group. Odds ratio measure shows the relationship/association between the exposure and outcome. Odds ratio quantifies the effect of the independent variables on the dependent variable. The ratio indicates how the odds of the target of dependent event change with respect to a one-unit increase in the value of predictor or independent variable.

The odds ratio for groups A and B is given as $\frac{\text{Odds for group A}}{\text{Odds for group B}}$.

The odds ratio concept interprets the results of logistic regression models. The odds ratio in the logistic function is $e^{\beta j}$ where **e** is the value of natural logarithm and β_j is the weight of the predictor or independent variable, X_j.

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An odds ratio exceeding one signifies the event has a higher likelihood in occurrence as the predictor value increases, an odds ratio of between 0 and 1 shows a lesser likelihood in occurrence as the predictor value decreases while an odds ratio equal of one shows no association between the predictor and the predicted variables.

Logit function and logistic regression

The logit function is the natural logarithm of odds of target variable being 1 (churn) versus 0 (not churn). The logit function transforms probabilities, lying between 0 and 1, into a continuous range of values from $-\infty\ to\ \infty$, that follows a linear model.

The logit function is expressed as $\log\left(\frac{p}{1-p}\right)$

With p representing the probability of event under enquiry occurring P(Y = 1|x).

The logit function is models the association between the binary outcome (target) variable and one or more independent predictor variables.

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \quad Equation\ 2$$

By multiplying both sides by the antilog natural logarithm(e) in the logit equation and making p the subject we can derive the probability of an event occurring as shown by equation(3).

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k$$

we get;

$$e^{\log\left(\frac{p}{1-p}\right)} = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k}$$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k}$$

$$p + p\left(e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k}\right) = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k}$$

$$p\left(1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k}\right) = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k}$$

$$p = \frac{e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k)}}{1 + e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k)}}$$

$$\hat{p} = \frac{e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k)}}{1 + e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k)}} \qquad Equation\ 3$$

MLE parameter estimation

The maximum likelihood estimators approximates the parameters $\beta_0, \beta_1, \ldots, \beta_k$ values. The likelihood function represent the possibilities of observed values based on model parameters $\beta = (\beta_0, \beta_1, \beta_2, \ldots, \beta_k)$.

Likelihood function for n observed values (y_i, x_i) L(β) is given by Equation 4;

$$L(\beta) = \prod_{i=1}^{n} [p(Y_i|X_i)]^{Y_i} [1 - p(Y_i|X_i)]^{1-Y_i}$$

Equation 4

The likelihood function for estimating co-efficients of the logistic model is thus found by substitution as;

$$L(\beta) = \prod_{i=1}^{n} \left(\frac{1}{1 + e^{(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik})}}\right)^{Y_i} \left(1 - \frac{1}{1 + e^{(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik})}}\right)^{1-Y_i}$$

The log-likelihood for the likelihood function, (β) is thus given as;

$$\log\left(L(\beta)\right) = \sum_{i=1}^{n} Y_i \log\left(\frac{1}{1 + e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k)}}\right) + (1 - Y_i) \log\left(\frac{1}{1 + e^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k)}}\right)$$

If we let $p_i = e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{k-1} X_{k-1} + \beta_k X_k)}$ then;

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$$\mathrm{Log\ L}(\beta) = \sum_{i=1}^{n}\left[\mathrm{Y_i}\log\left(\frac{1}{1+\mathrm{p_i}}\right) + (1-\mathrm{Y_i})\log\left(1-\left(\frac{1}{1+\mathrm{p_i}}\right)\right)\right]$$

$$\mathrm{Log\ L}(\beta) = \sum_{i=1}^{n}\left[\mathrm{Y_i}\log\left(\frac{1}{1+\mathrm{p_i}}\right) + \log\left(1-\left(\frac{1}{1+\mathrm{p_i}}\right)\right) - \mathrm{Y_i}\log\left(1-\left(\frac{1}{1+\mathrm{p_i}}\right)\right)\right]$$

$$\mathrm{Log\ L}(\beta) = \sum_{i=1}^{n}\left[Y_i\log\left(\frac{\left(\frac{1}{1+\mathrm{p_i}}\right)}{\left(1-\left(\frac{1}{1+\mathrm{p_i}}\right)\right)}\right) + \log\left(1-\left(\frac{1}{1+\mathrm{p_i}}\right)\right)\right]$$

$$\mathrm{Log\ L}(\beta) = \sum_{i=1}^{n}\left[Y_i\ \log\left(\frac{1}{p_i}\right) + \log\left(\frac{p_i}{1+p_i}\right)\right]$$

$$\mathrm{Log\ L}(\beta) = \sum_{i=1}^{n}\left[Y_i\ \log\left(\frac{1}{p_i}\right) + \log\left(\frac{p_i}{1+p_i}\right)\right]$$

$$\mathrm{Log\ L}(\beta) = \sum_{i=1}^{n}\left[Y_i\ \log\left(\frac{1}{p_i}\right) + \log\left(\frac{\frac{p_i}{p_i}}{\frac{1}{p_i}+\frac{p_i}{p_i}}\right)\right] = \sum_{i=1}^{n}\left[Y_i\ \log\left(\frac{1}{p_i}\right) + \log\left(\frac{1}{\frac{1}{p_i}+1}\right)\right]$$

$$\mathrm{Log\ L}(\beta) = \sum_{i=1}^{n}\left[Y_i\ \log\left(\frac{1}{p_i}\right) - \log\left(\frac{1}{p_i}+1\right)\right]$$

$$\mathrm{Log\ L}(\beta) = \sum_{i=1}^{n}\left[Y_i\ \log\left(\mathrm{e}^{-(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\cdots+\beta_k X_{ik})}\right) - \log\left(1+\mathrm{e}^{-(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\cdots+\beta_k X_{ik})}\right)\right]$$

Equation 5

To evaluate the estimates of parameters the log-likelihood function in equation 5 is differentiated partially to produce k derivatives all with respect to the respective parameters and equated to zero as equation 6. These equations are then solved simultaneously to get the estimates of β_j.

The partial derivatives of $\log \mathrm{L}(\beta)$ with respect to each coefficient βj, kj=0,1,…,k) are;

$$\frac{\partial \log \mathrm{L}(\beta)}{\partial \beta_j} = \sum_{i=1}^{n}\left[\mathrm{x_{ij}} - \frac{\mathrm{x_{ij}}\mathrm{e}^{(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\cdots+\beta_k X_{ik})}}{1+\mathrm{e}^{(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\cdots+\beta_k X_{ik})}}\right], \forall_j = 0,1,2,\ldots,k$$

Equation 6

Model Assumptions

There exists a linear association between perceived external predictor variables and logit of the outcome variables.

$$\mathrm{logit}(p) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

To ensure adherence of this the Box-Tidwell test was used. The predictor variable X_i interacts with its logarithm to form a term $X^*{}_i$.

$$X^*{}_i = X_i \log(X_i)$$

We then fit a new logistic regression model;

$$\log\left(\frac{p}{1-p}\right) = \beta^*{}_0 + \beta^*{}_1 X^*{}_1 + \beta^*{}_2 X^*{}_2 + \cdots + \beta^*{}_k X^*{}_k$$

Equation 7

If any $\beta^*{}_i$ in equation 7 was found to be statistically significant the relationship between X_i and the logit was non-linear violating

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the underlying assumption for linear association between predictor variables and the logit. Linearity association is only ascertained when the p-value is greater than the level of significance, (Box & Tidwell, 2012).

There should be no multicollinearity among perceived predictor variables.

The variance Inflation Factor, VIF was used to quantify multicollinearity through measuring the extent to which one predictor's variance was inflated due to correlation with other predictor variables. For predictor variable, X_i, the VIF is calculated as shown in equation 8;

$$VIF(X_i) = \frac{1}{1 - {R_i}^2}$$

Equation 8

With ${R_i}^2$been the co-efficient of determination found through regressing X_i on all other predictors. Multicollinearity is considered extreme if the $VIF(X_i) \geq 10$, multicollinearity with $VIF(X_i)$ values between 5 and 10 shows moderate correlation that affect regression estimates and $VIF(X_i)$ of between 1 and 5 shows low to moderate correlation between predictors. Low multicollinearity coefficients are considered ideal.

Mode errorsl are uncorrelated with each other.

The Runs Test for Randomness by Wald and Wolfowitz (1940) is used to check whether residuals were randomly distributed. Residuals showing patterns suggest correlation thus violating the assumption of independence.

Empirical Literature

Economic conditions are perceived to have a great effect on member retention rates. According to Park and Ahn (2022) economic downturns frequently result in an increase in churn rates as members give priority to essential expenses over subscribing to professional memberships. The analysis based on multiple professional organizations found out that in recession times members in cost sensitive groups like entry-level professionals who were more predisposed to cancel and /or fail to renew their memberships. The study showed that income level is negatively correlated to membership churn.

Routh, Roy, and Meyer (2020) examined the difficulty of anticipation of customer attrition in the times of competing risks. The study presented a methodology incorporating competing risk analysis in random survival forest framework allowing more accurate prediction of churn probability with no probability distribution assumptions. The study used data from the hospitality industry showing that their approach was more effective than standard probability models with 20% gain in precision. This study put emphasis on the need to accounting for competition in churn prediction during client retention tactics development (Routh, Roy, & Meyer, 2020).

Changes in standard practices, procedures and trends substantially impact on membership churn in areas like telecoms where customer expectations change more frequently. The study underlines that failure in reaction to these developments could potentially lead to higher churn rates as customers seek better and more favorable options. The research on the Malaysian telecommunications market revealed the efficacy of application of Net Promoter Scores (NPS) and data mining approaches to determine and quantify customer turnover. The study discovered that customers with low NPS levels were more likely to churn but with timely interventions of customer service improvement reduce the churn risk. The study also found out that the classification and regression trees method produced the best accurate churn predictions indicating that organizations should remain responsive to emerging industry developments to sustain customer loyalty and reduce churn (Moser et al 2018).

Social and political considerations of changes in government policy and social movements potentially have a significant effect on membership churn. Giudicati, Riccaboni and Romiti (2013) illuminated that shifts in social norms and underlying government rules have a tendency of altering customer expectations and behaviors resulting in increased churn if firms do not adjust effectively. The advocacy of societal movements towards ethical business practices put pressure on corporations to adopt new standards and failure to lead to customer churning. Changes in the government policy of new data protection requirements create compliance issues impacting consumer trust and retention. According to the report firms should be responsive in adapting to external influences to retaining clients and help in building long-term connections between members and the membership organization (Giudicati, Riccaboni, & Romiti , 2013).

The study's empirical literature demonstrates that all perceived external determinants all had significant impact on membership or customer churn rates in professional organizations. The external factors of economic conditions, competition from other professional bodies providing similar services and industry changes significantly affect churn rates necessitating responsive strategies to mitigate the inherent effect of the associated determinants.

III. Methodology

Research Design

Creswell (2014) defines a research design as a guided plan aiding the researcher in planning and implementation of the study in a

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systematic way that meets principle of validity and reliability of results. Mugenda and Mugenda (2003) states that descriptive research encompasses data collection methods for testing the study hypotheses or answering study. This research on logistic regression analysis of determinants associated with membership churn at the Kenya Institute of Management used the cross-sectional research design. According to Saunders, Lewis, and Thornhill (2016) a cross-sectional study methodology is best fit to examine how predictor variables of external factors influence membership churn. According to Creswell (2014) cross-sectional studies aids provide a summary of relationships of target and predictor variables at a single point. The methodology allows for thorough examination of complex interactions and causal pathways thus allowing KIM provision with insights for strategic planning and retention tactics.

Area of the study

The research was conducted within Kenya with data collection made at KIM with members located in 13 KIM branches located in various regions of the country. The geographic scope was significant for representative findings for the diverse membership base of KIM.

Study Population

A study population is an enumeration of all elements contained in the entire group of individuals from which the sample is drawn and about whom the researcher wants to make conclusions (Mugenda & Mugenda, 2003). The target population should contain all the subjects or units meeting the specified inclusion criterion in the study. All the active and fully subscribed members of the Kenya Institute of Management individual members in the year 2024 was the study's target population. As of the records provided by KIM's membership department during research period, KIM had 8,989 individual subscribed members.

Table 1: Target Population

Member Category	Frequency	Percentage
Student	1535	17%
Associate	2354	26%
Full Member	5100	57%
Total	8989	100%

Source: KIM Membership Department (2024)

Sample and Sampling Techniques

A study sample is a small part of the population that is selected for collecting and analysis in a study under consideration (Mugenda & Mugenda, 2003). The purpose of sampling is selection of a representative portion of the population whose statistics reflect the broader population's parameters thus aiding in facilitation of study's inferences about the population based on the sample selection (Creswell, 2014). To achieve a representative sample in the study stratified random sampling technique was used**.** The method involves division of a heterogeneous population of 8989 members into small homogeneous subgroups based on the membership grade referred to as strata. In this study each membership category, student, associate and full members formed an independent stratum and then random selection of elements from each stratum. This technique ensured that the different population segments were adequately represented in the population thus enhanced the validity and reliability of the results (Creswell, 2014).

Krejcie and Morgan (1970) formula was used evaluate the magnitude/size of the sample based on the finite target population of 8,989, the critical value of 1.96 at 95% confidence interval based on a normally distributed population, the perceived proportion of 0.5 aiding in maximizing variability of the population and a marginal error of 5% (Krejcie & Morgan, 1970). The sample size formula for finite populations is given by equation 9:

$$n = \frac{N * Z^2 * p * (1-p)}{(N-1) * E^2 + Z^2 * p * (1-p)}$$

Equation 9

N is the number of elements in the population

Z is the standardized critical value at 95% confidence level (1.96)

p is proportion of the population likely to churn and 0.5 for maximum variation E is the marginal error of 0.05

$$Sample\ size, n = \frac{8989^2 \times 1.96^2 \times 0.5 \times 0.5}{(8989-1) \times 0.05^2 + 0.05^2 \times 0.5 \times 0.5}$$

Sample size, $n \approx 384$

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The sample size for each stratum was obtained using proportion allocation as in equation 10. Proportional allocation ensures each membership category in the study population is well represented accordingly in the sample effectively reducing bias and thus increasing in precision of estimates. (Cochran, 1977)

$$n_s = \frac{N_s}{N} \times n$$

Equation 10

With: n_s as the proportionally allocated sample size for sth stratum, Ns as population size of sth stratum and N as size of population n is size of sample

Table 2: Sample Size

Member Category	Frequency	Sample Size	Percentage
Student	1535	66	17%
Associate	2354	100	26%
Full Member	5100	218	57%
Total	8989	384	100%

Source: Researcher (2024)

Instrumentation

Creswell (2014) defines instrumentation as tools and methods used in collection of data in a research exploration. Tools instrumentation encompasses the development, testing and the use of instruments such as questionnaires designed to gather information from target participants (Mugenda & Mugenda, 2003). The goal of instrumentation is to ensure that the data collected in the study are reliable and relevant to the research objectives (Creswell, 2014). In this study a questionnaire was used in data collection. A questionnaire is a research tool that consists of questions designed to obtain information from respondents in the study enquiry. The questionnaire consisted of closed-ended, open-ended and demographics aided in representative data collection.

Validity is the extent to how well a questionnaire as a research instrument captures what it is supposed to measure (Mugenda & Mugenda, 2003). Validity is precision and trustworthiness of the data collection tool in capturing the genuine core of the construct under study. Validity ensures that a study's findings are accurately reflecting the phenomenon investigated (Creswell, 2014). The questionnaire was pilot tested with a small group of 40 KIM members. According to Mugenda & Mugenda (2003), a pilot study should have 10% of the main study's sample size. Pilot testing aided in the detection of difficulties with question clarity, language and structure as well as determining whether the questions effectively measure the constructs intended to measure.

Reliability is consistency or reproducibility of measurements thus a trustworthy instrument consistently measures what it is designed to measure and produces similar results under consistent settings (Mugenda & Mugenda, 2003). High reliability results indicate that shows that the measurement is consistent throughout time and in a variety of scenarios (Creswell, 2014). The reliability of the Logistic regression analysis of determinants associated with Membership Churn at the Kenya Institute of Management was measured Cronbach's alpha value. This statistical measure was used to examine the questionnaire's internal consistency determining how closely a bunch of elements were related. A high Cronbach's alpha value of more than 0.7 imply good internal consistency meaning the items dependably assessed the same underlying concept (Tavakol & Dennick, 2011).

Data collection Procedure

The primary method of distribution of questionnaires in this study was online via google forms shared in net promoter score for fully subscribed members during the month of September 2024 by the KIM membership department in collaboration with the researcher. Study participants received a link to the online questionnaire completed at their own convenience. Members selected who had limited access to the internet used paper-based questionnaires distributed during KIM events and meetings during the study period. The completed questionnaires can be collected on-site or mailed back. Follow-up emails, WhatsApp messages and short text messages reminders were used to promote members' participation and ensured substantial response rate. Responses were collected until all the 66 responses from student members, 100 from associate members and 218 from KIM full members amounting to a total of 384 questionnaires were met in line with quota stratified sampling to ensure representativeness and diversity, (Cochran, 1977).

Data analysis

Logistic regression evaluates the probability value of a binary outcome (Y) based on the associated predictor variables; X_1, X_2, …, X_k. The outcome or target variable has two categories, 1 when the member churn and 0 when the member renews their membership.

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$$\hat{p} = \frac{e^{(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_{k-1}X_{k-1}+\beta_kX_k)}}{1+e^{(\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_{k-1}X_{k-1}+\beta_kX_k)}}$$

Equation 2

With co-efficients $\beta_0, \beta_1, \ldots, \beta_k$ being the model odds parameters for the Constant, $X_1, X_2, \ldots, X_k$ predictor variables respectively.

The logistic regression model for this study was as in equation 11.

$$\hat{p} = \frac{\exp(\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3)}{1+\exp(\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3)}$$

Equation 11

Whereby: X_1 is economic conditions, X_2 is availability of similar services and X_3 represents the changes in industry or profession.

Since the model is non-linear the logit link function was used to convert the function into a linear relationship in equation 12.

$$logit(\hat{p}) = \beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3 \qquad \text{Equation 12}$$

Statistical Significance of predictors

The p-value measure was used to determine the level of significance of the individual predictors in the logit model. P-value was used to show the probability that observed association between the predictor and outcome variables occurred by chance.

$$H_o: \beta_1 = \beta_2 = \beta_3 = \cdots = \beta_{k-1} = \beta_k$$

$$H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \cdots \neq \beta_{k-1} \neq \beta_k$$

The null hypothesis was rejected when p-value was less than the significance level of 0.05 at 95% confidence interval and showed that the predictor significantly manipulated the dependent variable.

Wald test presented in equation 13 tested the significance of coefficients of predictor variables in the model.

$$\text{Wald Statistic}, W = \left(\frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}\right)^2$$

Equation 13

The Wald statistics abide by the chi-square distribution with a single degree of freedom at 5% level of significance. The null hypothesis was rejected when $W > \chi^2_{0.05,1} = 3.841$

The odds ratio acts as the transformation in odds of the outcome occurrence for a one-unit increase in the value of predictor variable. A 95% confidence interval shows the range to which true odds ratio value is forecasted with 95% level of confidence. An odd ratio for a given predictor Xi in logistic regression was computed as:

$$Odds\ ratio = e^{\beta_i} \qquad \text{Equation 14}$$

The null hypothesis, $H_0: e^{\beta_i} = 1$ while Alternative hypothesis, $H_0: e^{\beta_i} \neq 1$. The CI for the coefficient is given by the limits;

$$Lower\ bound\ of\ CI = \beta_i - Z_{\alpha/2} * SE(\beta_i) \qquad \text{Equation 15}$$

$$Upper\ bound\ of\ CI = \beta_i + Z_{\alpha/2} * SE(\beta_i) \qquad \text{Equation 16}$$

The value of exponentiated bounds of the CI for the odds ratio was then given as;

$$\left(e^{\left(\beta_i - Z_{\alpha/2} * SE(\beta_i)\right)}, e^{\left(\beta_i + Z_{\alpha/2} * SE(\beta_i)\right)}\right) \text{ at } 100(1-\alpha)\% \text{ confidence interval.}$$

Evaluation of model fit

The Akaike Information Criterion (AIC) was used as an evaluation tool for comparing the goodness of fit across multiple competing models in the study.

The AIC for each model was calculated as AIC = −2log(L) + 2k with L representing the model's likelihood and k denoting the model parameters count.

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−2log(L) measured the model's fit with a lower value demonstrated a better fit while 2k is penalty for model complexity. The model with the lower AIC was significantly the model of best fit.

Ethical Consideration

In scientific research study, ethical considerations preserve respondents' rights and well-being and respect. All participants provided informed consent before their voluntary participation in the study. This method provided clear and thorough information on the study's purpose, procedures, possible risks and significance. Participants were given information that participation was entirely optional, and they could have withdrawn their comments at any given moment without penalization. Participants were provided with written consent as proof of agreement to participate in the study. The respondents' confidentiality and identities were preserved during the study using unique random identifiers. The study followed general data privacy guidelines as outlined in Kenyan legislation including the Data Privacy Act of 2019.

IV. Results and Discussions

Reliability Test

The reliability of scale of the data collection tool was conducted using the Cronbach alpha as shown in table 4.

Table 3: Reliability Statistics

Cronbach's Alpha	N of Items
0.81	11

Source: Research data (2024)

With the alpha of 0.81 the scale's reliability was considered reliable. This showed an indication that while the 11 items were reasonably consistent in measuring the same construct.

Descriptive Statistics

From the data analysis in table 5 it showed that 80.5% of members did not churn while 19.5% of respondent members churned thus demonstrated most respondents remained members though with great variability. Respondents reported varying degrees towards economic effect, 21.6% stated very significant effect and 18.2% reported no effect with mean score of 3.09 and a standard deviation of 1.411 indicated economic conditions played a moderate to significant role in membership churn. Similar services affected membership behavior where 20.1% reported very significant impact and 20.3% reported slight impact with mean score of 2.99 and a standard deviation of 1.418 thus gave a suggestion that competition played an influential role. Industry and professional changes influenced membership with 22.1% of respondents reporting significant influence while 17.4% reported no impact with mean score is 3.11 and a standard deviation of 1.404 showed that industry and professional shifts moderately influenced membership churn.

Table 4: Descriptive Statistics

Variable	**Indicator**	**N**	**Marginal Percentage**	**Mean**	**Standard deviation**
Churn	Not churn	309	80.50%	0.2	0.397
	Churn	75	19.50%		
	Associate	100	26.00%		
	Full member	218	56.80%		
Economic conditions	Not at all	70	18.20%	3.09	1.411
	Slightly	73	19.00%		
	Moderately	77	20.10%		
	Significantly	81	21.10%		
	Very Significantly	83	21.60%		
Similar services	Not at all	77	20.10%	2.99	1.418
	Slightly	78	20.30%		
	Moderately	76	19.80%		

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	Significantly	76	19.80%		
	Very significantly	77	20.10%		
Industry changes	Not at all	67	17.40%	3.11	1.404
	Slightly	75	19.50%		
	Moderately	74	19.30%		
	Significantly	85	22.10%		
	Very significantly	83	21.60%		

Source: Research data (2024)

Table 5: Case Processing Summary Table

Unweighted Cases		N	Percent
Selected Cases	Included in Analysis	384	100.0
	Missing Cases	0	.0
	Total	384	100.0
Unselected Cases		0	.0
Total		**384**	**100.0**

Table 6 shows the case processing summary for analysis that consisted of a total of 384 cases represented 100%. Missing and unselected absences showed data completeness ensured data integrity.

Model Assumptions

Linearity of logits

Table 7: Box-Tidwell Test for Linearity of logits

Term	Estimate	Std Error	Statistic	P-Value
Intercept	-5.703	2.165	-2.634	0.008
Economic conditions	0.489	0.969	0.504	0.614
Similar services	0.613	0.984	0.622	0.534
Industry changes	1.046	1.004	1.042	0.298
Log Economic Conditions	-0.118	0.464	-0.254	0.800
Log Similar Services	-0.209	0.472	-0.443	0.658
Log Industry Changes	-0.305	0.479	-0.636	0.525

Source: Research (2024)

Linearity of logits was based on the Box-Tidwell test as presented in table 7. The analysis showed that all the interaction between the continuous predictors and their logarithmic transformations was not significant at 5% level of significance. This showed no evidence of non-linearity in the association between the continuous predictors and the logit thus satisfied the assumption of linearity of the logit for the perceived predictors.

Test of multicollinearity

The test of multicollinearity in the logistic model was validated using variance inflation factor as shown in table 8. The VIF values for the predictor variables ranged from 1.2 to a maximum of 2.33 that were all less than 5, indicating multicollinearity was not a model's significant problem.

Table 8: VIF Values

Predictor	**VIF**
Economic conditions	1.616434

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Similar services	2.014424
Industry changes	2.300119

Source: Research data (2024)

Test of errors in independence

The runs test was used to rest independence of errors as shown in table 9. The test statistics of Z=0.048 were very close to zero and suggested no presence of significant deviations form randomness while the p-value of 1 showed that the null hypothesis of error sequence been random was not rejected further supported assumption of error randomness.

Table 9: Runs Test for Residuals Independence data: binary residuals

Standard Normal = 0.048, p-value = 1
alternative hypothesis: two-Sided

Source: Researcher (2024)

Logistic Regression Model Diagnostics

The full model was fitted to identify the relationship between member churn and the associated determinants as shown in table 10. The hypotheses tested were.

H0: There is no significant relationship between perceived external factors and membership churn at KIM.

$\boldsymbol{\beta_1 = \beta_2 = \beta_3 = \cdots \beta_k = 0}$.

H1: There is a significant relationship between perceived external factors and membership churn at KIM, $\boldsymbol{\beta_1 \neq \beta_2 \neq \beta_3 \neq \cdots \neq \beta_k \neq 0}$.

Table 6: Binary logistic regression full model based on effect ranks

Predictor	Estimate	S.E	Wald	df	Odds Ratio	Odds ratio 95% CI		P-Value
						Lower	Upper	
Intercept	-4.050	0.591	46.92	1	0.02			0.000
Industry Changes	0.410	0.099	17.21	1	1.51	1.25	1.84	0.000
Economic Conditions	0.244	0098	6.26	1	1.28	1.06	1.53	0.012
Similar Services	0.182	0.010	3.25	1	1.20	0.99	1.49	0.071

Source: Research Data (2024)

The estimate for the constant was -4.050 with a Wald statistic of 46.92 and p-value of 0.000. The odds ratio was 0.071 with the p-value less than 0.05 thus null hypothesis was rejected at the 5% significance level showing that the constant was significant.

The estimate for industry changes predictor was 0.410 with Wald statistic of 17.21 and p- value of 0.000. The odds ratio was found to be 1.51 with 95% confidence interval of 1.25 to 1.84. Therefore, by virtue of the p-value been less than 0.05, the Wald statistic greater than the chi-square statistic at 1 degree of freedom (3.841) and the predictor estimate not including the odds ratio of 1 the null hypothesis was rejected giving an indication that industry changes had a significant positive effect on member churn.

The estimate for similar services was 0.182 with Wald statistic of 3.25 and p-value been

0.071. The odds ratio was 1.20 with 95% confidence interval of 0.99 to 1.49 thus making availability of similar services an insignificant predictor supporting the p-value greater than 5%, Wald statistic of 3.25 that was less than chis-square statistic of 3.841 and the confidence limit having an odd ratio of 1 led to rejection of null hypothesis and thus similar services had no effect on membership churn.

The estimate for economic conditions was 0.244 with corresponding Wald statistic of 9.231 and p-value of 0.000. The odds ratio was 1.28 with the 95% confidence interval of 1.06 to 1.53. The p-value was less than 0.05, the Wald statistic (6.26) greater than the chi-square statistic at 1 degree of freedom (3.841) and the predictor estimate not including the odds ratio of 1, then the rejection of the null hypothesis at 5% level of significance indicated that economic conditions had a significant positive effect on member churn.

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Evaluation of model fit

The model was evaluated using both the deviance statistic and the Hosmer-Lemeshow test. The decreasing deviance as each of the predictor variables was added as indicated in table 8 showed that the model improved as an additional predictor was added into the model. This was also supported by the small p-values at 95% confidence interval. Additionally, the Hosmer-Lemeshow test in table 11 with χ^2 = 4.1822 and p-value of 0.8403 at 8 degrees of freedom showed that no existence of significant difference between the predicted and observed values. This was validated by the level of significance (0.05) been less than the test p-value (0.8403) showing no signs of misfitting.

Table 11: Hosmer-Lemeshow goodness of fit test

Hosmer and Lemeshow goodness of fit (GOF) test
data: model$y, fitted(model)
X-squared = 4.1822, df = 8, p-value = 0.8403

Source: Research data (2024)

Table 127: Model summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
350.22	0.453	0.722

Source: Research data (2024)

The logistic regression model to predict membership churn had a -2 Log Likelihood of 350.22 demonstrating how well the model fitted as compared to a baseline model that had no predictors as presented in table 12. The Cox & Snell R Square value of 0.453 suggested that an approximate 45.3% of the variance in membership churn was explained by the model's predictors and is a measure does not reach a maximum value of 1. In contrast the Nagelkerke R Square adjusted for the maximum possible value stood at 0.722, giving a reflection of about 72.2% of the variance in membership churn as explained by the model. This indicated a strong fit and demonstrated that the model provided a substantial explanation of the variability in membership churn.

The Logistic Model Selection

Table 13: Deviance, Residual Deviance and AIC Values for Predictors

Predictors	**Null deviance**	**Deviance**	**Residual deviance**	**Degrees of freedom**	**AIC**
Industry Changes	379.3	18.27	360.3	382	364.3
Economic Conditions	379.3	8.02	371.2	382	375.2
Similar Services	379.3	2.75	376.2	382	380.2
Industry changes, Economic conditions	379.3	-	353.5	381	359.5
Industry changes, Similar Services	379.3	-	356.7	381	362.7
Industry changes, Economic conditions, Similar Services	379.3	-	350.2	380	358.2

Source: Research data (2024)

Table 13 presented the null deviance of 379.3 at 383 degrees of freedom represents the magnitude of unexplained variation in the model when no predictors are included with only the intercept used as calculated with a base. This value serves as a benchmark for comparing with other models that have some predictors included. A high null deviance values shows that the intercept-only model does not explain variability to a high level in the outcome.

For each predictor added individually as in table 14 reported deviance shows the reduction in the overall deviance as compared relatively to the null model. When Industry Changes is used as the only churn predictor, the deviance is reduced by 18.27 units resulting in a residual deviance of 360.3 with 382 degrees of freedom. Thus, showing that the reduction quantifying the improvement in fit when industry changes is included.

In contrast, when economic conditions are used alone the deviance reduces by 8.02 units resulting in residual deviance changing to 371.2 while maintaining 382 degrees of freedom. Similarly, when Similar Services as the only predictor the deviance reduces by 2.75 units yielding a residual deviance of 376.2 with 382 degrees of freedom. The residual deviance values indicate that on an

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individual basis industry changes provide a stronger effect on improvement in model fit than economic conditions which also perform better than similar services.

The Akaike Information Criterion is used to compare the models while penalizing models for model's complexity. The model with industry changes alone has an AIC of 364.3, economic conditions alone yield an AIC of 375.2 and similar services alone gives an AIC of 380.2. When predictors are combined with industry changes the first to be included in the model since it has the least AIC with economic conditions the residual deviance drops further to 353.5 with 381 degrees of freedom leading to the AIC improvement to 359.5. Similarly, the combination of industry changes and similar services produced a residual deviance of 356.7 and a consequent AIC of 362.7. The full model all three predictors (industry changes, economic conditions and similar services availability) achieves the lowest residual deviance of 350.2 with 380 degrees of freedom and led to the lowest AIC of 358.2. This shows that the best model should comprise of all the perceived external determinants of churn.

Likelihood Ratio Test

From the results as in table 14 it was found that the reduced model without similar services predictor included had an AIC of 358.2 while that of the full model with the similar services predictor included had an AIC of 359.5. This yielded a chi-square statistic of 3.302 with one degree of freedom and the corresponding p-value of 0.692. Since the p-value is greater than the level of significance (5%), we fail to reject the null hypothesis and conclude that demonstrating that similar services as a predictor does not significantly improve the model at 5% level of significance. Similar services are thus removed as it does not substantially affecting the model's explanatory power.

Table 14: Likelihood Ratio Test Results

Model	Residual DF	Residual Deviance	AIC	DF Change	Deviance/Chi-Square Statistic	p-value	Decision
Reduced Model Without Similar Services	381	353.5	359.5	-	-	-	Baseline Model
Full Model with Similar Services	380	350.2	358.2	1	3.302	0.069	Fail to Reject H_0

From the logistic regression model outputs, the logit equation developed as presented equation 17.

$$\log\left(\frac{p}{1-p}\right) = -4.050 + 0.410\text{Industry changes} + 0.244\text{Economic conditions}$$

Equation 17

V. Discussion of findings

The constant term represents the log-odds of membership churn when all predictor variables were set to zero. The odds ratio for the constant was 0.02 representing the baseline odds of churning are very low when all predictor variables are at their reference levels. This low odds ratio demonstrates that in absence of the effects of external predictor variables the likelihood of churning is at its minimum.

For industry changes the odds ratio was 1.51 indicating that individuals affected by professional and industry changes are approximately 1.51 times more likely to churn as compared to those not impacted. This shows that an increase in one unit in economic difficulties leads to an increase in churn by 51%. This suggested that shifts and fluctuations within the industry and professional lines have a significant effect on membership retention. With the high level of significance of $p < 0.001$ the changes in industry and professional lines are a major external contributor of member churn, thus professional organizations should closely monitor these changes to mitigate and reduce the inherent effects.

The odds ratio of 1.28 for economic conditions showed that worsening economic conditions increased the odds of churn by 1.28 times. This shows that an increase in one unit of odds ration leads that an increase in membership churn by 28%. Even though this effect is not as strong as the effect of some of the other predictors is significant with $p = 0.012$ highlighting that broader economic challenges significantly influence members' decisions to discontinue their memberships. Organizations should be wary of the underlying macroeconomic environment and thus potentially offer flexible payment options during difficult times in order curb churn and retain their members in the long run.

The odds ratio for the Similar Services determinant was found to be 1.20 with a high p-value of 0.820. This odds ratio demonstrates that for every one-unit increase in the perception that similar services are available, the odds of a member churning increase by 20% when all other factors are held constant. However, despite this positive relationship, the predictor is statistically insignificant at the 5% significance level, showing that the observed effect could be due to random chance rather than a meaningful relationship. This means that KIM should focus less primarily on external competition but rather on internal retention strategies like member engagement, value differentiation and on external underlying economic conditions and changes in professional and industry changes.

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VI. Conclusions and Recommendations

Conclusions

Members affected by changes in their industries and/or professions are 1.58 times more likely to churn than those affected. This signifies that external industry trends, external threats and professional shifts significantly influence members' decisions to renew or fail to renew their annual memberships. KIM and other professional organizations should be agile towards adapting to industry changes through provision of relevant services and resources thereby enabling members to easily navigate professional transitions.

Worsening economic conditions increases the odds of churn by 1.28 times demonstrating that broader macroeconomic determinants influence members' ability and willingness to renew their memberships. This suggests that economic fluctuations and underlying personal financial constraints play a role in considerations of devising retention strategies and organizations should allow their members to pay subscription fees on instalments.

Recommendations

Based on the study findings and conclusions on logistic regression of determinants associated with membership churn at the Kenya Institute of Management the study recommends that in address the perceived external determinants of churn and improve member retention membership institutions should differentiate those of its competitors by offering unique products and services and put their emphasis on their distinct value proposition and they should endeavor to offer flexible payment plans during economic downturns in order to support its member thus reducing the financial constraints driven churn.

Recommendation for further study

The study recommends a study on “Modelling membership retention over time in Kenyan professional organizations: A longitudinal data survival analysis perspective."

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