Original Research Article

Exploring Cognitive Factors and Climate Change Mitigation Behaviour among Managers of Tourist Hotel Facilities within Naivasha Sub County, Kenya

Abstract

Cognition of causes, consequences and responses to climate change is considered as an important determinant of decisions made by any organisation on climate change mitigation behaviour (CCMB). There is, however, scant empirical information on the role of cognitive factors on tourist hotel managers' CCMB. A cross sectional survey was therefore conducted in a stratified random sample of 70 medium to luxury-priced tourist facilities with 182 managers. Data was collected from three managers in each sampled establishment using self-administered questionnaires. A beta regression model was used to establish the role of cognitive factors on CCMB. The study identified efficiency and curtailment practices as two categories of CCMB. In addition, the results revealed that the managers had moderate scores on CCMB. Moreover, the different dimensions of cognitive factors had divergent associations with both categories of CCMB.Cause knowledge was positively associated with both curtailment and efficiency CCMB. Consequence knowledge was negatively associated with curtailment but positively with efficiency practices. Response knowledge had no relationship with curtailment practices but had a positive association with efficiency CCMB.Findings indicate that policy frameworks to enhance CCMB among key decision-makers need to integrate cognition of climate change as a critical factor that can be improved through training and awareness creation efforts.

Keywords: *Climate Change, Cognitive factors, Efficiency, Curtailment, Beta regression*

1.0 Introduction

Climate change is one of a critical and contentious issues currently facing the world and is predicted to lead to adverse and irreversible impacts on the earth and ecosystems as a whole. Reversing the negative impacts of climate change isparamount.On its part, the international tourism industry which contributes 7% share of World's total exports (Rasool et al., 2021) is consideredas unique in the climate change discourse.The industry needs to be made aware of climate change and the need to set up programs to enable it to adapt and adjust its activities accordingly.The World Economic Forum (2009) estimates that, even allowing for greater energy efficiencies, carbon emissions in the tourism industry are forecast to grow at 3.2% per year, reaching 728 $MtCO_2$ by 2035 (Koçak *et al*., 2020). Based on this premise it becomes necessary for managers of tourism hotel facilities to take action in climate change mitigation in order to reduce carbon emissions.

Mitigation is defined generally as making the impacts of climate change less severe (Sharifi, 2020). Thus climate change mitigation behaviour (CCMB) largely relates to technological, economic and social changes and substitutions that lead to emission reductions that can be realized through either technological innovation and/or market mechanisms (Aghion et al., 2019). Managers, as the primary stakeholders of enterprises in the tourism industry, play a pivotal role in decision-making on mitigations against the negative effects of climate change (Dahlmann *et al*., 2019). Literature suggests that much of the focus on improving the sustainability of the tourism sector has been on encouraging the adoption of technologies and management systems that produce greater efficiencies (Asadi *et al*., 2020). Gössling & Lund-Durlacher, (2021)further note that most corporations have limited engagement in mitigation efforts beyond water conservation, energy efficiency and waste reduction. Concerns therefore, exist about the extent to which such measures may contribute to undesirable and unintended effects unless there is also simultaneous attention paid to changes in actual consumption behaviour as well as in the adoption of technological, behavioural and policy options that also contribute to greater sustainability (Xie *et al*., 2021).

Climate change mitigation behaviour can substantially reduce the risks associated with human-induced global warming. Mitigation responses to climate change as a pro-environmental behaviour, can be operationalized at multiple levels of analysis, such as individual, group, organizational, or regional/national levels (Ortega-Egea et al., 2014). The focus in this study is on individual-level, mitigation behaviours, that, according to previous literature, can be broadly described as comprising voluntary and future-oriented behavioural responses to climate change (such as, reduction in energy consumption with mid- to long-term positive impacts on climate change (LaFay, 2016). Given the multi-faceted nature of mitigation behaviour, it potentially encompasses a broad range of actions in private and public spheres of life, one-off and regular decisions, simple and more difficult steps, as well as low and high impact actions as regards their effectiveness in mitigating climate change (Ortega-Egea et al., 2014). This diversity of climate change mitigation behavioural actions is complex and influenced by numerous factors, which require empirical examination.

This study adapted a model on risk perceptions of climate change as an approach to analyse climate change mitigation behaviour. In this model, an individual's view of climate change as a risk can be described as a function of cognitive factors (that is, knowledge about the causes, impacts and solutions to climate change), while controlling for key socio-demographic characteristics (van der Linden, 2014a; Van der Linden *et al.*, 2015).This study extends the model among managers of tourist facilities in an important Ramsar site in a developing country.

The value of a social-psychological perspective in climate change is indispensable since climate change is driven by human behaviour (Tam et al., 2021). Nielsen et al., (2021) further observes that psychology can make a significant contribution to limiting the magnitude of climate change. This arises from appreciating the fact that the primary focus of (applied) psychology is understanding, explaining and changing behaviour in response to a some given problem (Yuriev et al., 2020). Generally, there is limited disagreement that psychology and more so environmental psychology is uniquely positioned to contribute to a better understanding of the human dimensions of climate change (Bradley et al., 2020; Linden, 2015; Stern, 2011).

The value of a psychological perspective is unmistakably the most important human-dimension of the climate change system (Gifford et al., 2011) and is yet the least understood and the most overlooked (Linden, 2015). Spence et al., (2014) contend that notwithstanding the importance of human, cultural and social dimensions of climate change, interventions are generally outlined in terms of either new technologies, industry incentives or other economic and market-based instruments. It has also been noted that insights from both social and environmental psychology continue to be under considered significantly in the climate change mitigation debate (Nielsen et al., 2021).

Although important in their own right, technological advances and economic strategies including incentives and price mechanisms tend to primarily focus on creating extrinsic motivation and in the process; they inadvertently crowd out people's intrinsic motivation to care for the environment (van der Linden, 2014a). Further, it has been said that external incentives are not stable, long-term drivers of pro-environmental behaviour (Bouman et al., 2020). This is despite the fact that the search for the determinants of stable pro-environmental conduct is a focal area of research in both social and environmental psychology (Gifford & Nilsson, 2014).

The challenge of climate change and the urgent need to mitigate the negative effects of climate change, behavioural change is critical. This strategy is however hampered by the limited knowledge that exists on human actions in regards to climate change mitigation. Generating sufficient knowledge regarding human behaviours that can help fight climate change is consequently imperative (Hornsey & Fielding, 2020). This is especially true in critical segments of the economy that are beneficial to many types of individuals and largely depend on the environment such as the tourist accommodation sub-sector.

Social psychology is the study of the dynamic relationship between individuals and the people around them (Vallacher & Nowak, 2007). Social psychologists believe that human behaviour is determined by both a person's characteristics and the social situation which is frequently a stronger influence on behaviour than are a person's characteristics (Cislaghi & Heise, 2020). The joint influence of person variables and situational variables, which is known as the person-situation interaction, is an important equation that indicates that the behaviour of a given person at any given time is a function of (depends on) both the characteristics of the person and the influence of the social situation (Stangor et al., 2017). As a discipline, social psychology, is well placed to illuminate what is 'social' about climate change since the groups we belong to and the social environments we inhabit can be powerful influences on our attitudes, beliefs and behaviours (Meagher, 2020). Studies are already applying social psychological theory and methods to the issue of climate change. This is due to the observation that the theories, models and research methods of social psychology can provide a powerful arsenal to complement the approaches of other disciplines (Fielding *et al*., 2014).

Literature suggests that cognition, a major concept in social psychology. is related to CCMBbut in diverse ways (Bamberg & Möser, 2007;Gholamrezai et al., 2021; Hossain et al., 2022; Zeng et al., 2023). Briefly, cognition measures the extent to which individuals know about the causes, impacts, and effective responses to climate change(Linden, 2014). This study builds on the limited and equivocal data on the role of cognitive factors on CCMB.It has been argued that broader and greater personal engagement in CCMB should depend on the knowledge about the causes and consequences of climate change and knowledge about available courses of action (Ortega-Egea et al., 2014).Literature linking cognition to CCMB(Gholamrezai et al., 2021; Hossain et al., 2022; Zeng et al., 2023) is however equivocal. A notable concern with this literature is the lack methodological rigor including inadequate adjustment for confounding variables and applying statistical models that are not appropriate for the data at hand. In particular, existing literature tends to apply statistical models that require strict assumptions of normality such as ordinary least squares.Assuming that perceptual CCMB data is normally distributed is inherently inappropriate since individuals differ in their knowledge and skills.

Beta regression is emerging as a novel approach to model relationships in data that is heteroskedastic and bounded (Cribari-Neto & Zeileis, 2010). A refined understanding on knowledge about climate change based on sound analytical methods would be important to help target interventions for individuals in order to improve CCMB. This is particularly crucial in developing countries like Kenya which are at an increased risk of the adverse effects of climate change. Studies applying novel approaches to measure CCMB and its associated factors are scant, limiting our understanding and consequently choice of appropriate interventions. The aim of this study was therefore to examine the relationship between cognition and CCMB among managers of tourist facilities in Naivasha Sub-County in Kenya using Beta regression models.

2.0 Materials and Methods

This study adopted a cross sectional survey research design. A cross sectional study design is described as a situation where the researcher measures some given phenomenon, in particular issues that are prevalent to a society at a specific point in time(Kumar, 2018). It is considered to be cost-effective and saves time. Other major advantages of a cross-sectional study include that it is cheap and fast to perform, multiple variables can be analyzed simultaneously and it can lead to additional research to perform.This study was primarily concerned with describing, recording and interpreting cognitive factors as correlates of CCMB among managers of the tourist hotel facilities in Naivasha sub-county in Kenya.

The target population constituted of 85 medium to luxury priced tourist accommodation facilities in Naivasha.Three groups of the hotels were identified based on the amount of licence fee paid as the stratification criteria as follows: category A (Ksh 75,000-100,000), category B (Ksh 50,000-70,000) and category C (Ksh 25,000-35,000).

A two-stage cluster samplingprocedure was utilized since a list of eligible tourist accommodation facilities was not readily available.This procedure involved the random selection of tourist accommodation facilities based on their licence groupings.At the first stage, a stratified sample of PSUs was selected with probability proportional to size (PPS) in each stratum (that is category of tourist accommodation facilities). In the selected PSU's, a listing procedure was performed such that alltourist accommodation facilitieswere identified. The resultant list had a total number of 85 facilities that pay annual licensing fees of between Kshs 25000 and 100000 of which 13 were in category A, 20 in category B and 52 in C. Using formula provided by Krejcie and Morgan (1970) a minimum of 70 facilities were identified as appropriate which were then subdivided as 11 in cluster A, 16 in clusterB and 43 in cluster C using the PPS approach.

At the second stage, managers were selected by using simple random sampling.The selected facilities were then contacted and asked to provide some basic information about the number of individuals in management positions. This exercise indicated that the typical number of managers in any given tourist accommodation facility was on averagethree which translated to a sample of 210 managers in the 70 facilities in the target area.

2.1 Study Instruments

The study used primary sources to generate quantitative data using a structured self-administered questionnaire.Data was obtained through the use of a set of closed ended questions to solicit for managers' and socio-demographic characteristics,knowledge about climate changeissues and their CCMB.This study measured the frequency of application of various CCMB recommended by the United Nations World Tourism Organization-Environment Programme (UNWTO-UNEP) for accommodation establishments to mitigate climate change World Tourism Organisation & United Nations Environment Programme, 2008). A total of 24 CCMB items were measured using a five point likert scale ranging from 1 = Never to 5 = Always.

The hotel managers' cognitive characteristics were collected using a Managers' Cognitive Questions (MCQ) instrument. This instrument comprised a set of questions that sought to establish the managers' knowledge on the causes, consequences and responses to climate changeusing five point likert scales. The questionnaire also had another section that established the general socio-demographics of the managers and their establishment. The managers' demographic data particularly on age, sex and education was also collected.

2.2 Data Management and Analysis

Data from the questionnaires was cleaned, counter-checked for accuracy entered into a computer while missing and spurious data were imputed automatically. Exploratory data analyses were conducted to verify whether the data violates the assumptions of a normal distribution. Numerical data were summarised using means (± SD), median and the 25th and 75th percentiles. On the other hand, categorical data was presented using frequencies and percentages. The data was further presented using graphs such as histograms, line graphs and tables.

The individual CCMB and cognitive characteristics scores that were in nature of the Likert scale were not be interpreted in their raw form but were converted to Percentage of Maximum Possible (POMP) scores. This involved taking the raw score and subtracting the minimum score and then dividing the result by the possible scoring range.Higher scores indicate a higher intensity of any given dimension of interest. If multiplied by 100, the converted scores effectively become percentages. This scoring method effectively standardizes the scores to allow comparison across alternative scoring methods and instruments (Fischer and Milfont, 2010). Consequently, each manager scored a theoretically possible minimum of zero or a maximum of 1 highlighting the bounded nature of each item in the response variable. POMP is rarely used but is a meaningful and highly communicative method of scoring that is easily presentable and used to undertake critical tasks facing behavioral scientists and characterization of material effects Alternative methods of scoring evaluated against articulated criteria representing the information conveyed by each are considered as inappropriate (Cohen et al., 1999).

Factor analyses using Principal component Analysis (PCA) were applied in order to isolate the major dimensions of CCMB. Items with either poor loading scores or cross-loadings were removed. The Kaiser rule of retaining only factors with Eigen values greater than one was used. The specific items in each of the identified dimensions of CCMB were aggregated for every respondent. These identified dimensions of the outcome were subsequently used in all other analyses in the study. The Cronbach's alphas (α) of the emergent scales were also computed.

A correlation analysis was initially conducted in order to examine the relationship between the different dimensions of CCMB and cognitive factors. This exercise also helped to identify if multicolinearity was an issue of concern with the measured variables. A beta regression model that is commonly used by practitioners to model outcome variables that assume values in the standard unit interval (0, 1) was then employed to establish examine the association between cognitive factors and CCMB.

$y_i = \beta_o + \beta_{1i}x_{1i} + \varepsilon_i$

Where; y_i= dimensions of CCMB

β_o = Constant or y-intercept

x_{1i} = dimensions of cognitive factors

β_{1i} = Slope or change in y_i given one unit change in x_{1i}

ε_i = Error term

This model is based on the assumption that the dependent variable is beta-distributed and that its mean is related to a set of regressors through a linear predictor with unknown coefficients and a link function (Cribari-Neto & Zeileis, 2010). The choice of this model was informed by the fact that it naturally incorporates commonly observed features such as heteroskedasticity or skewness which is usually notable in data taking values in the standard unit interval, for instance, proportions as was the case with CCMB in the current study. To help the interpretation of observed coefficients in this model, the marginal effects of the role of the cognitive correlates of CCMB were also calculated with the help of the R computing environment Version 4.2.2 (R Core Team, 2023). The ρ value was set at the conventional level of 0.05.

3.0 Results and Key Findings

A total of 182 managers responded to the survey tool out of the target sample size of 210 managers. This translated to a response rate of 86.67% which was deemed sufficient for analysis and generalization.

3.1 The Profile of the Managers of Tourist Facilities

The surveyed managers were not evenly-balanced in terms of sex, age, education attainment and job characteristics (Table 1). There was greater participation of males (70%), middle-aged (between 30 and 49 years at 93%) and moderately educated individuals (that is, diploma holders at 43%). Further, a majority of the respondents (37%) reported that they had 5-9 years' work experience. In addition, most of the respondents described their job title as head of department (41%). It is important to point out that 68% of the respondents indicated that they were not members of any environmental group.

Table 1: Demographic Profile of Respondents

	Frequency (n = 182)	Proportion (%)	SE	(95% CI)	
Gender					
Female	55	0.30	0.03	0.23	0.37
Male	127	0.70	0.03	0.63	0.77
Age					
Below 29 years	5	0.03	0.01	0.00	0.05
30-39 years	94	0.52	0.04	0.44	0.59
40-49 years	74	0.41	0.04	0.34	0.48
Above 50 years	9	0.05	0.02	0.02	0.08
Educational Attainment					
Secondary	30	0.16	0.03	0.11	0.22
Certificate	5	0.03	0.01	0.00	0.05
Diploma	78	0.43	0.04	0.36	0.50
Degree	67	0.37	0.04	0.30	0.44
Post Graduate	2	0.01	0.01	0.00	0.03
Work Experience					
Below 4 years	14	0.08	0.02	0.04	0.12
5-9 years	67	0.37	0.04	0.30	0.44
10-14 years	43	0.24	0.03	0.17	0.30
Above 15 years	58	0.32	0.03	0.25	0.39
Job Title					
General Manager	45	0.25	0.03	0.18	0.31
Head of Department	74	0.41	0.04	0.33	0.48
Head of Section	63	0.35	0.04	0.28	0.42
Member of Environmental Group					
No	124	0.68	0.03	0.61	0.75
Yes	58	0.32	0.03	0.25	0.39

3.2 Climate Change Mitigation Behaviour

Thedependentvariable containedquestionsonCCMB based on the frequency of applicationof variouspracticesrecommendedby theUnitedNationsWorldTourism Organization-EnvironmentProgramme(UNWTO-UNEP) for accommodation establishments to mitigate climatechange (World Tourism Organization & UNEP, 2008). Factor analyses were deemed appropriate in order to examine the dimensions of the ofthe 24 climate change mitigation items that were utilized in this study. Additional analyses indicated that the 24 items were amenable to factor analysis using several methods that are advocated in the literature (Gorsuch, 2015).

Principal components analysis (PCA) was used because the primary purpose was to identify and compute composite scores for the factors underlying the ~~short version~~ of the CCMB. Initial eigen values indicated that the first two factors explained 19%, and 16% of the variance respectively with each of the other factors explaining below 6% of the variance.The two factor solution, which explained 49% of the variance, was preferred because of: (a) its previous theoretical support; (b) the 'levelling off' of Eigen values on the scree-plot after two factors; and (c) the insufficient number of primary loadings and difficulty of interpreting the third factor and subsequent factors. There was little difference between the two factor varimax and oblimin solutions, thus both solutions were examined in subsequent analyses before deciding to use an oblimin rotation for the final solution.

The Cronbach's alphas of both dimensions were acceptable: 0.68 for efficiency and 0.63 for curtailment CCMB. Composite scores were created for each of the two factors. Higher scores indicate a greater use of the given mitigation practice. An oblimin rotationwas used since a strong positive correlation existed between the two dimensions of CCMB ($r = 0.64$, $p < 0.05$). Overall, these analyses indicated that two factors were underlying responses to the CCMB items and that each of the two factors was moderately internally consistent.

Descriptive statistics for both dimensions of CCMB are presented in Table 2. The skewness and kurtosis were not within a tolerable range for assuming a normal distribution and examination of the histograms suggested that the distributions were not approximately normal. Mitigation curtailment behaviour had a mean of 0.59 (SD = 0.20) but negatively skewed. Efficiency behaviour had a mean of 0.49 (SD = 0.16) with a positive skew. A One-sample Kolmogorov-Smirnov (K-S) test was used to check the normality of the data since the sample size was greater than 50. A normal distribution was not evident for the composite score data in the current study. Thus the data were well suited for beta regression analyses.

Table 2: Descriptive Statistics of the Two Dimensions of CCMB

Type of CCMB	Mean	Median (25th-75th Percentile)	Skewness	Kurtosis	K-S Score
Efficiency	0.49 (0.16)	0.46 (0.36-0.79)	0.43	2.17	D = 0.15, p < 0.05
Curtailment	0.59 (0.20)	0.66 (0.23-0.86)	-0.29	1.59	D = 0.16, p < 0.05

A visual presentationof the curtailment and efficiency CCMB data is offered in Figure 1. Curtailment CCMB appears to be amultimodal distribution. Additional inspection of the histogram shows that Efficiency CCMB was positively skewed. The results offered here are suggestive that further statistical analyses that require data to be normally distributed are not applicable with the reported data.

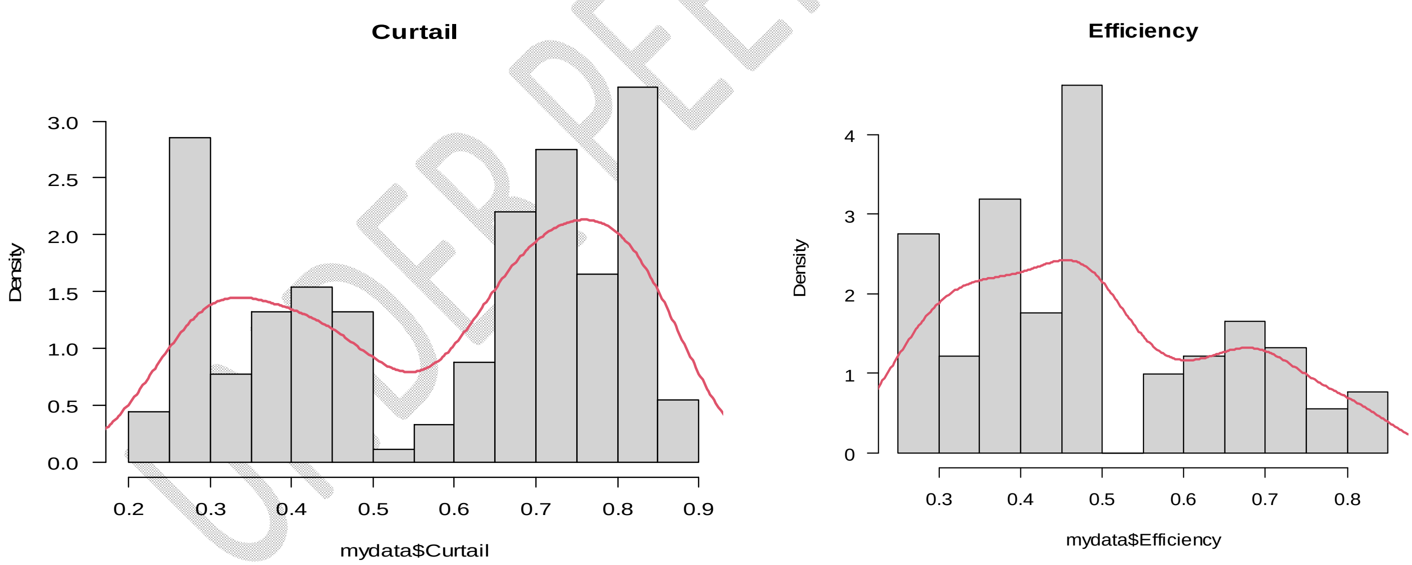

Figure 1: Distribution ofCCMB Scores (Left Curtailment Behaviour, Right Efficiency Behaviours)

3.3 The Role of Cognitive Factors on CCMB

The three dimensions of cognitive factors namely cause, consequences and response knowledge that have been described previously in climate change literature were considered.

Reliable scales were obtained for cause knowledge ($\alpha = 0.69$), consequence knowledge($\alpha = 0.69$) and response knowledge ($\alpha = 0.73$) to climate change.

All the surveyed managers had low levels of knowledge on the causes of climate change with a mean of 0.41 (± 0.14). Other pertinent descriptive statistics of the level of knowledge on consequences and responses to climate change are presented in Table (3).

Table 3: Descriptive Statistics of Cognitive factors

Type of Knowledge			Percentiles			Range	
	Mean	SD	25th	50th	75th	Minimum	Maximum
Cause	0.41	0.14	0.31	0.47	0.53	0.19	0.56
Consequence	0.71	0.15	0.66	0.73	0.77	0.41	0.93
Response	0.75	0.15	0.66	0.73	0.84	0.52	0.98

Due to the non-normal character of the data, a beta regression model was used to establish the role of cognitive factors on both dimensions of CCMB. Two models were run, one for curtailment CCMB and the other for efficiency CCMB.The utilized models were statistically informative with satisfactory log likelihood ratios and Wald test statistics(Table 4).The different dimensions of cognitive factors had divergent marginal effects on both categories of CCMB.Cause knowledge was positively associated with both curtailment ($\beta = 0.347$, $\rho < 0.05$) and efficiency ($\beta = 0.269$, $\rho < 0.05$) CCMB. Consequence knowledge was negatively associated with curtailment ($\beta = - 0.366$, $\rho < 0.05$) but positively with efficiency ($\beta = 0.199$, $\rho < 0.05$). Response knowledge had no effects on curtailment ($\beta = 0.092$, $\rho > 0.05$) but had positive effects on efficiency ($\beta = 0.36$, $\rho < 0.05$) CCMB.

Table 4: The Role of Cognitive Factors on CCMB

	Curtailment CCMB			Efficiency CCMB		
Variables	Mean Model	Precision Model	Marginal Effects	Mean Model	Precision Model	Marginal Effect
Age (30-39 years)	-0.92***		-0.18***	-0.889***		-0.210***
			(-0.05)			(-0.06)
Age (40-49 years)	-1.180***		-0.236***	-0.790**		-0.186***
	-0.336		-0.057	-0.314		-0.0693
Age (Above 50 years)	-0.32		-0.056	-0.18		-0.0399
	-0.359		-0.0618	-0.327		-0.072
Gender (Males)	-0.264**		-0.0575**	-0.383***		-0.0927***
	-0.134		-0.0291	-0.127		-0.0306
Academic (Certificate)	2.085***		0.435***	1.223***		0.287***
	-0.323		-0.0592	-0.304		-0.0659
Academic (Diploma)	1.857***		0.390***	0.649***		0.155***
	-0.179		-0.0306	-0.173		-0.0396
Academic(Degree)	1.821***		0.383***	0.378**		0.0890**
	-0.181		-0.0313	-0.178		-0.0412
Cause	3.281***		0.715***	1.299***		0.314***
	-0.499		-0.105	-0.48		-0.116
Consequence	-1.811***		-0.395***	1.169***		0.283***
	-0.375		-0.0805	-0.383		-0.0921
Response	0.115		0.0251	2.075***		0.502***
	-0.636		-0.139	-0.629		-0.151
Constant	-0.158	2.706***		-2.345**	2.601***	
	-0.961	-0.102		-0.954	-0.101	
Pseudo R^2	0.62			0.33		
Log Likelihood	135.90 (12df)			115.68 (12df)		
Wald's Chi^2 (10)	270.50, $\rho = 0.000$			80.17, $\rho = 0.000$		
Observations	182	182	182	182	182	182

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Relative to managers below 29 years, respondents aged between 30 and 39 years were 18 percentage points less likely to report engaging in curtailment CCMB. In addition managers aged between 40 and 49 years were 24 percentage points less likely to report undertaking curtailment CCMB when compared to those aged below 29 years. Managers aged above 50 years old were statistically equally likely practice curtailment CCMB. Males were 6 percentage points less likely to report having curtailment CCMB. When compared to secondary certificate holders, managers with higher levels of educational attainment were statistically more likely to undertake curtailment CCMB.

Relative to managers below 29 years, respondents aged between 30 and 39 years were 21 percentage points less likely to report undertaking efficiency CCMB. In addition managers aged between 40 and 49 years were 19 percentage points less likely to report practicing efficiency CCMB when compared to those aged below 29 years. Managers aged above 50 years old were statistically equally likely engage in efficiency CCMB. Males were 9 percentage points less likely to report having efficiency CCMB. When compared to secondary certificate holders, managers with higher levels of educational attainment were statistically more likely to undertake efficiency CCMB.

4.0 Discussions

This study provides important and previously unreported estimates of CCMB among managers of tourist accommodation facilities in Naivasha Sub-County in Kenya using recommended indicators. The study identified that efficiency and curtailment behaviours were two categories of CCMB practiced by the surveyed managers. This finding is consistent with some literature(Long et al., 2023; Matsumoto & Sugeta, 2022)but differs with another literature stream which shows that CCMB consists of many other dimensions(Gillis, 2016; Hamann, 2022; Melo et al., 2018).Variations in the findings may partly be due to differences in studied populations. It is more probable that the variation in findings may also be due to the type of measured indicators. The plethora of CCMB measures impedes cumulative science since incomparable measures have been used in different studies. Linking among different measures and consensus on standard CCMB measurement should now be prioritized. In addition, enabling widespread access to common measures is necessary to accelerate future progress.

The surveyed managers had moderate scores on climate change efficiency actions and curtailment actions which is inconsistent with the magnitude of the threat of climate change.

Comparing this finding to existing literature is not easy since incomparable CCMB measures have been used in different studies. The limited sources of climate change information may explain the unsatisfactory levels of knowledge among the surveyed managers. This study set itself apart by the use of recommended indicators of CCMB in the tourist hotel sector. The challenge now is on identifying appropriate interventions that can enhance CCMB in tourist accommodation facilities.

The different dimensions of cognitive factors had divergent associations with both categories of CCMB.Cause knowledge was positively associated with both curtailment and efficiency CCMB. Consequence knowledge was negatively associated with curtailmentbut positively with efficiency. Response knowledge had no statistical associations with curtailment but had positive relationships with efficiency CCMB.The findings of this study is are in line with findings inLinden(2014) and Sundblad et al., (2009).The results are however at variance with some studies that report no significant relationship between knowledge and CCMB (Rousell & Cutter-Mackenzie-Knowles, 2020, Frantzeskaki et al., 2019) and others that found that knowledge is negatively associated with climate change mitigation behaviours (Bergquist et al., 2022; Xie et al., 2019). Other studies (Hornsey & Fielding, 2020) provide mixed evidence, suggesting that increased knowledge about climate change only leads to higher concern and actions by some groups (such as the most educated) but not for others (for example, those with lesser educational attainment). This confusion has been explained partially as a result of the use of different classifications and measurements of the concept of cognition in different studies (Linden, 2014). Standardizing the measurement of cognition is therefore paramount.

This study established that age, sex and educational attainment are also important correlates of CCMB in addition to cognition. This is consistent with some literature (Ortega-Egea et al., 2014; Linden, 2014; Xiao & McCright, 2007)but not with others(Bamberg & Möser, 2007)provide a compelling review). The differences in opinion in existing literature are largely attributable to metrological properties (accuracy, validity and reproducibility) of utilized research tools. A key observation in this study is that socio-demographic variables may be representations for personal competencies, that is, the knowledge, skills and attitude necessary for actualize some given behavior. Thus, demographic variables like age, sex and education should be related to CCMB largelydepending on personal capabilities.

Overall,current studies on ecological issues use statistical methods that have strict statistical assumptions of normality of data. The use of a single measure of CCMB as opposed to the multidimensional nature of the concept is a further issue that may raise controversial results. The use of better analytical methods especially beta regression in the present study provide support for the proposition that cognition is an important correlate CCMB.

5.0 Conclusion

CCMB consists of two interrelated dimensions namely curtailment and efficiency behaviours. Curtailment behaviors are repetitive efforts that reduce consumption (such as turning off a light switch). Efficiency behaviors are one-time choices that involve the adoption of an efficient technology (for instance planting of trees and native plants in the hotel gardens). The surveyed managers did not demonstrate satisfactory levels of either dimensions of CCMB. Accordingly, an intense shift is needed in the behaviors of these managers' from limited action levels toward broader and greater levels of behavioural engagement in order to mitigate against the negative effects of climate change.

The various dimensions of cognition are diversely and significantly associated with both dimensions of CCMB.This study extends the discourse on the cognitive psychology of climate change by using data from a developing country and using the beta regression model as an emerging potent statistical framework. The reported findings indicate areas where action is required. Managers need to update their knowledge on the causes, consequences and responses to climate change in order to alter their behaviours accordingly.Moreover, educators and communicators need to acknowledge that a single intervention that is suitable for every purpose and every person is inappropriate to enhance CCMB. Additionally, policy initiatives on climate change need to integrate cognition in their pronouncements. Findings indicate that policy frameworks to enhance CCMB among key decision-makers need to integrate cognition of climate change as a critical factor that can be improved through training and awareness creation efforts.

Disclaimer (Artificial intelligence)

The Authors declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT and so on) and text-to-image generators have been used during writing or editing of manuscripts.

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