Evaluating the Constraints of Integrating Additional Climate Data in Developing Zambia's Rainfall Forecast based on Artificial Intelligence Models

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ABSTRACT
Rainfall forecasting is one of the most challenging topics across the earth and it remains one of the most complex domains. To generate accurate rainfall forecasts, requires use of more meteorological data from both ground and satellite observations with better spatial coverage. Medium and short term (ten days, seven days and daily) forecasts in Zambia are generated by analysing some global models which ingest few of the available surface land observations. While long term (Seasonal rainfall) forecast accuracy was improved when Artificial Intelligence techniques were applied, although only manual station and oceanic data sets were used. To assess the constraints of ingesting additional climate data in the current rainfall forecasting methods in Zambia, a survey questionnaire based on the Unified Theory of Acceptance and Use of Technology (UTAUT) Model was used. The results obtained have shown strong correlation between the independent variables and behavioral intention to use technology. It can therefore be concluded that there is user acceptance and willingness to ingest additional climate data and adopt artificial intelligence technologies in forecasting rainfall in Zambia, that could enhance forecast accuracy.

General Terms
Artificial Intelligence, Big Data Technologies, Machine Learning, Rainfall Forecasting, Climate Data Integration, Weather Prediction Systems.

Keywords
Artificial Intelligence, Big Data Technologies, Machine Learning, Rainfall Forecast, UTAUT Model.

1. INTRODUCTION
Rainfall is a significant factor around the world [1] and it impacts many economic sectors in Zambia such as; agriculture, water resource management, disaster risk, energy, tourism and health [2]. Rainfall forecasting is one of the most challenging topics across the earth and it remains one of the most complex domains [3]. It is challenging, demanding and complex due to the various dynamic environmental factors, both spatial and temporal random variations. Rainfall is a highly non-linear parameter [2].

One factor that can be used to enhance rainfall forecasts accuracy is vast knowledge of past and prevailing weather conditions over large areas [4]. Accurate rainfall forecast require a better understanding of the various dynamics processes and interactions that govern rainfall [5].

Current rainfall forecasting techniques in Zambia do not utilize much of the available data, yet weather conditions recorded at ground-based stations are considered the gold standard for meteorological data to be used in future weather projections [6]. Studies have shown that Big Data Technologies when applied with Artificial Intelligence (AI) does enhance accuracy of the rainfall forecast and could provide answers to the complexity of rainfall forecasting [2], [7]. Weather sensors with Internet of Things (IoT) technology such as Automatic Weather Stations (AWS) contribute greatly to collecting weather data at high speed [8] and this data could enhance rainfall forecast if used [9]. Machine Learning, a branch of AI focuses on the use of data and algorithms has been incredibly effective in identifying patterns in historical data for the identification of Fall Armyworm (FAW) Moths, which strength could enhance rainfall forecast accuracy by identifying patterns in historical climate data [10]. Thus, enhancing precipitation forecast accuracy is well worth studying for researchers.

The rainfall forecasts being generated in Zambia are the seasonal, ten (10) days, seven (7) days and daily forecasts. The ten (10) days, seven (7) days and daily forecasts are generated by analysing some global models, mainly the European Centre for Medium-Range Weather Forecasts (ECMWF), Global Forecast System (GFS), Action de Recherche Petite Echelle Grande Echelle (ARPEGE) and United Kingdom (UK) Met Office, whose initial data input is based on satellite and data from some World Weather Watch (WWW) stations [11]. A recently installed local model namely the Weather Research Forecasting (WRF) is also used to generate rainfall forecast for up to five (5) days, but likewise ingests data only from few stations [12]. The Seasonal rainfall forecasts accuracy was improved when Artificial Intelligence (AI) techniques were applied compared to when traditional statistical methods were used [13], although, only manual station and oceanic data sets were used.

In recent years, the number of Automatic Weather Stations in Zambia have increased [14]. The AWS collect weather data at high speed of every 10 minutes, but little or no data from the AWS is ingested in the global models. Increased data utilization in rainfall forecasting is key to foster accuracy of rainfall forecast [15], [16].

A World Meteorological Organisation (WMO) Integrated Global Observing System (WIGOS) Data Quality Monitoring System picture captured on 15th October, 2023 over Zambia and surrounding areas shows very few surface land observations over Zambia. This image is for a combined four (4) models namely German Meteorological Service (DWD), ECMWF, Japan Meteorological Agency (JMA) and National Centers for Environmental Prediction (NCEP) [17] and is given in Fig. 1 below.

Fig 1: Surface Land Observation for WIGOS [17]

Further, there is reanalysis climate data that strives to overcome weaknesses of both station observations (with limited coverage) and satellite (accuracy) by combining station observations and satellite data. Re- analysis data provides for better spatial coverage of the proxies with better accuracy of the ground observations [18]. Reanalysis data like Enhanced National Climate Services (ENACTS) data, has illustrated its potential to address data gaps and improve overall data quality [19], but this data is also not utilized in rainfall forecasting.

In this work, constraints in ingesting more climate data into current rainfall forecasting methods in Zambia are assessed. Evaluation used in this work is based on the amended Unified Theory of Acceptance and Use of Technology (UTAUT) Model.

2. THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT)

Information technology acceptance and adoption research has developed several competing and complementary models each with a different set of acceptance determinants. As a result of persistent efforts towards models' validation, extension works took place when each model was presented to the re- search community. These models have evolved over the years [20]. The Unified Theory of Acceptance and Use of Technology (UTAUT) is an empirically validated model combining eight major models of technology acceptance and their extensions namely the: Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), the combination form of TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), Motivational Model (MM), and the Social Cognitive Theory (SCT) [21]. Unified Theory of Acceptance and Use of Technology has been used in this study based on: its solid foundation as it presents an aggregation of other models; efficiency to gain access to the technology adoption probability of success and allows one to understand the acceptance factors [22].

UTAUT holds that four key constructs (Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions) are direct determinants or predictors of Behavior Intention and Usage [23]. Gender, age, experience, and voluntariness of use are posited to moderate the impact of the four key constructs. According to Venkatesh et al [23], UTAUT predictors are defined as:

- **Performance Expectancy (PE)**: - is the degree to which an individual believes that using the system will help him or her to achieve job performance;
- **Effort Expectancy (EE)**: - is the degree of ease associated with use of the system;
- **Social Influence (SI)**: - is the degree to which individuals perceive that someone accepts that they should use the new system;
- **Facilitating Conditions (FC):** - is the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system;
- **Behavioral Intention (BI)**: - is the strength of one's own intention to perform a certain behavior and the willingness of the respondent to use the system.

The UTAUT model is given in Fig. 2 below.

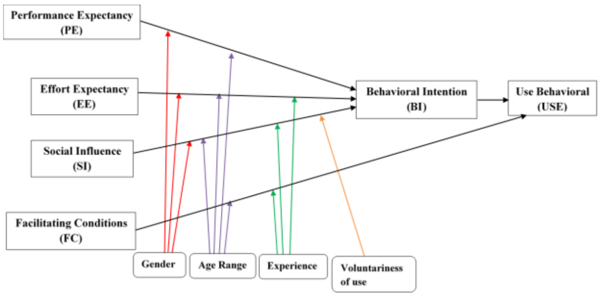


Fig. 2. UTAUT Model [23]

3. RELATED WORKS

UTAUT Model is a technology acceptance model which was developed by Venkatesh et al to describe the acceptance of technology among users [23]. The UTAUT model is one of the most powerful technology acceptance theories which were developed to examine the ability of users to accept technology and their intention to adopt new technologies. This theory has been developed by adopting the most important characteristics of eight old theories over the past years in order to be as a unified form to all of them [24]. The UTAUT model has been used to test many different systems such as:

Online learning system to; evaluate the adoption of technologies during the COVID-19 pandemic [25], mobile and distance learning that included empathic characteristics and affective principles to increase students' participation and motivation in educational contexts [26] and assess the effectiveness of the Learning Management System (LMS) Moodle [27].

Mobile learning (MLearning) adoption which emerged with the evolution of mobile devices, has extended the reach of e-learning and distance education systems by allowing educators and students to teach and learn anywhere, anytime and on the move [21]. It has also been used to assess the extent of disturbance during mobile learning since learners use smart phones largely for socialization purposes [28].

Electronic banking system (eBanking) to; analyze the untapped behavioral, environmental and technological dimensions of mobile banking acceptance which supports traditional bank to enhance quality service and decrease service cost [29]. It has been used to investigate the direct effects of mobile banking acceptance determinants and evaluate the impact of culture on mobile banking [30] and understand that the main determinants of internet banking adoption is important for banks while the role of users' perceived risk in Internet banking adoptionis limited [31].

Electronic Government services(eGovernment) to; identify factors that influenced citizens to accept and use e-government services [20], determine factors that affect users in using mobile commerce to buy online [32], and provide a theoretical analysis of e-Commerce adoption in least developed countries [33].

Electronic Document Management System (EDMS) to; understand the factors that affect the intention of use while EDMS offers many benefits to its users [34], assess why implementation of EDMS has a low rate of success [35], investigate the mediating role of adoption readiness on the relationship between user resistance as well as user anxiety and attitude toward using a system [36]. Investigate factors that cause adoption and usage of Document Workflow Management System to be found wanting [37];

Mobile Health Services (mHealth); determining factors affecting acceptance and Use of (mHealth) Services using UTAUT model since healthcare service is not only a health-related issue but also a development issue [38]. It has been used to explore perceptions of older people toward mHealth in order to identify potential facilitators of and barriers to its adoption [39]. Further UTAUT model has been used to predict digital immigrants' technology use [40].

Premised on the positive results of the use of the UTAUT model on the various stated applications above, this work hypothesized the appropriateness on the use of this model on factors that affect the intention of use and adoption in forecasting rainfall in Zambia.

4. METHODOLOGY

4.1 Research Model

This work empirically tests the proposed extended unified theory of acceptance and use of technology (e-UTAUT) model in users' intention and use behavior towards the use of available data sets by relying on big data and artificial intelligence technologies to forecast rainfall in Zambia. The research model depicted in Fig. 3 below, is based on the works of Venkatesh et al [23].

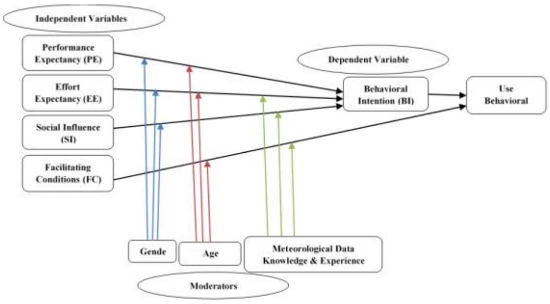


Fig. 3. Research Model

In thi investigation, behavioral intention is considered as a key indicator of the actual influence on technology service usage. Studies indicate that behavioral intentions will have a positive and direct influence on usage behavior [23]. Irani et al. also highlight that behavior intention is commonly used to predict technology adoption [41] and Ajzen further emphasizes the direct impact of behavioral intention on technology adoption [42].

For brevity, in this study the behavioral intention to use technology will be used to measure the actual adoption of big data and artificial intelligence techniques in forecasting rainfall in Zambia, given its strong correlation with usage behavior.

4.2 Research Hypotheses

The researchers' hypothesized relationships between variables are shown in table 1 below.

Table 1. Research Hypothesis

No.	Hypothesis
H1	Performance expectancy will have a positive influence on behavioral intentions to utilize artificial intelligence and big datatechniques in forecasting rainfall
H1a	Gender will positively moderate the influence of performance expectancy on behavioral intentions to utilize artificial intelligenceand big data techniques in forecasting rainfall
H1b	Age will positively moderate the influence of performance expectancy on behavioural intentions to utilize artificial intelligence and big data techniques in forecasting rainfall
H2	Effort expectancy will have a positive influence on behavioral intentions to utilize artificial intelligence and big data techniquesin forecasting rainfall
H2a	Gender will positively moderate the influence of effort expectancy on behavioral intentions to utilize artificial intelligence and bigdata techniques in forecasting rainfall
H2b	Age will positively moderate the influence of effort expectancy on behavioral intentions to utilize artificial intelligence and big datatechniques in forecasting Rainfall
H2c	Knowledge and experiences of meteorological data will positively moderate the influence of effort expectancy on behavioral intentions to utilize artificial intelligence and big data techniques in forecasting rainfall
H3	Social influence will have a positive influence on behavioral intentions to utilize artificial intelligence and big data techniquesin forecasting rainfall
H3a	Gender will positively moderate the influence of social influence on behavioral intentions to utilize artificial intelligence and bigdata techniques in forecasting rainfall
H3b	Experiences with and knowledge of meteorological data will positively moderate the influence of social influence on behavioralintentions to utilize artificial intelligence and big data techniques in forecasting rainfall
H4	Facilitating conditions will have a positive influence on behavioral intentions to utilize artificial intelligence and big data techniquesin forecasting rainfall
H4a	Age will positively moderate the influence of facilitating conditions on behavioral intentions to utilize artificial intelligence andbig data techniques in forecasting rainfall
H4b	Experiences with and knowledge of meteorological data experiences will positively moderate the influence of facilitating conditions on behavioral intentions to utilize artificial intelligenceand big data techniques in forecasting rainfall

4.3 Data Collection

In this study, quantitative research method was used to conduct an interpretive study using questionnaires' survey. Leedy and Ormrod alleged that quantitative research is specific in its surveying and experimentation, as it builds upon existing theories [43]. The questionnaire consisted well-structured questions divided into different sections for easy reading and completion. A Likert scale with five levels of possible answers in respect to UTAUT model (from Strongly Disagree to Strongly Agree) was used.

Questionnaire respondents were purposefully sampled targeting researchers, policy makers and meteorology or climatology personnel of different ages and employment statuses. A total of 160 questionnaires were distributed, of which 112 were completed and usable for this study.

5. DATA ANALYSIS AND RESULT

Data was gathered through a survey and was analyzed using the Statistical Packages for Social Sciences (SPSS) and SmartPLS. The study employed Structural Equation Modeling (SEM) to assess the interrelations within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework and to verify the proposed hypotheses concerning the model's variables. SEM is a confirmatory statistical technique that is used for hypothesis testing in the analysis of data that represents certain phenomena [44] and is used to reveal the relationships between observed variables and latent variables [34]. The subsequent sections will illustrate the study analysis in more detail.

5.1 Descriptive Statistical Perspective

Table 2 below provides a general overview of the respondents that participated in this study in terms of the demographic information, such as gender, age-range, qualification and career

Table 2. Respondents Demographic Information

Variable		Frequency	Percent
Gender	Male	74	66.1%
	Female	38	33.9%
Age Range	21-30 years	6	33.9%
	31-40 years	23	20.5%
	41-50 years	36	32.1%
	51-60 years	32	28.6%
	61 years +	15	13.4%
Qualification	Diploma	1	0.9%
	Degree	35	31.2%
	Masters	60	53.6%
	PhD	16	14.3%
Career	Meteorology	43	38.4%
	Researchers	37	33.0%
	Policy Makers	32	28.6%

5.2 Reliability Verification

Reliability in measurement denotes the extent to which an instrument is devoid of random error, emphasizing the measurements consistency and stability. Internal consistency tends to be a frequently used type of reliability in the Information System (IS) domain [45]. This work utilized Cronbach's alpha coefficients, which are calculated based on the average inter-item correlations and were used to measure internal consistency [46]. Cronbach's alpha is the most common measure of internal consistency and Cronbach alpha values of 0.7 or higher indicate acceptable internal consistency [47]. Reliability coefficients is presented in Table 3 below.

Table 3. Cronbach Alpha Reliability Results

Constructs	Cronbach Alpha(a)	No. of Items
Performance Expectancy (PE)	0.811	5
Effort Expectancy (EE)	0.869	5
Social Influence (SI)	0.838	5
Facilitating Conditions (FC)	0.865	5
Behavioral Intention (BI)	0.880	5

Internal Consistency Reliability test determine how all factors on the test relate to all other factors [46]. Internal Consistency Reliability results demonstrate that all the Cronbach alpha values for the instruments used in the study are reliable, confirming their adequate construct reliability.

5.3 Validity Test

Construct validity is the degree to which an operational measure correlates with the investigated theoretical concept [48]. In this study, confirmatory factor analysis was conducted to assess the overall measurement models and examine the convergent and discriminant validity.

Confirmatory Factor Analysis (CFA) evaluates how well an operational measure like a questionnaire, aligns with the underlying theoretical concept it aims to capture, that is assessing whether the measurement accurately reflects the construct it intends to measure [49]. This is a statistical technique used to test the fit of a hypothesized measurement model against observed data with the goal to assess how well the observed data align with the proposed model [50]. In this research work, CFA was conducted to evaluate the overall measurement models and examine the convergent and discriminant validity.

5.3.1 Convergent Validity

Convergent validity examines whether different indicators of the same construct converge (correlate) as expected, and is achieved when multiple indicators operate in a consistent manner [51]. Convergent Validity assesses whether different measurement scales (indicators) that are supposed to measure the same underlying concept (construct) indeed converge or correlate as expected. When multiple indicators consistently operate in a consistent manner and align with the theoretical construct, convergent validity is achieved. High convergent validity indicates that the indicators consistently measure the same underlying construct [52].

In confirmatory factor analysis, convergent validity relies on Average Variance Extracted (AVE) as a base. AVE quantifies the proportion of variance captured by the latent construct (factor) relative to the measurement error [53]. AVE values range from 0 to 1, where higher values indicate better convergent validity. It is calculated by summing the squared factor loading of each indicator associated with the construct and dividing it by the sum of the error variances. Constructs have convergent validity when the composite reliability exceeds the criterion of 0.70 and the average variance extracted is above 0.50 [54]. Given in Table 4 is the Convergent validity results. These results show that all composite reliabilities exceeded the criterion of 0.70.

Table 4. Convergent Validity Results

Constructs	Composite Reliability	Average Variance Extracted
Performance Expectancy (PE)	0.811	0.531
Effort Expectancy (EE)	0.869	0.592
Social Influence (SI)	0.838	0.522
Facilitating Conditions (FC)	0.865	0.563

5.3.2 Discriminant Validity

Discriminant validity examines whether constructs that theoretically should not be related to each other are, in fact, unrelated (i.e. do not correlate too strongly). It is the extent to which scales reflect their suggested construct differently from the relation with all other scales in the research model. Discriminant validity ensures that different constructs are not confused with each other. Low correlation between unrelated constructs demonstrate discriminant validity [55].

Discriminant validity is assessed by comparing the square roots of average variance extracted (AVE) to the inter-factor correlations between constructs. If the AVE is higher than the squared inter-scale correlations of the construct then discriminant validity is supported [54]. Results given in Table 5 below, indicate that all the square roots of AVEs (diagonal cells) are higher than the correlations between constructs and thus confirming adequate discriminant validity.

Table 5. Discriminant Validity – Fornell Larcker Criterion

CONSTRUCTS	BI	EE	FC	PE	SI
Behavioral Intention	0.780				
Effort Expectancy	0.875	0.770			
Facilitating Conditions	0.879	0.986	0.750		
Performance Expectancy	0.874	1.027	0.874	0.728	
Social Influence	0.990	1.048	1.012	0.974	0.723

5.4 Chi-Square Test for Association

A chi-square test is a statistical test that is used to compare observed and expected results, with the goal to identify whether a disparity between actual and predicted data is due to chance or to a link between the variables under consideration. It is used to examine independence across two categorical variables or to assess associations between categorical variables [56], [57].

A chi-square test is required to test the hypothesis that there is no relationship between two categorical variables. It compares the observed frequencies from the data with frequencies which would be expected if there was no relationship between two variables [58]. Pearson's Chi-Squared tests were carried out to assess whether there was no relationship between the following categorical variables and the tests outputs are given in tables 6 - 10 below:

- Performance Expectancy and Behavioral Intention;
- Effort Expectancy and Behavioral Intention;
- Social Influence and Behavioral Intention;
- Facilitating Conditions and Use Behavioral; and
- Behavioral Intention and Use Behavioral.

For the purpose of this analysis, only the Pearson Chi-Square statistic was assessed. When P-value <0.05, it can be said that there is a statistically significant relationship between the two variables [59]. The P-value for the chi-square statistic from all the five tests is 0.000, which is smaller than the alpha level of 0.05.

Table 6. PE - BI Chi-Square Test

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	66.608[a]	12	0.000
Likelihood Ratio	58.408	12	0.005
Linear by Linear Association	27.931	1	0.005
N of Valid Cases	112		

a. cells (70.0%) have expected count less than 5. The minimum expected count is 0.03

The relationship between the categorical variables, Performance Expectancy (PE) and Behavioral Intention (BI) was examined to look for associations and a chi-squared test with 6 degrees of freedom was performed resulting in a test statistic of 66.608[a].

Table 7. EE - BI Chi-square test

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	78.788[a]	12	0.000
Likelihood Ratio	74.552	12	0.000
Linear by Linear Association	45.635	1	0.000
N of Valid Cases	112		

a.11 cells (55.0\%) have expected count less than 5. The minimum expected count is 0.08

The relationship between the categorical variables, Effort Expectancy (EE) and BI was examined to look for associations and a chi-squared test with 6 degrees of freedom was performed resulting in a test statistic of 78.788[a].

Table 8. SI - BI Chi-Square Test

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	52.337[a]	16	0.000
Likelihood Ratio	53.678	16	0.000
Linear by Linear Association	14.069	1	0.000
N of Valid Cases	112		

a.16 cells (64.0\%) have expected count less than 5. The minimum expected count is 0.01

The relationship between the categorical variables, Social Influence (SI) and BI was examined to look for associations and a chi-squared test with 6 degrees of freedom was performed resulting in a test statistic of 52.337[a].

Table 9. FC - UB Chi-Square Test

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	46.839[a]	12	0.000
Likelihood Ratio	37.172	12	0.043
Linear by Linear Association	12.742	1	0.005
N of Valid Cases	112		

a.15 cells (75.0\%) have expected count less than 5. The minimum expected count is 0.03

The relationship between the categorical variables, Facilitating Conditions (FC) and Use Behavioral (UB) was examined to look for associations and a chi-squared test with 6 degrees of freedom was performed resulting in a test statistic of 46.839[a]

Table 10. BI - UB Chi-Square Test

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	61.160[a]	12	0.000
Likelihood Ratio	43.216	12	0.043
Linear by Linear Association	14.743	1	0.005
N of Valid Cases	112		

a.11 cells (55.0\%) have expected count less than 5. The minimum expected count is 0.006

The relationship between the categorical variables, BI and UB was examined to look for associations and a chi-squared test with 6 degrees of freedom was performed resulting in a test statistic of 61.160a.

These results for all in asymptotic Pearson value are less than 0.001. Positive results from the chi- square tests indicates that there is some kind of relationship between the two variables but we do not know what sort of relationship it is [60]. Therefore, there is strong evidence to reject the null hypothesis that; PE and BI are independent; EE and BI are independent; SI and BI are independent; FC and UB are independent; and BI and UB are independent.

5.4.1 Validity

Chi-square tests are only valid when you have reasonable sample size, less than 20% of cells have an expected count less than 5 and none have an expected count less than 1 [61]. From the outputs in tables 6 to 10 above, a footnote on each table indicates that the analysis is valid and no cells have expected counts less than 5.

5.5 Independent t-Tests

Independent Samples t-Test compares the means of two independent groups in order to determine whether there is statistical evidence that the associated variable means are significantly different. The independent samples t-Test is used to compare the mean scores of two groups of variables [61], [62]. Independent Samples t-Test is a simple and straight forward test that is easy to understand and implement. It is a powerful test that can detect even small differences between two groups [63].

For the purpose of this Independent Samples T- Test analysis, only the Sig. (2-tailed) p-value is checked. The p-value indicates if the correlation was significant at the chosen alpha level and if it can be considered. Given in Tables 11 below are the outputs for the independent samples t-Tests between:

- Performance Expectancy and Behavioral Intention;
- Effort Expectancy and Behavioral Intention;
- Social Influence and Behavioral Intention;
- Facilitating Conditions and Use Behavioral;
- Behavioral Intention and Use Behavioral; and
- Experience and Performance Expectancy.

The Sig. (2-tailed) p-value on Performance Expectancy with Behavioral Intention is 0.000 for equal variance assumed and 0.002 for equal variance not assumed. The Sig. (2-tailed) p-value of Effort Expectancy with Behavioral Intention is 0.000 for equal variance assumed and 0.004 for equal variance not assumed.

The Sig. (2-tailed) p-value of Social Influence with Behavioral Intention is 0.003 for equal variance assumed and 0.004 for equal variance not assumed. The Sig. (2-tailed) p-value of Behavioral Intention with Use Behavioral is 0.000 for equal variance assumed and 0.004 for equal variance not assumed.

The Sig. (2-tailed) p-value of Facilitating Conditions with Behavioral Intention is 0.017 for equal variance assumed and 0.000 for equal variance not assumed. The Sig. (2-tailed) p-value of Experience on Use Behavioral is 0.000 for equal variance assumed and 0.004 for equal variance not assumed.

The P-value of alpha level of 0.05 indicates significant correlation [64]. Sig stands for significance level and the p-values for all the six independent sample t-Tests outputs are smaller than the alpha level of 0.05, indicating that there is significant correlation [59].

Table 11. Independent Samples T-Tests

PE - BI										
Levene's test for Equality of Variance						**T-test for Equality of means**			**95% Confidence Interval Difference**	
		F	**Sig.**	**I**	**df**	**Sig.(2-tailed)**	**Mean Difference**	**Std Error Difference**	**Lower**	**Upper**
BI	Equal Variance Assumed	0.709	0.404	-3.767	50	0.000	- 1.769	0.469	- 2.712	- 0.826
	Equal Variance not assumed			- 5.021	2.492	0.002	- 1.769	0.352	- 1.419	- 0.359
EE - BI										
Levene's test for Equality of Variance						**T-test for Equality of means**			**95% Confidence Interval Difference**	
		F	**Sig.**	**I**	**df**	**Sig.(2-tailed)**	**Mean Difference**	**Std Error Difference**	**Lower**	**Upper**
BI	Equal Variance Assumed	1.023	0.317	- 4.048	48	0.000	- 0.889	0.220	- 1.331	- 0.447
	Equal Variance not assumed			- 3.693	10.940	0.004	- 0.889	0.241.	- 1.419	- 0.359
SI - BI										
Levene's test for Equality of Variance						**T-test for Equality of means**			**95% Confidence Interval Difference**	
		F	**Sig.**	**I**	**df**	**Sig.(2-tailed)**	**Mean Difference**	**Std Error Difference**	**Lower**	**Upper**
BI	Equal Variance Assumed	5.004	0.031	- 3.123	39	0.003	- 0.917	0.294	- 1.510	- 0.323
	Equal Variance not assumed			- 8.472	35.000	0.004	- 0.917	0.108.	- 1.136	- 0.697
BI - UB										
Levene's test for Equality of Variance						**T-test for Equality of means**			**95% Confidence Interval Difference**	

		F	Sig.	I	df	Sig.(2-tailed)	Mean Difference	Std Error Difference	Lower	Upper
	Equal Variance Assumed	2.316	0.132	- 2.778	75	0.000	- 0.616	0.222	- 1.057	- 0.174
UB	Equal Variance not assumed			- 3.132	34.841	0.004	- 0.616	0.197	- 1.015	- 0.217
FC - UB										
Levene's test for Equality of Variance						**T-test for Equality of means**			**95% Confidence Interval Difference**	
		F	**Sig.**	**I**	**df**	**Sig.(2-tailed)**	**Mean Difference**	**Std Error Difference**	**Lower**	**Upper**
	Equal Variance Assumed	6.613	0.014	- 1.378	43	0.017	- 0.698	0.506	- 1.719	- 0.323
BI	Equal Variance not assumed			- 6.459	42.000	0.000	- 0.698	0.108	- 0.916	- 0.480
EXPERIENCE - UB										
Levene's test for Equality of Variance						**T-test for Equality of means**			**95% Confidence Interval Difference**	
		F	**Sig.**	**I**	**df**	**Sig.(2-tailed)**	**Mean Difference**	**Std Error Difference**	**Lower**	**Upper**
	Equal Variance Assumed	4.620	0.037	2.107	45	0.041	1.156	0.548	0.51	2.260
BI	Equal Variance not assumed			- 10.101	44.000	0.004	1.156	0.548	- 0.925	1.386

5.6 Linear Regression

Linear regression is a statistical model which estimates the linear relationship between an independent variable and a dependent variable [65]. The goal of simple linear regression is to build a model that will use the value of a continuous variable to predict the value of another continuous variable. An independent variable is used to predict a dependent variable [66] which can be expressed in the form of an equation as shown in equation 1 below:

$$y = mx + c \qquad (1)$$

Where:
y = the predicted value of the dependent variable;
m = the slope of the regression line and the value of m predicts how much the dependent variable changes when the independent variable increases;

x= the value of the independent variable; and
c = the constant.

The linear relationship was assessed between the following variables to check different assumptions and interpret results:

- Performance Expectancy and Behavioral Intention;
- Effort Expectancy and Behavioral Intention;
- Social Influence and Behavioral Intention;
- Facilitating Conditions and Use Behavioral; and
- Behavioral Intention and Use Behavioral.

5.6.1 Assumptions of Simple Linear Regression

The assumptions of simple linear regression are checked before interpreting the results to ensure not drawing false conclusions from the analysis.

5.6.1.1 Absence of Extreme Outliers

A common concern in empirical research is whether findings might be invalidated by a set of outlying observations. Since regression analysis is sensitive to outliers, it is important to check for possible outlier contamination in the data set. This is done by reviewing the Minimum and Maximum columns of the Standard [67], [68].

A data point with a standardized residual that is more than +/-3 is usually considered to be an outlier. In other words, if the value in the Minimum column of the Std. Residual row is less than -3, and if the value in the Maximum column of the Std. Residual row is greater than 3, the data should be investigated for possible outliers [69]. Residual Statistics tables are given from tables 12 to 16 below.

Table 12. PE - BI Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.07	4.56	3.78	0.621	112
Residual	-1.186	1.304	0.000	0.575	112
Std. Predicted Value	-2.749	1.262	0.000	1.000	112
Std. Residual	- 2.018	1.717	0.000	0.977	112

The Std. Residual for Performance Expectancy on Behavioral Intention is; minimum value -2.018 and maximum value 1.717.

Table 13. EE - BI Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.60	4.60	3.77	0.618	112
Residual	-1.599	1.023	0.000	0.533	112
Std. Predicted Value	-1.882	1.344	0.000	1.000	112
Std. Residual	- 1.933	1.577	0.000	0.977	112

The Std. Residual for Effort Expectancy on Behavioral Intention is: minimum value -1.933 and maximum value 1.577.

Table 14. SI - BI Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.35	4.84	3.77	0.649	112
Residual	-1.867	1.089	0.000	0.495	112
Std. Predicted Value	-2.181	1.655	0.000	1.000	112
Std. Residual	- 2.331	1.768	0.000	0.977	112

The Std. Residual for Social Influence on Behavioral Intention is; minimum value -2.331 and maximum value 1.768.

Table 15. FC - UB Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.62	4.25	3.13	0.575	112
Residual	- 2.053	1.951	0.000	0.902	112
Std. Predicted Value	- 2.636	1.935	0.000	1.000	112
Std. Residual	- 2.224	2.013	0.000	0.977	112

The Std. Residual for Facilitating Condition on Use Behavioral is; minimum value -2.224 and maximum value 2.013

Table 16. BI - UB Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.43	4.94	3.81	0.540	112
Residual	- 2.519	1.672	0.000	0.884	112
Std. Predicted Value	- 2.651	2.086	0.000	1.000	112
Std. Residual	- 1.785	1.849	0.000	0.977	112

The Std. Residual for Behavioral Intention on Use Behavioral is; minimum value -1.785 and maximum value 1.849.

Residual outputs above indicates that this data set does not include any extreme outliers.

5.6.1.2 Checking Assumptions of Normality

Normality assumption is necessary to unbiasedly estimate standard errors and enhance confidence intervals and P-values. Violations of the normality assumption often do not noticeably impact results in large sample sizes [70]. Normal P-Plot is used to test the normality assumption in simple linear regression. Given in Fig. 4 below is the normal plot.

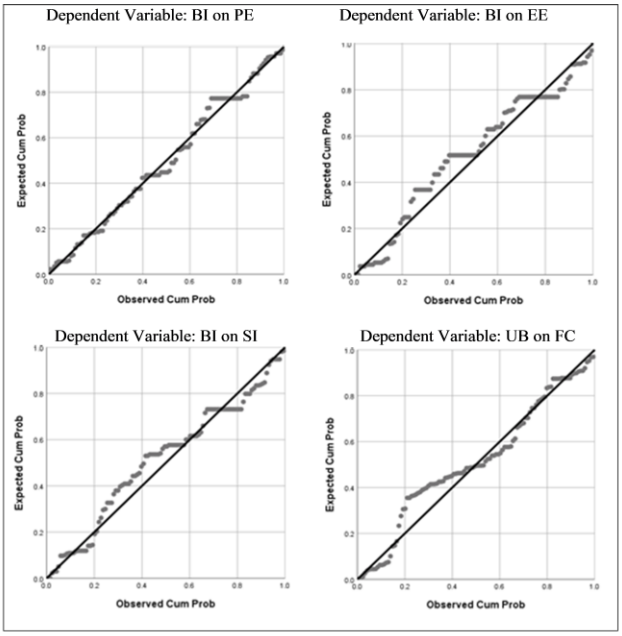


Fig. 4. Normal P-Plot of Regression Standardized Residual

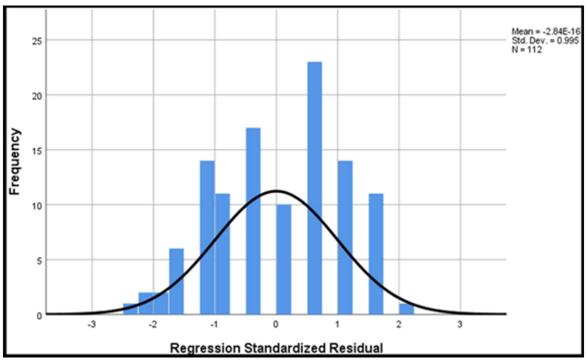
This assumption has been met because the dots on the P-Plot are on, or close to, the diagonal line, as shown in both Fig. 4 above.

5.6.1.3 Checking Assumptions of Histogram

Histogram of standardized residuals can be used to check whether the variance is normally distributed. Given in Fig. 5 below is the histogram for Use Behavioral on Behavioral Intention and Behavioral Intention on Effort Expectancy respectively.

Use Behavioral on Behavioral Intention distributed around zero indicates that the normality assumption is likely to be true. If the histogram indicates that random error is not normally distributed, it suggests that the models underlying assumptions may have been violated for the dependent variable is also reviewed to test the assumption [71].

From the graph in Fig. 5 below, the histogram assumption is met because the residuals are approximately normally distributed



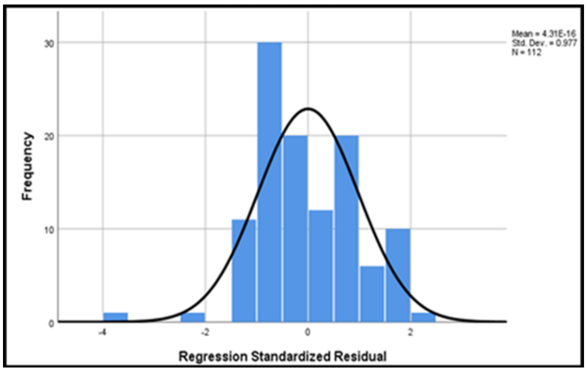


Fig 5. Histogram

5.6.1.4 Checking Assumptions of Independence of Observation

Most statistical tests assume that the value of one observation does not affect the value of other observations. Independence of observation check isused to determine whether the data satisfies the independence of observations assumption [72]. Independence of observation check is achieved by assessing the value of the Durbin-Watson statistics in the Model Summary output table given in tables 17 to 21 below. For Independence of observation output, values between 1.5 and 2.5 are normally.

Table 17. PE - BI MODEL Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.734^a	0.539	0.517	0.588	1.744

a. Predictors:(Constant) PE; Dependent Variable: BI

Table 18. EE - BI MODEL Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.875^a	0.574	0.554	0.545	1.970

a. Predictors:(Constant), EE; Dependent Variable: BI

Table 19. SI - BI MODEL Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.795^a	0.632	0.615	0.506	1.878

a. Predictors:(Constant), SI; Dependent Variable: BI

Table 20. BI - UB MODEL Summary^b

Model	R	R Square	Adjusted R Square		Std. Error of the Estimate	Durbin-Watson
1	0.905^a	0.606	0.474		0.912	1.557

a. Predictors:(Constant), BI; Dependent Variable: UB

Table 21. FC - UB MODEL Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.637^a	0.389	0.355	0.723	1.644

a. Predictors:(Constant). FC; Dependent Variable: UB

The Independence of observation outputs given above show that, Durbin-Watson values for PE-BI Model Summary is 1.744, EE-BI Model Summaryis 1.970, SI-BI Model Summary is 1.878, BI-UB Model Summary is 1.557 and FC-UB Model Summary is 1.644 which all fall well within the independence of observation range of between 1.5 and 2.5. Thus, confirming that the value of one observation does not affect the value of another observation.

5.6.2 Linear Regression Results and interpretation

To interpret the results, we review the Model Summary tables 17 to 21 above and check the ANOVA tables 21 to 25 below:

5.6.2.1 Model Summary Table

A model summary is automatically created when running a regression modeling or a classification modeling. The model summary displays the name of the model, the model type, and the model formula. The R value indicates the strength of correlation/ linear relationship between two quantitative variables [73].

The relationship between two variables is generally considered strong when their r value is larger than 0.7. From the Model Summary outputs above, there is a strong correlation of 0.734 between PE and BI, 0.875 between EE and BI, 0.795 between SI and BI. While there is a very strong relationship of 0.905 between BI and UB, and moderately strong correlation of 0.637 between FC and UB.

5.6.2.2 ANOVA Table

Analysis of variance (ANOVA) is a statistical test used to assess the difference between the means of more than two groups. ANOVA test is used to determine the influence of independent variables on the dependent variable in a regression study [74]. To determine whether this regression model predicts the dependent variable better than one would expect, the Sig. value in the ANOVA table is checked. ANOVA tables are given from table 22 to 25 below.

Table 22. ANOVA^a BI - PE

Model		Sum of Squares	df	Mean Square	F	Sig
1	Regression	42.780	5	8.556	24.753	0.000^b
	Residual	36.640	106	0.346		
	Total	79.420	111			

a. Dependent Variable: BI, b. Predictors: (Constant), PE

Table 23. ANOVA^a BI - EE

Model		Sum of Squares	df	Mean Square	F	Sig
1	Regression	42.459	5	8.492	28.570	0.000b
	Residual	31.506	106	0.297		
	Total	73.964	111			

a. Dependent Variable: BI, b. Predictors: (Constant), EE

Table 24. ANOVA^a BI - SI

Model		Sum of Squares	df	Mean Square	F	Sig
1	Regression	46.782	5	9.356	36.485	0.000^b
	Residual	27.183	106	0.256		
	Total	73.964	111			

a. Dependent Variable: BI, b. Predictors: (Constant), SI

Table 25. ANOVA^a UB - FC

Model		Sum of Squares	df	Mean Square	F	Sig
1	Regression	36.671	5	7.334	8.608	0.000^b
	Residual	90.320	106	0.852		
	Total	126.991	111			

a. Dependent Variable: UB, b. Predictors: (Constant), FC

The Sig. values are all variables is 0.000 which is less than 0.05, thus indicating that the regression models are all significant.

6. HYPOTHESIS TESTING RESULTS

Hypothesis tests are another way of expressing confidence intervals and every hypothesis test based on significance can be obtained via a confidence interval, and every confidence interval can be obtained via a hypothesis test based on significance [75]. The purpose of hypothesis testing is to identify which independent variables (predictors) significantly contribute to explaining the behavior of dependent variables [54]]. In this study, hypothesis testing was performed using AMOS 29.0. Table 31 represents the results of testing the research hypotheses. The conclusion column indicates whether that hypothesis was supported or not supported depending on the result coefficients beta.

Table 26. Hypothesis Testing Results

Hypothesis/Path	Findings	Conclusion
H1(PE →BI)	Beta = 0.780	supported
H1a	not significant	not supported
H1b	not significant	not supported
H2(EE →BI)	Beta = 0.820	supported
H2a	not significant	not supported
H2b	not significant	not supported
H2c	0.128	supported
H3 (SI →BI)	Beta = 0.927	supported
H3a	not significant	not supported
H3b	0.074	supported
H4 (FC →UB)	Beta = 0.838	supported
H4a	not significant	not supported
H4b	0.125	supported

7. DISCUSSION

In this section, the survey results based on the findings from our hypotheses are discussed. As presented in Table 26, the impact factors on the adoption process of the study model were categorized into significant and non-significant factors.

7.1 Significant Factors and Moderators

Performance Expectancy (PE) had a positive influence on behaviour intention, but gender and age did not moderate this relationship. In other words, performance expectancy maintains a positive impact on behavioral intention regardless of an individuals' gender or age [23].

Effort Expectancy (EE) had a positive effect on behavioural intention to use big data and artificial intelligence technology. This positive effect would be moderated by knowledge and experience with meteorological data only, while gender and age were not considered important moderators in this connection. This result demonstrate that effort expectancy is a significant predictor of behavioural intention [23].

Social Influence (SI) had a positive effect on behavioural intention to use big data and artificial intelligence technology. This positive effect would be moderated by knowledge and experience with meteorological data only. Gender had no effect as a moderator in this connection [23].

Facilitating Conditions (FC) had a positive effect on behavioural intention to use big data and artificial intelligence technology and this positive relationship would be moderated by knowledge and experience with meteorological data only. Gender and age do not moderator this relationship [23].

Knowledge and experience with meteorological data was found to be a significant moderator in terms of influencing the behavioural intention to use big data and artificial intelligence technology in forecasting rainfall in Zambia.

7.2 Non-Significant Moderators

Age and gender were found to be insignificant in terms of moderating the behavioural intention to use big data and artificial intelligence technology in Zambia.

8. CONCLUSIONS

In this study, we applied an adapted version of Unified Theory of Acceptance and Use of Technology model to explore user acceptance and adoption of big data and artificial intelligence technologies to be used in forecasting rainfall in Zambia.

Based on the different data analysis performed, all the results showed that there is adequate construct reliability and all the constructs have convergent validity since the composite reliability exceeds the criterion of 0.70. Also, all the square roots of average variance extracted are higher than the correlations between constructs which confirms adequate discriminant validity. The p-values for all the six independent sample t-Tests outputs were smaller than the alpha level of 0.05, that indicated that there is significant correlation.

Further, the data sets do not include any extreme outliers and the value of one observation does not affect the value of another observation. The outputs also showed that, there is correlation between the independent variables and dependent variables, and the correlation is quite strong.

The Independence of observation outputs given in the Model Summary tables confirming that the value of one observation does not affect the value of anotherobservation. The Sig. values are all variables was 0.000 indicating that the regression models are all significant.

Thus, it can be concluded that Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions influence the peoples' willingness to adopt and utilize big data and artificial intelligence technologies in forecasting rainfall in Zambia. Knowledge and experience with meteorological data influenced the independent variables, while age and gender had no impact.

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