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DEVELOPING INFORMATION TECHNOLOGY-BASED TOURISM: STUDY ON A TOURIST VILLAGE

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ABSTRACT

Advances in information technology demand adaptation in all aspects of life, including the tourism sector. The development of technology-based tourism must align with the increasingly massive use of social media, internet and the emergence of a cashless society. This study aims to analyze the factors that influence tourists' perceptions of the development of technology-based tourism and the determinants of tourists' decisions to revisit tourist destinations, with the OLS and Logistic Model. The regression analysis shows that the increasing use of social media, cashless habits, and the younger age are prefer to develop technology-based tourism. Tourists will revisit the destination if the tourist attraction and satisfaction level are more reliable.

Keywords: tourism, information technology, logistics model

JEL Classification: C25, D12, L83, L86, O33

ABSTRAK

Kemajuan teknologi informasi menuntut adaptasi di segala aspek kehidupan termasuk sektor pariwisata. Pengembangan pariwisata berbasis teknologi harus dilakukan seiring dengan makin masifnya penggunaan media sosial dan internet serta munculnya cashless society. Penelitian ini bertujuan untuk menganalisis faktor-faktor yang mempengaruhi persepsi wisatawan terhadap pengembangan pariwisata berbasis teknologi dan faktor penentu keputusan wisatawan untuk berkunjung kembali de destinasi wisata. Berdasarkan analisis menggunakan regresi dan model logistik menunjukkan bahwa penggunaan media sosial yang semakin meningkat, perilaku cashless, dan usia yang semakin muda semakin sepakat untuk mengembangkan pariwisata berbasis teknologi. Wisatawan akan melakukan kunjungan kembali jika daya tarik wisata dan tingkat kepuasan semakin tinggi.

Kata kunci: pariwisata, teknologi informasi, model logistic

JEL Classification: C25, D12, L83, L86, O33

INTRODUCTION

The development of information technology has led to revolutionary change in terms of the promotion and function of the tourism sector (Ubavić, 2015). The information revolution rapidly permeating all economic sectors, including the tourism sector, is the best opportunity to maintain or enhance market position and survive in the competition (Tüzünkan, 2017). There is a need to keep up with the ever-changing trends of the tourism industry to understand better tourists' demands (Chen et al., 2011). The dynamic competition in the tourism sector encourages the industry to create a competitive advantage. Surviving in the market is insufficient if not accompanied by continuous innovation. Therefore, efforts are needed to encourage and improve this sector through the information technology (Ilić & Nikolić, 2019).

Much of the research in this area tends towards developing tourist villages as a product (Briedenhann, 2006). Due to the scarcity of resources, technology is considered one of the tools to encourage the tourism sector (Singh, 2015; Nair & Hussain, 2013). The implementation of technology in the development of tourist villages aims to benefit every stakeholder, from partner villages to users of the tourism industry. However, the tourist village is also inseparable from its externalities (Sibila & Milfelner, 2006). Another interesting issue is the sustainable development of the tourism sector (Nair et al., 2015). Based on research gaps, this research focuses on applying information technology in developing tourist villages to promote rural development towards smart villages.

Tourism is one of the most dynamic industries in the world. Changes in tourism management occur along with the influence of the industrial revolution 4.0, which also affects the industrial sector. This can be proven by the impact of the increasingly widespread use of the internet in today's industry. The era of technological disruption, including the Internet of Things (IoT), plays an essential role in understanding and managing the tourism industry, especially in how to link supply and demand in tourism. The various variations of IoT applications in the tourism industry show competition between tourism actors and tourist destinations.

Meanwhile, cities today are also starting to apply the Smart City concept, where there is a transformation of conventional government management with management based on information technology. Cities with tourism attractions also apply the Smart City concept, and their tourism management also utilizes information technology known as Smart Destination. Smart City is characterized by intelligent management of different sectors. Smart Destinations also require intelligent management of this as integration between processes related to stakeholders in all fields. In this process, IoT has an essential role in improving the tourist experience, managing tourist destinations more efficiently, and offering a channel to exchange tourism information. In the end, more efficient destination management, by offering a more memorable experience for tourists, will increase the destination's competitiveness and the life quality improvement.

IoT is any technology connected to the internet, usually consisting of devices, networks, and applications (DNA). With this technology, some tourists travel independently, commonly referred to as "Self-organized holidays & independent travelers." So that the tour will lead to individual and very personal. From the side of tourism service providers, this technology can save business expenses (*cost reduction*) because, with the internet, tourism service providers can save time and expenses from geographical barriers. For example, tourism service providers can quickly enter foreign markets and reach more customers, and vice versa, customers can easily reach these tourism service providers.

Big Data technology also has a strategic role in the tourism industry. Big Data is data obtained from digital traces of tourists obtained from various sources, such as social media, tourist portals, business applications, chatbots, and others. This data can be obtained directly (*real-time*), so it is beneficial for decision-making speed. With this big data, actors in the tourism industry such as tourism service providers or destination managers can easily obtain data on tourist behavior such as their movements, preferences, purchasing decisions, activities carried out, and others.

Furthermore, Augmented Reality (AR) technology is a form of the application whose use is highly dependent on the need for additional hardware, the inbuilt camera of a mobile device. Augmented reality is a technology that combines two-dimensional and or three-dimensional virtual objects into a natural three-dimensional environment and then projects these virtual objects in real-time. Unlike virtual reality, which completely replaces reality, AR adds or complements reality.

In tourism 4.0, this AR technology can allow tourists to carry out activities such as booking hotels, accessing information while at destinations, navigating to and around destinations, translating writing or signs and conversations, finding alternative dining and entertainment options all can be done through an application on a mobile device or smartphone. Therefore, this technology can revolutionize tourists' travel experience to be smoother & easier (seamless), interactive, and more straightforward.

Indonesia is one of the tourism destinations in the world. Improving the position of Indonesian tourism in the world can be done through leveraging the use of new technologies to automate processes in the tourism to adapt and align with the needs of tourists. In this case, the application installed on the smartphone must have the ability to manage tourist profiles, including the ability to manage travel experiences, transportation, and tourist directions, information, and real time ticket reservations. Information technology makes it easier to know and understand the consumer needs, as a means of building good strategies of all components involved in the tourism industry.

LITERATURE REVIEW

The existence of industrial globalization has also resulted in changes in the tourism industry, the emergence of new tourism destinations, with an unusually high level of development of tourism activities. In Indonesia today, many new tourist destinations are starting to take advantage of these areas' local wisdom, uniqueness, and distinctiveness. With the increasing number of people visiting various tourism destinations and the increasing importance of sustainable management in tourism, a solution that utilizes new technologies to help manage tourism destinations become more efficient and productive is needed.

Rapid technological advances affect the tourism sector, with much relevant literature. The research of Tsokota et.al (2014) identifies that the lack of government policies, ICT laws, weak internet networks, and commitment from organizations are obstacles in adopting information technology in the tourism industry in Zimbabwe. Bilgihan & Nejad (2015) state that the digital innovation had played an important role in the development of tourism and there is an increase in consumer demand for digitalization.

Tourist villages have a positive effect on the development of rural economy through the entrepreneurial attitude, establishing SMEs, and infrastructure improvement (Reddy et.al, 2016). Vanitha and Vezhaventhan (2018) analyzed rural area development and policy implementation. The rural government have to concern with the information technology in rural areas, including stable internet connectivity.

Tourism is a complex business, not only focus on the product. Competitive advantage can be achieved by innovation and improve the tourist experience (Kozak et al., 2010). Innovation and information technology-oriented tourism policies will accelerate economic productivity and promote growth (Tüzünkan, 2017). It is creating a database for innovations that need to be made in products, processes, markets, or organizations. The tourism industry cannot be considered separate and apart from the technology information. Gretzel et al. (2015) emphasize that information and telecommunications in the tourism sector are mobile and modernized through integration with global distribution channels, central reservation systems, social media adaptation, and web-based technologies. Ali & Frew (2014) researched tourism sector innovation and demonstrated new technologies and broader applications for sustainable tourism.

Tourism village is the theme of many studies that have been carried out, but there has been a shift in the policymaker orientation of regarding tourism (Farsani et al., 2011). Tourism is an object of improvement to support the local economic development (Ridderstaat et al., 2013; Pratt, 2014). The tourism development affect the rural socio-economic development and reduce poverty (Zapata et al., 2011; Yang & Hung, 2014). Tourism can act as an engine of growth and increase the productivity of local community. Therefore, pro-active policy of the local government must considering the dynamics of tourism trends along with the development of information technology progress.

METHOD

This study used primary data of 109 respondents who were visiting Taman Ingas Kali Gawe, one of tourist destination in Srimartani Village, Bantul Regency. The selection of respondents was based on a random sampling technique. The analytical tools used are Ordinary Least Squares (OLS) model analysis and logistic model analysis.

Regression is an approach to make prediction models such as linear regression, commonly referred to as Ordinary Least Squares (OLS) regression. The difference is that in logistic regression, the researcher predicts the dependent variable on a dichotomous scale. The dichotomous scale in question is a nominal data scale with two categories: Yes and No, Good and Bad, or High and Low.

Suppose the OLS requires conditions or assumptions that the error variance (residual) is normally distributed. On the other hand, this regression does not need this assumption because this type of logistic regression follows a logistic distribution. Logistics regression assumptions include:

1. Logistic regression does not require a linear relationship between the independent variable and the dependent variable.
2. The independent variable does not require the assumption of multivariate normality.
3. The assumption of homoscedasticity is not required
4. The independent variables do not need to be converted into metric form (interval or ratio scale).
5. The dependent variable should be dichotomous (2 categories, e.g., high and low, or good and bad)
6. Independent variables must not have the same diversity among groups of variables.
7. Category in the independent variables must be separated from each other or mutually exclusive.
8. Samples are needed in relatively large quantities, and a minimum required up to 50 data samples for a predictor variable (independent).
9. Can select the relationship because it uses a non-linear approach to log transformation to predict the odds ratio. Odds in logistic regression are often expressed as probabilities.

The commonly used algebraic equation model like OLS is as follows: $Y = B_0 + B_1X + e$. Where e is the error variance or residual. This regression model does not use the same interpretation as the OLS regression equation. The equation formed is different from the OLS equation. Here is the equation:

$$\ln\left(\frac{\hat{p}}{1-\hat{p}}\right) = B_0 + B_1X$$

Ln is the Natural Logarithm, where $B_0 + B_1X$ is an equation commonly known in OLS. P Accent is the logistic probability obtained by the following formula:

$$\hat{p} = \frac{\exp(B_0 + B_1X)}{1+\exp(B_0 + B_1x)} = \frac{e^{B_0+B_1x}}{1+e^{B_0+B_1x}}$$

Where exp or written "e" is the exponential function, the exponential is the opposite of the natural logarithm. The natural logarithm is a form of logarithm but with a constant value of 2.71828182845904 or usually rounded to 2.72. Of course, with the equation model above, it will be very difficult to interpret the regression coefficient. Therefore, the term introduced *Odds Ratio* or commonly abbreviated as Exp(B) or OR is. Exp(B) is the exponent of the regression coefficient. So, suppose the slope value of the regression is 0.80, then Exp(B) can be estimated as follows:

$$2{,}72^{0{,}8} = 2{,}23$$

The value of Exp(B) can be interpreted as follows. For example, the value of Exp (B) the effect of travel satisfaction on the decision to travel again is 2.23. It can be concluded that satisfied people prefer to travel again compared to dissatisfied people. This interpretation is interpreted if the coding of categories for each variable is as follows:

1. The independent variable is satisfaction: Code 0 for dissatisfied, code 1 for satisfied.

2. The dependent variable is the decision to travel: Code 0 for not traveling, code 1 for traveling.

Another difference is that there is no R Square value to measure the magnitude of the simultaneous influence of several independent variables on the dependent variable in this regression. In logistic regression, the term known Pseudo R Square is the value that means identical to R Square in OLS. If the OLS uses the F Anova test to measure the level of significance and how well the equation model is formed, then this regression uses the Chi-Square Value. The calculation of the Chi-Square value is based on the Maximum Likelihood calculation.

RESULT AND ANALYSIS

The development of technology-based tourist destinations (Y) can be influenced by various factors, such as the use of social media (X1), technology utilization (X2), cashless behavior (X3), and internet behavior (X4). Model 1 shows that respondents' perceptions of the development of technology-based tourism are significantly affected by variables X1 and X3 at a significance level of 5 percent (Table 1).

Table 1
OLS Model Regression Results: Model 1

Dependent Variable: Y
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.334260	0.417107	3.198842	0.0018
X1	0.299688	0.093096	3.219112	0.0017
X2	0.016127	0.134872	0.119570	0.9051
X3	0.293039	0.065212	4.493616	0.0000
X4	0.014812	0.078675	0.188270	0.8510

Table 2
Classical Assumption Test OLS model: Model 1

Classical Assumption Test	Test Results	Conclusions
Normality	Prob Jarque-Bera = 0.977	Data are normally distributed
Heteroscedasticity	Prob Obs*R-squared = 0.771	No heteroscedasticity
Multicollinearity	Covariance Matrix value < 0.8	No multicollinearity
Autocorrelation	Prob Obs*R-squared = 0.7435	No autocorrelation

As active users of social media, respondents strongly agree that the development of tourism must take advantage of developments in information technology to introduce destinations to a broader market. Respondents who have a higher preference for non-cash transactions increasingly agree that tourism development is based on technology. With non-cash transactions that can be carried out, it can increase efficiency and better data management than manual recording systems. The utilization of information systems in recording every transaction can make it easier to make decisions and policies related to the development of tourist destinations.

Other factors that influence respondents' perceptions of the development of technology-based tourist destinations (Y) are income, age, gender, and education. The results of this Model 2 regression can be seen in Table 3. The results show that only the age factor significantly affects respondents' perceptions of the development of technology-based tourist destinations at a significance level of 10 percent. The regression coefficient, which is negative, indicates that the younger, tend to agree that the development of tourism is based on technology. This shows that the younger generation, which is often referred to as the millennial generation, is more technologically literate than the older generation. The older generation who are technologically savvy tends to have no preference for technology-based tourist destination development because it is difficult to adapt to technological developments that are already comfortable with things that are conventionally usually done, such as cash transactions or knowing information about destinations only through word of mouth.

Table 3
OLS Model Regression Results: Model 2

Dependent Variable: Y
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.645828	0.248854	14.65047	0.0000
INCOME	-0.052671	0.060180	-0.875218	0.3835
AGE	-0.010409	0.005605	-1.856899	0.0662
GENDER	-0.233048	0.146773	-1.587808	0.1154
EDU	0.051147	0.054289	0.942123	0.3484

Table 4
Classical Assumption Test Results OLS Model: Model 2

Classical Assumption Test	Test Results	Conclusions
Normality	Prob Jarque-Bera = 0.898	Data normally distributed
Heteroscedasticity	Prob Obs*R-squared = 0.148	No heteroscedasticity
Multicollinearity	Covariance Matrix value < 0.8	No multicollinearity
Autocorrelation	Prob Obs*R-squared = 0.054	No autocorrelation

Other factors such as income level, gender, and the level of education have no significant effect on respondents' perceptions of the technology-based. The negative income variable coefficient indicates the higher income tends to disagree regarding the development of technology-based tourism. Likewise, the coefficient of the gender variable is negative. This means that men tend to disagree with technology-based development, rather than women.

Logistic model analysis was carried out for models with dependent variables having values of zero and one. In Models 1 and 2, the dependent variable is the tourist's decision to visit destination. The variable is worth one if tourists visit again and zero if they do not want to revisit the destination.

Table 5
Logistics Model Regression Results: Model 1

Dependent Variable: REPEAT
Method: ML - Binary Logit (Quadratic hill climbing)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.110133	1.618448	-1.303800	0.1923
ATTRACT	0.949252	0.510180	1.860620	0.0628
AKSES	0.020921	0.395791	0.052858	0.9578
INFRA	1.097451	0.619538	1.771401	0.0765

Results of logistic regression models model 1 in Table 5 shows that the variables of tourist attraction (Attract), accessibility to the location (Akses), and the adequacy of infrastructure and facilities have a positive regression coefficient value. This means that the increase in the three variables will increase the tendency of tourists to revisit the destination. Statistically, at the level of significance (alpha) of 10 percent, the variables of tourist attraction and the adequacy of infrastructure and facilities have a significant effect. In contrast, the accessibility of the destination has no significant effect on the tendency of tourists to revisit. These results indicate that although access to Taman Ingas Kali Gawe is relatively more difficult, it does not reduce the interest of tourists to revisit the destination because of the tourist attraction and the supporting facilities.

Table 6
Logistics Model Regression Results: Model 2

Dependent Variable: REPEAT
Method: ML - Binary Logit (Quadratic hill climbing)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.526606	1.808702	-1.396917	0.1624
SATISFIED	1.279617	0.564305	2.267599	0.0234
ACCESS	0.159659	0.464724	0.343557	0.7312
INFRA	0.137973	0.759033	0.181775	0.8558

The logistic model regression model 2 in Table 6 show that the variables of satisfaction level (Satisfied), accessibility to location (Access), and the adequacy of infrastructure and facilities have a positive regression coefficient value. Statistically, at the 5 percent significance level, only the satisfaction level variable has a significant effect on the tendency of tourists to revisit the destination. The higher level of satisfaction will increase the tendency of tourists to visit again. This is very important for destination managers to always strive for a high level of satisfaction for their visitors. Both in terms of products, facilities, and services so that visitors feel comfortable and safe during their trip.

CONCLUSION AND RECOMMENDATION

Community activities that are increasingly inseparable from technological advances encourage tourism managers to continuously adapt to the technological progress in the era of the industrial revolution 4.0. Conventional management practices can no longer survive in the disruptive era, and continuous innovation is needed to survive in the market. This study shows how the use of social media, cashless behavior, and the millennial generation affect respondents' perceptions regarding the development of technology-based tourism. However, this study has limitations in selecting instruments that reflect technology. Further research can develop the variables and analytical methods used.

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Appendix 1 Ordinary Least Square: Model 1

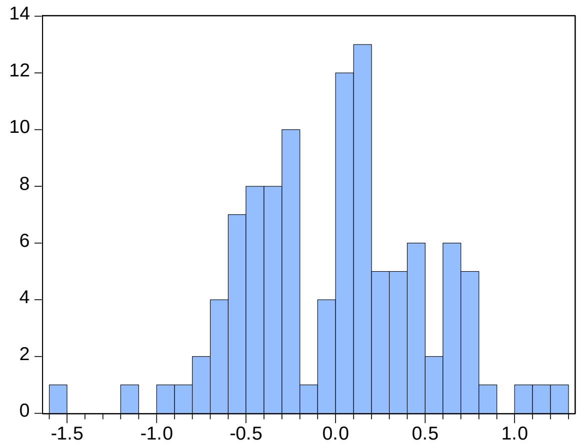
Dependent Variable: Y
Method: Least Squares
Date: 05/10/21 Time: 18:26
Sample: 1 109
Included observations: 106

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.334260	0.417107	3.198842	0.0018
X1	0.299688	0.093096	3.219112	0.0017
X2	0.016127	0.134872	0.119570	0.9051
X3	0.293039	0.065212	4.493616	0.0000
X4	0.014812	0.078675	0.188270	0.8510

R-squared	0.333166	Mean dependent var	3.327830
Adjusted R-squared	0.306757	S.D. dependent var	0.617564
S.E. of regression	0.514191	Akaike info criterion	1.553577
Sum squared resid	26.70364	Schwarz criterion	1.679211
Log likelihood	-77.33960	Hannan-Quinn criter.	1.604497
F-statistic	12.61549	Durbin-Watson stat	1.790896
Prob(F-statistic)	0.000000		

Appendix 2 Classical Assumption Test: Model 1

Normality Test



Series: Residuals	
Sample 1 109	
Observations 106	
Mean	2.05e-16
Median	0.059567
Maximum	1.267885
Minimum	-1.552011
Std. Dev.	0.504302
Skewness	-0.038004
Kurtosis	3.069096
Jarque-Bera	0.046602
Probability	0.976968

Heteroskedasticity Test

Heteroskedasticity Test: Glejser

F-statistic	0.438009	Prob. F(4,101)	0.7809
Obs*R-squared	1.807416	Prob. Chi-Square(4)	0.7711
Scaled explained SS	1.642469	Prob. Chi-Square(4)	0.8011

Test Equation:
Dependent Variable: ARESID
Method: Least Squares
Date: 05/19/21 Time: 10:39
Sample: 1 109
Included observations: 106

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.563418	0.243448	2.314329	0.0227
X1	-0.006419	0.054336	-0.118128	0.9062
X2	-0.035110	0.078719	-0.446020	0.6565
X3	0.037106	0.038062	0.974892	0.3319
X4	-0.029527	0.045919	-0.643028	0.5217

R-squared	0.017051	Mean dependent var	0.405727
Adjusted R-squared	-0.021878	S.D. dependent var	0.296881
S.E. of regression	0.300111	Akaike info criterion	0.476695
Sum squared resid	9.096750	Schwarz criterion	0.602329
Log likelihood	-20.26482	Hannan-Quinn criter.	0.527615
F-statistic	0.438009	Durbin-Watson stat	1.798855
Prob(F-statistic)	0.780868		

Multicolliearity Test

	C	X1	X2	X3	X4
C	0.173978	-0.004357	-0.038618	-0.001773	-0.000727
X1	-0.004357	0.008667	-0.004876	0.000230	-0.002534
X2	-0.038618	-0.004876	0.018190	-0.002050	-0.002378
X3	-0.001773	0.000230	-0.002050	0.004253	-0.000824
X4	-0.000727	-0.002534	-0.002378	-0.000824	0.006190

Autocorrelation Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.101114	Prob. F(1,100)	0.7512
Obs*R-squared	0.107073	Prob. Chi-Square(1)	0.7435

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/19/21 Time: 10:42
Sample: 1 109
Included observations: 106
Presample and interior missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009222	0.419978	0.021957	0.9825
X1	-0.006975	0.096052	-0.072620	0.9423
X2	0.003479	0.135917	0.025597	0.9796
X3	-0.001782	0.065744	-0.027101	0.9784
X4	0.002349	0.079372	0.029600	0.9764
RESID(-1)	0.034665	0.109014	0.317984	0.7512

R-squared	0.001010	Mean dependent var	2.05E-16
Adjusted R-squared	-0.048939	S.D. dependent var	0.504302
S.E. of regression	0.516495	Akaike info criterion	1.571435
Sum squared resid	26.67666	Schwarz criterion	1.722195
Log likelihood	-77.28604	Hannan-Quinn criter.	1.632539
F-statistic	0.020223	Durbin-Watson stat	1.832916
Prob(F-statistic)	0.999827		

Appendix 3 Ordinary Least Square: Model 2

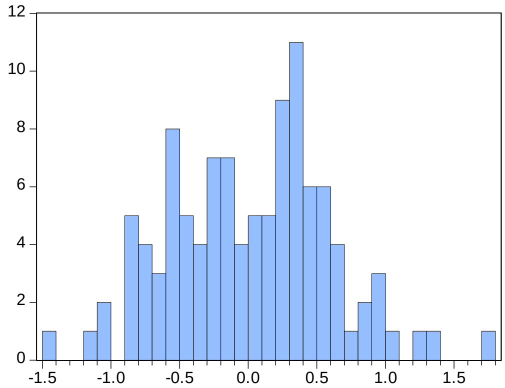
Dependent Variable: Y
Method: Least Squares
Date: 05/10/21 Time: 19:27
Sample: 1 109
Included observations: 107

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.645828	0.248854	14.65047	0.0000
INCOME	-0.052671	0.060180	-0.875218	0.3835
AGE	-0.010409	0.005605	-1.856899	0.0662
GENDER	-0.233048	0.146773	-1.587808	0.1154
EDU	0.051147	0.054289	0.942123	0.3484

R-squared	0.086817	Mean dependent var	3.334112
Adjusted R-squared	0.051006	S.D. dependent var	0.618069
S.E. of regression	0.602100	Akaike info criterion	1.868816
Sum squared resid	36.97752	Schwarz criterion	1.993715
Log likelihood	-94.98167	Hannan-Quinn criter.	1.919448
F-statistic	2.424299	Durbin-Watson stat	1.499591
Prob(F-statistic)	0.052852		

Appendix 4 Classical Assumption Test: Model 2

Normality Test



Series: Residuals	
Sample 1 109	
Observations 107	
Mean	0.006399
Median	0.035060
Maximum	1.757700
Minimum	-1.485757
Std. Dev.	0.590385
Skewness	0.103257
Kurtosis	2.927922
Jarque-Bera	0.213302
Probability	0.898839

Heteroskedasticity Test

Heteroskedasticity Test: White

F-statistic	1.470353	Prob. F(13,93)	0.1435
Obs*R-squared	18.24260	Prob. Chi-Square(13)	0.1485
Scaled explained SS	15.99464	Prob. Chi-Square(13)	0.2494

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/20/21 Time: 10:44
Sample: 1 109
Included observations: 107
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.019912	0.688668	1.480994	0.1420
INCOME	-0.253710	0.237254	-1.069362	0.2877
INCOME^2	0.011843	0.044827	0.264184	0.7922
INCOME*AGE	0.001378	0.005409	0.254669	0.7995
INCOME*GENDER	0.031457	0.155384	0.202447	0.8400
INCOME*EDU	0.057787	0.050417	1.146183	0.2547
AGE	-0.022942	0.032446	-0.707075	0.4813
AGE^2	0.000138	0.000408	0.338240	0.7359
AGE*GENDER	-0.016986	0.012733	-1.334008	0.1855
AGE*EDU	0.002094	0.005511	0.380039	0.7048
GENDER	0.994405	0.511220	1.945160	0.0548
GENDER*EDU	-0.066924	0.115265	-0.580615	0.5629
EDU	-0.055086	0.226109	-0.243625	0.8081
EDU^2	-0.020924	0.024882	-0.840936	0.4025

R-squared	0.170492	Mean dependent var	0.345338
Adjusted R-squared	0.054539	S.D. dependent var	0.482320
S.E. of regression	0.468983	Akaike info criterion	1.444953
Sum squared resid	20.45491	Schwarz criterion	1.794669
Log likelihood	-63.30501	Hannan-Quinn criter.	1.586724
F-statistic	1.470353	Durbin-Watson stat	1.875032
Prob(F-statistic)	0.143520		

Multicolliearity Test

	C	INCOME	AGE	GENDER	EDU
C	0.061928	0.001208	-0.000994	-0.005207	-0.008689
INCOME	0.001208	0.003622	-8.68E-05	-0.003057	-0.001050
AGE	-0.000994	-8.68E-05	3.14E-05	9.17E-05	2.99E-05
GENDER	-0.005207	-0.003057	9.17E-05	0.021542	0.000619
EDU	-0.008689	-0.001050	2.99E-05	0.000619	0.002947

Autocorrelation Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.928447	Prob. F(2,100)	0.0581
Obs*R-squared	5.835953	Prob. Chi-Square(2)	0.0540

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/20/21 Time: 12:46
Sample: 1 109
Included observations: 107
Presample and interior missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.030626	0.252049	-0.121509	0.9035
INCOME	0.012973	0.062102	0.208894	0.8350
AGE	-0.000445	0.005685	-0.078345	0.9377
GENDER	-0.031714	0.146774	-0.216072	0.8294
EDU	0.011636	0.054696	0.212732	0.8320
RESID(-1)	0.256071	0.102089	2.508311	0.0137
RESID(-2)	-0.072332	0.105938	-0.682779	0.4963

R-squared	0.054542	Mean dependent var	0.006399
Adjusted R-squared	-0.002186	S.D. dependent var	0.590385
S.E. of regression	0.591030	Akaike info criterion	1.849282
Sum squared resid	34.93161	Schwarz criterion	2.024139
Log likelihood	-91.93656	Hannan-Quinn criter.	1.920167
F-statistic	0.961467	Durbin-Watson stat	1.918036
Prob(F-statistic)	0.455339		

Appendix 5 Logistic Model

Model 1

Dependent Variable: REPEAT
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/24/21 Time: 09:14
Sample: 1 109
Included observations: 106
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.110133	1.618448	-1.303800	0.1923
ATTRACT	0.949252	0.510180	1.860620	0.0628
AKSES	0.020921	0.395791	0.052858	0.9578
INFRA	1.097451	0.619538	1.771401	0.0765

McFadden R-squared	0.120753	Mean dependent var	0.858491
S.D. dependent var	0.350202	S.E. of regression	0.335161
Akaike info criterion	0.792399	Sum squared resid	11.45792
Schwarz criterion	0.892906	Log likelihood	-37.99715
Hannan-Quinn criter.	0.833135	Restr. log likelihood	-43.21558
LR statistic	10.43685	Avg. log likelihood	-0.358464
Prob(LR statistic)	0.015195		
Obs with Dep=0	15	Total obs	106
Obs with Dep=1	91		

Model 2

Dependent Variable: REPEAT
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 05/24/21 Time: 11:15
Sample: 1 109
Included observations: 101
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.526606	1.808702	-1.396917	0.1624
PUAS	1.279617	0.564305	2.267599	0.0234
AKSES	0.159659	0.464724	0.343557	0.7312
INFRA	0.137973	0.759033	0.181775	0.8558

McFadden R-squared	0.128592	Mean dependent var	0.891089
S.D. dependent var	0.313081	S.E. of regression	0.302063
Akaike info criterion	0.679141	Sum squared resid	8.850460
Schwarz criterion	0.782710	Log likelihood	-30.29664
Hannan-Quinn criter.	0.721069	Restr. log likelihood	-34.76745
LR statistic	8.941636	Avg. log likelihood	-0.299967
Prob(LR statistic)	0.030077		
Obs with Dep=0	11	Total obs	101
Obs with Dep=1	90		