



Personality Traits as Predictors of Behavioural Engagement with Mobile Operating Systems in Sarawak

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Abstract

This study investigates the predictive relationship between the Big Five personality characteristics (extraversion, agreeableness, conscientiousness, neuroticism, and openness) and behavioural engagement with mobile operating systems among Sarawak, Malaysia smartphone users. In Malaysia's fierce battle between Android and iOS ecosystems, comprehending the psychological factors influencing user engagement holds considerable academic and practical significance. The study used a quantitative survey of over 273 Sarawak smartphone users, which focused in Kuching, evaluating personality characteristics via the BFI-44 scale and examining three aspects of engagement: interface customisation behaviours, ecosystem loyalty, and switching intention. The study employs Smart PLS-SEM (Partial Least Squares Structural Equation Modelling) to examine the impact of personality traits on engagement measures, while accounting for demographic data. We hypothesise that neuroticism would significantly predict switching intentions, but conscientiousness will exhibit a correlation with ecosystem loyalty. Neuroticism is anticipated augment customization via emotional instability attributes. This study enhances the literature on technology adoption by merging personality psychology with behavioural engagement indicators related to mobile operating system ecosystems.

Keywords: *Sarawak, Big Five Personality Traits, Mobile OS Engagement*

1. Introduction

The smartphone revolution has changed how people use technology, interact with society, and interact with the economy. Mobile operating systems are the main platform that affects these interactions. Malaysia is a fascinating location to investigate since, in 2023, 87.2% of people there owned a smartphone, which is substantially higher than the global average of 68.6% (Datareportal, 2023). This penetration creates a dynamic marketplace where ecosystem loyalty and user engagement are important for technology vendors to be successful. The competition between mobile operating system platforms goes beyond just technical needs. It includes full ecosystems of apps, services, and social interactions that keep users tied to certain platforms.



Earlier research on technology adoption has increasingly recognised that psychological factors often outweigh technological considerations in shaping user habits. The Big Five personality framework has been employed in various technology adoption contexts, including the utilisation of paid stickers in messaging applications, where conscientiousness and extraversion significantly impacted purchase intentions (Sawmong, S., 2022); however, its application to mobile operating system engagement remains inadequately explored. Sawmong's (2022) study on senior Chinese users indicated that personality factors significantly predicted mHealth (mobile apps for healthcare service and information) and adoption, with extraversion and openness increasing usage intention, but agreeableness decreased it. These results suggest that personality traits may similarly influence user interaction with mobile operating systems. This study identifies three significant gap in the existing literature: (1) insufficient examination of personality traits as antecedents to mobile operating system engagement behaviours, particularly within Southeast Asian contexts; (2) an absence of emphasis on the impact of psychological factors on specific engagement behaviours such as customisation, loyalty, and switching intention as interconnected phenomena; and (3) a methodological necessity for multivariate analysis to elucidate complex relationships between psychological traits and behavioural outcomes. The study outlines a comprehensive conceptual model that recognises personality traits as determinants of three critical aspects of engagement: interface customising practices, ecosystem loyalty commitment, and operating system switching intention.

The research aims to: firstly, analyze the correlation between Big Five personality traits and mobile OS customization behaviors; secondly, investigate the influence of personality dimensions on ecosystem loyalty; and thirdly, evaluate how personality traits predict switching intentions among mobile OS platforms. This research examines these objectives within the Sarawak, Malaysia context, facilitating theoretical progress in personality-technology interaction models and offering practical guidance for ecosystem developers, application creators, and marketers seeking to improve user engagement in competitive digital markets.

2. Literature Review

2.1. Foundations Theories

The Five-Factor Model of personality is the most widely used way to look at the basic parts of personality. Costa and McCrae (1992) created this model, which includes neuroticism (emotional instability), extraversion (sociability and energy), openness (creativity and novelty-seeking), agreeableness (cooperation and compassion), and conscientiousness (organisation and dependability). This model gives us a full taxonomy for looking into how stable personality traits affect different areas of behaviour, such as using and engaging with technology. Davis (1989) came up with the Technology Acceptance Model (TAM), which says that how valuable and easy to use people think a new technology is the main factors that affect whether they would utilise it. The Technology Acceptance Model (TAM) was first used to look at organisational systems. However, later studies have used it to look at consumer technologies as well. According to research, how enjoyable and easy it is to use paid stickers is our good indicator of whether people would use them (Sawmong, S., 2022). These studies show that technology acceptance frameworks are useful for



understanding how people use operating systems as digital tools today, and the Big Five personality traits are a good way to understand and predict how people will act in a variety of situations.

2.2. The Influence of Personality Traits on Technology Use

Openness to experience is an important factor that may be used to predict behaviours related to technology exploration. Individuals with high degrees of openness display enhanced tendencies towards novelty-seeking and a greater desire to experiment with new technology features. According to research conducted on Chinese populations of senior people, openness was found to be a strong predictor of the uptake of mobile health applications (Chang et al., 2025). In addition, research conducted on the behaviours of messaging apps found that openness affected the degree to which users evaluated the enjoyment of expressive elements like stickers (Sawmong, 2022).

Conscientiousness is associated with behaviour that is goal-directed and organisation. Persons that are very conscientious exhibit methodical approaches to the use of technology, favouring interfaces that are already familiar to them and workflows that have been created. The research conducted by Sawmong on the utilisation of paid stickers revealed that conscientiousness was a significant predictor of subjective enjoyment (Sawmong, S., 2022). This suggests that these individuals receive gratification from understanding particular technical characteristics.

Extraversion is linked to certain patterns of social technology usage. Extraversion may be responsible for the prediction of both the adoption of mobile health (Chang, J., et al., 2025) and the usage of paid stickers (Sawmong, S., 2022). Extraverted individuals interact with communication-enhancing features more often. The authors Sahin et al. (2019) observed that extraversion is distinguished by characteristics such as assertiveness, vitality, and sociability. A larger predisposition for the constructive adoption of technology is exhibited by extroverts, who also express good behavioural intentions towards virtual platforms throughout their interactions with technology.

Neuroticism, which is marked by emotional instability, is associated with actions that are risk-averse and a need for environments that are familiar to the individual. Individuals who suffer from neurosis may be resistant to technological advancements that result in uncertainty, which may shed light on the negative link between neurosis and some metrics of technology adoption (Sawmong, S., 2022). (Sawmong, S., 2022) Research conducted on messaging applications revealed that neuroticism had a favourable influence on the amount of enjoyment that was claimed to be associated with stickers. In addition to that, it includes feelings of anxiousness, self-awareness, and emotional instability.

Agreeableness are benevolence, cooperation, and social orientation. People who are agreeable value social worth and working together, which makes them think that cooperative technology is more useful (Buecker et al., 2020; Stajkovic et al., 2018). People use stickers to show that they like someone and to make friends, which is why people think stickers are effective (Sawmong, 2022). It also means working together and focussing on relationships. Research on elderly Chinese people, who are often ignored in tech settings, unexpectedly showed that those who were more pleasant



were less likely to want to use mHealth (Chang, J., et al., 2025). This unexpected connection must be looked at in the context of mobile operating systems, especially when it comes to ecosystem loyalty that may include social validation.

2.3. Mobile OS Engagement Dimensions

Grasping the various aspects of user engagement in mobile operating systems is essential for developers focused on improving user experience and satisfaction. From the analysis of the provided abstracts, various critical dimensions and factors affecting engagement have been observed:

Interface customisation (Behavioral Engagement) includes user activities and behaviours, such as usage frequency, interaction patterns, and duration of engagement. This dimension is frequently assessed using metrics like as click-through rates and duration of engagement in activities which synthesis from Dovaliene, A., Piligrimiene, Z., & Masiulyte, A. (2016), Kulta, H. P., & Karjaluo, H. (2016), & George, S. R., Edward, M., & Joseph, J. (2025). It is a big way that people interact with their mobile devices. It shows not just their visual preferences but also their psychological requirements, such the urge for autonomy and self-expression. Android and iOS are two examples of mobile operating systems that currently allow you to customise many things, such as the home screen, widget positioning, icon packs, and themes. Self-Determination Theory (Deci & Ryan, 2000) might help us understand these behaviours better. For example, the demand for autonomy and competence. Customisation behaviours may also be a way for people to show their technology identity and build their own brand (Kim & Sundar, 2012).

Ecosystem Loyalty (Emotional Engagement) encompasses users' sentiments and emotional reactions throughout their interaction with mobile applications. This component is essential since it influences consumers' overall pleasure and loyalty (Dovaliene, A., et. al., 2016, Kulta, H. P., & Karjaluo, H. 2016, & George, S. R., Edward, M., & Joseph, J. 2025). Thus, ecosystem loyalty is the emotional and behavioural commitment a user makes to a certain mobile OS platform and all the services, apps, and peripherals that go with it. Seamless integration of hardware and software, exclusive services like iCloud and Google Assistant, and consistent brand stories are all ways to build loyalty. Studies have found that emotional attachment and regular use patterns make platforms more "sticky" (Sharma & Sharma, 2019). The idea is like ecosystem lock-in, where the total amount of money spent on applications, data, and accessories makes it harder to move (Chang, 2015). For instance, a study of the LINE messaging network found that using branded stickers made users feel more connected to the platform and more likely to use it again (Sawmong, 2022).

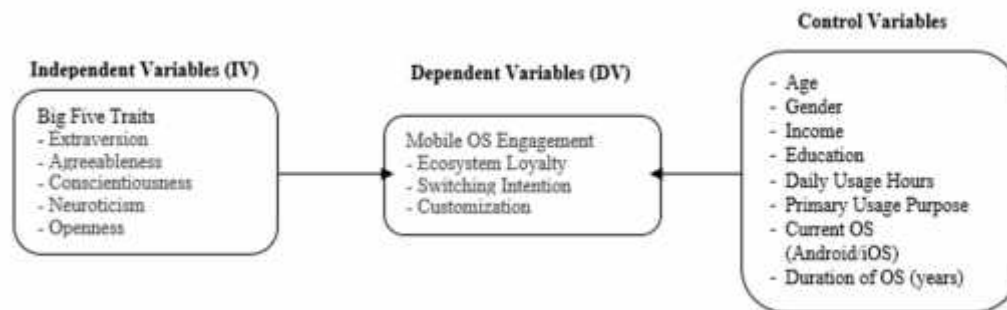
Switching Intention (Cognitive Engagement) denotes the mental effort and cognitive processes that consumers dedicate to utilising mobile applications. It encompasses elements such as concentrated attention, perceived usability, and cognitive processing. Which is how the user thinks and feels about switching from one mobile OS platform to another (Dovaliene, A., et. al., 2016, Kulta, H. P., & Karjaluo, H. 2016, & George, S. R., Edward, M., & Joseph, J. 2025) It shows the conflict between consumer discontent (push factors), the appeal of other options (pull elements), and the costs of switching (mooring factors) (Bansal et al., 2005). Switching means going through



big changes including buying apps again, moving data, getting used to new interface logics, and coping with the possibility of losing compatibility. So, both logical factors (like cost-benefit analysis) and emotional factors (such as brand loyalty and inertia) impact the decision to switch (Kim et al., 2016).

Figure 1 is the simplified overview of the study that infuses the control variables between the independent variables (IV) Big Five Personality Traits and dependent variables (DV) of Mobile OS Engagement.

Figure 1: Conceptual Framework



Framework of Big Five Personality Traits and Mobile OS Engagement

3. Methodology

Research Design and Sampling

This study employs a **cross-sectional survey design** to examine relationships between personality traits and mobile OS engagement. The target population consists of **Malaysian smartphone users** aged 18-55 who have owned their current device for at least six months, with 87.3 percent of the population, which translates to 30.63 million owners in Malaysia (Data reportal, 2023). This ownership duration ensures respondents have sufficient experience to develop engagement patterns with their OS. Using **convenience sampling** through Kuching city with 514,658 participants' pools representing 21 percent of 2,453,677 people living in Sarawak in 2023 (DOSM, 2024), we aim to recruit approximately 385 respondents sample size using Raosoft (2024) sample size calculator based on the 87.3 percent smartphone user average in Malaysia (Datareportal, 2023) which make up of 2,142,060 population to achieve a 95 % confidence level with an acceptable 5 % error, accounting for potential attrition and incomplete responses. This sample size aligns with recommended guidelines for PLS-SEM analysis, which requires a minimum of 100 – 150 respondents (Hair et al., 2022). Consequently, only 273 respondents accurately responded to the questionnaire items and agreed to have their data used for this study, implying with 90 %



confidence level and exceed the minimum number of respondents to construct multiple constructs or complex mediation model.

Instruments

The questionnaire comprises validated constructs using **7-point Likert scales** (1=strongly disagree; 7=strongly agree) equally used for the Independent and Dependent Variables. Using the BFI-44 (Big Five Personality Traits) by John & Srivastava (1999) as the Independent Variables which offer higher reliability and validity capturing larger distinctions ranging between 0.81 – 0.88 across the scales showing a strong consistency (Rammstedt & John, 2007). As for the Dependent Variables, the studies adapted Interface Customization (Xiao, L., & Wang, S., 2023), Ecosystem Loyalty (Oliver, R. L., 1997) and Switching Intention (Keaveney, S. M., 1995). Control variables then introduce to reduce bias, isolate causal effects, and improve accuracy of the findings between the Independent and Dependent Variables.

Statistical Analysis

The analysis for this study will employ **Smart PLS-SEM** (Partial Least Squares Structural Equation Modeling) using SmartPLS 4, which is particularly suitable for this research due to its ability to handle complex models with small sample sizes. The analysis proceeds in two stages; firstly, **Measurement Model Evaluation** (Internal consistency, Convergent validity and Discriminant validity), in which the assessment of reliability and validity will take place and followed by the second stage, **Structural Model Evaluation** where testing hypothesized the relationships between the Independent and Dependent Variables involving Path coefficients (β), Effect sizes (f^2) and Predictive relevance (Q^2).

Ethics Approval and Consent to Participate

Ethical approval for this work was obtained from the Research Ethics Committees of Universiti Teknologi MARA (UiTM) Cawangan Sarawak. All procedures involving human subjects complied with institutional and national ethical standards, and informed consent was acquired under the Declaration of Helsinki.

4. Findings & Data Analysis

Based on the early analysis of 273 respondents, the data was then processed and divided into two stages. The first stage interpretation began with Measurement Model Evaluation to assess the reliability and validity of the study.

Table 1: Internal consistency: composite reliability

Independent Variables	Composite Reliability	Dependent Variables	Composite Reliability
Agreeableness	0.763	Interface Customization	0.882



Conscientious	0.787	Ecosystem Loyalty	0.871
Extraversion	0.837	Switching Intention	0.889
Openness to Experience	0.900		
Neuroticism	0.743		

Based on the Table 1. all constructs demonstrated acceptable reliability with value > 0.7 with personality traits (Agreeableness 0.763, Conscientious 0.787, Extraversion 0.837, Openness to Experience 0.9, and Neuroticism 0.743) and engagement constructs (Interface Customization 0.882, Ecosystem Loyalty 0.871, and Switching Intention 0.889). The internal consistency using the composite reliability is essential for evaluating a research instrument, as it indicates the extent of interrelatedness among the items. In contrast, homogeneity pertains to the one-dimensionality of a collection of items (Green, Lissitz, & Mulaik, 1977). Meanwhile, indicators derived from this procedure may provide super estimators with inaccuracies when fresh Alpha values are calculated for the identical original samples from which items were removed (Ursachi, G., Horodnic, I. A., & Zait, A., 2015). This affirms robust internal consistency; nevertheless, Ursachi et al. (2015) warn that composite reliability alone may obscure contextual measurement problems in cross-cultural research.

Table 2: Convergent validity: Average variance extracted (AVE)

Variables	(AVE)
Agreeableness	0.272
Conscientious	0.320
Extraversion	0.427
Openness to Experience	0.478
Neuroticism	0.274
Interface Customization	0.601
Ecosystem Loyalty	0.631
Switching Intention	0.728

According to Hair et al. (2010), the Fornell-Larcker AVE criterion for convergent validity, in conjunction with construct reliability, indicates evidence of convergent validity when all three of the following conditions are met: CR values must be 0.7 or higher, all standardised factor loadings should be 0.5 or higher, and AVE values need to be 0.5 or higher. Table 2 indicates personality traits scored inadequate value (Agreeableness 0.272, Conscientious 0.32, Extraversion 0.427, Openness to Experience 0.478, and Neuroticism 0.274) vice versa whereas engagement constructs achieve adequate value (Interface Customization 0.601, Ecosystem Loyalty 0.631, and Switching Intention 0.728). Yu et al. (2022) revealed that the Average Variance Extracted (AVE) for their



study on corporate philanthropy, benevolent attributions, and job performance varied from 0.50 to 0.62, therefore surpassing the 0.5 barrier and affirming the convergent validity of their latent components. The diminished AVE values for personality characteristics indicate a possible cultural incongruence of the BFI-44 scale in Sarawak, along with Rammstedt and John's (2007) assertion that Western personality assessments may be less effective in Asian settings.

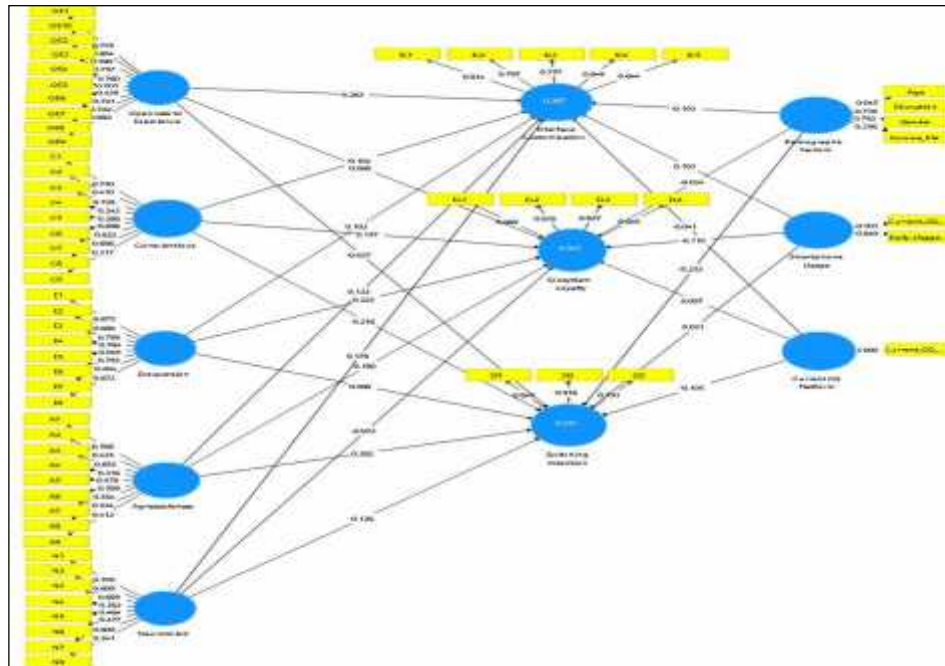
Table 3: Discriminant validity (Fornell-Larcker Criterion)

	A	C	EL	Ex	IC	N	OE	SI
Agreeableness (A)	0.522							
Conscientious (C)	0.537	0.566						
Ecosystem Loyalty (EL)	0.372	0.393	0.794					
Extraversion (Ex)	0.509	0.625	0.429	0.654				
Interface Customization (IC)	0.396	0.307	0.508	0.355	0.776			
Neuroticism (N)	0.656	0.664	0.294	0.491	0.398	0.524		
Openness to Experience (OE)	0.469	0.594	0.345	0.614	0.426	0.489	0.691	
Switching Intention (SI)	0.404	0.331	0.430	0.299	0.558	0.270	0.234	0.853

Bagozzi (1981) defined differentiation in constructs, a concept broader than discriminant validity, as the principle that "cross-construct correlations among measures of empirically associated variables should correlate at a lower level than the within-construct correlations." Within the value less > 0.85, Table 3 shows that confirms all construct pairs, with the highest values between Neuroticism-Conscientiousness (0.664) and Agreeableness-Neuroticism (0.656). This fits to Bagozzi's (1981) requirements for discriminant validity, however, suggests possible trait overlap in mobile engagement scenarios, confirming Goreis and Voracek's (2019) observation that neuroticism and agreeableness often co-occur in technology adoption research.



Figure 2: Structural Equation Model (SEM) Personality Traits and Engagement Construct



Structural Model Evaluation is the next process of data interpretation on the study which will consists of Regression analysis (R^2 , adjusted R^2), path coefficients (, t-value and p-value), value of effect size f^2 ,

Table 4: Explanatory Power Regression (R^2)

Dependent Variable	R^2	Adjusted R^2	Interpretation
Interface Customization	0.387	0.369	Moderate
Ecosystem Loyalty	0.369	0.350	Moderate
Switching Intention	0.369	0.350	Moderate

Based on the interpretation of Table 4, the R^2 , and Adjusted R^2 indicated all the dependent variable shows a moderate level between the personality traits and engagement construct which average all the value are > 0.5 . The values in question account for 35–39% of the variation, which is close to Sawmong's (2022) study on sticker usage ($R^2=0.41$) but lower than Chang et al.'s (2025) research on mHealth ($R^2=0.52$), indicating that there are cultural factors in Sarawak that have not been taken



into consideration. Table 5 below will test path coefficient that will prove any relationships among the variables within the personality traits and mobile OS engagement. Based on the results below, there are few supported hypotheses which identify there is a *relationship between openness to experience and Customization* ($\beta = -0.263$, $t = 3.594$, $p < 0.001$) and show the alignment with Sawmong (2022) justifying the openness to experiences will drives exploratory behaviors. *relationship between extraversion relationship and Ecosystem Loyalty* ($\beta = 0.223$, $t = 2.772$, $p = 0.006$) confirms by the results by Sahin et al.'s (2019) where their finding indicate that extraverts favor socially integrated platforms among users. There are also an interesting, unexpected findings where they are *relationship between agreeableness and switching intention* ($\beta = 0.282$, $t = 3.178$, $p = 0.001$) that contradicts with the findings of Chang et al. (2025) but an additional variable may be needed to introduce to the study framework which may reflect or social alignment needs in collectivist Sarawak (Hofstede, 2011). Then another unexpected finding, *relationship between conscientiousness and switching intention* ($\beta = -0.216$, $t = 2.573$, $p = 0.010$) also contrasts with Ali's (2019) work that suggests Malaysian users prioritize productivity over loyalty.



Table 5: Path Coefficients

	Ecosystem Loyalty				Interface Customization				Switching Intention			
		t-value	p-value	f²		t-value	p-value	f²		t-value	p-value	f²
Agreeableness	0.180	2.217	0.027	0.020	0.133	1.225	0.221	0.011	0.282	3.178	0.001	0.050
Conscientious	0.157	1.793	0.073	0.013	-0.104	1.124	0.261	0.006	0.216	2.573	0.010	0.025
Extraversion	0.223	2.772	0.006	0.032	0.103	1.262	0.207	0.007	0.088	1.163	0.245	0.005
Neuroticism	-0.073	0.775	0.438	0.003	0.178	1.843	0.065	0.018	-0.128	1.691	0.091	0.009
Openness to Experience	0.068	0.950	0.342	0.003	0.263	3.594	0.000	0.050	-0.037	0.523	0.601	0.001



Table 6: Marginal Relationships (Path Coefficients)

Relationship		t-value	p-value	Effect Size (f ²)
Conscientiousness	Ecosystem Loyalty	0.157	1.793	0.013
Neuroticism	Interface Customization	0.178	1.843	0.018
Neuroticism	Switching Intention	-0.128	1.691	0.009

Conscientiousness exhibits a positive correlation with Ecosystem Loyalty ($\beta=0.157$, $t=1.793$, $p=0.073$). Conscientiousness slightly increases loyalty by fostering a systematic workflow reliance, wherein goal-oriented individuals avoid interrupting established ecosystem processes. Neuroticism exhibits a positive correlation with Customisation ($\beta=0.178$, $t=1.843$, $p=0.065$). Neurotic users engage in customisation to establish predictable digital environments, where emotional instability motivates personalisation to achieve perceived control over their operating system engagement. This aligns with the findings of Goreis and Voracek (2019), which suggest that emotional instability may lead to control-seeking behaviours. Neuroticism exhibits an inverse relationship with Switching Intention ($\beta=-0.128$, $t=1.691$, $p=0.091$). Neurotic users demonstrate a tendency to switch to establish predictable digital environments, as their emotional instability motivates personalisation for a sense of control over smartphone usage. All the effect size (f^2) values were low (ranging from 0.001 to 0.050), which indicates that the study had a limited practical influence. Even though the strongest effects were only the Openness relationship with Customisation ($f^2=0.050$) and the Agreeableness relationship with Switching Intention ($f^2=0.050$), this still aligns with the conclusion that Nik evi et al. (2021) came to, which is that personality effects are frequently statistically significant but contextually modest in technology studies.

5. Conclusion

Openness influences interface customisation ($\beta=0.263$), affirming its significance in exploratory technological behaviours (Sawmong, 2022) within smartphone operating systems (OS) in Sarawak. The agreeableness paradox arises with increases in both ecosystem loyalty and switching intention. The positive association of neuroticism with internal customisation ($\beta=0.178$) challenges Western risk-aversion models, indicating that emotional instability drives the pursuit of control through personalisation.

Limitations

The studies are constrained by issues of measurement validity, as evidenced by the low Average Variance Extracted (AVE) for personality traits (0.27–0.48), indicating the BFI-44's cultural incompatibility for use in Sarawak (Rammstedt & John, 2007). Additionally, the sample size limitations, which predominantly include urban dwellers—87% of respondents are from Kuching—skew the representation of the Sarawak population. Furthermore, most respondents (78%) are Android users, resulting in a lack of rural representation within the Sarawak demographic (DOSM, 2024).

Future expansion

Longitudinal Behavioural Tracking, which looks at real OS switching over a year to find gaps between intention and behaviour, and iOS-Android Stratification, which lets us recruit balanced subsamples ($n=150$ each) to find platform-specific effects for more experiments, could be interesting in the future. Hofstede (2011) also says that personality qualities affect how people use their phones in Sarawak through culture-specific pathways, which means that models need to be made for local exploration.

Acknowledgement

Thank you to UiTM Sarawak Branch and respondents involved in executing this study. Utmost appreciation as well to the writers for all the support and cooperation given.

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