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Hybrid Machine Learning Approach for Predicting E-wallet Adoption Among Higher Education Students in Malaysia

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ABSTRACT

In today's digitised world, e-wallets have been sprouting thick and fast in Malaysia as they contribute significantly to expediting online transactions. The E-wallet system is not only a mechanism for businesses to acquire profit but is also one of the most secure payment options for customers, particularly during the COVID-19 pandemic. However, the adoption of e-wallets among higher education students remains unfavourable, eliciting only minimal response. This study aims to analyse higher education students' adoption of e-wallets using a hybrid machine learning method, combining clustering and decision trees. This approach provides deep insights into user behaviour, improving prediction accuracy and enabling personalised strategies for enhanced user experiences. It profiles and classifies students based on demographics and traits such as age, year of study, gender, frequency of use, future use intention, lifestyle compatibility, perceived trust, risk perception, convenience, and security factors. The analysis reveals the segmentation of the dataset into four distinct clusters, each characterised by shared attributes. These clusters are subsequently labelled descriptively and incorporated into the dataset. The dataset, now enriched with cluster information, serves as the foundation for constructing a decision tree model. The outcome of the decision tree indicates that Cluster 2 and Cluster 3 are hesitant towards e-payment. In contrast, Cluster 1 and Cluster 4 are more receptive despite security concerns, as e-wallets offer convenience despite lacking full trust, with security being a prominent concern amidst rising cyber threats. This study helps the Malaysian government and service providers promote cashless transactions and shape students' financial independence based on their traits.

Keywords: E-wallet Adoption, Higher Education Students, Clustering, Decision Tree, Machine Learning.

INTRODUCTION

Google created the first electronic wallet (e-wallet) utilising near-field communications (NFC) technology, which is extensively used for daily transactions through computers or smartphones (Navanwita, 2019). The present cashless tendency is regarded as the norm, particularly during the global Covid-19 pandemic. Similarly, with an increasing people sensitised by COVID-19 quarantines, cash is becoming a disappearing commonplace (Mohd Zahari et al., 2021). As a result, digitalisation has brought about new ways of life. According to Uduji et al. (2019), the e-popularity wallet is expanding due to its convenience, high security, and speed, which brings great potential in the e-commerce market (Lee et al., 2022; Trust payment, 2023).

In actuality, the mobile payment bandwagons benefit users in a variety of ways. It enables users to execute transactions by linking debit or credit cards to their digital wallet (Gomes, 2022). Aside from that, it also allows consumers to store physical card information such as personal details, driving licenses, demographics, documents, and bank account numbers in order to perform certain payment operations (Ray, 2017; Arbor Financial Credit Union, 2021). Therefore, it is designed not only for financial transactions but also to authenticate the holder's credentials. Furthermore, the quick payment method is gaining popularity because customers can hold their phone over the payment terminal to validate their purchase in seconds. Alam et al. (2021) indicated that e-wallet payments are more time- and money-efficient than payments made using standard banking methods since they are quicker and more convenient. Consequently, cash is being phased out in numerous nations, including Belgium, Hong Kong, Canada, and Singapore, where the government encourages digital payment for even small purchases (Karim et al., 2020; Ong & Chong, 2023).

Due to the clear advantages of implementing a cashless economy, e-wallet services have considerably increased use in Malaysia. Security issues and time savings throughout the transaction are the two most concerning factors (Nizam et al., 2018), followed by the factors of convenience, comfort, and quickness in its application and operation (Liébana-Cabanillas et al., 2014; Punwatkar & Verghese, 2018). Besides that, the utilisation of QR codes by vendors in e-wallet transactions has contributed significantly to the widespread adoption and increased popularity of this payment method. In other words, customers can conveniently make payments for their purchases by scanning a QR code, which directs them to the vendor's website, where they can complete their electronic payment transactions. Therefore, these e-wallet services have done an excellent job of transforming the nation into a cashless economy, where cash is no longer required for most transactions (Ong & Chong, 2023). At the moment, there are over 50 e-wallets in Malaysia, such as Boost, CIMB pay, TnG, GrabPay, FavePay, WeChat Pay, AEON wallet, MAE (Maybank), Zapp etc. To encourage higher education students to use the e-wallet, Bank Islam Malaysia Berhad launched the KipleUNI, which promotes campus digital payment. KiplePay and the e-wallet service application work seamlessly (Abdul Rani, 2020). Not only that, the Malaysian government earlier announced an RM200 e-wallet credit aid for youths aged 18 to 20, as well as university students in that age range. The eTunai Belia Rahmah programme is now available to all Malaysian university students, regardless of age (Ridzaimi, 2023).

Following the COVID-19 outbreak, e-wallet transactions grew to an average of 25 percent, demonstrating Malaysians' continued use of digital payments due to their convenience. During the Malaysian Banking and Finance Summit 2021, the former Malaysian Finance

Minister said that as of June 2021, e-wallet traffic has grown by 89 percent, or 468 million transactions, in just a year (Birruntha, 2021). According to an Oppotus (2022) study on e-wallet usage, 68 percent of Malaysian customers utilised digital wallets in the first quarter of 2022. This figure is expected to rise to more than 25 million by 2026. However, in relation to this, the concerns about risk and security, trust, utility, and interest remain as the number of people being duped by online fraud is growing. At the same time, cybersecurity threats continue to loom on the horizon, prompting customers to be careful of this payment method. Despite numerous studies investigating the pros and cons of mobile payment consumer adoptions (Teng & Khong, 2021), there remains a gap in research focusing on higher education students' behaviour and proneness to using e-wallets; thus, studying e-wallet usage in Higher Education not only provides insights into students' financial behaviour, technological preferences, security concerns, and accessibility but also aids in the development of tailored financial literacy programs, thereby enhancing the overall student experience on campus. In this study, a hybrid machine learning approach that uses a clustering-based decision tree is preferred over other current methods for analysing higher education students' adoption of e-wallets due to its ability to provide a comprehensive understanding of adoption patterns, achieve higher prediction accuracy, offer enhanced interpretability, facilitate the development of personalised strategies, and provide scalability and flexibility in analysis. This approach allows researchers to identify distinct student segments, understand the factors influencing adoption within each segment, and tailor interventions to address specific barriers or motivations for adoption, ultimately leading to more effective strategies for promoting e-wallet adoption among higher education students.

RELATED WORKS

In the modern era, the improvement of technology has profoundly influenced various aspects of human life, actively engaging in fields such as medicine (Malik et al., 2019), entertainment (Martucci et al., 2023), socialisation (Duradoni, 2023), physics (Gudmundsson, 2020), chemistry (Chen et al., 2021), education (Singh, 2021) and psychology (Berton et al., 2021). Financial and information technologies, among the most important of these developments, have different innovations to facilitate the lives of individuals (Uddin & Akhi, 2014; Gomes, 2022). Payment by e-wallet is currently regarded as one of the most popular transaction methods owing to the convenience, flexibility, and security afforded by an electronic transaction (Uddin & Akhi, 2014). Digital wallets are also popular for their novel features, such as customisation and real-time communication (Osakwe & Okeke, 2016). Rosnidah et al. (2019) stated that e-wallets have become more popular as the number of e-payment systems increases by providing a variety of services in the transportation sector, food delivery, and bill payment.

Although e-payment systems have generally been widely used, e-wallets continue to receive great public attention, especially regarding the level of credibility of technology. Undale et al. (2021) indicated that security concerns are still prevailing and growing. The use of e-wallets surged dramatically during the COVID-19 pandemic, but this should warn developers and service providers that it was a forced adoption rather than a conscious decision (Undale et al., 2021). According to the Nielsen Payment Landscape Report, 38 percent of non-users are concerned about missing transactions, while 59 percent feel that using e-wallets might result in credit and debit card fraud (Digital News Asia, 2019). Tan (2019) found that 46 percent of non-users perceive security concerns as the primary obstacle to adopting e-wallets. According to Widodo et al. (2019), perceived risk includes the potential losses that buyers must evaluate while making a transaction. These losses might take the form of financial setbacks, breaches of privacy, safety concerns, poor user experiences, or even wasted time. Tan (2022) stated that users who utilise e-wallets run the risk of having their personal information leaked to unauthorised parties. Rajni and Zareen (2021) discovered that although young people are aware of the idea of mobile money and are familiar with at least one mobile money provider, they are hesitant to utilise these services for their regular transactions.

The security risks, low merchant adoption and poor user interface are the major concerns in this issue (PricewaterhouseCoopers, 2018). As a British international Internet-based market research and data analytics firm (YouGov) claimed, 83 percent of 750 respondents are aware of contactless payments, but only 34 percent use them (Noordin, 2017). According to Abdullah et al. (2020), four factors, which are performance expectancy (PE), social influence (SI), facilitating conditions (FC), and trust (T), are discovered to have a substantial impact on the adoption of e-wallets among public university students. The most important contributing element to Malaysians' adoption of e-wallets is Facilitating Conditions (FC). Several studies have highlighted concerns regarding the adoption of e-wallets among young people, including issues related to malware and software, as well as the potential risk of using mobile devices for transactions (Tan, 2019). Seng et al. (2023) found that trust and security are the main drivers of e-wallet adoption among Malaysian university students, as many of them still exhibit apprehension towards mobile payments due to security concerns. Nonetheless, it has been revealed that the other characteristics investigated, namely lifestyle compatibility, perceived utility, and perceived ease of use, had a favourable impact on Malaysian university students' propensity to use e-wallets. Yong et al. (2021) found that university students in Malaysia's Klang Valley exhibit a low level of interest in e-wallet usage. Conversely, Ali et al.'s (2021) study, which was also conducted in Klang Valley, revealed that perceived compatibility is a significant predictor of mobile payment adoption among students at higher education institutions, while personal innovativeness and facilitating conditions had no discernible effect on their intention to accept mobile payment.

Mohd Razif et al. (2020) investigated the perceived risk associated with e-wallet usage among young adults using structural equation modelling and the current technology acceptance model. They found that the acceptability of digital wallets is significantly influenced by factors such as behavioural intention, perceived privacy risk, perceived benefits, trust, perceived overall risk, and perceived performance risk. Similarly, Mohammad Anuar et al. (2020) suggested that reducing the barriers of value, usage, risk, and perceived cost is crucial for increasing the level of e-wallet adoption among university students in Malaysia. Besides that, Yang et al. (2023) also investigated the elements that influence consumers' use of the Alipay e-wallet system in an emerging market, as well as the moderating function of perceived trust and perceived service quality. The study applied the technology acceptance model (TAM) and the theory of planned behaviour (TPB) as the guiding principles. The findings showed that perceived usefulness and perceived simplicity of use influence consumers' intentions to use Alipay in a developing market. Lee et al. (2022) investigate the correlation among mobile wallet app characteristics, perceived enjoyment, user experience, and impulse buying behaviour. The study highlights that perceived interactivity and visual appeal are crucial predictors that will likely influence users to engage in impulsive buying when utilising an e-wallet for payment transactions, particularly in the Malaysian context.

Despite several concerns, e-wallets offer several benefits, such as quick, simple, and secure transactions, with reduced fraud risk due to their trackability (Chelvarayan, 2022). Students have also acknowledged the need for authentication prior to payment, ensuring that even if their phone is stolen, the funds in their e-wallet remain secure. Additionally, the shift towards digital transactions and the desire of consumers to make purchases online ensure the long-term sustainability of digital wallets (Arbor Financial Credit Union, 2021). To summarise the above, five major concerns regarding e-wallet adoption are lifestyle compatibility, perceived trust, risk, convenience, and security, each of which is discussed in detail below.

Lifestyle Compatibility

The logical convergence of lifestyle preferences and values is known as lifestyle compatibility. This aspect of lifestyle compatibility, which considers a user's beliefs, experiences, lifestyle, and preferences, is crucial for reducing any potential ambiguity associated with using technology (Chawla & Joshi, 2020). In fact, the emergence of e-commerce is a global phenomenon across developing countries. These e-wallets can do more than just accept payments. Each provider sprinkles their own set of features that will benefit their target audience. The ability to transfer payments between people is the most popular, but other features, such as buyer protection, loyalty card integration, and unique magnetic strip technology, are also available. Every organisation has accelerated its digital transformation path to shape the new lifestyle and embrace the current trend (Hamid et al., 2016). Companies are learning to alleviate client annoyances and meet their unmet and evolving wants by updating the most recent systems and utilizing developing technology. When a customer feels empowered by payment options, especially ones that are frictionless and correspond with how they are already dealing with a shop, the likelihood of conversion increases (Bauer, 1960).

Perceived Trust

Public trust is necessary for any technology involving financial transactions. For mobile wallets to be sustainable in the long run, user perception and acceptability are important (Hamid et al., 2016). Users may encounter a variety of uncertainties during transactions that are out of their control, such as the autonomous activities of others (e.g., potentially trustworthy web vendors, hackers, and unknown new technologies). Trust is crucial in reducing some risk factors when customers are assured in such uncertain circumstances. As a result, building trust is a crucial tactic for reducing the perceived risk associated with ambiguous and unpredictable interactions (Krisnawati et al., 2021).

Risk

Despite all the potential benefits for marketers and customers, digital wallets still provide certain obstacles and hazards (Ezeudu, 2023). Approximately 70 percent of individuals feel that mobile wallet payments raise the danger of fraud and identity theft (Bashir & Madhavaia, 2015). Although Fintech provides so many benefits, this does not guarantee that its users will be protected from various uncertainties, losses, and other risks. It is important for users to perceive the potential risks associated with digital payments, as highlighted by Bashir and Madhavaia (2015). The inability to forecast the outcomes of using a service brings various losses, including financial, social, privacy, and performance losses. These losses can further amplify the perceived risks associated with digital payments, leading to decreased trust and acceptability among users. Therefore, it is essential to minimise such losses and create a sense of security and assurance among users when it comes to digital payments (Mohamad Shafi & Misman, 2019). Haga and Omote (2021) propose a secure automated payment system using contract wallets to protect cryptographic assets in pay-as-you-go businesses to reduce the risk of cryptographic asset theft due to private key theft.

Convenience

Alongside the Covid-19 pandemic, the new contactless lifestyle is preferable these days. Movement Control Orders (MCO) have accelerated the use of e-wallets, since the circumstance has compelled customers to make cashless purchases as a result of their new purchasing and payment habits (Loh, 2020; England, 2023). The digital programme also supports online e-commerce activities, including making purchases, paying bills, transferring money, and booking flights. E-wallet transactions soared to an average of 25 percent post-COVID-19, indicating that users would continue to use e-wallet due to its convenience, according to Google's e-Conomy South-East Asia 2020 research (Birruntha, 2021). Abdul-Halim et al. (2021) found that perceived ease of use (PEU) has a significant influence over other factors as it makes humans understand the convenience of using modern technologies (Kee et al., 2022).

Security

Another concern keeping customers from purchasing things using digital wallets is a lack of security and privacy (Milberg et al., 2000; England, 2023). Payment using an e-wallet without security features might result in unauthorised access to personal information, which may result in the exploitation of information (Kaur, 2018). As a result, many people still fear making transactions as they do not trust the information system unless privacy and security features are involved (Gitau & Nzuki, 2014; Marimuthu & Roseline, 2020). According to Ahmad et al. (2010), the rapid advancement of technology has resulted in users' reluctance to provide financial information (i.e., debit or credit card numbers) and personal details via the Internet and e-commerce sites. Undale et al. (2021) found that women have a higher level of concern about e-wallet security than men, whereas middle-class individuals express more concern about the security of digital payments than low-income individuals.

In conclusion, adopting e-wallets raises five major concerns: lifestyle compatibility, perceived trust, risk, convenience, and security, all warrant careful consideration in promoting widespread acceptance and usage of digital payment solutions.

Clustering

A clustering approach is being utilised to profile the characteristics of students. Clustering is an unsupervised technique that groups data points based on their similarity, assigning objects with higher homogeneity to the same group (Alashwal et al., 2019; Omran et al., 2007). Various clustering techniques exist, each designed to handle different types of data, as discussed below:

Centroid-based Clustering

A Centroid-based Clustering organises the data into non-hierarchical clusters. Here, k is a hyperparameter to the algorithm and denotes the number of clusters. The fundamental principle of the algorithm is to discover k centroids, then k sets of points that are clustered according to their proximity to the centroid to minimise the squared distances between the points in the cluster and the centroid (Uppada, 2014; Prasetyadi et al., 2022). Due to the difficulty of this optimisation, an approximation is utilised to resolve the issue. The algorithms are as follows:

i. Select k points at random as centroids/cluster centres is selected.
ii. Assign data points to the closest cluster based on Euclidean distance.
iii. Compute the centroid of all points within the cluster.
iv. Repeat iteratively till convergence.

Hierarchical-based Clustering

Hierarchical-based clustering is a tree-type structure where each newly formed cluster is made using priorly formed clusters. There are two types, namely, the agglomerative (bottom-up approach) and divisive (top-down approach) approaches. The agglomerative Hierarchical Clustering is a "bottom-up" approach where each observation starts in its cluster and merges the other clusters as one moves up the hierarchy. Divisive clustering is a top-down clustering technique in which all observations are first assigned to one cluster, then divided into the two groups with the least similarities. The hierarchical-based clustering method can be performed using either a distance matrix or raw data. When raw data is provided, the distance matrix will be automatically computed (Murtagh, 2011; Sangma, 2022).

Density-based Clustering

Density-based clustering detects the concentrated and separated areas. Points not part of a cluster are labelled as noise or outliers. Optionally, the time of the points can be used to find groups of points that cluster together in space and time. It is also possible to use the points' times to locate points that cluster together in both space and time. In short, it recognises patterns automatically based on geographical position and the distance to a certain number of neighbours (Ester, 2009).

Distribution-based Clustering

Distribution-based clustering directly relates to using statistical distribution models, namely Gaussian mixture models. Fundamentally, the likelihood that the contained objects belong to the same distribution is used to define clusters. Although correlation of object attributes, for example, can provide information beyond the cluster assignments of objects, distribution-based models can have overfitting issues if the complexity of the model utilised is not controlled (Xu et al., 1998).

Classification and Regression Tree

A decision tree is a tree-structured classifier where core nodes represent the characteristics of a dataset, branches represent the decision rules, and leaf nodes represent the outcomes (Ch'ng & Mahat, 2014; Hong et al., 2023). Classification and regression tree algorithm (CART) is a type of classification algorithm that uses Gini's impurity index to build a decision tree model (Breiman et al., 1984). It offers a wide range of use cases and is a fundamental machine-learning method. A classification tree is used when the target variable takes a discrete set of values, whereas a regression tree is used to forecast the value of a continuous variable. CART allows only binary split and uses the Gini impurity to rank tests. A cost-complexity model, whose parameters are calculated by cross-validation, is used by CART to prune trees. In addition, when the value of the tested attribute is unknown, CART searches for surrogate tests that resemble the results. The Gini index is a metric for classification tasks in CART. Gini impurity determines the likelihood of a particular characteristic being wrongly categorised when chosen randomly (Gorunescu, 2011; Ch'ng & Mahat, 2020). It stores the sum of the squared probabilities of each class. The Gini Impurity formula is shown in Equation 1.

$$Gini = 1 - (\sum_{i=1}^{K} p_i)^2 \tag{1}$$

where

K is the number of the class label

P_i is the proportion of i^{th} class label

The lower the Gini impurity indicates the higher homogeneity of the node. The Gini Impurity of a pure node (same class) is zero.

MATERIALS AND METHOD

Survey Development

For this study, a web-based questionnaire consisting of two parts was developed. The first part collected demographic data from the participants, while the second part included 30 questions to measure the model constructs. The items are rated using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The construct measures are derived from the literature and adapted to fit the specific context of this study.

Data Collection

This study utilised a quantitative research methodology that employed an online questionnaire as the data collection tool to gather responses from higher education students enrolled in a management university in Malaysia. A total of 385 responses were obtained using a random sampling technique based on representing three colleges that comprised 16 schools in the university. Electronic platforms such as email, WhatsApp, WeChat, Instagram, and online learning are used to collect the data from the participants.

Data Analysis

The respondents' descriptive data is analysed using IBM SPSS, EXCEL, and SAS Enterprise Miner. Before conducting the clustering analysis, a preliminary analysis is performed to explore the data's fundamental characteristics and provide a quantitative summary. Clustering is then applied to group the higher education students based on their traits and demographics. These groups are assigned as target variables for developing a decision tree model to predict their likelihood of using e-wallets. The questionnaire, written in English, had two sections (A and B), with section A consisting of demographics (age, gender, year of study, and future use) and section B focusing on the students' e-wallet preferences. The 30 questions in section B are integrated into five domain factors: lifestyle compatibility, perceived trust, risk, convenience, and security.

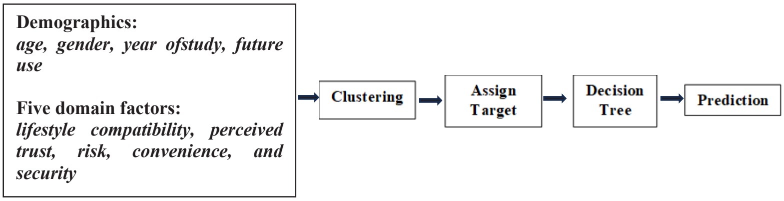
Ward's method, also known as the Minimum Variance Method or Ward's Minimum Variance Clustering Method, is employed as a single-link clustering method in this study. This method is favoured due to its ability to produce compact and evenly-sized clusters (Szmrecsanyi, 2012). Although Ward's method is computationally intensive, like most clustering methods, it requires fewer computations than other methods. Initially, clusters are created, each containing a single object, and are then combined to form a single cluster containing all objects. At each step, the process creates a new cluster that minimises variance, as measured by the sum of squares index, (Glen, 2019.). The algorithms are as follows:

i. The mean value of each cluster is determined.
ii. The distance between each object in a particular cluster and that cluster's mean is computed.
iii. The differences from Step 2 are squared.
iv. The squared values from Step 3 are summed.
v. All the sums of squares from Step 4 are added up.

The next step involved assigning the clusters to each observation as a target or class for decision tree generalisation. Decision trees are a popular classification technique that produces a tree structure resembling a flowchart, where each node represents a test on an attribute value, and each branch signifies the result. This technique can recursively split a huge collection of data into smaller sets. Once the clusters are obtained, they are labelled for each object in the data to develop a predictive model. For this purpose, the Classification and Regression Tree (CART) model was chosen to classify students into different classes using a set of rules. CART splits the feature space and applies rules until it reaches the default threshold values. The process flow is shown in Figure 1.

Figure 1

Process Flow



RESULTS AND DISCUSSION

Descriptive Analysis

Table 1 presents the demographic characteristics of the e-wallet users, including 277 females and 108 males. Among the age groups, the majority (94.8%) of students are below 25 years old, with a female-to-male ratio of approximately 3:1. Notably, 234 respondents, accounting for 60.77 percent of the total, reported rare usage of e-wallets in their daily routines. Among these, a significant proportion falls within the age range of 21 to 24, with individuals 27 or above constituting a minority (only one person). Although e-wallets are commonly utilised by higher education students, especially those aged 21 to 24, for online purchases, their usage is generally confined to a limited scope. However, most may not enjoy utilising e-wallets for more than one purpose due to limited acceptance by establishments, preference for cash transactions, perceived complexity, security concerns, limited functionality, cultural influences, and financial constraints. Students primarily used e-wallets to purchase products, particularly during the pandemic.

Interestingly, final-year students are not motivated to use digital payments instead of cash. Furthermore, among those aged 20 or below, 15 students were willing to adopt e-wallets in the future, while seven students indicated a lack of interest. In the 21-22 age bracket, 132 respondents affirmed their intention to use e-wallets, whereas 34 expressed a negative stance. Similarly, among students aged 23-24, 115 expressed a positive inclination towards future e-wallet usage, while 62 indicated otherwise. Ten students in the 25-26 age group expressed interest in future e-wallet adoption, while nine students expressed disinterest. Remarkably, among respondents aged 27 or above, no individuals indicated an intention to use e-wallets in the future, with only one respondent expressing a negative stance.

Below is the description of each purpose of using e-wallets in Higher Education (HE):

i. Recharging (R): This involves adding credit or value to various accounts within the university ecosystem, such as meal plans, library printing credits, or transportation passes, using the e-wallet system.
ii. Fund transfer (FT): E-wallets facilitate the transfer of funds between students, allowing them to reimburse each other for shared expenses, split bills, or send money for group projects or events.
iii. Bill payments (BP): Students can use e-wallets to conveniently pay for university-related expenses, including tuition fees, dormitory charges, textbooks, or campus events and activities.
iv. Purchase products (PP): E-wallets are a digital payment method for purchasing goods and services both on and off campus, enabling students to buy textbooks, meals, and other necessities from affiliated vendors or online merchants.

Table 1

Demographic Profile

Variables	Criteria	Age				
		20 or below	21 - 22	23 - 24	25 - 26	27 or above
		Count	Count	Count	Count	Count
Gender	Female	18	119	127	12	1
	Male	4	47	50	7	0
Year of study	First year	20	50	2	0	0
	Second year	2	67	25	3	0
	Third year	0	46	85	3	0
	Final year	0	3	65	13	1
How often do you use e-wallet?	Daily	0	4	8	1	0
	Never	2	8	7	1	0
	Often	4	55	56	5	0
	Rarely	16	99	106	12	1
Future use	Yes	15	132	115	10	0
	No	7	34	62	9	1
Why do you use e-wallet?	BP	1	9	9	0	0
	FT	3	10	9	0	0
	R	2	7	12	0	0
	PP	8	56	64	12	0
	BP, PP	0	15	9	2	0
	FT, BP	1	4	9	1	0
	FT, PP	3	12	19	1	1
	R, BP	0	2	2	0	0
	R, FT	0	3	3	0	0
	R, PP	0	14	9	0	0
	FT, BP, PP	0	9	12	1	0
	R, BP, PP	0	5	3	0	0
	R, FT, BP	1	2	2	0	0
	R, FT, PP	0	5	8	0	0
	R, FT, BP, PP	3	13	7	2	0

Reliability Test

Thirty higher education students volunteered to assess the instrument's reliability and consistency. The reliability was assessed using

Cronbach's alpha, a statistical measure that indicates the instrument's internal consistency. The resulting Cronbach's alpha value was 0.713, which suggests a satisfactory level of dependability, exceeding the commonly accepted threshold of 0.7 (as presented in Table 2). The results also verify the consistency of the constructs measured by the instrument, indicating no intercorrelation among the items. Therefore, the instrument measures distinct constructs, and the items are independent.

Table 2

Cronbach's Alpha

Reliability Statistics	
Cronbach's Alpha	Number of Items
0.713	5

Central Tendency and Dispersion

Table 3 presents several variables' central tendency and dispersion, all measured on a 5-point Likert scale (except age). The mean age of the higher education students who participated in the study is approximately 22 years old, with the median and mode being 23 years old. The results indicate that students are generally resistant to modern payment methods, with an overall score of only 1.33 out of 5 points for frequency of use. It may be due to their strong concerns about security risks and perceived poor protection measures. However, they recognised the importance of using e-wallets and acknowledged that digital payments could provide convenience (score of 4.12), especially during the COVID-19 pandemic, which has permanently altered how people consume and pay. Skewness values are between -1 and 1, indicating a close-to-symmetrical data distribution, while kurtosis values were close to 0, denoting a mesokurtic or normal distribution. The data showed low variability, as the small standard deviation values indicated. Finally, there are no missing values in the collected data.

Table 3

Central Tendency and Dispersion

Factors	Age	Frequent Use	Lifestyle Compatibility	Perceived Trust	Risk	Convenient	Security
Valid (N)	385	385	385	385	385	385	385
Missing (N)	0	0	0	0	0	0	0
Mean	22.07	1.33	3.88	3.77	3.4	4.12	3.59
Median	23	1	4	4	3.33	4	3.5
Mode	23	1	4	4	3.00[a]	4	4
Standard Deviation	1.27	0.62	0.79	0.84	0.89	0.72	0.74
Skewness	0.36	0.49	-0.57	-0.48	-0.27	-0.92	-0.04
Kurtosis	-0.57	0.28	0.68	0.18	-0.02	1.69	-0.01

a. Multiple modes exist. The smallest value is shown

Clustering Analysis

The demographic variables (age, gender, year of study, future use, and frequent use) and the five domain factors (lifestyle compatibility, perceived trust, risk, convenience, and security) are employed in developing clusters (see Figure 1). A cubic clustering criterion (CCC) plot is used to estimate the number of clusters using Ward's minimum variance method. The cluster analysis results, as shown in Figure 2 and Figure 3, indicate that four distinct clusters have been successfully developed based on their similar traits. The most prominent cluster is Cluster 4, which contains the highest number of students, with 224 (58.2%). More than half of the selected students exhibit characteristics similar to Cluster 4. On the other hand, Cluster 2 has the smallest number of students, with only seven individuals (1.8%). It suggests that the student in this cluster exhibits unique characteristics that differentiate them from the rest of the sample. Figure 3 provides a visual representation of the clusters' relative distances from each other. Cluster 2 is the farthest from the other three proximity clusters. This indicates that the students in this cluster have distinctive traits different from those in the other clusters.

Figure 2

Clusters Segmentation

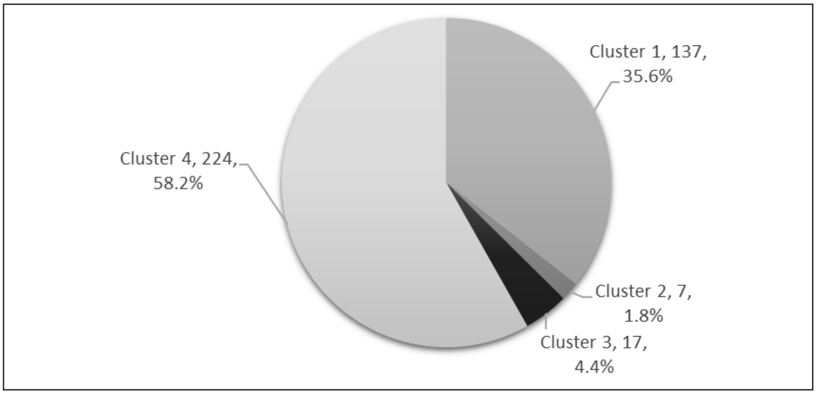


Figure 3

Clusters Distance

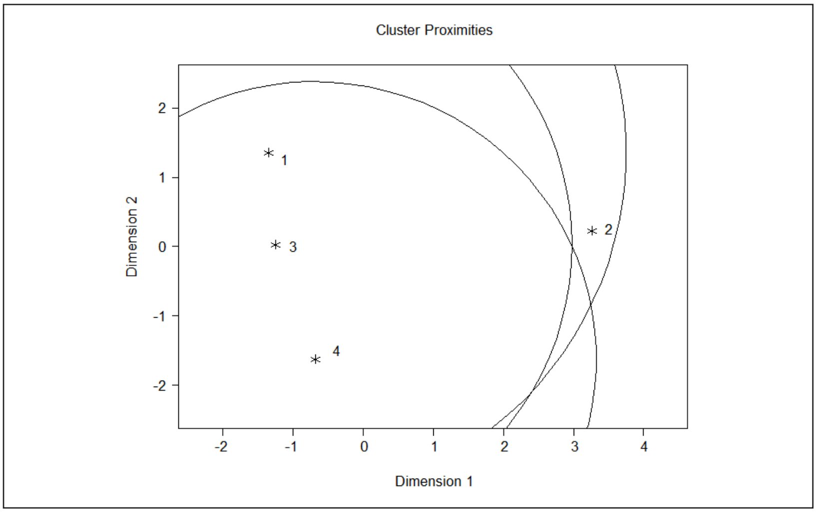


Table 4 displays the distance metrics obtained from a clustering analysis using the Euclidean distance measure to determine the similarity between data points. The distance metric represents the distance or dissimilarity between each pair of data points in the dataset based on their attribute or feature values.

Table 4

Distance Measures of Each Cluster

Cluster	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
1	22.13	3.78	1.21	3.16	3.49	3.07	3.36	0	1	0.77	0.23	0.21	0.23	0.37	0.19
2	21.57	1.76	0.71	2.43	2.86	2.64	2.43	1	0	1.00	0.00	0.29	0.43	0.29	0.00
3	22.96	3.92	0.76	2.82	4.12	2.63	3.12	1	0	0.76	0.24	0.12	0.29	0.41	0.17
4	22.05	4.41	1.47	4.25	3.32	4.00	4.3	0	1	0.68	0.32	0.17	0.26	0.33	0.24

Notation

V1 = Age	V6 = Security	V11 = Gender (M)
V2 = Convenience	V7 = Lifestyle	V12 = Year (1st)
V3 = Frequent use	V8 = Future Use (No)	V13 = Year (2nd)
V4 = Perceived trust	V9 = Future Use (Yes)	V14 = Year (3rd)
V5 = Risk	V10 = Gender (F)	V15 = Year (Final)

Table 5 generates each factor's worth or importance values in 4 clusters. Clusters Worth Value in cluster analysis typically refers to assessing or evaluating the identified clusters' worth or importance. It involves assigning a value or score to each cluster based on criteria such as cluster size, homogeneity within the cluster, distinctiveness from other clusters, and relevance to the research objectives or practical applications. The characteristics of each cluster are explained below.

Table 5

Clusters Worth Value

Cluster 1	Worth	Cluster 2	Worth	Cluster 3	Worth	Cluster 4	Worth
Perceived_ Trust	0.1890	Convenience	0.0231	Future_use	0.0587	Perceived_ Trust	0.2697
Security	0.1775	Future_use	0.0099	Security	0.0143	Security	0.2510
Lifestyle_ compatibility	0.1622	Lifestyle_ compatibility	0.0081	Perceived_ Trust	0.0067	Lifestyle_ compatibility	0.2321
Convenience	0.0953	Security	0.0034	Frequent use	0.0045	Convenience	0.1364
Risk	0.0327	Perceived_ Trust	0.0028	Lifestyle_ compatibility	0.0044	Frequent use	0.0473
Frequent use	0.0184	Risk	0.0027	Risk	0.0037	Future_use	0.0450
Future_use	0.0168	Frequent use	0.0010	Convenience	0.0017	Risk	0.0035
Gender	0.0028	Year	0.0003	Age	0.0003	Gender	0.0056
Year	0.0026	Gender	0.0003	Year	0.0002	Year	0.0031
Age	0.0021	Age	0.0002	Gender	0	Age	0.0016

Cluster 1

Cluster 1 is the second-largest group of 385 respondents after Cluster 4, comprising 137 higher education students. Based on Table 3, approximately 77 percent of the students in this cluster are female. Most individuals in this category are third-year students, with an average age of 22.13. The primary concerns highlighted within this group revolve around issues of trust (3.16), security (3.07), and risks (3.49) associated with electronic transactions. As incidents of hacking events, ransomware attacks, and data leaks continue to rise, students have become increasingly hesitant to upload all their financial information to one location. Thus, the transition to digital payments is still impeded by perceived trust, security, and fraud issues.

Cluster 2

Cluster 2 consists solely of female students in their first and second semesters and is the smallest group among the 385 respondents. Due to their youth (under 22 years old) and limited experience, this group is reluctant to embrace digital payments and lacks confidence in their proficiency to utilise them. Despite perceiving the convenience of using e-wallets for daily transactions to some extent, these students have no intention of using them in the future. It is important to note that this group's resistance to digital payments may be due to various factors, including a lack of exposure, knowledge, or awareness of the benefits associated with digital payments. Further research may be necessary to understand the reasons behind this resistance and identify strategies to encourage this group to embrace digital payments.

Cluster 3

Among the respondents, 17 students between 21 and 23 expressed concerns about the risks associated with e-wallets, which they view as a major deterrent to adoption (see Table 3). This group believes that using e-wallets could lead to fraud or unauthorised access to their debit and credit card information, resulting in the loss of transactions and sensitive data. Therefore, their decision not to use e-wallets in the future is based on the uncertainty of the potential negative effects of new technology. In short, this group's apprehension highlights the importance of addressing risks in designing and implementing digital payment systems to promote user confidence and trust. As a result, policymakers and industry stakeholders must collaborate to develop and implement effective measures to mitigate security risks and build trust among users.

Cluster 4

Cluster 4, the largest group among the 385 respondents, comprises 224 students with a female-to-male ratio of 3:1. This group exhibits significant concern about the trust issue associated with using e-wallets, with the majority perceiving that cybercriminals continue to employ various tactics to scam e-wallet users (see Table 3). They feared being tricked into downloading bogus yet legitimate-looking e-wallet apps that contain malware designed to infect their devices used for digital payments. Despite their apprehensions, the students in Cluster 4 are still willing to use e-wallets in the future because of their perceived convenience. Although they do not entirely trust mobile wallets, the potential benefits outweigh the potential risks. The variables of gender, year, and age do not play a significant role in forming the clusters. The study found that frequent use of e-wallets is not a primary concern for most students among the five core factors identified.

Decision Tree Induction for Classifying Student Tendency of E-wallet Adoption

To categorise prospective students' preferences, we construct a decision tree using the four clusters described above as the labels for each observation. Table 6 displays the significance levels, the number of dividing rules, and the number of surrogate rules used in constructing the decision tree model. The result shows that the primary determinant of the splitting rules is security, followed by the variable of compatibility lifestyle, perceived trust, convenience, frequent use, and future use. On the other hand, gender and age contribute little to creating the decision tree model and are the least important components. Consequently, these two variables are not used in the tree model.

Table 6

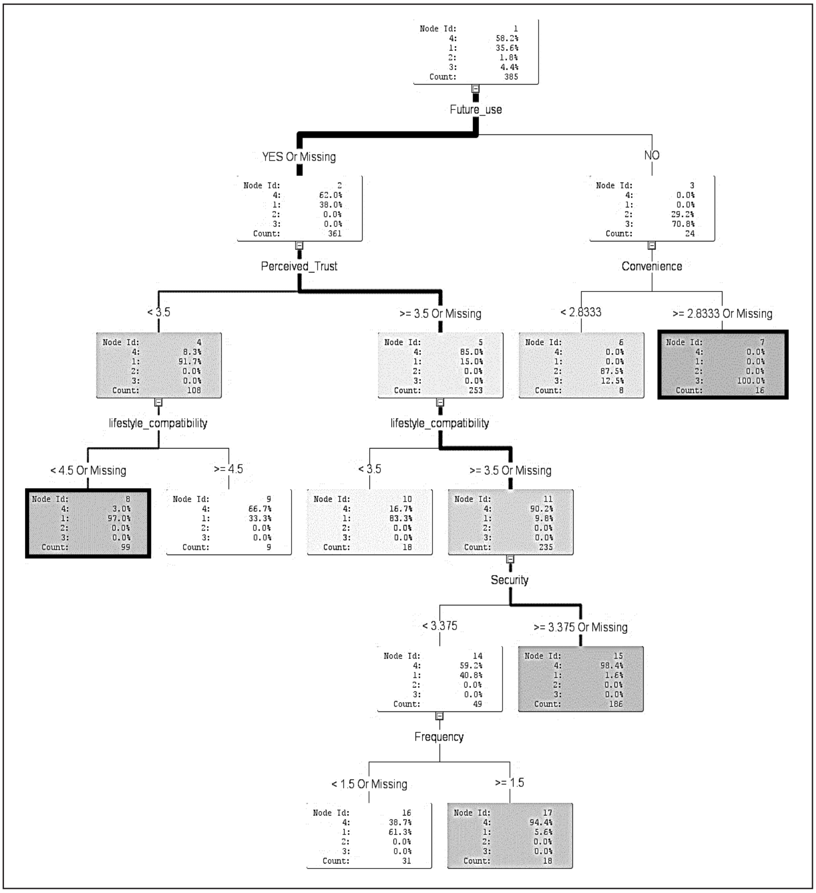
Importance Value of Variables for Developing a Decision Tree Model

Variable Name	Number of Splitting Rules	Number of Surrogate Rules	Importance
Security	1	5	1.0000
Lifestyle_compatibility	2	3	0.9762
Perceived_Trust	1	2	0.9351
Convenience	1	4	0.9178
Frequent use	1	2	0.7646
Future_use	1	0	0.4300
Risk	0	3	0.3561
Gender	0	1	0.1929
Year	0	0	0.0000
Age	0	0	0.0000

Figure 4 illustrates the structural layout of the decision tree, along with examples of the key rules from nodes 7 and 8, as depicted in the SAS output. The results of this study suggest that security and compatibility lifestyle are the two most important factors influencing students' preferences for digital payments.

Figure 4

Decision Tree Model



The rules presented above illustrate two examples (Node Id 7 and Node Id 8) of decision paths within the decision tree model. Figure 4 displays the output of the decision tree, which consists of six levels and eight leaves, with the majority displaying homogeneity levels above 80 percent (Node Id 6, Node Id 7, Node Id 8, Node Id 10, Node Id 15 and Node Id 17). Node Id 7 has the highest homogeneity percentage, with 100 percent of the students in Class 3 being homogeneous. Four variables, namely Risk, Year, Gender, and Age, were not selected in this study due to their low importance value, as shown in Table 5. Overall, students who expressed no intention of using e-wallets in the future were categorised into Class 2 and Class 3, whereas those inclined to use e-wallets were assigned to Class 1 and Class 4. In supervised learning, classes represent predefined categories or labels assigned to data points, whereas in unsupervised learning, clusters denote groups of data points sharing similarities based on their features. The findings underscore the significance of security concerns and compatibility with lifestyle as critical factors for encouraging the adoption of digital payments among students. Notably, the output reveals that a majority of students are inclined to use digital payments in the future due to their perceived convenience and alignment with lifestyle preferences.

Discussion

The key distinction between this study and the previous one lies in the implementation of a hybrid machine learning approach, specifically combining the clustering and decision tree models. Previous research using only one technique limits the comprehension of complex data relationships and patterns, potentially missing valuable insights for decision-making. Additionally, relying on a single technique may lead to overgeneralisation or oversimplification of the data, potentially overlooking crucial nuances or variations within the dataset. By amalgamating clustering algorithms, institutions can categorise students based on spending patterns, financial behaviours, and demographic data, offering tailored financial assistance and budgeting advice. Decision trees further refine this analysis by predicting future spending trends and identifying students at risk of financial strain, enabling proactive intervention strategies. Combining clustering and decision trees enhances financial literacy programs, improves student financial management, and fosters a more supportive and inclusive higher education environment. This integrated approach allows for examining crucial factors such as lifestyle compatibility, perceived trust, risk, convenience, security, and relevant demographic background information.

Throughout the study, a strategy for uncovering student characteristics and capturing current trends and the popularity of e-wallet usage among university students is improved. The implications of the findings have the potential to assist the government in promoting and increasing the adoption of e-wallets among users within this specific age range. This may involve targeted marketing campaigns, education and awareness initiatives, and other efforts to encourage young people to try e-wallets. The government could launch education and awareness campaigns to inform students about the benefits of using e-wallets and how to use them safely. These campaigns could also address the various security features of e-wallet apps to dispel some of the students' concerns about security.

CONCLUSION

The rapid development of financial technology has revolutionised the business ecosystem worldwide. However, the adoption rate of e-wallets among university students in Malaysia remains low due to safety concerns and other uncertainties. This study uses a hybrid model that combines descriptive and predictive approaches. First, the clustering technique is used to segment unlabelled data into four distinct groups, Cluster 1 to Cluster 4, which reveals valuable patterns, characteristics, and insights. The labels obtained from the clustering stage are then assigned to the data, and a decision tree model is constructed. This model anticipates students' likelihood of adopting e-wallet payments daily. The outcome in the decision tree has revealed that students can be categorised into four distinct classes based on their behaviour, with Classes 2 and 3 being conservative and reluctant to adopt E-payment. Conversely, Classes 1 and 4 are more open to using e-wallets in the future due to their perceived convenience, despite lacking complete faith in mobile wallets. Security is a major concern and has become a prime target for hackers and fraudsters. Recent incidents of mobile wallet assaults have resulted in the loss of hundreds of millions of dollars as well as the release of sensitive data. It underscores the potential danger of experienced hackers gaining access to the users' mobile payment app. Therefore, the government must continually enforce strict regulations on mobile payment security, invest in cybersecurity infrastructure and research, foster ongoing collaboration among stakeholders, educate consumers on safe mobile payment practices, and monitor and enforce compliance with security standards.

This study has limitations as it only includes undergraduates in a management university in Malaysia aged between 19 and 28 years old. Future research should include a more diverse sample of undergraduates from various universities and possibly postgraduate students to increase the generalizability of the findings. Additionally, the methods used in this study are limited to a hybrid machine-learning approach that integrates clustering and decision trees. Other techniques should be explored to improve the model. Moreover, this study only examines five major variables related to e-wallet adoption. Despite efforts to ensure confidentiality and anonymity, participants may have felt inclined to respond in a socially desirable manner or may have had difficulty recalling certain details accurately. It could introduce bias and affect the reliability and validity of the data collected.

Future research could consider investigating other impactful factors, such as the complexity of the technology, the pervasiveness of technology use, and the attitudes of tech-savvy future generations. Comparative comparisons across different educational institutions are another promising area for future research. Comparing adoption rates, usage patterns, and influencing factors between public and private institutions, various academic disciplines, or institutions located in different locations could be part of this. Such comparative research would aid in identifying contextual elements that may contribute to differences in e-wallet acceptance and guide strategies for increasing wider adoption in certain educational settings. Besides that, gender differences in e-wallet adoption among higher education students also merit exploration.

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REFERENCES

Abdul-Halim, N. A., Vafaei-Zadeh, A., Hanifah, H., et al. (2022). Understanding the determinants of e-wallet continuance usage intention in Malaysia. *Quality & Quantity*, *56*(6), 3413–3439. https://doi.org/10.1007/s11135-021-01276-7

Abdul Rani, N. A. (2020, February 25). E-wallet promotes cashless community on campus. *The Star*. https://www.thestar.com.my/metro/metro-news/2020/02/25/e-wallet-promotes-cashless-community-on-campus

Abdullah, N., Redzuan, F., & Daud, N. A. (2020). E-wallet: Factors influencing user acceptance towards cashless society in Malaysia among public universities. *Indonesian Journal of Electrical Engineering and Computer Science*, *20*(1), 67–74. https://doi.org/10.11591/ijeecs.v20.i1

Ahmad, K., Khan, M. I., & Jan, M. T. (2010). Online banking acceptance in Malaysia: A students' behaviour perspective. *Malaysian Management Review*, *45*(2), 1-14

Alam, M. M., Awawdeh, A., & Muhamad, A. I. (2021). Using E-wallet for business process development: Challenges and prospects in Malaysia. *Business Process Management Journal*, *27*(4), 1142-1162. https://doi.org/10.1108/BPMJ-11-2020-0528

Alashwal, H., El Halaby, M., Crouse, J. J., Abdalla, A., & Moustaf, A. A. (2019). The application of unsupervised clustering methods to Alzheimer's disease. *Frontiers in Computational Neuroscience 13*(31). https://doi.org/10.3389/fncom.2019.00031

Ali, T. F., Sundra Raj, M. S., & Singh, J. S. K. (2021). A quantitative study on the factors influencing higher education institutions students' acceptance of mobile payments in Klang Valley, Malaysia. *Electronic Journal of Business and Management*, *6*(3), 15-43

Arbor Financial Credit Union. (2021, November 17). 5 Benefits of a Digital Wallet. Retrieved from https://www.arborfcu.org/blog/5-benefits-of-a-digital-wallet

Bashir, I., & Madhavaiah, C. (2015). Consumer attitude and behavioral intention towards internet banking adoption in India. *Journal of Indian Business Research*, *7*(1), 67–102. https://doi.org/10.1108/JIBR-02-2014-0013

Bauer, R. A. (1960). Consumer behavior as risk taking. In *AMA Proceedings* (Vol. 123, pp. 389-398). Chicago

Berton, A., Longo, U. G., Candela, V., Fioravanti, S., Giannone, L., Arcangeli, V., Alciati, V., Berton, C., Facchinetti, G., Marchetti, A., Schena, E., De Marinis, M. G., & Denaro, V. (2020). Virtual reality, augmented reality, gamification, and telerehabilitation: Psychological impact on orthopedic patients' rehabilitation. *Journal of Clinical Medicine*, *9*(8), 2567. https://doi.org/10.3390/jcm9082567

Birruntha, S. (2021, October 18). Pandemic pushes more than 80% growth for e-wallet players. The Malaysian Reserve. Retrieved from https://themalaysianreserve.com/2021/10/18/pandemic-pushes-more-than-80-growth-for-e-wallet-players/

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and Regression Trees*. Monterey, CA: Wadsworth and Brooks

Chawla, D., & Joshi, H. (2023). Role of mediator in examining the influence of antecedents of mobile wallet adoption on attitude and intention. *Global Business Review*, *24*(4), 609-625. https://doi.org/10.1177/0972150920924506

Chelvarayan, A., Yeo, S. F., Han, H. Y., & Hashim, H. (2022). E-wallet: A study on cashless transactions among university students. *F1000Research*, *11*, 1-13. https://doi.org/10.12688/f1000research.73545.1

Chen, S., Chang, X., Sun, G., Zhang, T., Xu, Y., Wang, Y., Pei, J., & Gong, J. (2021). Propane dehydrogenation: Catalyst development, new chemistry, and emerging technologies. *Chemical Society Reviews*, *50*(5), 3315-3354. https://doi.org/10.1039/D0CS00814A

Ch'ng, C. K., & Mahat, N. (2014). Winsorised Gini Impurity: A resistant to outliers splitting metric for classification Tree. *AIP Conference Proceedings*, 716-723

Ch'ng, C. K., & Mahat, N. I. (2020). Winsorize tree algorithm for handling outlier in classification problem. *International Journal of Operational Research*, *38*(2), 278-293. https://doi.org/10.1504/IJOR.2020.107073

Digital News Asia. (2019, July 1). Nielsen sees security concerns as main barrier to e-wallet adoption. Digital News Asia. Retrieved from https://www.digitalnewsasia.com/digital-economy/nielsen-sees-security-concerns-main-barrier-e-wallet-adoption

Duradoni, M., Spadoni, V., Gursesli, M. C., & Guazzini, A. (2023). Development and validation of the need for online social feedback (NfOSF) Scale. *Human Behavior and Emerging Technologies*, *2023*, 1-11. https://doi.org/10.1155/2023/5581492

England, J. (2023, April 25). Unfolding e-wallets and the evolution of the payments sector. *FinTech Magazine.* Retrieved from https://fintechmagazine.com/articles/unfolding-e-wallets-and-the-evolution-of-the-payments-sector

Ester, M. (2009). Density-based clustering. In L. Liu & M. T. Özsu (Eds.), *Encyclopedia of Database Systems*. Springer. https://doi.org/10.1007/978-0-387-39940-9_605

Ezeudu, M. (2023, March 28). Risks and benefits of a digital wallet for everyday transactions. *Payswix*. https://payswix.com/risks-and-benefits-of-a-digital-wallet-for-everyday-transactions/

Gitau, L., & Nzuki, D. (2014). Analysis of determinants of m-commerce adoption by online consumers. *International Journal of Business, Humanities and Technology*, *4*(3), 88-94

Glen, S. (2019, March 18). K-nn clustering explained in one picture. Data Science Central. Retrieved from https://www.datasciencecentral.com/author/stephanieglen/page/14/

Gomes, V. (2022). E-wallet: Digital payments pivotal to Malaysia's financial services industry. *The Edge Markets*. Retrieved from https://www.theedgemarkets.com/article/ewallet-digital-payments-pivotal-malaysias-financial-services-industry

Gorunescu, F. (2011). Classification and decision trees. In Data Mining (Intelligent Systems Reference Library, Vol. 12). Springer. https://doi.org/10.1007/978-3-642-19721-5_

Gudmundsson, J. T. (2020). Physics and technology of magnetron sputtering discharges. *Plasma Sources Science and Technology*, *29*(11), 113001. https://doi.org/10.1088/1361-6595/abb7bd

Hamid, A. A., Razak, F. Z. A., Bakar, A. A., & Abdullah, W. S. W. (2016). The effects of perceived usefulness and perceived ease of use on continuance intention to use E-government. *Procedia Economics and Finance*, *35*, 644-649. https://doi.org/10.1016/S2212-5671(16)00079-4

Haga, S., & Omote, K. (2021). IoT-based autonomous Pay-As-You-Go payment system with the contract wallet. *Security and Communication Networks*, *2021*. 1-10. https://doi.org/10.1155/2021/8937448

Hong, C. M., Ch'ng, C. K., & Roslan, T. R. N. (2023). Predicting students' inclination to TVET enrolment using various classifiers. *Pertanika Journal of Science & Technology*, *31*(1), 475–493. https://doi.org/10.47836/pjst.31.1.28

Karim, M. W., Haque, A., Ulfy, M. A., Hossain, M. A., & Anis, M. Z. (2020). Factors influencing the use of e-wallet as a payment method among Malaysian young adults. *Journal of International Business and Management*, *3*(2), 1-12. https://doi.org/10.37227/jibm-2020-2-21

Kaur, R., Li, Y., Iqbal, J., Gonzalez, H., & Stakhanova, N. (2018). A Security Assessment of HCE-NFC Enabled e-wallet Banking Android Apps. In *2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC)* (pp. 492-497). IEEE

Kee, M. H., Lai, K. H., Lee, J. C., Lee, K. J., Lee, J. L., Yosanti, I., & Aryani, D. N. (2022). Do you have a digital wallet? A study of e-wallet during the COVID-19 pandemic. *International Journal of Accounting and Finance in Asia Pacific*, *5*(1), 24-38. https://doi.org/10.32535/ijafap.v5i1.1413

Krisnawati, M., Wienadi, J., & Wiradinata, T. (2021). The effect of consumer trust and perceived risk on e-wallet adoption: Consideration for technology startup entrepreneurs. *Jurnal Entrepreneur dan Entrepreneurship*, *10*(2), 111–118. https://doi.org/10.37715/jee.v10i2.221

Lee, Y. Y., Gan, C. L., & Liew, T. W. (2022). The impacts of mobile wallet app characteristics on online impulse buying: A moderated mediation model. *Human Behavior and Emerging Technologies*, *2022*, 1-15. https://doi.org/10.1155/2022/2767735

Liébana-Cabanillas, F. J., Sánchez-Fernández, J., & Muñoz-Leiva, F. (2014). Role of gender on acceptance of mobile payment. *Industrial Management and Data Systems*, *114*(2), 220–240. https://doi.org/10.1108/IMDS-03-2013-0137

Loh, M. (2020). MCO: CIMB says Touch 'n Go eWallet continues to see healthy volumes for essential services, online-based transactions. *The Edge Markets*. Retrieved from https://www.theedgemarkets.com/article/touch-n-go-digital-sees-more-cashless-payments-postcovid-19

Malik, P., Pathania, M., & Rathaur, V. K. (2019). Overview of artificial intelligence in medicine. *Journal of Family Medicine and Primary Care*, *8*(7), 2328. https://doi.org/10.4103/jfmpc.jfmpc_440_19

Marimuthu, M., & Roseline, A. (2020). A study on consumer perception towards e-wallet. *OurHeritage*, *68*(17), 283-288

Martucci, A., Gursesli, M. C., Duradoni, M., & Guazzini, A. (2023). Overviewing gaming motivation and its associated psychological and sociodemographic variables: A PRISMA systematic review. Human Behavior and Emerging Technologies, 2023, 1–156. https://doi.org/10.1155/2023/5640258

Milberg, S. J., Smith, H. J., & Bruke, S. J. (2000). Information privacy: Corporate management and national regulation. *Organization Science*, *11*(1), 35-57. http://www.jstor.org/stable/2640404

Mohammad Anuar, N. I., Nik Mahdi, N. M., Nik Hashim, N. A., Mohamad, S. R., Zainuddin, S. A., Azmi, N. F., & Wan Zulkiffli, W. F. (2020). The barriers towards the adoption of e-wallet payment system. *International Journal of Engineering*

Research and Technology, *13*(11), 3772-3777. https://dx.doi.org/10.37624/IJERT/13.11.2020.3772-3777

Mohamad Shafi, R., & Misman, F. (2019). The perceived benefit and risk framework of e-wallet adoption among the early adopters in Malaysia. In *Proceedings of the 2nd Economics and Business International Conference* (pp. 579-584)

Mohd Razif, N. N., Misiran, M., Sapiri, H., & Md Yusof, Z. (2020). Perceived risk for acceptance of e-wallet platform in Malaysia among youth: SEM approach. *Management Research Journal*, *9*, 1–24. https://doi.org/10.37134/mrj.vol9.sp.1.2020

Mohd Zahari, M. F., Ahmad, S., Hambali, M. A., & Pisol, M. I. M. (2021). The effects of COVID-19 pandemic and cashless society. In *Proceedings of the 5th National Pre-University Seminar 2021 (5th NPreUS 2021)* (pp. 138-142)

Murtagh, F. (2011). Hierarchical Clustering. In M. Lovric (Ed.), *International Encyclopedia of Statistical Science*. Springer. https://doi.org/10.1007/978-3-642-04898-2_288

Navanwita, S. (2019). The evolution of e-wallets: History, benefits, and withdrawals. Retrieved from https://sociable.co/mobile/evolution-ewallets-history-benefits-withdrawals

Nizam, F., Hwang, H. J., & Valaei, N. (2018). Measuring the effectiveness of e-wallet in Malaysia. In *3rd IEEE/ACIS International Conference on Big Data, Cloud Computing, and Data Science Engineering* (pp. 59-69). Springer

Noordin, K. A. (2017). Fintech: Mobile payments for more secure transactions. Retrieved from http://www.theedgemarkets.com/article/fintech-mobile-payments-moresecure-transactions

Omran, M., Engelbrecht, A., & Salman, A. (2007). An overview of clustering methods. *Intelligent Data Analysis*, *11*(6), 583–605. https://doi.org/10.3233/IDA-2007-11602

Ong, H. B., & Chong, L. L. (2023). The effect of cashless payments on the internet and mobile banking. *Journal of Financial Services Marketing*, *28*(2), 178–188. https://doi.org/10.1057/s41264-022-00145-0

Oppotus (2022). Share of people who used digital wallets in Malaysia from 1st quarter 2019 to 1st quarter 2022. Statista. Retrieved from https://www.statista.com/statistics/1327192/malaysia-e-wallet-usage-rate/

Osakwe, C. N., & Okeke, T. C. (2016). Facilitating mCommerce growth in Nigeria through mMoney usage: A preliminary analysis. *Interdisciplinary Journal of Information, Knowledge, and Management*, *11*, 115-139. https://doi.org/10.28945/3456

Prasetyadi, A., Nugroho, B., & Tohari, A. (2022). A hybrid K-means hierarchical algorithm for natural disaster mitigation clustering. *Journal of Information and Communication Technology*, *21*(2), 175-200. https://doi.org/10.32890/jict2022.21.2.2

PricewaterhouseCoopers (2018). Banking on the e-wallet in Malaysia. Retrieved from https://www.pwc.com/my/en/perspective/deal-strategy/181003-banking-on-the-e-wallet-in-malaysia.html

Punwatkar, S., & Verghese, M. (2018). Adaptation of e-wallet payment: An empirical study on consumers' adoption behavior in Central India. *International Journal of Advances in Management, Technology, and Engineering Sciences*, *8*(3), 1147–1156

Rajni, A., Zareen, & Chaddha, P. (2021). Awareness and use of mobile money among college students in university. *Proceedings of the International Conference on Advances in Management Practices (ICAMP 2021)*. Available at SSRN: https://ssrn.com/abstract=3993107

Ray, A. (2017). What are the different types of e-commerce payment systems? Amazon Services. Retrieved from https://services.amazon.in/resources/seller-blog/different-types-of-e-commerce-payment-systems.html

Ridzaimi (2023). PM: All Malaysian university students will get RM200 eWallet aid regardless of age. TechNave. Retrieved from https://technave.com/gadget/PM-All-Malaysian

Rosnidah, I., Muna, A., Musyaffi, A. M., & Siregar, N. F. (2019). Critical factor of mobile payment acceptance in millennial generation: Study on the UTAUT model. In *International Symposium on Social Sciences, Education, and Humanities (ISSEH 2018)*. Atlantis Press. 10.2991/isseh-18.2019.30

Sangma, J. W., Sarkar, M., & Pal, V. (2022). Hierarchical clustering for multiple nominal data streams with evolving behavior. *Complex and Intelligent Systems*, *8*, 1737–1761. https://doi.org/10.1007/s40747-021-00634-0

Seng, N. D., Ibrahim, N. F., Yin, L. S., & Maiyus, M. B. (2023). An empirical study on acceptance of e-wallet among Malaysian university students. I*nternational Journal of Academic Research in Business and Social Sciences*, *13*(1), 1099–1112. http://dx.doi.org/10.6007/IJARBSS/v13-i1/15728

Singh, M. N. (2021). Inroad of digital technology in education: Age of digital classroom. *Higher Education for the Future, 8*(1), 20–30. https://doi.org/10.1177/2347631120980

Szmrecsanyi, B. (2012). *Grammatical Variation in British English Dialects: A Study in Corpus-Based Dialectometry*. Cambridge University Press

Tan, J. Y. (2019). Nielsen sees security concerns as the main barrier to e-wallet adoption. *Digital News Asia*. Retrieved from https://www.digitalnewsasia.com/digital-economy/nielsen-sees-security-concerns-main-barrier-e-wallet-adoption

Tan, Z. Y. (2022). e-wallet: Cybersecurity: How much cash would you keep in your e-wallet? *The Edge Markets*. Retrieved from https://www.theedgemarkets.com/article/ewallet-cybersecurity-how-much-cash-would-you-keep-your-ewallet

Teng, S. S., & Khong, K. W. (2021). Examining actual consumer usage of e-wallet: A case study of big data analytics. *Computers in Human Behavior*, *121*, 1–12. https://doi.org/10.1016/j.chb.2021.106778

Trust Payment. (2023, September 12). The rise of mobile wallets in 2023.

Uddin, M. S., & Akhi, A. Y. (2014). E-wallet system for Bangladesh: An electronic payment system. *International Journal of Modeling and Optimization*, *4*(3), 216–226. 10.7763/IJMO.2014.V4.376

Uduji, J. I., Okolo-Obasi, E. N., & Asongu, S. A. (2019). The impact of e-wallet on informal farm entrepreneurship development in rural Nigeria. *The Electronic Journal of Information Systems in Developing Countries*, *85*(3), 1 - 27. https://doi.org/10.1002/isd2.12066

Undale, S., Kulkarni, A., & Patil, H. (2021). Perceived eWallet security: Impact of COVID-19 pandemic. *Vilakshan - XIMB Journal of Management*, *18*(1), 89–104. https://doi.org/10.1108/XJM-07-2020-0022

Uppada, S. K. (2014). Centroid-based clustering algorithms: A clarion study. *International Journal of Computer Science and Information Technologies, 5*(6), 7309–7313

Widodo, M., Irawan, M. I., & Sukmono, R. A. (2019). Extending UTAUT2 to explore digital wallet adoption in Indonesia. In *International Conference on Information and Communications Technology* (pp. 878–883). https://doi.org/10.1109/icoiact46704.2019.8938415

Xu, X. W., Ester, M., Kriegel, H. P., & Sander, J. (1998). A distribution-based clustering algorithm for mining in large spatial databases. In *Proceedings 14th International Conference on Data Engineering* (pp. 324–331). https://doi.org/10.1109/ICDE.1998.655795

Yang, M., Al Mamun, A., Mohiuddin, M., Nawi, N. C., & Zainol, N. R. (2021). Cashless transactions: A study on intention and adoption of e-wallet. *Sustainability*, *13*(2), 831. https://doi.org/10.3390/su13020831

Yang, T., Chan, T. J., Mohd Suki, N., & Mohd Ariff, K. (2023). Moderating role of perceived trust and perceived service quality on consumers' use behavior of Alipay e-wallet system: The perspectives of technology acceptance model and theory of planned behavior. *Human Behavior and Emerging Technologies*, *2023*. https://doi.org/10.1155/2023/5276406

Yong, I. I., Wong, T. K., & Lim, P. Y. (2021). Intention to use e-wallet amongst the university students in Klang Valley. *International Journal of Business and Economy*, *3*(1), 75–84. https://myjms.mohe.gov.my/index.php/ijbec/article/view/12747