Big data analytics application in multi-criteria decision making: the case of eWallet adoption

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Babak Naysary[1], Mehdi Malekzadeh[2], Ruth Tacneng[3], Amine Tarazi[3 4]
[1] Monash University, School of Business, Selangor, Malaysia
[2] ServiceRocket Inc., Kuala Lumpur, Malaysia
[3] Université de Limoges, LAPE, 5 rue Félix Eboué, 87031 Limoges Cedex 1, France
[4] Institut Universitaire de France (IUF), 1 rue Descartes, 75231 Paris Cedex 05, France

This draft: February 24, 2022

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Abstract
This multidisciplinary study aims to overcome the shortcomings of traditional data collection methods used in the literature to investigate drivers of e-wallet adoption. We apply big data analytics to gather and analyze real-world data from users' sentiments and opinions available on online platforms. We use a text analytics approach to identify and categorize principal themes of concern affecting user adoption. After, we use the Analytical Hierarchy Process (AHP) technique to weigh and rank these themes and subsequently construct a structural framework for choosing the optimal e-wallet alternative in the market. Our results identify 10 clusters of e-wallet adoption drivers that can be categorized into three groups. The first group includes factors such as usefulness, ease of use, trust, risk security, and associated costs, confirming existing findings in the literature. The second group reinforces the importance of more implicit factors which existing theories fail to integrate, such as customer service, user interface, and promotional rewards. And finally, the last group comprises interoperability, highlighting the importance of e-wallet connectivity and how conveniently it performs transactions with other platforms, systems, and applications. Based on the results of clustering and the AHP model, we provide several managerial recommendations that can guide decision-making and eventually optimize the performance of e-wallets. Our study makes significant contribution by adopting a holistic, multi-criteria framework to evaluate e-wallet adoption comprehensively.

Keywords: E-wallet adoption, big data analytics, AHP, mobile payment, text mining
JEL codes: G10, G23, D81, O33

[1] Email: bnaysary@hotmail.com
[2] Email:me.malekzadeh@gmail.com
[3] Email:ruth.tacneng@unilim.fr
[3,4] Email:amine.tarazi@unilim.fr

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Abstract

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1. Introduction

The development of financial technology (fintech), particularly e-wallets, coupled with the entrance of Bigtech firms (e.g. Google, Apple, and Samsung) in the digital payment industry, pose potential disintermediation risk to banks. The prospect of a China-like situation where millions of customers jumped to mobile wallets, leapfrogging the use of bank cards, is not far-fetched (Sharma, 2019). Global initiatives towards facilitating contactless and mobile payments, for example, demonetization policy in India in 2016 to push for digital payments (Rolfe, 2020), the European Union's second Payment Services Directive (PSD2) mandated in 2020 to promote competition between banks and fintech service providers, the launch of fintech regulatory sandbox by the Central Bank of Malaysia in 2016 to encourage the development of fintech services including payments and launching a WhatsApp-based digital payments service by Facebook for the app's 120 million Brazilian users (Murphy, 2020) support this notion. However, despite these initiatives and various benefits that may be derived from using mobile payments, such as convenience (Pham & Ho, 2015), lower service cost, and increased value-added service (Apanasevic & Arvidsson, 2016) provided by new technological enablers such as Quick Response (QR) code, wearables, and various applications (Capgemini, 2016), e-wallet adoption worldwide is still low (Teng & Khong, 2021). For example, 79 percent of in-store transactions in India were settled in cash in 2019 (Statista, 2019). In the United States and South America, e-wallet and mobile payment usage are only 23.7 percent and 13.8 percent, respectively (Statista, 2019). In Malaysia, 72 percent of total transactions in 2020 were cash-based (Bruno et al., 2020). In France, bank cards are still the dominant payment method for e-commerce accounting for 53.9 percent of transactions (J.P. Morgan, 2019). This is surprising since smartphone use, and internet connectivity is high, almost to the point of saturation even in developing countries (Economic Times, 2017). Consequently, several studies have been conducted to identify key factors affecting e-wallet adoption. They rely on different theoretical perspectives such as the theory of diffusion of innovation (DOI) (Apanasevic & Arvidsson, 2016; Johnson et al., 2018; Kapoor et al., 2015; Shao et al., 2019), innovation resistance theory (Kaur et al., 2020; Leong et al., 2020); perceived risk theory (Barkhordari et al., 2017; de Kerviler et al., 2016; Yang et al., 2015); technology acceptance model (TAM) (Pu et al., 2020; Sharma et al., 2019; Singh et al., 2020; Williams, 2021) and; unified theory of acceptance and use of technology (UTAUT) (Cao & Niu, 2019; Chaiyasoonthorn, 2019; Hussain et al., 2019; Teo et al., 2015). However, results from these studies are inconclusive and, in some cases, contradictory, as shown in Table 1.

Table 1: Factors influencing the use of e-wallets: a survey of results in the literature

	No. of respondents	Perceived security	Perceived trust	Perceived risk	Usefulness	Social influence	Ease of use
Barkhordari et al., 2016	246	✓	✓				
Cao and Niu, 2019	614			✓	✓	✓	
Hussain et al., 2018	247				✗	✓	✓
Johnson et al., 2018	275	✓		✓			✓
Kapoor, 2014	323						✓
Kaur et al., 2020	1256		✓	✓			
Leong et al., 2019	478			✓			
Pu et al., 2020	165		✗		✓		✗
Shao et al., 2019	784		✓	✓			
Sharma et al. 2019	212	✓	✓		✓		✗
Singh et al., 2020	439	✗			✗	✓	✓
Teo et al., 2015	194				✗	✗	✓
Williams 2021	237	✗	✗	✗	✓		✗
de Kerviler et al., 2016	363			✓		✓	✓

We note that these studies mainly rely on traditional data collection methods such as surveys and interviews, which often suffer from limited reachability to respondents. Thus, results from these studies might be only applicable to the respondents and not to all types of users. Moreover, most of these studies employ a simplistic approach, often using only one modeling approach to study a complex phenomenon encompassing economic, social, and individual perception factors. To address these research limits and gaps, we employ big data analytic techniques to examine the reasons behind low e-wallet adoption. For this purpose, we study one of the biggest e-wallet providers in Malaysia, BigPay, to better understand the factors influencing the optimal use of e-wallets amongst users. We collect real-world data (from May 2019 to June 2021) of e-wallet users' opinions and sentiments from social media platforms using web scraping software. We then use text mining to identify and categorize themes discussed by users. Further, we use the Analytical Hierarchy Process (AHP) method to construct a structural framework to define the optimal e-wallet provider in the market. AHP is a commonly-used MCDM techniques that is appealing due to its ease of applicability, providing a clear picture of e-wallet providers' performance using a hierarchy of predetermind criteria. Incorporating various analytical approaches, we investigate two main research questions: (1) what are the main factors influencing e-wallet adoption?; and (2) based on these factors, what is the optimal framework for choosing an e-wallet provider? The novelty of this study comes from two aspects: First, this is among the first attempts to employ big data analytic techniques to collect a significant volume of real-world data in the context of e-wallet adoption. Second, it is among the few studies to identify and prioritize the antecedents of e-wallet adoption using a multi-criteria decision-making (MCDM) approach. The holistic structural model we developed based on the inputs gathered from social media users ensures greater practical validity enabling managers of e-wallet service providers to have a more realistic and comprehensive view of customers' perceptions and analyze the performance of their operations more efficiently and systematically.

The remainder of the paper is organized as follows. Section 2 provides an overview of the related literature, while Section 3 provides an account of the methods employed, and Section 4 presents and discusses the results. Finally, closing observations comprising study limitations and recommendations for additional work are presented in Section 5.

2. Related Literature

2.1. E-wallets

Financial technology (fintech) has become an integrated part of everyday life for the past decade by revolutionizing business models in the financial industry, eliminating barriers to access to financial services, and increasing the efficiency of financial services provision. One of the most prominent and fastest-growing fintech innovations, constituting more than 50 percent of the industry, is mobile payment fintech solutions (Williams, 2021). Mobile payments can be defined as "a type of payment transaction processing in which the payer uses mobile communication techniques in conjunction with mobile devices for initiation, authorization, or completion of payment" (Goeke & Pousttchi, 2010). Approaches to mobile payments include but are not limited to: near field communications (NFC), barcode or QR code, mobile phone card reader, and direct mobile payments without using banks (Lee & Shin, 2018). According to the Bank for International Settlements (BIS), the payment chain can be structured in five stages: (1) pre-transaction, (2) authorization, (3) clearing, (4) settlement, and (5) post-transaction (BIS, 2014). Financial incumbents often outsource payment and technology-related services for front-end (authorization, pre, and post-transaction) and back-end (clearing and settlement) services. In contrast, as shown in Fig. 1, e-wallets have been recently undertaking the whole payment chain (BIS, 2014).

Among the reasons behind the popularity of e-wallets is the range of advantages they provide to both merchants and consumers. Benefits to businesses include brand promotion, increased profits by facilitating impulsive purchase and attracting new customers (Mallat & Tuunainen, 2008), lower fees, lower payment processing cost, and speeding up settlement (Hayashi & Bradford, 2014). For consumers, e-wallets enable purchases independent of time and location. Hence, they are more convenient to use (Mallat & Tuunainen, 2008), offering additional services like peer-to-peer money transfer, ticketing, and loyalty programs (Apanasevic & Arvidsson, 2016). We note, however, that their adoption rate is still low despite their advantages and the fact that fintech services play a significant role in promoting financial inclusion worldwide (Teng & Khong, 2021). Therefore understanding consumers' perspectives on what drives or inhibits e-wallet adoption is essential.

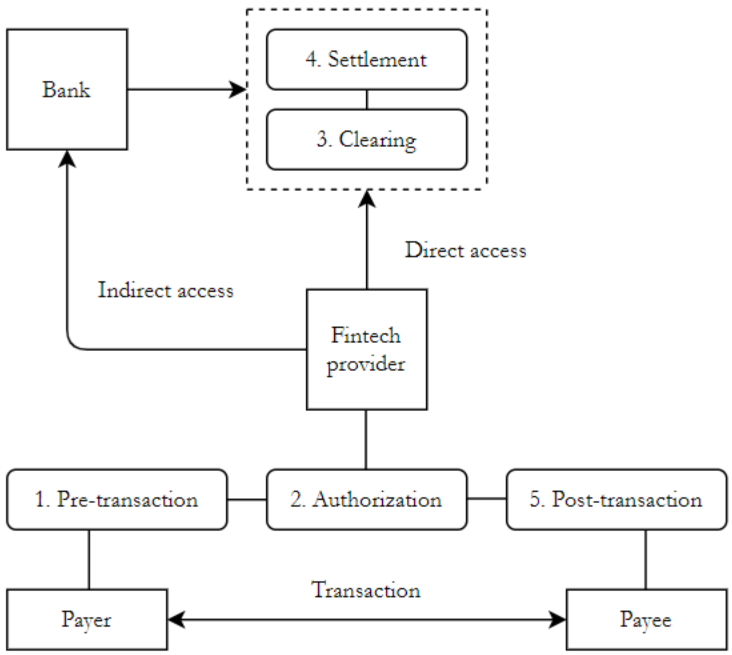

Fig. 1. Fintech payments landscape. Source: Adapted from (BIS, 2014).

2.2. Mobile payment adoption

Various approaches have been used in the literature to predict the likelihood to use mobile payments; however, the results are fragmented and, in many cases, contradictory. For instance, TAM theorizes that an individual's behavioral intention to use technology is determined by two beliefs: perceived usefulness and perceived ease of use (Davis et al., 1989). On the one hand, perceived usefulness is the extent to which a person believes that using the technology will enhance his or her performance. Cao & Niu (2019), Pu et al. (2020), Sharma et al. (2019), and Williams (2021) find usefulness to be one of the most influential factors in mobile payment (m-payment) adoption. In contrast, Hussain et al. (2019), Singh et al. (2020), and Teo et al. (2015) argue that mobile phone users may not be attracted to the usefulness gained from m-payment use.

On the other hand, perceived ease of use encompasses the belief that technology use will be free of effort. The results of de Kerviler et al. (2016), Hussain et al. (2019), Johnson et al. (2018), Kapoor et al. (2015), Singh et al. (2020) on the significance of ease of use contradicts the findings of Pu et al. (2020), Sharma et al. (2019) and, Williams (2021). The latter studies find no relationship between ease of use and m-payment adoption. As an extension to TAM, UTAUT has also been used to measure the influence of information technology on user adoption behavior (Venkatesh et al., 2012). In the UTAUT model, user adoption is affected by social influence, performance expectancy, and effort expectancy. Social influence is the degree to which individuals perceive that important others (exp. family and friends) believe they should adopt a particular technology (Venkatesh et al., 2012). Several authors find social influence a significant determinant in m-payment adoption intention (Cao & Niu, 2019; de Kerviler et al., 2016; Hussain et al., 2019). However, other findings (Singh et al., 2020b; Teo et al., 2015) indicate that m-payment users make their adoption decisions independent of their peers and social influence. Moreover, performance expectancy is the degree to which an individual believes that using the system will help him or her attain gains in job performance (Venkatesh et al., 2012). While some authors find a positive link (Cao & Niu, 2019; Hussain et al., 2019) between performance expectancy and m-payment adoption, others find no significant relationship between the two (Teo et al., 2015), arguing that this may be due to respondents' difficulty to comprehensively assess m-payment's perceived benefits. Effort expectancy is the degree of ease associated with using the system (Venkatesh et al., 2012). Most studies (Cao & Niu, 2019; Hussain et al., 2019; Teo et al., 2015) find a significant positive impact of effort expectancy on intention to adopt mobile payment.

The theory of diffusion of innovations (DOI), which was proposed in 1962 by Rogers, (Rogers, 2003, p.5), defines the diffusion process as the communication of an innovation "through certain channels over time among the members of a social system." Among the factors included in DOI is the visibility or observability of innovation are visible to others (Apanasevic & Arvidsson, 2016). While Johnson et al. (2018) show a direct positive impact of visibility on the intention to adopt m-payment services, Kapoor et al. (2015) do not find image and application visibility influential on consumers' m-payment decisions. Perceived risk (Yang et al., 2015) or the uncertainties due to the technology itself, vendor, regulatory environment, and the nature of the service may also affect m-payment use. Perceived uncertainty comprises perceived technological, information, regulatory uncertainty, and service intangibility. Results of several studies (Kaur et al., 2020; Leong et al., 2019; Shaor et al., 2019) provide credence to this except for Williams (2021). He suggests that the perception of a secure environment appears to only partially influence the intention to use m-payments.

As mentioned in Chaiyasoonthorn (2019), applying individual theories in m-payment adoption studies may not comprehensively picture the factors affecting m-payment adoption. Indeed, some studies using the same model produce different and, in many cases, contradictory results. We argue that one of the possible reasons behind this inconsistency is the application of traditional survey methods to explain a ubiquitous and complex phenomenon. Another shortcoming of these methods is that they don't distinguish between users and non-users of m-payments in surveys, solely focusing on the intention to use. To overcome these gaps and address the need to involve a broader range of actual users (Teng and Khong, 2021) to study e-wallet adoption and integrate data science approaches to understand business needs, we argue that it is imperative to use big data analytics to extract a large volume of data from actual eWallets users in social media.

2.3. Big data analytics

Big data analytics has been at the forefront in response to the need for sufficient and high-quality data for efficient decision-making. Big data describes large volumes of high velocity, complex and variable data that require advanced information analysis techniques (Vu et al., 2012). One of the largest Big data sources is social media, which provides an enormous amount of continuous real-time data making traditional techniques unsuitable for data analysis (Injadat et al., 2016). In business studies, Davenport and Patil (2012, p.73) indicate that it is essential to "…understand how to fish out answers to important business questions from today's tsunami of unstructured information". Thus, various attempts have been made to use data mining to analyze unstructured data, such as text mining techniques to unearth hidden patterns or trends and construct models to interpret data. For instance, Dinçer et al. (2020) employ data mining techniques to evaluate customer satisfaction for mobile applications in 24 Turkish banks using 500 customer reviews. Employing data mining techniques, they identify keywords from customers' comments and classify them into four categories. Using the fuzzy methodology, they weigh the dimensions and identify functionality and usability to be the most critical factors for customers in mobile banking applications. Similarly, Goyal and Kar (2020) find network quality, service interaction quality, and customer support as key factors in customer satisfaction of telecommunication companies in India using data mining on Twitter accounts. Data mining techniques have also been used in financial studies. For example, Fung et al. (2003) use text mining on textual documents and time series techniques to predict the stock price movement based on news articles. Moreover, Vu et al. (2012), show a significant relationship between customer sentiment and stock price movement by using text mining on Twitter messages. Jin et al. (2013) identify the effect of Bloomber news articles on the foreign exchange market by mining the news articles and forecasting the trends and future movement of currencies.

Despite the significance and use of Big data and data mining techniques to assess and evaluate existing real-world data (Lin et al., 2021), very few studies focus on its application toward fintech use, particularly e-wallet adoption. Therefore, this study aims to fill this gap in the literature by using real-world customer data and data and text mining techniques to identify the drivers and inhibitors of e-wallet adoption.

3. Research design

3.1. Case study

Given the multifaceted and context-dependent nature of mobile payments, this research applies an exploratory case study approach to identify and explain what drives mobile payment adoption. Chae and Hedman (2015) argue that case studies are valuable when the research aim is to gain a comprehensive understanding of the context of a particular research field. Therefore, we adopt a case study approach to provide an in-depth and contextual understanding of e-wallet adoption by focusing on BigPay in Malaysia. Since its launch in 2018 until 2021, BigPay has reached 1.3 million customers and 800 thousand merchants in Malaysia. According to the Ministry of Finance in the eBelia[5] program (a government initiative to assist and encourage youth to use cashless payments in 2021), BigPay is the newest of the top four e-wallet providers in Malaysia. Studying BigPay is relevant for the e-wallet adoption research because apart from market and customer reach, it provides varied and extensive payment services, such as providing Mastercard® that can be used for global remittances and ATM withdrawals. BigPay also offers flexibility in top-up services, including cash top-ups in 7-Eleven supermarkets across the country (Digital News Asia, 2021) which are not provided by any of the top eWallet providers.

According to the World Bank, although 85% of the population in Malaysia have bank accounts and thus, have access to traditional financial services, only 55% receive their wages through bank account and only 34% use their bank account for savings (Luna Martinez, 2017). As indicated in the Global Findex Report (Demirguc-Kunt et al., 2018), while 41% of adults in Malaysia own debit cards, only 19% use them in their transactions. A recent study by Loo (2019) supports this, reporting that more than 40% of working adults in Malaysia still receive their salary in cash. Moreover, because of the extensive use of mobile internet in the country (93.5 percent of the population according to Statista (2021)), the increasing number of e-money providers (48 as of 2021), the plan to launch digital banks by 2022, and several government initiatives toward digitalization (exp. eBelia program), Malaysia is an ideal setting to analyze mobile payment adoption. We note that Malaysia shares similar characteristics in terms of financial inclusion and access index score with some other countries in the region such as Singapore, Brunei Darussalam and Thailand (OECD (2018)); therefore, the results of this study can be extended to these contexts.

3.2. Knowledge discovery in databases

In this paper, we identify and interpret the factors affecting e-wallet adoption using data mining techniques through a process called knowledge construction. Knowledge construction pertains to the active process of manipulating data to arrive at abstract models in the real world, thus facilitating our

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[5] Source: https://www.mof.gov.my/-/ebelia-rm300-million-e-wallet-credit-for-2-million-youths-and-full-time-students-opens-on-1-june-2021

understanding of the studied phenomenon (Lee et al., 2019). We use knowledge discovery in database (KDD), a nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data (Nelson, 2021). As shown in Figure 2, KDD is a multi-step process including web scraping, preprocessing, transformation, clustering, and interpretation, where data mining algorithms play a central role (Lee et al., 2019). Data mining in this research is conceptualized similarly to KDD, which includes the use of a vast database, computational techniques, automatic or semiautomatic search, and extraction of implicit, previously unknown, and potentially valuable patterns hidden in the data.

3.2.1. Web Scraping

We extract real-world data on the actual usage of BigPay from the website Lowyat.net (available at https://forum.lowyat.net/), which is Malaysia's largest online community launched in 2002 and allows users to create discussion threads to post comments on specific topics. The comments on Lowyat.net are individually-registered, enabling us to parse individual reviews and aggregate them for analytical purposes. For this, we develop a web crawler program using the Beautiful Soup[6] HTML parser package in Python on June 3, 2021 and download the HTML source of the relevant web pages. After cleaning and preprocessing the collected data, we gather a total of 12434 comments. Table 2 presents statistics on the length of comments in terms of the number of words.

3.2.2. Preprocessing

It is difficult, in general, to analyze free-form text from online comments because it does not have a standard structure. Moreover, in most cases, only a few words are informative regarding users' perception of e-wallet adoption. Therefore, we implement similar preprocessing steps used in the studies of Lucini et al. (2020), Teng & Khong (2021). We conduct 'text parsing' in Python using Natural Language Toolkit (NLTK) (available at https://www.nltk.org/), which is a set of libraries and programs for statistical natural language processing (NLP). It contains text processing libraries for tokenization, parsing, classification, stemming, tagging, and semantic reasoning for English language. To convert the unstructured text into a structured form suitable for data mining, first, we break down the continuous string of characters of each sentence into linguistic units called tokens. After tokenization, we reduce the words into their stem or roots (stemming). Next, we apply part-of-speech (POS) tagging to identify the syntax function of each token (Teng & Khong, 2021).

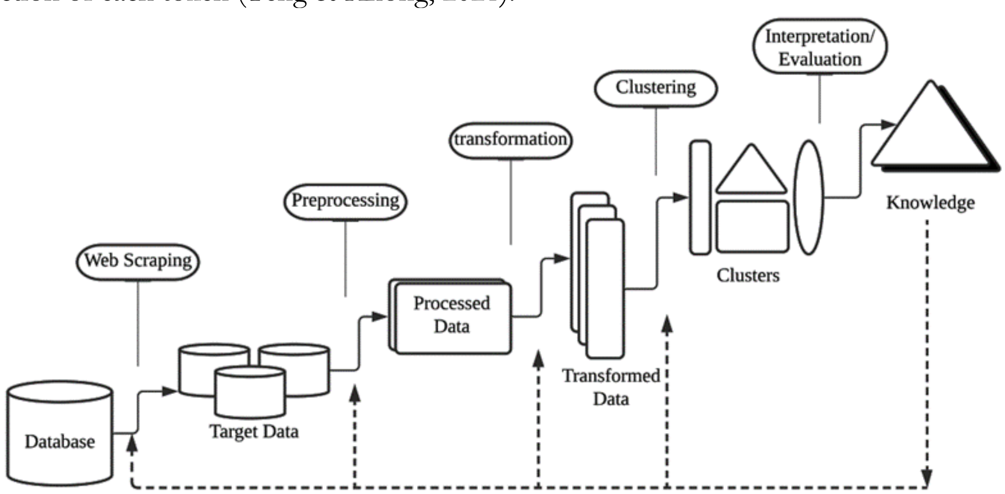

Fig. 2. Knowledge Discovery in Database (KDD) (adapted from Lee et al. (2019))

[6] https://beautiful-soup-4.readthedocs.io/en/latest/

Table 2: Statistics on the comments made on BigPay in terms of the number as of June 2021

Minimum	Q1	Median	Q3	Maximum	Mean
1	22	39	65	2243	53.527

Note: Q1 first quartile, Q3: third quartile. Source of comments: Lowyat.net

3.2.3. Transformation

After text parsing, we perform text filtering to reduce the total number of terms. We use the English language in the filtering process. Furthermore, we remove pronouns, prepositions, auxiliary verbs, and conjunctions to reduce the noise.

Finally, consistent with Lucini et al. (2020), we exclude low-frequency tokens (i.e., below 2 percent). Thus, for example, an original comment that read:

"I have issues to reload my wife bigpay using my cc since 1/6"

became

"'issue', 'reload', 'wife', 'bigpay', 'use', 'cc', '1/6'"

Once all comments have been transformed, we create a matrix indicating the occurrence of tokens in comments. We fill out matrix cells using the term frequency and inverse document frequency (TF-IDF) (Lucini et al., 2020). The TF-IDF approach uses total document frequency matrix weights (Eq. 1).

$$tf - idf = tf \times log \frac{no\ of\ docs}{docs\ containing\ term} \quad (1)$$

where *tf* is the term frequency, *idf* is the inverse document frequency and *log (no. of docs/docs containing term)* is thelogarithmically scaled inverse fraction of the documents that contain the word.

Using the TF-IDF approach, we minimize the effect of stop words, i.e., common words are given lower weights. In comparison, significant words that only frequently appear in a small number of documents are assigned higher weights.

3.2.4. Clustering

Since a manual check of all collected information is impractical, we use clustering to identify groups of similar documents in the collection (Allahyari et al., 2017). Clusters can reveal the central themes and key concepts in the documents, which facilitate the understanding and summarizing of the collection without going through each document individually (Härkänen et al., 2019). For this purpose, we implement a clustering algorithm in Python. Clustering algorithms are distance-based; they use similarity functions to measure the distance between the texts (Allahyari et al., 2017). Accordingly, we use the weighted Euclidean distance and a term based on stylistic information (Eq. 2). We define the distance between D_u and D_v as follows:

$$\Delta(D_u,D_v) = \alpha\cdot \Delta^{(f)} (D_u,D_v) + (1 - \alpha) \cdot \Delta^{(s)}(D_u,D_v) \quad (2)$$

Where α represents the weight, and $\Delta^{(f)}$ and $\Delta^{(s)}$ are the Euclidean and stylistic terms, respectively. The calculated distance between clusters represents the association amongst the key terms. To make sense of the themese of the topics, besides the text clustering results from Python, we perform manual data interpretation and cluster labeling based on existing studies in the literature. We also observe and explain additional patterns which are not considered in previous studies. We show the results of text clustering in Table 3.

Table 3: Clustering Results

Clusters	Interpretations (Labels)	High loading terms
0	Usefulness	Card, use, transfer, pay, cash, merchant, bill, petrol
1	Ease of use	Bank, credit, account, withdraw, atm, reload, easy, MasterCard
2	Risk	Fail, wrong, error, risk, lose, refund, remove
3	Customer service	Ask, call, service, wait, support, long, replace
4	User interface	App, system, update, feature, login, notification
5	Security	Fraud, scam, security, freeze, otp, verification
6	Interoperability	Boost, shopee, paypal, tng, aeon, Lazada, grab, fave
7	Associated costs	Exchange, charge, currency, conversion, fee, cost
8	Promotional reward	Point, cashback, airasia, reward, flight, earn, redeem
9	Trust	Settle, trust, sure, reject, unable, success, issue

To have a clear projection of the clustering of comments, we use t-distributed stochastic neighbor embedding (t-SNE)[7] to get centroids in two dimensions (see Fig. 3). T-SNE is a non-linear technique for dimensionality reduction that is particularly well suited for visualizing high-dimensional datasets. It is advantageous over the principal component analysis (PCA) because of its ability to retain non-linear variance, and hence, local variance. The projection shows that the bordering of the classified 10 clusters is narrow with overlapping layers.

3.2.5. Interpretation

To interpret the data generated by the text mining process highlighted in the previous sections, we employ an inductive approach, which is a systematic procedure to analyze data, guided by specific evaluation objectives. This approach allows the research findings to emerge from significant themes without the restraints imposed by structured methodologies. Thus, we review the comments extracted from the Lowyat.net website about high loading terms in each cluster individually. To explain the clusters, we adopt a narrative approach following the study of Teng & Khong (2021), which comprises the analysis of users' comments excerpts to highlight the real-world human experience with e-wallet adoption. We discuss the cluster interpretations in Section 4.

[7] https://www.scikit-yb.org/en/latest/api/text/tsne.html

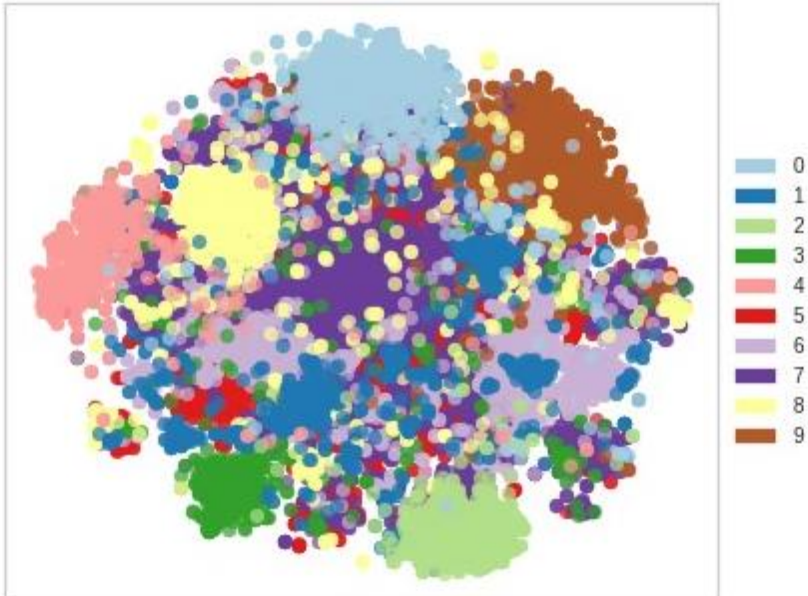

Fig. 3. t-SNE projection of 12434 comments

3.3. Data analysis

To evaluate the proportional weight of the identified factors in the previous section and construct the framework for the optimal selection of e-wallet alternatives in the market, we use the Analytical Hierarchy Process (AHP) technique. The AHP, which is a multi-criteria decision-making (MCDM) method developed by Saaty (1990), is one of the most widely-used and effective tools for assessing multifaceted and intuitive decision-making problems (e.g., Kheybari et al., 2019). In the context of this study, we build hierarchical and alternative structures, as shown in Fig. 4 below.

As shown in Fig. 4, the AHP hierarchy is composed of the goal, criteria, and alternatives. In this research, the criteria, initially identified from previous studies, are extracted from real-world comments using data mining techniques. The alternatives i.e. competing service providers, were chosen amongst the top e-wallet providers in Malaysia as described in previous sections. To rank them, we execute pairwise comparison by completing a questionnaire with AHP linguistic scales (see Table 4) distributed to 19 experts who were chosen among the university faculty members (12 respondents) and banking professionals (7 repondents).

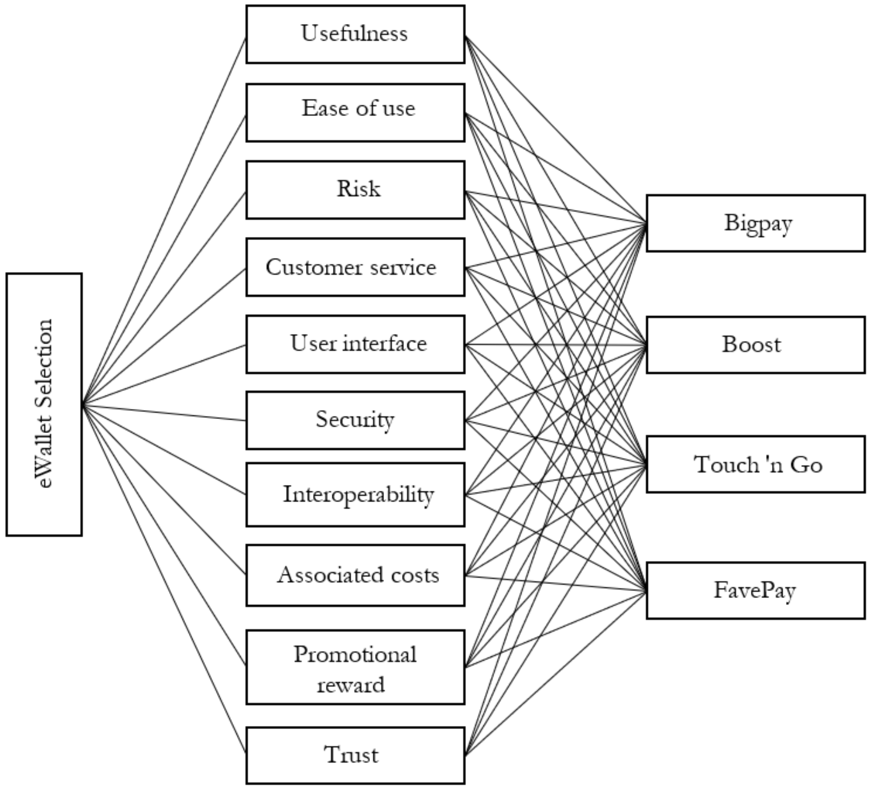

Fig. 4. Hierarchy of Criteria and Alternatives

Table 4: Linguistic values for each criteria

Linguistics values	AHP Equivalent
Extreme importance/preference	5
Very strong importance/preference	4
Strong importance/preference	3
Moderate importance/preference	2
Equal importance/preference	1

We record the experts' judgments in a matrix of pairwise comparisons $A = (a_{ij})_{n\times n}$, where *n* represents the number of parameters, and a_{ij} denotes the pairwise comparison of parameter *i* with parameter *j*. To aggregate the responses into one individual judgment a_{ij}^{group}, we calculate the geometric mean:

$$a_{ij}^{group} = \sqrt[m]{\Pi_{k=1}^{m} a_{ij}{}^{k}} \tag{3}$$

Where $a_{ij}{}^{k}$, k = 1, ..., m are the individual judgments of m decision-makers or experts. Saaty & Özdemir (2014) indicate that the geometric mean (Eq. 3) is the most appropriate method to aggregate experts' preferences as it satisfies necessary axiomatic conditions such as preserving reciprocity. To run the AHP analysis, we use the software 'SuperDecisions version 3.2' developed in 1996 by Thomas Saaty.

4. Results

In this section, we present 1) the interpret the ten clusters identified through the KDD process to answer the first research question: what drives e-wallet adoption?, and 2) the results of the AHP analysis to assess the relative importance of the clusters and consequently answer the second research question: what is the optimal framework for choosing an e-wallet provider?

4.1. Cluster interpretation

The data mining process has produced ten different clusters. We report in this sub-section the results of the inductive approach, which consists of analyzing users' comments excerpts to understand their actual experiences, to interpret the identified clusters.

4.1.1. Usefulness

A considerable number of users' comments were about BigPay's usefulness, corroborating the TAM theory, which suggests that perceived usefulness is one of the critical indicators of users' technological adoption intention (Davis et al., 1989). Perceived usefulness pertains to the degree to which a person believes that using a particular technology enhances and facilitates his or her performance. Most of the comments in this cluster indicate positive perception and functionality of BigPay in online booking (e.g., Agoda), bill payments and bill-splitting, ticketing and payment for public transportation, and student loan payments (e.g., National Higher Education Fund Corporation), to name a few.

New BP user here. successfully paid unifi bill yesterday.

Have used it last month in MRT Singapore. Works well, same charges as for EZ link card.

However, some comments indicated user dissatisfaction with BigPay's refund process in cases of purchase cancellations, and double billings by merchants.

One thing I am very unhappy with BigPay is that they hold unsuccessful transaction amount for 7 to 10 days. Very classic example is pumping petrol which happens like at least once a month and RM40 to RM50 has to be pending for more than a week.

Several users also commented on the eventual addition of a feature that allows BigPay to integrate DuitNow QR payments, Malaysia's national QR code standard, which enables individuals and businesses to transfer money to mobile numbers and personal national ID or business registration numbers.

I hope bigpay keep evolving like integrate NFC payment into the app. Deploy DuitNow and DuitNow QR payment sooner.

This supports the results of Sharma et al. (2019), who indicate that the perceived usefulness of mobile payment services impacts consumers' intention to adopt them, implying that to attract potential customers, service providers must continuously improve their services and increase awareness of their functionality.

4.1.2. Ease of use

The second cluster can be linked to the ease of use, which according to the TAM theory is the degree to which a person believes that using a particular system would be free of effort (Davis et al., 1989). In contrast to other e-wallet providers in Malaysia, BigPay users commended the provision of a Mastercard, which can be used for online and offline, contactless (payWave) payments, and also for ATM withdrawals. In addition, the recent feature that enables customers to reload their accounts with cash was also deemed beneficial by the users.

I'm finally at Budapest now and been using BigPay for dining and groceries, small amount with no extra charge. So convenient and the metro ticket machine also accepts the card (PIN & Pay - 6 digits and contactless). I have not exchanged any Hungarian Forint yet, let's see how long I can survive.

Just reload my bp at 7eleven using barcode, had to explain to the cashier though as she was clueless at first.

Users, however, seem to be face issues brought by the non-recognition of BigPay Mastercards in some ATMs. Users have also commented on the daily withdrawal, bank transfer, and contactless payments limits. Moreover, some users also expressed their dismay at the additional costs of the cash top-up feature. We discuss further details about these costs in sub-section 4.1.8.

RHB TTDI Branch ATM retained my card as well. Tried to withdraw 4k but the limit was only 2k.

Tried to withdraw from HLB ATM and failed with the following error, anyone has the same?

Was expecting the points to be more achievable. Else, there's not much of a reason to use bigpay as a primary contactless payment method.

This result is consistent with Hussain et al. (2019), who find a positive link between ease of use and the actual use of m-payment services.

4.1.3. Risk

The third identified cluster is perceived risk, which may refer to potential losses due to technology adoption and subjective uncertainty of the outcomes and unfavorable consequences. It may pertain to different aspects such as financial risk, performance risk, and physical risk (Li & Huang, 2009). In the mobile payment studies, it was further incorporated in the theory of perceived risk and UTAUT as one of the decisive factors in m-payment adoption. Under this cluster, most of the comments mentioned issues related to ATM withdrawal, charging the client without disbursing the amount.

In bali, Indonesia right now. Running out of cash. Tried use bigpay withdraw, cash didn't dispense but bigpay app show amount deducted. Dealing with their CS now.

The first transaction passed through however the second time i tried to withdraw it showed transaction declined. However the money in my BP apps already being deducted. Currently already the 3rd months of the dispute investigation

However, other problems faced by the customers include long delays in the refund process, card malfunction with some merchants, and failure in online transactions and online top-ups from debit cards. Users also cited difficulties linking the app with Air Asia account to use the reward points, application bugs, and unsolicited transactions, some of which performed abroad.

I got charged twice from Bigpay and they promise to refund in 7 days. After 7 days, they asked me to fill a form and the refund now is in 60 days.

Hi, I tried to use bigpay for petrol at petronas. Use it like usual. But it gave me error55. What is that error?

top up bigpay with debit card, tac entered, money from bank deducted but bigpay show error and the money is not in bigpay. who should i call? my bank or bigpay?

In line with these, Cao and Niu (2019) indicate that perceived risk plays a significant role in mobile payment adoption by negatively influencing the customers' intention to use m-payments. They suggest that managers must enhance transparency and information about their products and improve defects and problems that could impact customers' perception

4.1.4. Customer service

Although not included among the adoption factors in conventional m-payment studies and the established theories until recently (Teng & Khong, 2021), we identify customer service as one of the essential quality dimensions in mobile payment services (e.g., Apanasevic & Arvidsson, 2016; Pu et al., 2020) from the clustering results. Based on BigPay user experience, a recurring topic concerns fake calls by scammers to obtain confidential customer information and access their accounts. We further discuss this issue in sub-section 4.1.6. *Security.* Additionally, there were few complaints about the lack of proper response and guidance by customer service.

so far only petrol station will require to key in pin, not all accept 6 digit pin….I do ask Bigpay customer service about using 4 digit pin, but however none of their answer usable.

But I do think banks have a better customer service. It has been horrible for me. I've been connected to at least 6 supports and none can give me a definitive answer. There's also no way for me to call them. I've emailed them too and no reply.

However, in various threads, users also express their satisfaction with the in-app customer support chat facility. Moreover, many indicate that compared to other e-wallet platforms, BigPay provides relatively better customer service.

BP having the best cs support among all others e wallet. U should try boost and see what happen, u never get any feedback at all is very common over there.

Comparing with other current e-wallet, BigPay still have the advantage of better customer service

4.1.5. User interface

The significance of user interface in m-payment adoption is, for the most part, covered under the umbrella of its perceived ease of use in the literature (i.e., Apanasevic & Arvidsson, 2016; Pu et al., 2020). However, the clustering results identify the user interface as an independent factor which highlights the significance of user experience with the app apart from other features and services offered by e-wallet providers, consistent with the results of Teng & Khong (2021). Issues highlighted by users range from different topics such as performed transactions not appearing in their app to restrictions on screenshots in the BigPay app (mainly for Android users).

The screenshot restriction only for certain android phone it seems? Bcoz my mi phone also can screenshot Bigpay app

I am using Android. I never used the BP card at any Apple devices. The transaction was performed on 11/10/19 (I didn't receive any notification till this morning) but settled on 13/10/19. Very abnormal, hopefully it is just a technical glitch.

They got back to me showing that the transaction was actually refunded. I refreshed my BP and yea the transaction appeared but balance remained. I contacted them again and they sent me a full bank statement showing with the balances after each transaction done. So yea. looks like they are having issue with the refunds being displayed but actually the amount was already in your BP balance all this while.

Furthermore, one of the recurring themes that appeared in the comments was the issue that Android users were facing while receiving the one-time password (OTP), which necessitated them to go to their messages and exit the BigPay app. This results in the user being logged out and transactions being terminated. Some users mentioned that they had to use two phones to overcome this issue, particularly for top-ups.

4.1.6. Security

Security concerns serve as attitudinal barriers for m-payment adoption and have been an integral part of predominant theories in the literature such as DOI, TAM, and UTAUT (e.g., Barkhordari et al., 2017; Johnson et al., 2018; Sharma et al., 2019). According to BigPay users' comments, the security concerns include scammers pretending to be customer support representatives. They ask for customers' OTP and attempt to withdraw cash using duplicated cards. Some users lament unknown transactions being charged to their account and transactions going through with invalid CVV. However, one of the positive points mentioned by users about BigPay's security is the availability of the Freeze option in the application, which allows them to immediately freeze their account without the need to contact the service provider.

Hi all, i just noticed that once a credit card is registered to "top up source", topup using that registered card does not validate the cvv anymore. I tested with multiple wrong cvv and the topup just went through. This is kinda dangerous right? Did anyone actually know about this? What's the point of requesting to key in the cvv then?

My Bigpay just got hacked with three unauthorized transactions charged to an unknown pharmacy in US while I'm in the UK. Ask for refund but the customer service team says it will take 60days for investigation.

Someone try to get out my money from ATM, the card is with me.......so dangerous.

4.1.7. Interoperability

With the availability of interoperability of e-wallet providers (including with bank and non-bank service providers), users can carry out transactions regardless of which e-wallet they own (Gomes, 2018). According to Boost CEO, Mohd Khairil Abdullah, interoperability is the industry's future and can lead to a smooth user experience, accelerating cashless adoption in the country (Safri, 2020). BigPay has the advantage of providing a Mastercard, which can be used more extensively in online transactions and payments to other e-wallets. However, users identify problems while transferring money to other service providers, including transaction limits. One of the initiatives taken by BigPay, as pointed out by users, is the ability to transfer loyalty points to other platforms such as Fave (e-wallet) and MESRA (petrol station). To our knowledge, the impact of interoperability on e-wallet adoption has not been tackled in the literature.

Anyone having problem top up boost with bigpay? I always receive 2 OTP but transaction fail after trying both.
Other than airasia, what other things can we spend with big points? Favepay or Petronas fuel (Kad Mesra).
The main purpose i use BP…. double/triple dip with other ewallets (get grabpoints/fave cashback + Bigpoints)
I just got my bp card last 2 weeks, previously only use for Shopee (I have change BP card as the only credit card when doing payment) and also top up to boost account.

4.1.8. Associated costs

According to DOI, service cost is one of the factors that reflects the relative advantage of provided services (Rogers, 2003) and can be considered along with the concepts such as economic benefits and added value of a service. In the literature, the associated costs of m-payment services are an impeding factor to users' intention to adopt these services (i.e., Apanasevic & Arvidsson, 2016; Kapoor et al., 2015). Most of the comments indicate a positive perception of users on the associated costs of BigPay services such as waived annual fees and currency conversion fees, advantages of BigPay in offering superior exchange rates compared to banks, and low cost of card replacement.

BP never fails to make me happy with super good forex rate. Gonna load in some money for my Euro trip in 2 weeks time, at least I don't need to change so much of Euro from Malaysia and then exchange from Euro to Hungarian Forint/Czech Koruna.
I'm interested in bigpay because i heard no yearly charges and no currency conversion charges.

However, there are unsatisfactory comments on the charges for the newly-introduced cash top-up service and the ATM withdrawal charges.

they imposed cash top-up fee now. RM2 per transaction of RM100 top up and RM5 per transaction above RM100. I would say bye bye to BP.

4.1.9. Promotional reward

Another determining factor identified in the clustering process influencing users' intention to adopt e-wallets and is, for the most part, disregarded in the conventional m-payment literature is the promotional reward and rebates. Awards and cashback on transactions are important selling points and often a competitive tool among e-wallet providers, as recognized in recent studies (Teng & Khong, 2021). BigPay offers cashback and rebates on top-ups and transactions (up to 10%) and provides Bigpoint rewards which can be redeemed for Air Asia flight fares or converted into other service providers points such as Petronas MESRA (Petrol station).

I am spending >RM1000 every month! Electricity, water, assessment bills, supermarkets, tuition, dining etc. Up to 7% rebate!
Cardholder rewards such as loyalty points and cash rebates are funded by merchants who are likely to recover such cost through higher prices of goods and services.
At last, somewhere to use my BIG Points. but very disappointed when look at the rate: 1,250 BIG points to 600 Mesra Points

However, it is worth mentioning that recently, all card issuers have been reducing their rewards/rebates because of restrictions imposed by Bank Negara's Payment Card Reform Framework.

4.1.10. Trust

As an essential factor for service quality in the m-payment industry, trust is conceptualized as the general belief by customers that their vulnerabilities will not be exploited by the services provider (Pu et al., 2020). Moreover, trust has been an integral part of dominant m-payment adoption theories such as TAM (Singh et al., 2020a) and UTAUT (Qasim & Abu-Shanab, 2016). The issue of trust among BigPay users, for the most part, revolves around complexities in the refund process and long dispute resolutions, uncertainty about maintaining the confidentiality of user information by the service provider, uncertainties on cash withdrawal in ATMs, and application-related issues such as performed transactions not appearing on the app and unknown transactions included in the list.

the issue I see from bp is their lack of experience and support to handle transaction disputes. they are young, compared to existing conventional banks which has established their cc business and processes for decades.
I like the whole idea of the card, unfortunately, some serious issue comes with it. they take your money and only give it back to you months later. In my case, I got charged twice from Bigpay and they promise to refund in 7 days. After 7 days, they asked me to fill a form and the refund now is in 60 days. What a reliable trustworthy institution.
Given the high number of reported cases on scam calls, just wondering if there's actually any leakage out there.

4.2. Analytic hierarchy process

In this section, we present the results and discuss the weights of the various e-wallet adoption criteria (identified through the KDD process). We also tackle the weights and discuss the ranks of alternative e-wallet providers.

This paper identifies 10 clusters or criteria affecting users' decision to adopt e-wallets that experts further evaluated. In the first step, each criterion was compared pairwise with other criteria on a scale of 1 to 5 to determine their relative importance. To ensure consistent perception among the experts, we defined each criterion at the beginning of the questionnaire. We present the global weight of each criterion in Table 5, with the last column indicating its overall ranking.

Table 5: Global weight of criteria

Criteria	Global weight	Rank
Usefulness	0.2350	1
Risk	0.2130	2
Ease of use	0.1617	3
Customer service	0.1595	4
User interface	0.0953	5
Trust	0.0500	6
Promotional reward	0.0334	7
Associated costs	0.0198	8
Interoperability	0.0170	9
Security	0.0152	10

According to the results, usefulness is the most crucial factor for the users while considering the e-wallet followed by risk, ease of use, customer service, user interface, trust, promotional reward, associated costs, interoperability, and security.

Similarly, the alternatives in the third level of the hierarchy are pairwise-compared to their associated criteria at the second level. In other words, the advantage and preferability of each e-wallet provider based on each criterion were compared to other e-wallet providers in a pairwise matrix. We show the comparison values for each alternative in Table 6 with their final weight and ranking in the last row.

Table 6: Performance of alternatives in criteria

Criteria	BigPay	Boost	Touch'n Go	FavePay	CR
Usefulness	0.0459	0.3031	0.5177	0.1334	0.0891
Risk	0.0479	0.2027	0.5988	0.1506	0.0969
Ease of use	0.1096	0.1433	0.6974	0.0497	0.0993
Customer service	0.0429	0.1612	0.6171	0.1787	0.0951
User interface	0.0515	0.1704	0.6531	0.1250	0.0834
Trust	0.0877	0.2758	0.5846	0.0519	0.0886
Promotional reward	0.0460	0.2157	0.6218	0.1165	0.0984
Associated costs	0.0818	0.2855	0.5842	0.0484	0.0935
Interoperability	0.0972	0.2087	0.6428	0.0512	0.0900
Security	0.0456	0.2097	0.6350	0.1098	0.0984
Weight	0.0604	0.2129	0.6049	0.1219	-
Rank	4	2	1	3	-

Throughout the evaluation process, the consistency ratio (CR), reported in the last column, of each paired comparison matrix should be less than the threshold value 0.1 (Saaty, 1990). Based on the results, the respondents were consistent in ranking the alternative e-wallet providers according to attributes. Touch'nGo e-wallet was ranked first, followed by Boost, FavePay, and BigPay.

5. Discussions and conclusion

In response to a backdrop of practical relevance and inconclusive results, this paper has set out to contribute to the body of knowledge towards a better understanding of the factors influencing users' intention to adopt e-wallets. Additional novel aspects include the use of big data analytics including web-scraping and text mining, in particular, to collect real-world user data, along with the application of the AHP model to weight and rank the factors and rank the e-wallet providers using experts' opinions.

Factors identified through the clustering process can be divided into three groups. The first group includes factors that are established as an integral part of existing theories in m-payment research including usefulness and ease of use (TAM theory), risk (perceived risk and UTAUT theory), trust (TAM and UTAUT theory), associated costs (DOI theory) and security (TAM, UTAUT, and DOI theory). The second group includes factors which although not directly indicated as adoption factors in conventional m-payment studies and theories, but have been identified as important quality dimensions in m-payment services including customer service, user interface (Apanasevic & Arvidsson, 2016; Pu et al., 2020) and promotional reward (Teng & Khong, 2021). This research reinforces the importance of these factors as they were ranked even higher than security and trust, and recognizes the need for theoretical modification in m-payment literature. The last group contains the only remaining factor which is interoperability. Introduced through clustering and further interpretation of comments, interoperability refers to the connectivity of e-wallet and how conveniently it performs transactions with other platforms, systems, and applications, particularly with regards to top-ups, transfer of loyalty points, and recognition by various merchants and online shopping platforms. Identification of this factor is one of the practical contributions of this paper as the m-payment literature is for the most part silent in this regard. It is worth mentioning that, there exist factors such as visibility (Johnson et al., 2018; Kapoor et al., 2015) and social influence (Cao & Niu, 2019; Hussain et al., 2019) indicated in the literature which was not identified in the course of the clustering process. Additionally, information such as age, education, nationality, and income could not be extracted from the data which is considered a limitation for the present paper. Although based on the research method, no particular theory was employed, but the most commonly used theories and their results were studied and referred to by cross-checking the results of this paper with their findings in the literature, which provides a basis for researchers for further refinement of individual models in m-payment adoption and can be a starting point for future research.

The application of AHP as a multi-criteria decision making framework provides several managerial implications. Based on the results and also data on financial inclusion in Malaysia is it clear that service providers are not dealing with the unbanked but rather it is underbanked who needs to be served. A task in which the current conventional banking system has failed. The results of AHP together with the interpretation of clustering through users' comments, provide necessary information about the influential measures which can be used by e-wallet providers in Malaysia to improve their service quality. Accordingly, the following recommendations can be considered: more efficient refund process in cases of double billing and cancelations, reconsidering daily withdrawal limits, employing more informed and knowledgeable customer service or providing continuous necessary training for existing employees, resolving technical difficulties such as having to exit the app upon receiving OTP and redo the transaction which results in customers being logged out, reconsidering extra charges imposed on top-ups and withdrawals considering the intense competition in e-wallet market in Malaysia, continue to expand connectivity with other service providers, impose more security measures to safeguard the customers and strengthen the consumer data protection measures. In this regard, Touch'nGo can be considered as a model for service providers as it was ranked first with considerably higher weight.

Limitations of the current study are acknowledged in terms of its inability to collect users' demographic information and also separating the comments for people who are already using the e-wallet and those who are planning to use it. Future research can replicate the current study by using users' data from other social media platforms such as Facebook and Twitter. Furthermore, as this study is limited to the Malaysian e-wallet market, future studies can explore other regions including countries with higher and lower fintech development levels to strengthen the generalizability of results.

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